D^{4}AR- 4 DIMENSIONAL AUGMENTED REALITY- MODELS FOR AUTOMATION AND INTERACTIVE VISUALIZATION OF CONSTRUCTION PROGRESS MONITORING

BY

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DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Civil Engineering
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2010

Urbana, Illinois

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ABSTRACT

Early detection of actual or potential performance deviations in field construction activities is critical to project management as it provides an opportunity to initiate proactive actions to avoid these deviations or minimize their impacts. Despite the importance, (1) current monitoring methods require manual as-built data collection and extensive as-planned data extraction; (2) due to extensive workload, observations are sometimes conducted infrequently and progress is measured with non-systematic metrics; and (3) current reporting techniques are visually complex which requires more time to be spent on communicating the status of a project. There is a need for a systematic approach allowing data to be collected easily, processing the information automatically and reporting back in a format useful for all project participants.

This research addresses these challenges by introducing D^4AR – 4D Augmented Reality – models as integrated as-built and as-planned environments. These models, generated for automated tracking and visualization of construction performance deviations, take advantage of two emerging sources of information: (1) Unordered daily construction photo collections, which are nowadays collected at almost no cost on all construction sites; and (2) Building Information Models (BIMs), which are increasingly turning into binding components of Architecture/Engineering/Construction (AEC) contracts and if linked with construction schedule, can serve as powerful baselines for tracking and visualization of performance deviations.

In this research, an approach based on structure-from-motion technique is presented which operates on a set of unordered and uncalibrated daily construction photographs, automatically computes photographer's locations and orientations, and generates a 3D point cloud representation of the as-built site. Within such an environment, images are registered in 3D, allowing large unstructured collections of daily photos to be sorted, interactively browsed and explored. Reconstructed as-built point clouds, generated with different photo collections assembled in different days, are automatically superimposed over one another using an iterative closest point algorithm and consequently result in 4D as-built models. Next, 4D BIMs are fused into 4D as-built point cloud models by control based registration-steps and generate D^4AR models. The as-built point cloud models are enhanced with a multi-view stereo algorithm and are fed into a novel voxel coloring and labeling algorithm to increase density of the as-built point cloud models, and traverse and label the integrated as-built and as-planned models for expected visibility and observed occupancy. Finally, a machine learning scheme built upon a Bayesian probabilistic model is presented which automatically detects physical progress in presence of occlusions and demonstrates that component-based progress monitoring at schedule activity-level could be automated. The system developed in this research enables as-planned and as-built models to be jointly explored with an interactive, image-based 3D viewer wherein deviations are automatically color-coded over the BIM using a simple traffic-light metaphor.

The resulting D^4AR models overcome the challenges of current progress monitoring practice and further enable AEC professionals to conduct various decision-making tasks in virtual environments rather than the real world where it is time-consuming and costly. To that extent, the underlying hypotheses and algorithms for generation of integrated 4D as-built and as-planned models as well as automated progress monitoring are presented. Promising experimental results are demonstrated on several challenging building construction datasets under different lighting conditions and sever occlusions. This marks the D^4AR modeling approach to be the first of its kind to take advantage of existing construction photo collections for the purpose of automated monitoring and visualization of performance deviations. Unlike other methods that focus on application of laser scanners or time-lapse photography, this approach is able to use existing information without adding burden of explicit data collection on project management and reports competitive accuracies compared to those reported with laser scanners especially in presence of sever occlusions.

To my beautiful wife, Bita
For your endless love,
and for always being a great source of motivation and inspiration

To My lovely family,
For all your support and prayers

ACKNOWLEDGEMENTS

I am truly thankful for the continuing support, encouragement and help of many individuals and organizations. My wife, Bita, made countless sacrifices during my graduate education before and after joining me in Urbana. My family provided me with a lot of help and emotional support. I dedicate this thesis to them all and thank them for giving me their support that I needed to go through this journey.

I am grateful for the support, constructive advice, and encouragement from my advisor, Feniosky Peña-Mora. Feny expects and demands the best from his students and I strived to live up to those expectations. Feny provided me with countless opportunities to work with the best in academia and industry and the freedom to pursue those opportunities, starting with work at Turner Construction. These opportunities at University of Illinois and elsewhere contributed tremendously to my research and professional career and I am greatly in debt for his trust in me to explore every feasible opportunity. I also want to extend my sincere appreciation to Silvio Savarese, my co-advisor, for his patient guidance, encouragement and constructive advice. Silvio hosted me in Ann-Arbor and with his extensive knowledge of computer vision and image processing provided me with invaluable insight on many scientific methods used in this research. I consider myself extremely lucky to have such advisors and I am greatly in debt for all their support and encouragements.

A great thank you also goes to the other three member of my dissertation committee: Liang Liu, Khaled El-Rayes, Carlos A. Arboleda for their service on my thesis supervisory committee and all their guidance and constructive feedbacks. Special thanks go to Carlos who worked closely with me in earlier stages of this research and helped me to form practicality of the D^4AR modeling concept. Carlos continuously supported me through countless opportunities he provided me with to present my research to his students and also top construction companies. Further special thanks go to SangHyun Lee who worked with Feniosky to form the idea of superimposing 3D models over photos and later on worked with me in early stages of this research to further form the concept. I am also grateful to Jochen Teizer (especially for his collaboration on chapter 5), Ioannis Brilakis, Lucio Soibelman, Fei-Fei Lee, and Frank Boukamp for all their guidance and constructive feedbacks. I am also thankful to Jesus de la Gaza, Mike Garvin, Sunil Sinha, Deborah Young-Corbett and Samuel Easterling at Virginia Tech for their support and early confidence in me and my work to recruit me as part of the Vecellio Construction Engineering and Management faculty at Virginia Tech.

This dissertation reflects collaborations with many professionals and fellow students through my research, and professional work during this thesis. At University of Illinois, my dear friends and colleague provided ongoing encouragement, listened and collaborated. These include Hamid Tabdili, Reza Shiftehfar, Ibrahim Odeh, Sangwon Han, Carol Menassa, Albert Yo-Jen Chen, Aravind Srihdaran, Shohbit Mathur, Xinyi Song, Seungjun Roh, Joyce Thomas, Saumil Mehta, SangUk Han, Leila Hajibabai Dizaji, Changbum Ahn and Kwassy Surheyao. Many thanks go to the students who worked with me to collect visual data and develop Building Information Models from architectural drawing. These include Erik Johnson, Edgar Mata, Sebastian Derza, Calvin Young, Ahmed Ahmed, Laurie Gawinski, Lesley Santa, Joe Blecha, Jonathan Gomez, Pok-Ki Tsang, Jesus Celis, Jasmine Winston, Luis De Pombo, James Patton, Joe Garb and Mauro Rodriguez.

I am particularly indebted to Gregory Cuttell, Robert Bursack, Nicholas Canellis, Shane Hill, Adam Kimball, Tony Odendahl, Bryan Carper, Ian Sykes and Cristina Ehler at Turner Construction for providing me with the opportunity to be part of Ikenberry Student Dining and Residence Hall construction projects and also for their input in inspiring some aspect of this research. A special thanks go to the Facilities and Services and Housing divisions at the University of Illinois, particularly Elizabeth Stegmaier, Myron Thompson, Clifford Carey, James Spease and Clark Wise; Univ. of Illinois Housing, Wayne Shaw, Jack Collins, John Humlicek, and Jeff Riddle as well as Kipling Mecum, Univ. of Illinois director of Emergency Planning. Special thanks go to Wayne Shaw. During my time at Turner, Wayne and I had many constructive discussions. He continuously supposed me and opened my eyes to new opportunities through D^4AR modeling.

I am thankful to multiple companies for providing me access to their projects throughout the research that lead to this dissertation. These include O'Neil Construction (Special thanks go to Rich Erickson, Patt McGawin, Dean Arnold and Kevin Foster), Gilbane Construction Co. (Special thanks to Mark Tallbot), Williams Brothers Construction Co. (Special thanks to Skip Kleist and Dean Schneider), Granluh Construction Co. (Special thanks to Adrian Ledbetter and Nick Roussy), Ken Dwarak at Land Capital Management, Kansas City, MO., BNIM Architects in Kansas City, MO (Special thanks to Brad Clark and Laura Lesniewski), Moshe Safdie and Associates, Boston, MA., Cesar Pelli & Associates Architects, New York, NY., Core Construction Company, Chicago, IL., Teng & Associates, Inc., Chicago, IL; University of Illinois College of Business, Post Genomics Institute, special thanks to Brian Stauffer and also Steve Hass, assistant director of office for Information Management.

A special thanks to Susan Hale in the Civil and Environmental Engineering department for helping me out with almost everything at Illinois and the university.

Finally, I would like to acknowledge financial support and recognition of my work by the National Science Foundation (Awards CMMI-0800500, CMS-0324501 and CMS-0427089), W.E. O'Neil Construction Company, Construction Management Association of America and FIATECH.

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CHAPTER 1. INTRODUCTION

1.1 Overview and Problem Statement

Early detection of actual or potential schedule delay or cost overrun in field construction activities is critical to project management (Halpin 2006). It provides an opportunity to initiate remedial actions and increases the chance of controlling such overruns or minimizing their impacts. Since schedule delays and cost overruns diminish profits of a project, it is easy to see why both project managers and project executives are perceptive to any deviation. This entails project managers to design, implement, and maintain a systematic and comprehensive approach for *progress monitoring* to promptly identify, process and communicate discrepancies between actual (as-built) and as-planned performances as early as possible. In this dissertation, monitoring is defined as *collecting*, *analyzing*, *recording*, and *reporting* information concerning key aspects of project performance at the appropriate level of detail required by project managers and decision makers. Despite importance of progress monitoring, systematic implementation can be challenging because:

1. Current progress monitoring is time-consuming as it needs extensive as-planned and as-built data extraction (Navon and Sacks 2007). Current methods require manual data collection and also extensive data extraction from construction drawings, schedules, and budget information produced by project teams in which none is independent (Navon 2007). Field staffs collect progress data from the construction site, analyze, and deliver them to project managers in a format specific to their areas of expertise, e.g., construction drawings, spreadsheets, bar charts, critical path method (CPM), or progress site photographs or videos. Such discrete and exhaustive reports could be produced but may not explicitly convey level of performance, problems, and their causes and impacts on construction performance (Song et al. 2005). Consequently, project managers need to devote significant amount of time and effort to sort out, prioritize, and interpret these data. Figure 1.1.a presents an example of such data that needs to be collected. As observed in this figure, significant number of daily reports are collected from contractors and sub contractors which require to be sorted out and interpreted.

2. The excessive amount of work required to be performed, may cause human-errors and reduce the quality of manually collected data. Furthermore, since only an approximate visual inspection is usually performed, the data collection becomes subjective and may not reveal the impact of site circumstances on construction progress (personal communication with field staffs on seven ongoing construction projects (9/2006–6/2010); Navon and Sacks 2007). This may affect the quality of the collected data and makes progress analysis error prone since the ability of anticipating possible outcomes will solely depend on the

ability and expertise of the project manager in interpreting limited collected information. Figure 1.1.b presents an example of a daily construction report. As observed in this report, drywall contractor has only reported that in a particular day "framing" has been conducted, without specifying the location of the work performed or the amount of progress made.

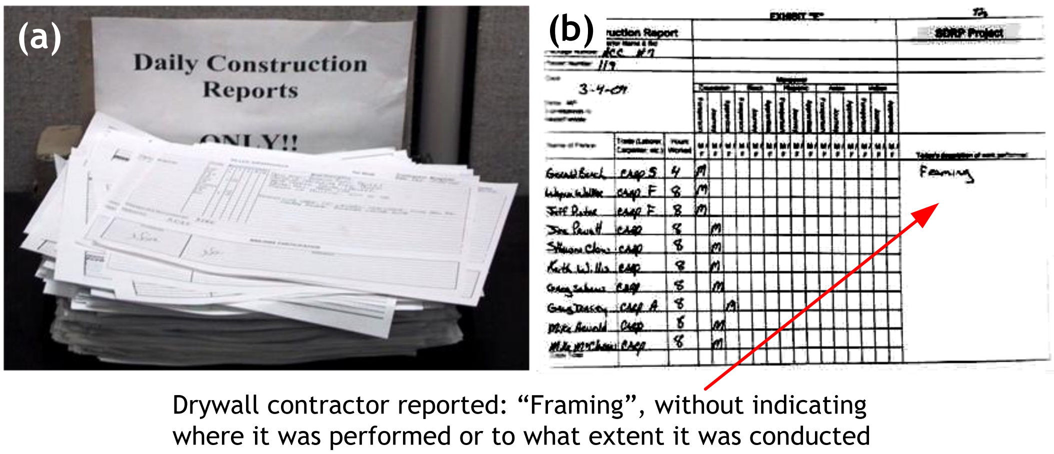

Figure 1.1. (a) A typical daily construction report pile. Image courtesy of Frank Boukamp and Turner Construction (used by permission); (b) An example of a daily construction report. As observed little information is shared through these reports.

3. Existing methods of measuring progress are nonsystematic and generic. Accurate measurement of the progress performance usually poses the most difficult data gathering problem as there may be a tendency to let project inputs serve as surrogate measures for output (Meredith and Mantel 2003). For example, a concrete subcontractor reports to the project manager that they have completed 60% of their work or reached 60% of their performance goal. Does it mean 60% of the planned area/volume of concrete pouring is finished? Is it 60% of the planned concrete that has been used? Or is it 60% of the planned man hour that is spent? If the item being referenced is a small work unit, it may not have a significant difference; however, in case where the references are to the whole task or project, assumption of input/output proportionality could be very misleading (Meredith and Mantel 2003) (See Figure 1.1.b). Thus, the most commonly used methods to monitor progress are: (a) Monitoring physical progress in percentile: used in most construction fields that heavily relies on experience and knowledge of the project management personnel. This metric is used subjectively and is inefficient at presenting progress due to its abstract nature representation of physical progress (Song et al. 2005); (b) Budget based monitoring: based on percentage of the budget paid to contractors according to the schedule-based inspections. This method of monitoring creates time lag between progress estimations and schedule updates; besides, judgments are usually subjective and misleading especially if a field manager makes any erroneous decision (Shih and Wang 2004). Without a specific comparative analysis on construction plan, resources, and cost data,

wrong assumption and inaccurate measurement on the progress status could be made. Mistakes such as over paying and overlook of expected delay might appear.

4. Progress monitoring reports are visually complex. Kerzner (2005) argues that 30 to 40 different data representations are currently being used in construction industry. These graphical representations can serve several functions such as representing data, forming baselines for analysis, and communicating different aspects of construction performance (Oglesby et al. 1989). These methods require drawing, sketches (to show layout and physical details), and graphs and charts (which present numerical data and the results obtained by observation) to represent schedule, cost, and performance. The choice among them is dependent on the intended audience. For example, upper level management may be interested in costs and integration of activities with very little detail; hence summary-type charts normally suffice for this purpose. Daily practitioners, on the other hand, may require as much detail as possible in daily schedules. In addition, understanding the situation only based on the schedules may be difficult as they lack information relating to spatial context and complexities of project components (Koo and Fischer 2000). None of the existing reporting methods effectively present multivariable information (i.e., schedule, cost, and performance) in a holistic manner nor do they reflect the spatial and visual aspects of as-planned and as-built construction and their associated complexities simultaneously (Kymell 2008, Poku and Arditi 2006, Koo and Fischer 2000). Current reporting methods increase the time required to describe and explain the progress situation in coordination meetings and in turn could delay decision making process (as observed on seven ongoing construction projects (9/2006–6/2010) and as reported in Golparvar-Fard et al. 2006). Figure 1.2.a, b and Figure 1.3 show a typical contractor coordination meeting room. As observed various as-planned and as-built information are presented separately which requires more time to be spent on communicating status of a project. In summary, current reporting methods affect the ability of effectively communicating progress information which is a definite prerequisite for successful project management.

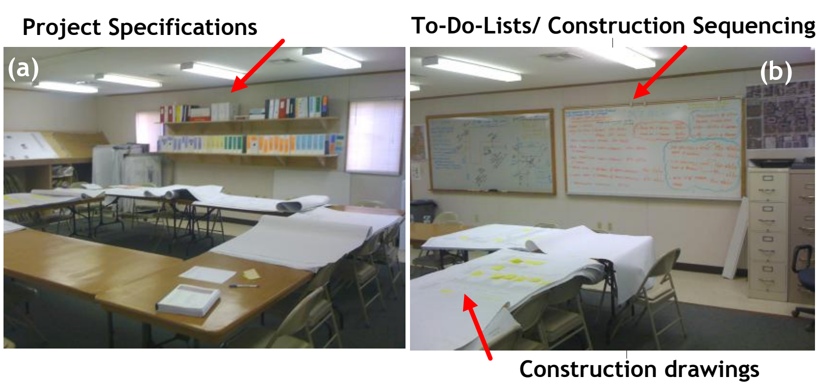

Figure 1.2. A typical contractor coordination meeting room. Various as-planned and as-built information are represented separately from one another.

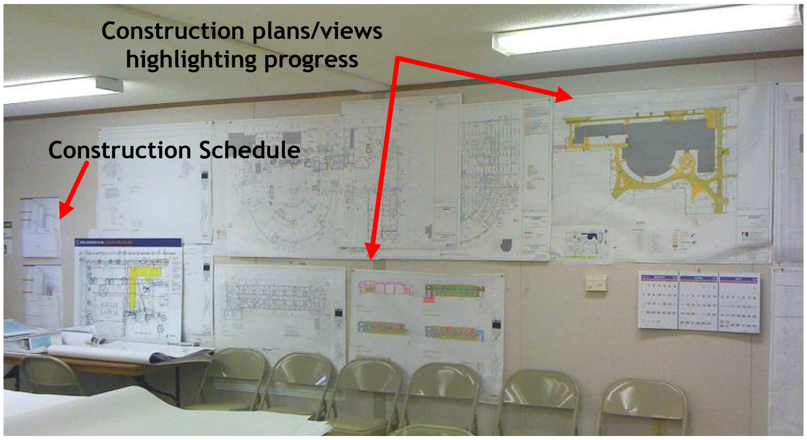

Figure 1.3. In current practice progress information is presented through multiple discrete representations.

In the meantime, most of the current techniques for automating progress data collection (such as laser scanners, RFID and embedded sensors) are promising if one wishes to eliminate labor-intensive and non-value adding tasks associated with manual progress data collection. A drawback is the necessity to add new tasks that need to be performed before, during, or after utilization of such technologies at a construction site (El-Omari and Moselhi 2008, Kiziltas et al. 2008, Akinci et al. 2006). Barcodes and RFID sensors are excessively time consuming to set up and costly for many projects. Additionally they cannot be attached to many types of components or capture progress of partially installed components. Laser scanners are also expensive, require experienced people for operation, could document excessive noise within dynamic scenes, and require manual data processing and selection as well as a preparation time for warming up (Kiziltas et al. 2008). In addition, laser scanners only provide Cartesian coordinate information of the scanned scene. Working with such featureless data and without any semantic information of the scene (Kiziltas et al. 2008), geometric reasoning is challenging and induces estimation errors. Also none of these techniques (other than when site images are overlaid on laser scanning point clouds as in El-Omari and Moselhi (2008)) provide reliable visual information about work sequence or site logistics. In this research to address these challenges that are associated with the current construction progress monitoring practice, a simple yet robust approach is suggested which takes advantage of already available information on construction site to automatically track and visualize construction performance discrepancies. Such information is categorized in two fronts:

1.1.1. As-built progress data

Considering current technical inefficiencies of available data collection technologies; i.e., laser scanners, bar codes and RFID tags, in this research processing daily construction site photographs for enhancing collection, analysis and communication of as-built data is investigated. Digital photography together with internet has enabled construction management companies as well as sub contractors, project owners and architects to share progress photographs on a truly massive scale. Nowadays it is a common practice for jobsite images to be gathered periodically, stored in central databases, and utilized in communication and coordination of project tasks (Soibelman et al. 2008). Site photographs not only have the advantage of being understandable to those who are not well-versed in studying written material or numerical data analysis or even those who question verbal or written reports (Oglesby et al. 1989), but also allow a large amount of progress data to be understood and absorbed quickly. Just as the Chinese proverb says "A picture is worth a thousand words", it could be imagined how daily site photograph logs, which consist of many site images, can help as comprehensive sources of as-built data. Furthermore photographs provide a visual value in understanding large amount of information, and could be automatically processed and converted into information regarding construction progress (Brilakis and Soibelman 2008, Golparvar-Fard and Peña-Mora 2007, Navon and Sacks 2007, Wu and Kim 2004, Abeid et al. 2003) and yet compared to other data collection techniques, do not burden efficiency of the project management processes by requiring significant data collection efforts. In this research application of two different types of daily construction photos: (1) time-lapsed photos and (2) unordered daily construction photo collections that are casually collected by all project participants, are considered.

1.1.2. As-planned progress data

In this research application of three-dimensional/ four-dimensional Building Information Models (BIMs) as a baseline for automating progress monitoring and visualization is considered. BIMs which are increasingly turning into binding components of Architecture/Engineering/Construction (AEC) contracts as as-planned data repositories, facilitate accessing geometrical information, visualizing planned schedule and communicating progress. Linked with construction schedule, 4D BIMs enables project participants and clients, regardless of their level of construction knowledge and expertise, to identify spatial layouts and explore construction processes (Hartmann et al. 2008, Hartmann and Fischer 2007, Woksepp and Olofsson 2006). In addition, 3D/4D BIMs provide consistent visual base-line of as-planned information (Golparvar-Fard et al. 2009a, Song, Pollalis, and Peña-Mora 2005) and act as an underlying structure for monitoring progress where deviations between the as-planned and as-built progresses could be visualized.

In this dissertation, the focus is on the joint application of daily construction site photo collections and 3D/4D BIMs to automatically track and visualize performance deviations. The following outlines the specific objectives, hypotheses and significance of the research conducted in this dissertation:

1.2 Research Objectives

1.2.1 Research objective 1

To develop a framework for collecting rich, visual, as-built datasets of exterior/façade components of construction projects using field webcams and still cameras. In order to achieve this objective, answers to the following questions need to be established:

(1) Given the limitations of field of view, visibility, occlusion and blind spots for webcams and still cameras in a construction sites, how can progress of exterior/façade components be visually tracked?

(2) How the photographs taken from fixed and mobile camera visually cover progress exterior/façade of the building components on a construction site?

Figure 1.4. Time-Lapsed Photographs taken from a fixed camera; Project: College of Business Instructional Facility, UIUC.

Hypothesis: Collections of daily construction site photographs will allow physical and non-physical construction progress to be visually captured from different angles and different points of view, under various illumination, weather, site and occlusion conditions. (See Figure 1.4)

Significance: A complete visual as-built database of a project serves as the backbone for automated progress tracking and visualization.

1.2.2 Research objective 2

To develop an AR environment by superimposing an as-built sparse (point cloud) 3D model from site photographs on the as-planned model. In order to achieve this objective, answers to the following questions need to be established:

(1) What is the feature space of each construction site photograph which could be used to automatically match any pair of photographs to create the baseline for sparse as-built model?
(2) How can these pairs and their feature spaces reconstruct a sparse as-built 3D model (cloud of feature points)?
(3) How can the as-built 3D sparse model be accurately registered with the as-planned 3D model?

Figure 1.5. Camera Location of randomly taken photographs after the SfM algorithm; (b) Augmented photograph representing the as-planned model superimposed on a photo (Photo Subject: College of Business Inst. Facility, UIUC).

Hypothesis: Using a robust Structure from Motion (SfM) approach (Hartley and Zisserman 2004), an as-built 3D model could be sparsely reconstructed from a collection of photographs taken from different points-of-view at different times as to allow the photographs and the as-built sparse model to be perfectly registered with the 3D as-planned model (See Figure 1.5.a).

Significance: Superimposition of as-planned and as-built models allows construction components to be visible in an AR environment of a project from different angles and points of view, allowing the user to walk through at specific project intervals and analyze progress by observing physical deviations between as-planned 3D and as-built models.

1.2.3 Research objective 3

To automate progress tracking of the building components visible from outside the building using site photographs taken at different progress stages.

(1) How could different construction components with various materials and shapes automatically be detected from photographs?
(2) How could construction components under partial visual occlusion caused by construction workers, machinery, temporary structures, shadows casted from adjacent components or buildings and/or under different weather conditions be detected?

Figure 1.6. Correlation of shape and material recognition will identify the progress status of construction component under study.

Hypothesis: Using stereo vision, texture and shape recognition techniques and Exchangeable Image File Formats (EXIF data), location, date, as well as material and shape progress information of construction components could be extracted from image content.

Significance: The achievements of this objective will allow physical progress of the construction components to be automatically tracked and recognized from photographs, dramatically minimizing the time required for as-built data collection. (See Figure 1.6)

1.2.4 Research objective 4

To develop a progress analysis engine based on Earned Value Analysis (EVA) to compare the as-built progress with the as-planned model. In order to achieve this objective, answers to the following questions need to be established:

(1) How could project performance information (e.g., schedule, cost, quality, safety, productivity, conflicts, environmental and political aspects) link up to 3D models in order to represent a rich baseline for as-planned model to be effectively used for Earned Value Analysis (EVA)?
(2) To what level of detail, this model needs to represent the as-planned progress? (Can a "general contractor" schedule be used as the baseline for progress comparison or a 4D model which represents construction activities at the level of a subcontractor visualizing temporary structures needs to be developed)?
(3) How supportive schedule activities such as mobilization or quality control be represented in the visual as-planned model?

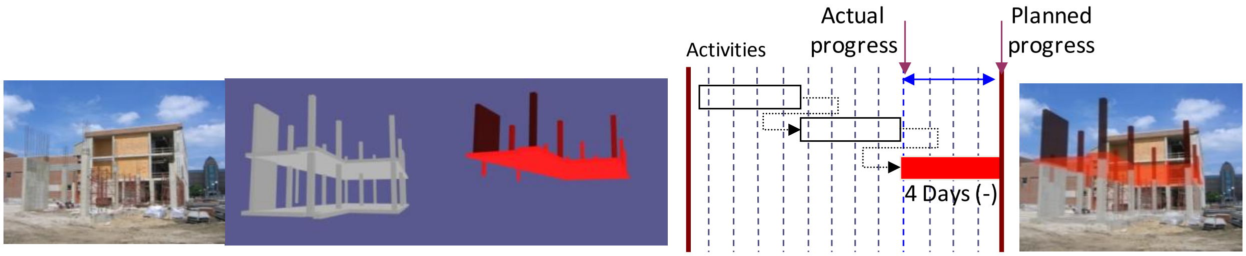

Figure 1.7. a) Site photograph; b) 4D model; c) progress deviation based on work schedule and d) the augmented photograph visualizing progress deviation (extended from Lee and Peña-Mora 2006 – first realization of Peña-Mora's 1989 concept).

Hypothesis: A multi-variable progress model with a desired level of detail (e.g., owner or sub-contractor schedules) could be developed for a robust progress monitoring process. (See Figure 1.7)

Significance: A framework for modeling a rich as-planned dataset against as-built field data will allow for a robust systematic progress monitoring process.

1.2.5 Research objective 5

To apply different visualization techniques for the D^{4}AR model to allow progress deviations to be visually and interactively represented in different representation environments such as online browsers and wearable computers. In order to achieve this objective, answers to the following questions need to be established:

(1) How can progress deviations be easily represented in visually understandable imageries?

(2) How could visualization techniques be used to remove occlusions and allow the integrity of the depth and point-of-view to be preserved in an AR environment?

(3) What are the interactive ways that the user can walk through an AR environment or browse a collection of AR photographs and be able to easily observe progress discrepancies?

(4) How can project managers remotely conduct walk-through in buildings and enhance their observation of progress monitoring information?

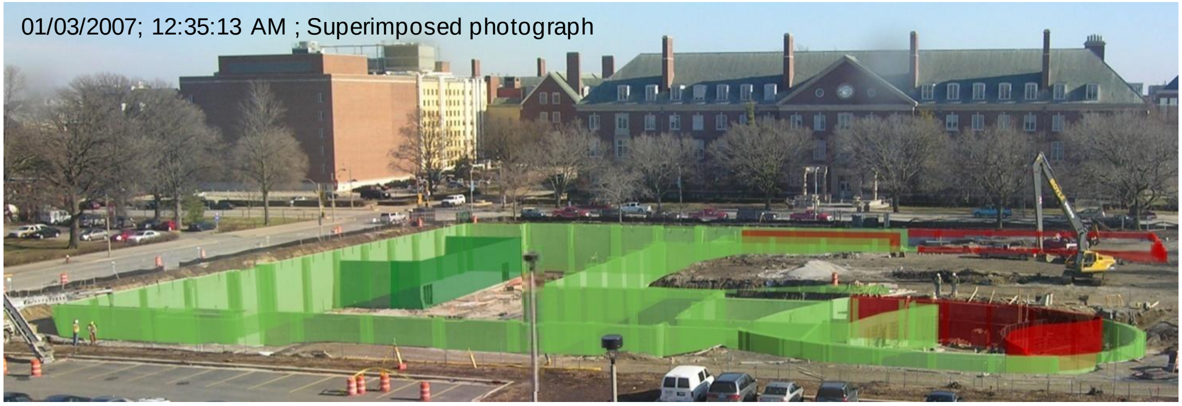

Figure 1.8. A color-coded superimposed image visualizing progress: entities in light green are on schedule, dark green ahead of schedule and red behind schedule (College of Business Inst. Facility; Facilities & Services, UIUC).

Hypothesis: Conceptual visualization techniques (e.g., color and color-gradients spectrum and quadrangles based on traffic light metaphor) and natural human-computer interaction techniques (e.g., gestures, audio commands) will allow project manager to effectively communicate concurrent progress information to project participants, allowing for real-time and quick control decisions. (See Fig. 5)

Significance: Visualization of progress monitoring with an interactive AR system, ubiquitously accessible through online browsers, PDAs and eye-wears allows project managers to interactively visualize progress information and effectively communicate it with the various stake holders involved in a project.

1.3 Research Methodology

The objectives of the conducted research are achieved through a formal cycle of data collection, formalization, systematization, testing/validation, and refinement. In this process, research, practice, and education were integrated in order to create a robust framework for automated visualization of progress monitoring. Figure 1.9 shows a mapping between monitoring challenges, research objectives, and the steps on our research methodology, highlighting their interconnections.

Progress Monitoring Challenges	*Objectives*	*Methodology Steps*
• Data collection is ***time-consuming*** and ***labor-intensive***. • There is almost no ***visual progress information*** available from most of the existing automatic data collections techniques.	**Objective I.** Develop a rich ***visual as-built dataset*** from time-lapsed photos automatically taken from fixed locations and a collection of randomly taken photos from different points-of-view and at different times.	DATA COLLECTION • Conduct literature review on monitoring analysis. • Conduct literature review on automatic as-built 3D modeling and progress detection, Augmented Reality and Visualization Techniques. • Collect photographs and build 4D models from different construction site for the purpose of automating data collection.
• Quality of manually collected data may depend on the assumption made by field engineer and the expertise of project manager to interpret it, which may make it susceptible to data error.	**Objective II.** Develop an integrated AR environment where all as-planned and as-built data (e.g., Schedule, Cost and Performance) is integrated and visualized. **Objective III.** Develop a framework for automatic progress data ***identification*** and ***assessment***.	FORMALIZATION • Develop concepts of ***material*** and ***shape recognition*** to ***automate progress tracking*** of exterior/ façade. • Transform retrieved visual information to meaningful as-built dataset. • Framework to develop an ***as-built sparse 3D model*** from site photographs. • Framework to generate an online ***AR environment*** where as-built sparse 3D model is superimposed on as-planned model. • Link ***Schedule***, ***Cost*** and ***Performance*** data to the AR model, allowing an integrated model to be analyzed.
• Due to the large amount of data to be collected and processed, non-systematic monitoring and generic metrics are used.	**Objective IV.** Develop a progress monitoring system based on ***Earned Value Analysis*** to systematically compare as-built progress and as-planned data.	SYSTEMATIZATION • Develop a prototype system for automatic progress monitoring and visualization • Segmentation and Removal of occluders for preserving depth and perspective. • Apply visualization techniques (e.g., color, weather and x-ray metaphors) to AR model. • Using ***Eye-wear*** and ***hand gestures*** to interact with AR the model on job site. • Provide ***interactive walk-through*** *or* ***browse through of augmented photos***.
• ***Quick decision- making is*** difficult. • Progress reports are ***visually complex***. • Significant amounts of time can be lost in communicating progress using existing representations.	**Objective V.** a) Reduce the time for describing and explaining progress with more ***effective representation***. b) Allow quick and remote decision-making using ***ubiquitous interactive visualization***.	TESTING & VALIDATION • Test the usability of visualization techniques for progress monitoring. • Conduct case studies to test the usability of automatic progress monitoring system on projects with different sizes and complexities.

Figure 1.9. Mapping of progress monitoring challenges, research objectives and methodology steps

1.4 Dissertation Organization

This dissertation includes a total of seven chapters including the current chapter. These chapters are as follows:

Chapter 2: This chapter presents an augmented reality modeling approach which presents how augmented imagery could be generated for visualization of construction progress monitoring. The objective of this chapter is to generate the framework on how performance deviations can be visualized using time-lapsed photographs along with Building Information Models. The model presented in this chapter is applied to a real case study to demonstrate applicability of the suggested approach in addressing challenges and limitations of the monitoring practice. Limitations and challenges of using time-lapsed photographs for the purpose of automating and visualizing construction progress monitoring are also discussed as well.

Chapter 3: This chapter focuses on exploring application of unsorted daily progress photo collections available on any construction site as a data collection technique. It presents a framework and a fully automated image-based modeling approach which is based on computing- from the images themselves- the photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using daily progress photographs and superimposition of the reconstructed scene over as-planned 4D models. Within such an environment, progress photographs are registered in the virtual as-planned environment and this allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes superimposed over 4D models allow site images to be geo-registered with the as-planned components and consequently, location-based image processing technique to be implemented and progress data to be extracted automatically. The results of progress comparison between as-planned and as-built performances are visualized in the D^4AR (4D Augmented Reality) environment using a traffic light metaphor. This chapter also presents preliminary results on three ongoing construction projects and discusses implementation, perceived benefits and future potential enhancement of this new technology in construction, in all fronts of automatic data collection, processing and communication. It further roadmaps how using D^4AR models, progress can be automatically tracked.

Chapter 4: This chapter presents (1) automated acquisition of as-built point clouds from unordered site daily photo collections and geo-registration of site images; (2) automated generation of 4D as-built point clouds, as well as (3) semi-automated superimposition of the integrated as-built model over 4D (3D + time) BIMs to generate integrated 4D as-built and as-planned visualizations. The limitations and benefits of each modeling approach, the motivations for development of D^4AR - 4 Dimensional Augmented Reality - environments for integrated visualization of as-built and as-planned models, as well as perceived and observed applications and benefits in seven case studies are discussed. This chapter further demonstrates that not only D^4AR models visualize construction processes and performance deviations, but they can also be significantly used as tools for automated and remote progress and safety monitoring plus quality control and site layout management, enabling enhanced coordination and communication.

Chapter 5: This chapter presents and compares two methods for obtaining point cloud models for detection and visualization of as-built status for construction projects: (1) the method of automated image-based reconstruction and modeling of the as-built project status using unordered daily construction photo collections through analysis of Structure from Motion (SfM) which was presented in Chapters 3 and 4; (2) 3D laser scanning and analysis of the as-built dense point cloud. These approaches provide robust means for recognition of progress, productivity, and quality on a construction site. In this chapter, an overview of the automated image-based reconstruction approach and exclusive features which distinct it from other image-based or conventional photogrammetric techniques is presented. Subsequently the terrestrial laser scanning approach - which was carried out for reconstruction and comparison of as-built scenes by Jochen Teizer and Jeff Bohn at Georgia Tech as a collaborative project- is presented. Finally the accuracy and usability of both of these techniques for metric reconstruction, automated production of point clouds, 3D CAD shape modeling and visualization of the as-built scenes is evaluated and compared on eight different case studies. Compared to laser scanning point clouds, it is shown that for precise defect detection or alignment tasks, SfM point clouds automatically reconstructed from daily construction site photographs may not be as accurate and dense as those of the laser scanners nevertheless provide an opportunity to extract semantic information of the as-built scene (i.e., progress, productivity, quality and safety) through the content of the images, are easy to use, do not need add burden on project management teams by requiring expertise for data collection or analysis and automatically provide photo alignment and image-based renderings which can remarkably impact automation and visualization of the as-built scenes.

Chapter 6: In this research, a new automated approach for recognition of physical progress is presented. First, given a set of unordered and uncalibrated site photographs, an automated approach based on structure-from-motion, multi-view stereo, and voxel coloring and labeling algorithms is presented to calibrate cameras, photo-realistically reconstruct a dense as-built point cloud in 4D (3D + time), and traverse and label the scene for occupancy. This strategy explicitly accounts for occlusions and allows input images to be taken far apart and widely distributed around the environment. An IFC-based (Industry Foundation Class) BIM is subsequently fused into the as-built scene by a robust control-based registration-step and is traversed and labeled for expected progress visibility. Next, a machine learning scheme built upon a Bayesian probabilistic model is proposed that automatically detects physical progress in presence of occlusions and demonstrates that component-based progress monitoring at schedule activity-level could be fully automated. Finally, the system enables the expected and reconstructed elements to be explored with an interactive, image-based 3D viewer where deviations are automatically color-coded over the IFC-based BIM. To that extent, underlying hypotheses and algorithms for generation of integrated 4D as-built and as-planned models plus automated progress monitoring are presented. Furthermore, experimental results are presented for challenging image datasets collected under different lighting conditions and sever occlusions from two ongoing building construction projects; marking the proposed model to be the first probabilistic model for automated progress tracking and visualization of deviations that incorporates unordered daily construction photographs and BIMs in a principled way.

Chapter 7: This chapter summarizes the main contributions of this research and provides recommendations for future research in this area.

CHAPTER 2. VISUALIZATION OF CONSTRUCTION PROGRESS MONITORING WITH 4D SIMULATION MODEL OVERLAID ON TIME-LAPSED PHOTOGRAPHS

2.1 Overview

The ability to effectively communicate progress information and represent as-built and as-planned progress discrepancies are identified as key components for successful project management that allow corrective decisions to be made in a timely manner. However, current formats of reporting (e.g., textual progress reports, progress curves, and photographs) may not properly and quickly communicate project progress. Current monitoring methods also require manual data collection and extensive data extraction from different construction documents, which distract managers from the important task of decision making. Therefore, to facilitate progress monitoring, this chapter proposes visualization of performance metrics that aims to represent progress deviations through superimposition of four-dimensional (4D) as-planned model over time-lapsed photographs in single and comprehensive visual imagery. As a part of the developed system, registration of the 4D model with photographs, augmenting photographs, and occlusion removal for progress images are presented. While contextual information is preserved, the as-built photographs are enhanced and augmented with 4D as-planned model in which the performance metrics are visualized. The augmented photographs provide a consistent platform for representing as-planned, as-built, and progress discrepancies information and facilitate communication and reporting processes.

2.2 Introduction

Accomplishing desired performance during construction is a challenging task. Most construction projects or their individual work phases are relatively short duration and are performed at variable locations by a temporary alliance among multiple organizations (Slaughter 1998). Operations are generally conducted outdoors and are subject to interruptions and variations in site conditions and other difficulties such as unforeseen weather conditions (Oglesby et al. 1989). These circumstances cause errors and changes within a project and their corresponding results are schedule delay and cost overrun which challenge construction operations productivity (Peña-Mora et al. 2008).

For the purpose of effectively managing project development, a systematic and comprehensive approach for progress monitoring needs to be developed so that discrepancies between as-planned and as-built progress are identified and reported to the project managers as early as possible (Lee and Peña-Mora 2006). In this chapter, monitoring is defined as *collecting*, *recording*, and *reporting* information concerning any or all aspects of project performance which highlights presence of progress discrepancies and facilitates project managers and decision makers to take corrective actions in a timely manner (Meredith and Mantel 2003).

Today, decision making for corrective actions and schedule revisions usually takes place in coordination meetings where a wide range of individuals (e.g., from the owners to subcontractor organizations) with diverse expertise and interest attend the meeting. In these face-to-face communications, progress information needs to be easily and quickly communicated among the participants. Currently, none of the existing reporting methods (e.g., progress *S* curves, schedule bar charts, and photographs and textual reports) effectively present and visualize multivariable information (i.e., schedule, cost, and performance) in a holistic manner nor do they intuitively and simultaneously reflect information pertaining to the as-planned and as-built spatial and visual aspects of construction as well as their associated complexities [as stated by Lee and Peña-Mora (2006), Poku and Arditi (2006), Korde et al. (2005), Song et al. (2005), Kamat and Martinez (2002), and Koo and Fischer (2000)]. These representations result in significant amount of information to be inefficiently presented in meetings and as a result, time is spent on describing existing problems and explaining the rationale of decisions rather than evaluating alternatives and discussing what-if scenarios and corrective actions (Golparvar-Fard et al. 2006). With textual representations, it is difficult to understand the situation clearly and quickly. It is even more troubling when the need for frequent remote and quick decision making in construction is considered (Lee and Peña-Mora 2006). Besides, most organizations do not have standardized reporting procedures or employ different control systems which create miscommunication in progress reporting. In this case, the ability to effectively communicate progress information and represent the discrepancies is a definite prerequisite for a successful project management.

Visualization of progress through visual imagery has been recognized by a number of researchers as an effective way to communicate progress monitoring metrics (Lee and Peña-Mora 2006; Poku and Arditi 2006; Kerzner 2005; Song et al. 2005; Abeid et al. 2003). For the purpose of progress monitoring, this requires both as-planned and as-built information to be integrated and visualized to provide a holistic view of all processes during construction progress. Therefore in this chapter, a visualization technique for progress monitoring is presented that visualizes progress deviations through superimposition of four-dimensional (4D) as-planned model on real time-lapsed photographs in single and comprehensive visual imagery.

Visualization of the as-planned progress in 4D environment enables project participants and clients — regardless of their level of construction knowledge and expertise — to understand spatial constraints and explore design and construction alternatives before construction starts. It provides a consistent visual platform and a common language of as-planned construction that could be extended to the monitoring phase (Song et al. 2005). In addition, visualization of as-built progress in photographs not only has the advantage of being understandable to those who are not well versed in studying written material or numerical data analysis or even those who question verbal or written reports (Oglesby et al. 1989), but also allows large amount of data to be understood and absorbed quickly. Compared with progress reporting techniques which generate words and numbers, techniques such as time-lapse photography and videotaping provide a rich data set that can be a good source for *as-built data collection* and act as good *communication tools* for progress monitoring among the project participants.

Considering these advantages, the presented visualization model integrates the 4D model and time-lapsed photographs within an augmented reality (AR) environment where progress discrepancies are identified and visualized. To present this model, this chapter begins with introducing the challenges of progress monitoring followed by the proposed methodology that visualizes discrepancies between the as-planned and as-built progress. In the subsequent sections, three important steps for the augmented photograph are explained in details: (1) 4D simulation as the underlying context for representing visualized metrics; (2) Time-lapse photography and real-time filming for as-built progress data collection; and (3) Visualization techniques to represent performance metrics on augmented photograph. As a part of the system, registration of the 4D model with photographs, augmenting photographs and occlusion removal for progress images of the building structure and façade are presented. While contextual information in photographs is preserved, the real-world image is enhanced and augmented with 4D simulation model where performance metrics are visualized. The augmented photographs provide a consistent platform for representing as-planned, as-built, and progress discrepancies information and facilitate communication and reporting processes.

2.3 Challenges with Construction Progress Monitoring

Project managers require a robust monitoring system that ensures most up-to-date design, schedule, cost, and progress performance data are *delivered* and *represented* in a *timely* and a *comprehensive* manner so that control decisions could be made as quickly and easily as possible. Proper implementation of such a system reduces the time for routine decision makings and in turn overall project cost and duration. According to Barrie and Paulson (1992) such a system should have these characteristics:

1. To provide an efficient and effective means of *measuring*, *collecting*, *verifying*, and *quantifying* as-built data reflecting the progress and operations with respect to schedule, cost, resources, procurement and quality.

2. To accurately *convert* as-built progress data from construction operation into information. The system should be realistic and should recognize means of processing the information, the skills available, and the value of information compared with the cost of obtaining it.
3. To *identify* and *assess* the critical information from a given progress situation.
4. To *report* the information to managers *in time* and in a *form* which can best be interpreted by management, and at an appropriate level of detail for the individuals who will be using it so that *corrective action* could be taken on the progress situation that generated the data in the first place.
5. To *record* the control action taken; to represent the as-built performance of the project.

Without data collection, thorough comparison of the planned and as-built performance and a proper communication and recording, there may be no basis for proper project control and decision making. This requires progress data to be analyzed and maintained in a desired level of detail (i.e., according to decision maker's needs) so that understanding the progress would be easier (Jung and Kang 2007); however the process of monitoring is faced with a series of challenges such as

1. Current progress monitoring is time consuming and labor intensive. Projects are not constantly monitored making it very difficult to take corrective actions in a timely basis. Current methods require manual data collection and also extensive data extraction from construction drawings, schedules, and budget information produced by project teams in which none is independent (Navon 2007). Field staffs collect progress data from the construction site, analyze, and deliver them to project managers in a format specific to their areas of expertise, e.g., construction drawings, spreadsheets, bar charts, critical path method (CPM), or progress site photographs or videos. Such discrete and exhaustive reports could be produced but do not explicitly convey level of performance, problems, and their causes and impacts on construction situation (Song et al. 2005). Consequently, project managers need to devote significant amount of time and effort to sort out, prioritize, and interpret these data.

2. Quality of manually collected and extracted progress data are low. Manual collection of progress information — usually acquired by field staff — is dependent on the status seen on site and the information collected which in turn makes it subjective and may not reveal the impact of site circumstances on construction (personal communication with field staffs on five different projects (9/2006–6/2007); Navon and Sacks 2007). This may affect the quality of the collected data and makes it error prone since the ability of anticipating possible outcomes based on the collected information, depends on the ability and expertise of the project manager.

3. Existing methods of measuring progress are nonsystematic and generic. Accurate measurement of the progress performance usually poses the most difficult data gathering problem as there may be a tendency

to let project inputs serve as surrogate measures for output (Meredith and Mantel 2003). For example, a concrete subcontractor reports to the project manager that they have completed 60% of their work or reached 60% of their performance goal. Does it mean 60% of the planned area/volume of concrete pouring is finished? Is it 60% of the planned concrete that has been used? Or is it 60% of the planned man hour that is spent? If the item being referenced is a small work unit, it may not have a significant difference; however, in case where the references are to the whole task or project, assumption of input/output proportionality could be very misleading (Meredith and Mantel 2003). Thus, the most commonly used methods to monitor progress are: (a) Monitoring physical progress in percentile: used in most construction fields that heavily relies on experience and knowledge of the project management personnel. This metric is used subjectively and is inefficient at presenting progress due to its abstract nature representation of physical progress (Song et al. 2005); (b) Budget based monitoring: based on percentage of the budget paid to contractors according to the schedule-based inspections. This method of monitoring creates time lag between progress estimations and schedule updates; besides, judgments are usually subjective and misleading especially if a field manager makes any erroneous decision (Shih and Wang 2004). Without a specific comparative analysis on construction plan, resources, and cost data, wrong assumption and inaccurate measurement on the progress status could be made. Mistakes such as over paying and overlook of expected delay might appear.

4. Progress monitoring reports are visually complex. Kerzner (2005) argued that 30 to 40 different data representations are currently being used in construction industry. These graphical representations can serve several functions such as *showing data*, *analysis methodology*, and *communication means* (Oglesby et al. 1989). These methods require drawing, sketches (to show layout and physical details), and graphs and charts (which present numerical data and the results obtained by observation) to represent schedule, cost, and performance. The choice among them is dependent on the intended audience. For example, upper level management may be interested in costs and integration of activities with very little detail; hence summary-type charts normally suffice for this purpose. Daily practitioners, on the other hand, may require as much detail as possible in daily schedules. In addition, understanding the situation only based on the schedules may be difficult as they lack information relating to spatial context and complexities of project components (Koo and Fischer 2000). None of the existing reporting methods effectively present multivariable information (i.e., schedule, cost, and performance) in a holistic manner nor do they reflect the spatial and visual aspects of as-planned and as-built construction and their associated complexities simultaneously. Consequently it affects the ability of communicating effective progress information which is a definite prerequisite for successful project management. Based on the deficiencies mentioned and considering challenges with current reporting formats and communications, the visualization of

progress monitoring is presented. In the following section, components of the visualization technique which results in augmented photographs are discussed.

2.4 Visualization of Progress Monitoring

Visualization techniques have been widely adopted in construction, from visualizing construction management data (e.g., Korde et al. 2005; Songer and Heys 2003) to the physical artifacts that are to be built to facilitate constructability reasoning or workability of the operation methods selected for its construction (e.g., Kamat and Martinez 2003). However the focus of the visualization techniques in this chapter is on their application of as-planned 4D simulations to augment as-built progress photographs with the purpose of project monitoring and control. In this context, Song et al. (2005) introduced project dashboard as a three-dimensional (3D) model visual representation to show a holistic picture of a project by applying the multiple project data sets to the geometric attributes (e.g., shape, faces, and edges) of the building product model through color-tone variations and motion. It was suggested that consistent application of colors would allow project performance metrics to be represented easily. This would also purge visual complexities which could be caused by complexities associated with large and sophisticated building product models. Nonetheless in their presented system, as-built progress was not visualized using photographs or any other means different from that of as-planned model. Rather, geometric attributes of the building product model were used to communicate progress. Based on the same concept of consistent visual representation, Lee and Peña-Mora (2006) superimposed planned product models with photographs and initiated a new paradigm on visualization of construction progress monitoring where deviations between planned and as-built performance models were conceptually represented in an AR environment. AR is an environment where in virtual and real world are combined to enhance user's experience of the virtual world through contextual information (Wang and Dunston 2005; Azuma 1997). It gives the user the ability of observing the background environment and superimposes virtual model over the real-world background. Considering the benefits of visualization techniques and AR environment for visualization and automation of progress monitoring specifically assisting project managers, a new approach is presented which integrates three different modules.

1. 4D Simulation as the as-planned progress information,
2. Time-lapse photography and videotaping as the as-built progress data collection, and
3. Visualizing progress through augmenting the as-built photograph with the as-planned data

2.4.1 4D simulation as the as-planned progress data

4D simulations have been developed for the main purposes of detecting spatial and temporal conflicts, understand construction logistics, coordinate the construction with subcontractors and trades, and demonstrate the planned progress to the owners (Tabesh and Staub-French 2006; Kamat and Martinez 2003; Kam and Fischer 2002). This kind of a time-based monitoring focuses on a preconstruction study that will allow for better management of a site afterward (Haymaker and Fischer 2001). So far, 4D tools have not been used for project progress management through as-built data collection during the construction phase (Chin et al. 2005). Currently 4D applications are able to detect some scheduling errors in the construction and enable project participants and clients, regardless of their level of construction knowledge, to understand the spatial constraints and explore design and construction alternatives before construction starts. However, a preconstruction simulation cannot necessarily take into account every incident that might occur to the parts of a building under construction but could be used as a base for the as-planned information. 3D and 4D models can provide realistic visual expression, a consistent visual platform, and a common language of as-planned information for all parties involved within a project (Song et al. 2005). Specifically, an industry foundation classes (IFC)-based 4D system that contains all the information of the as-planned parts and their relationships, not only can serve as a complete as-planned database but also serves as the underlying structure for monitoring progress where deviation between the as-planned and as-built progress could be visualized. Figure 2.1 demonstrates snapshots of a 4D simulation superimposed on time-lapsed photographs.

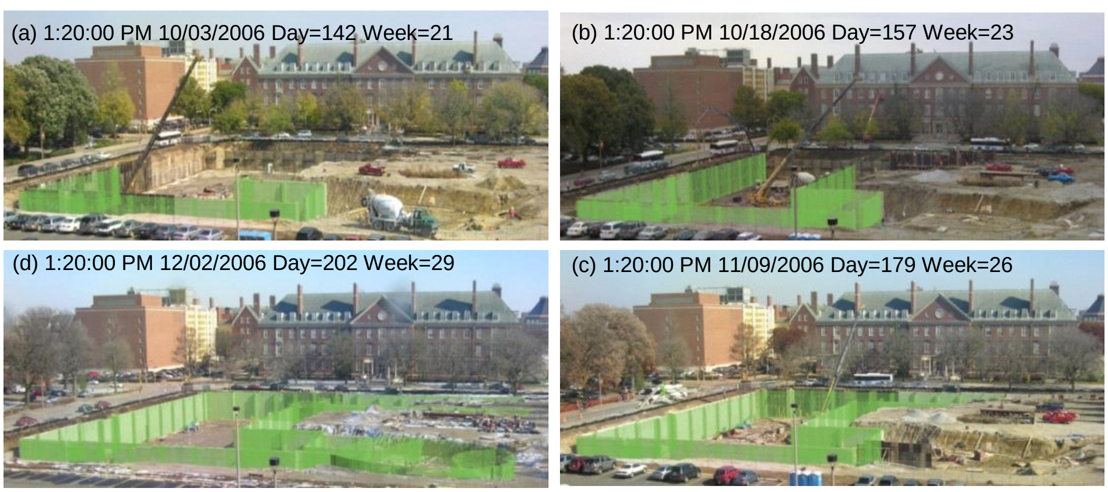

Figure 2.1. Augmented progress images: 4D simulation superimposed on time-lapsed photographs of a building construction project clockwise from 10/03/2006 to 12/02/2006 (Photograph subject: College of Business Instructional Facility, UIUC; Source: Facilities and Services, UIUC).

2.4.2 Time-lapse photography and videotaping as as-built progress data collection techniques

Photography and filming have proved for many years to be very useful means for recording site progress photo logs and work-face activities (Brilakis et al. 2005). With the advances of digital photography and webcams, these methods of information gathering are more cost-effective, practical, and acquiring a substantial footage is not costly. They have all the advantages found in time studies without the disadvantage of high data gathering costs. Owners and contractors usually acquire construction site time-lapsed photographs from a fixed location or capture videos for a series of functions (1) to create a photo log for dispute resolutions and litigation purposes and (2) permanently record certain field operations of an individual or a crew or a machine and the interactions among them for progress monitoring records and reports. Figure 2.2 shows four construction progress photographs out of a time-lapsed photograph collection for a construction site over a two year period.

Table 2.1 demonstrates the advantages/drawbacks of time-lapse photography and videotaping. Despite their various advantages, photographs may not demonstrate construction site information in very severe weather, illumination and shadow conditions. For example, Figure 2.3.a. and c demonstrate the construction site under fog, rain and snow weather conditions respectively and shows how weather conditions can affect the quality of time-lapsed photographs in a construction site. Shadow is another problem which is caused by adjacent buildings or elements (temporary or permanent) and affects visual quality of photographs.

Figure 2.2. Progress images from a construction site time-lapse photography camera clockwise from 08/04/2004 to 08/04/2006 (Photograph subject: Institute of Genomics Biology, UIUC; Source: Information, Technology & Communication Services, College of ACES, UIUC).

Table 2.1. Advantages and drawbacks of time-lapsed photography and videotaping

Advantages	Drawbacks
• Easy to obtain progress images • Inexpensive • Time-Lapse photography continuously records and yields benefits of filming without diminishing understanding of the operations that is recorded • Easily understandable by any visually able person • Provide more detailed and dependant information • Making possible review and study by analysts, management, or other groups away from hustle and bustle of the work site • Suitable for progress monitoring and productivity analysis	• Distortion of images – make it challenging to superimpose images • Show what is not obstructed by objects such as construction machinery or scaffoldings • Show what is within range and view field • Various illumination, shadows, weather and site conditions makes it difficult for image analysis • Storage of digital photographs/ videos

Figure 2.4.a and c show three photographs that are selected out of a working day photo log. These photographs show how shadow affects the visibility of the work site and how these effects may reduce visibility of the elements on a photograph. However since a full set of photographs are collected during working hours, different zones and locations on the jobsite could be studied at different times. Since progress is usually measured within weeks or even days (not hours), this allows the selection of more visible photographs for the purpose of analysis and representation. Furthermore, application of robust image analysis and pattern recognition techniques such as Gaussian filters (Forsyth and Ponce 2003) allows the photographs to be enhanced which in turn reduces and/or neutralizes these effects. Overall, compared with techniques that generate only words and numbers, photography has the advantage of being easily understandable and believable to those who are not well versed in studying material or numerical data analysis or who question verbal and written reports (Oglesby et al. 1989). This technique is particularly useful when the activities depicted are not going as smoothly as they might, since it is difficult for anyone to argue successfully that the photographs do not portray the as-built work situation.

Figure 2.3. Different weather conditions during a construction project: a) fog, b) rain and c) Snow (Photograph subject: Institute of Genomics Biology, UIUC; Source: Information, Technology & Communication Services, College of ACES, UIUC).

Figure 2.4. Effect of shadow on a single working day (Photograph subject: Institute of Genomics Biology, UIUC; Source: Information, Technology & Communication Services, College of ACES, UIUC).

2.4.3 Visualizing construction progress

Considering the existing generic progress monitoring methods, earned value analysis (EVA) can provide a monitoring basis and allows the future performance to be forecasted. Although EVA has some limitations as referred in Kim and Ballard (2000), but since in EVA, all the construction work is planned, scheduled, and budgeted in time-phased planning value increment, it can constitute a performance measurement baseline (Abba 1997) which is useful for comparison. EVA provides information in terms of as-built conditions, potential issues, prior concerns, and future scenarios in one construct. Along with time photography as an automated data collection method, 4D model and cost database, for every decision making, EVA performance metrics needs to be calculated and visualized. The scheme of using this methodology is further explained in the subsequent section.

2.5 Progress Monitoring Visualization System Scheme

Visualization process consists of a series of modules which results in color coded time-lapsed AR imageries. Figure 2.5 summarizes the information action-representation-environment perspectives for the proposed system. As represented in Figure 2.5, raw data are collected from two different sources: the *as-planned* and the *as-built* performance environments. The collected information represents *product* models, i.e., IFC 3D as-planned model and site photographs (Figure 2.5, 1-A and 1-C), *process* models, i.e., working schedule and operation process (Figure 2.5, 3-A and 3-C) and *cost* modules, i.e., estimated and performed costs (Figure 2.5, 4-A and 4-C). Collected information from these two environments is merged to produce a 4D as-planned simulation and time-lapsed photographs (Figure 2.5, 2-A and 2-C, respectively). For any given time, the as-planned model is superimposed on the as-built performance model (i.e., site photograph) (Figure 2.5, 2-B). This process involves proper registration of the 3D virtual world and photograph coordinates. The superimposed imagery would allow discrepancy to be either manually or automatically *detected* and *quantified* (Figure 2.5, 3-B and 4-B). At this stage, cost values are extracted from estimated and actual construction cost modules and are integrated to the system (Figure 2.5, 4-A and 4-C). This would allow cost information required for EVA to be derived. This information is appended to the known as-planned and as-built information and allows the budget spent to be properly assessed and the cost discrepancies to be understood.

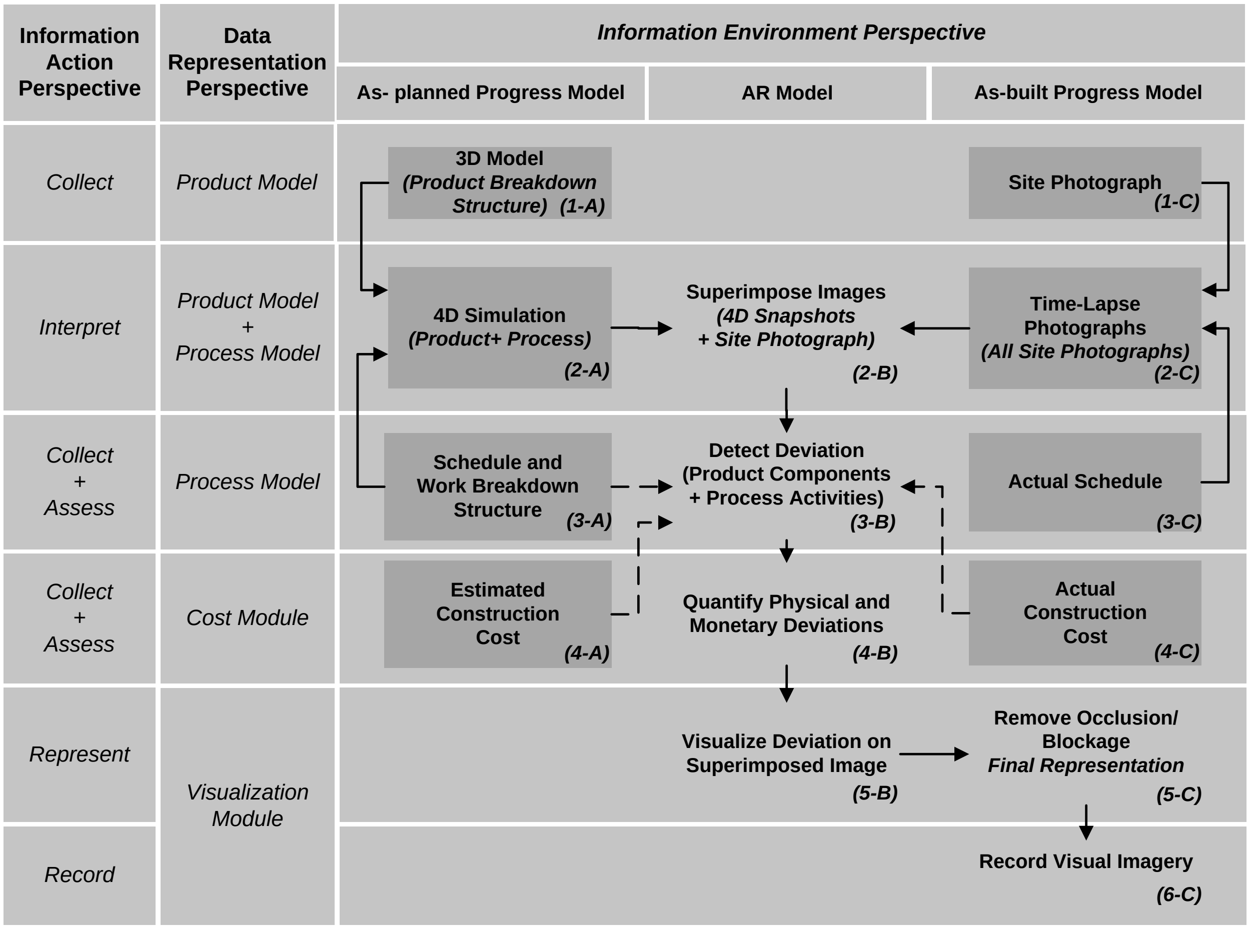

Figure 2.5. Information Action-Representation-Environment perspectives for visualization of construction progress monitoring.

The next step is to monitor progress against the performance measurement baseline, or the planned value. The physical earned value performed is then related to the actual costs spent to accomplish the physical work performed, providing a measure of the project's cost performance. To establish the guideline for the proposed system, the IFC as-planned model and the work break down structure in the schedule are considered as the basis of monitoring (Figure 2.5, 2-A). The level of details is based on the product and process work breakdown structures and cost estimating scheme in the as-planned model. For example if a general contractor schedule is provided, only major activities associated with building elements are visualized in the 4D model and monitoring system only involves that level of details in the schedule as the baseline for measurements. If a detailed daily schedule is available, the 4D as-planned model may further visualize the dynamics of the construction operations and the site, such as temporary structures and site layout. In this case, a more detailed progress measurement is possible. However, visualizing detailed construction activities such as electrical rough-ins may not be possible and therefore at this stage, the proposed model only incorporates construction schedules with a visible physical progress level in terms of the building structure and façade. Based on the guideline set during the planning phase and generation of the as-planned model, interpretation and assessment of the data would be performed in the subsequent steps.

At the following step, a series of visualization techniques is applied to visualize EVA metrics (Figure 2.5, 5-B); i.e., according to the status of the progress, the as-planned model would be color coded and superimposed on top of the photograph. Once the status of the progress is represented on the superimposed image, any occlusion and blockage caused by the superimposition should be removed. Therefore depth and perspective integrity of the virtual and actual environments is maintained (Figure 2.5, Figure 2.6.C). The final imageries are represented for decision making and are kept as a record for progress monitoring photo log. Figure 2.6 shows a color coded superimposed image where the progress status is visualized. In this figure, on-schedule entities are represented in light green entities, ahead of schedule entities in dark green, and behind-schedule entities in red color.

This reporting process is repeated for every coordination cycle where control actions are taken and the construction schedule is revised and updated by project participants. For example, if architectural/engineering/construction teams have coordination meeting every other week, this report would provide progress information from the last meeting to the current meeting considering the same time period for future activities that may have been performed in the project. In this section, an overview of the data collection, comparison baseline, and assessment processes have been discussed. In the sections that follow, each of the steps (i.e., registration, assessment, representation, and recording) is discussed in detail.

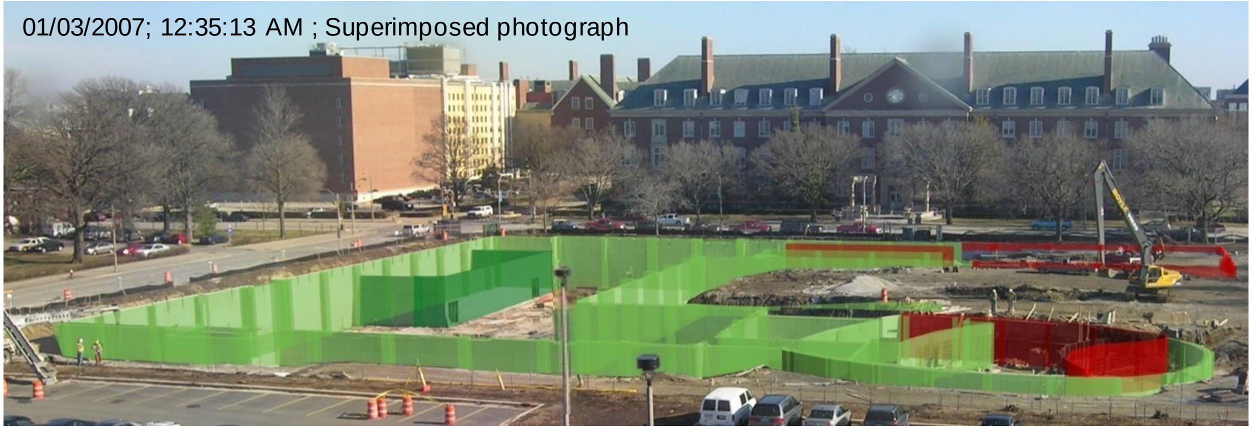

Figure 2.6. A color-coded superimposed image visualizing the progress status: entities that are in light green are on schedule, entities on dark green ahead of schedule and red entities are behind schedule (Photograph subject: College of Business Instructional Facility, UIUC; Source: Facilities and Services, UIUC).

2.5.1 Geometric camera calibration

The first task in generating superimposed images is to relate the 3D virtual model to the two-dimensional photograph. This means any point in the 3D model such as $P(x, y)$ needs to be precisely related to image coordinates $p(u,v)$. In the case of time-lapsed photographs, the camera location is fixed on the construction site, therefore, ideally, if camera is registered once, the correspondences between the photographs and the virtual model would be set for all subsequent images; i.e., with the same correspondence relationship, all the images of the 4D environment could be superimposed on the photographs. However, photographic cameras, webcams, and/or video recorders similar to any surveying camera are subject to displacement and vibration caused by gravity and lateral forces such as wind. Figure 2.7 shows the camera registration error. A deviation in camera angle can make a major error in registration. As seen, perspective views A and B are seen from the same location with different view angles. Due to these potential registration errors, the camera needs to be regularly adjusted. In this scenario, it is assumed that the location of the camera will be regularly fixed at all times and the same correspondence relationship between the 3D virtual world and the photograph coordinates could be applied to all time-lapsed photographs.

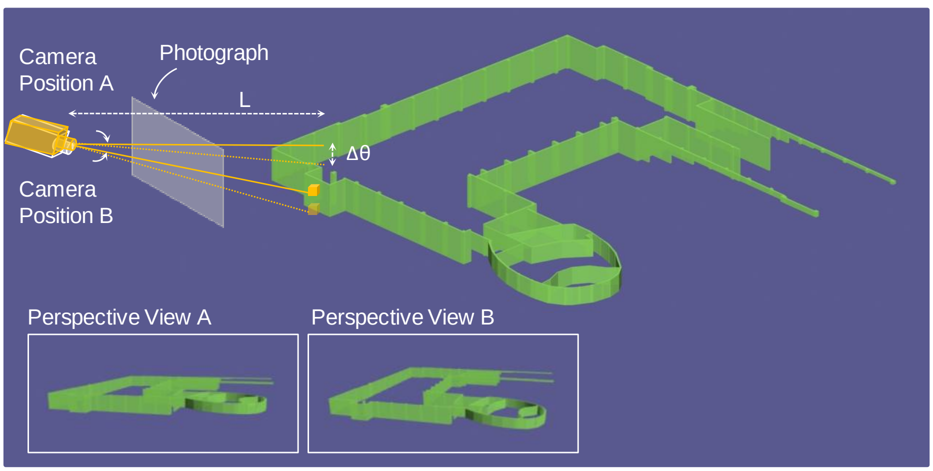

Figure 2.7. Camera registration error: A deviation in the camera angle within the distance of the camera to the site could generate a major error in registration. Perspective views A and B show the result of deviation in the photograph taken by the camera from the same location.

Then after knowing the camera is fixed, correspondence between the 3D model and photograph needs to be set. The photograph and camera coordinate systems are related by a set of physical parameters, such as the focal length of the camera lens, the size of the pixels, the position of the principle point (of the lens), and the position and orientation of the real world (Forsyth and Ponce 2003). In order to register the camera, these *intrinsic* and *extrinsic* parameters of the camera should be defined. Intrinsic parameters relate the camera coordinate system to the idealized coordinate system (i.e., effective focal length, aspect ratio, image center coordinates, and radial distortion coefficient) and extrinsic parameters relate camera's coordinate system to a fixed camera coordinate system and specify its position and orientation in space (i.e., rotation matrix and translation vector) (Forsyth and Ponce 2003). Estimating these parameters of a camera is called *geometric camera calibration* (Forsyth and Ponce 2003). If we consider $p=(u,v,1)$ and $P=(x, y, z,1)$ to be the homogenous coordinates of the points in the photograph and the virtual world, the relationship between these points in general terms can be represented as :

$$p = \frac{1}{z} MP \tag{2.1}$$

where $M_{3\times 4}$=projection matrix and z=depth of the point. To solve Eq. 2.1 for M, a set of features (i.e., points) with known positions in the photograph and the 3D environment are required. In order to achieve good and predictable results for M, there is a certain amount of preparation that needs to be done manually. This preparation consists of two main areas: (1) Identifying "matchable" features in the photograph and (2) associating 3D features (from the virtual model) to the features chosen in the photograph. It is extremely important for setting correspondences and solving the equation to choose accurate features (points) within photograph and 3D model. However, since photographs are formed in pixels, finding the accurate positions for features could be a very challenging task. For example, let's assume that the selected feature to be the top corner of two converging concrete walls. In a low quality photograph, this point could be located in-between pixels and it affects the quality of the preferred location for registration purposes which affect preciseness and quality of registration. An alternative to increase the accuracy for solving this equation is to extract more features from the photograph. Therefore, by selecting more features to establish the correspondence, the error in a single feature selection would not significantly affect the overall registration outcome and therefore the cumulative error in feature selection would be minimized. Figure 2.8 shows an example of feature selection and setting correspondence relationships for three points. As shown in Figure 2.8, the points extracted from photograph pixels with plus symbols "+" are related to 3D world coordinates indicated with cross symbols "×".

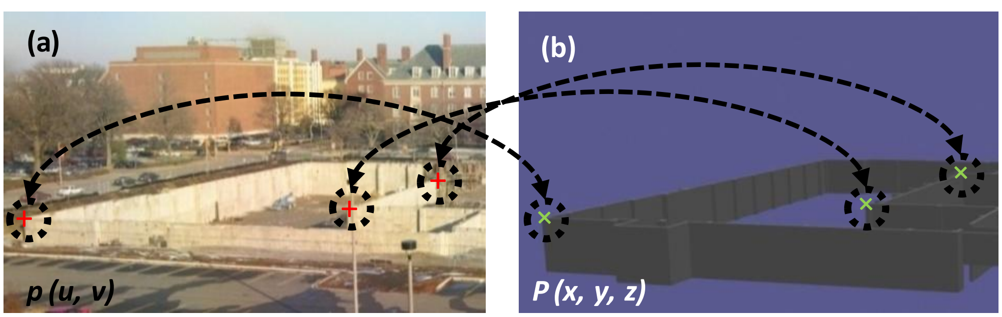

Figure 2.8. Feature selection and setting correspondences between a part of a photograph and 3D coordinate system. Plus symbols (+) in (a) show the pixels correspondences of cross symbols (×) within the 3D coordinate system in (b).

In this situation where more than minimum required features are selected, instead of directing solving the equation, camera calibration Eq. 2.1 would turn to an optimization process for the error function where the discrepancy between image features and their positions in the virtual world with respect to the camera's intrinsic and extrinsic parameters is minimized. It is also imperative to have features spread out evenly throughout the photograph — which represent the space from foreground to background as well as the side-to-side and up and down distance — to allow a more accurate calibration. To automatically perform the registration, Autodesk Viz (2007) camera matching toolbox has been used. This toolbox requires at least five points to calculate a solution based on aforementioned error function; however, it is better to choose more features to refine the matching through the iteration. Figure 2.9 shows how feature selection and the correspondence setting is performed for a photograph. In this case, surveying information of the site (location of the benchmarks) is not known and the matching needs to be performed given the photograph information and the 4D model. Therefore, first, an IFC-based model of the building at an early stage of the 4D environment is imported to Autodesk Viz. (2007) A photograph of the same time frame of construction in which various features of the construction entities could be detected is placed as the background in the matching window. Now a set of features are selected from the photograph and will be matched to their correspondence in the 3D model. Particularly, corners of converging entities (e.g., top and bottom corners of converging foundation walls) would be a good choice. Despite diminishing effects of shadow with reducing visibility of the images, shadow could be very helpful in camera calibration, since it would allow corners of any selected entity to be easily chosen. To increase the accuracy of registration and minimize the effect of pixelized photographs, fifteen features are selected from various surfaces and different elevations within the photograph (i.e., top and bottom corners of converging foundation walls and converging walls/ columns). The number of features required to achieve a precise registration (in this case 15 features) is selected through an iterative process in which a desired visual registration is achieved, i.e., a minimal error in the matched figure visually resides. Figure 2.9.c shows some of these selected features where the plus sign shows the location in the photograph and the cross sign, the location of those features within the 3D model. In this case, a cumulative registration error of 1.45 pixels is achieved which has resulted in a visually precise registration. The superimposed 3D on the photograph is shown in Figure 2.9.d.

2.5.2 Progress assessment on the superimposed imageries

Once the camera is registered, the as-planned model can be superimposed on the photograph. At this step, discrepancies between the as-planned model and the photograph (as-built) can be easily identified. Given the deviations observed, EVA metrics are obtained (compared to schedule or cost information, Figure 2.5) and a color (depending on the progress status) is assigned to the planned model.

Figure 2.9. From Top to Bottom: (a) Site Photograph superimposed with 3D model in Autodesk Viz environment, (b) site photograph, (c) close view on feature selection and matching between the photograph and the 3D model and (d) superimposed 3D model on the site photograph (Photograph subject: College of Business Instructional Facility; Facilities and Services, UIUC; Application: Autodesk Viz).

Figure 2.10 shows the assessment of the schedule deviation on a building project. Before a coordination meeting, a series of actions are performed to prepare the visualized progress monitoring status. A photograph of the basement level of a building taken on December 2, 2006; 1:13 p.m. and a registered snap-shot of the 4D as-planned model taken on the same time are represented in Figure 2.10.a and b, respectively. Based on the visual comparison between the photograph and the as-planned model, discrepancies are identified. These discrepancies have been manually analyzed and the physical components of the basement level that are behind or on-schedule are identified. The schedule deviation is quantified by the management team based on the construction schedule and based on the EVA analysis performed. Then, different colors (light green for on schedule and red for behind schedule) are assigned to each of the components depending on its progress status.

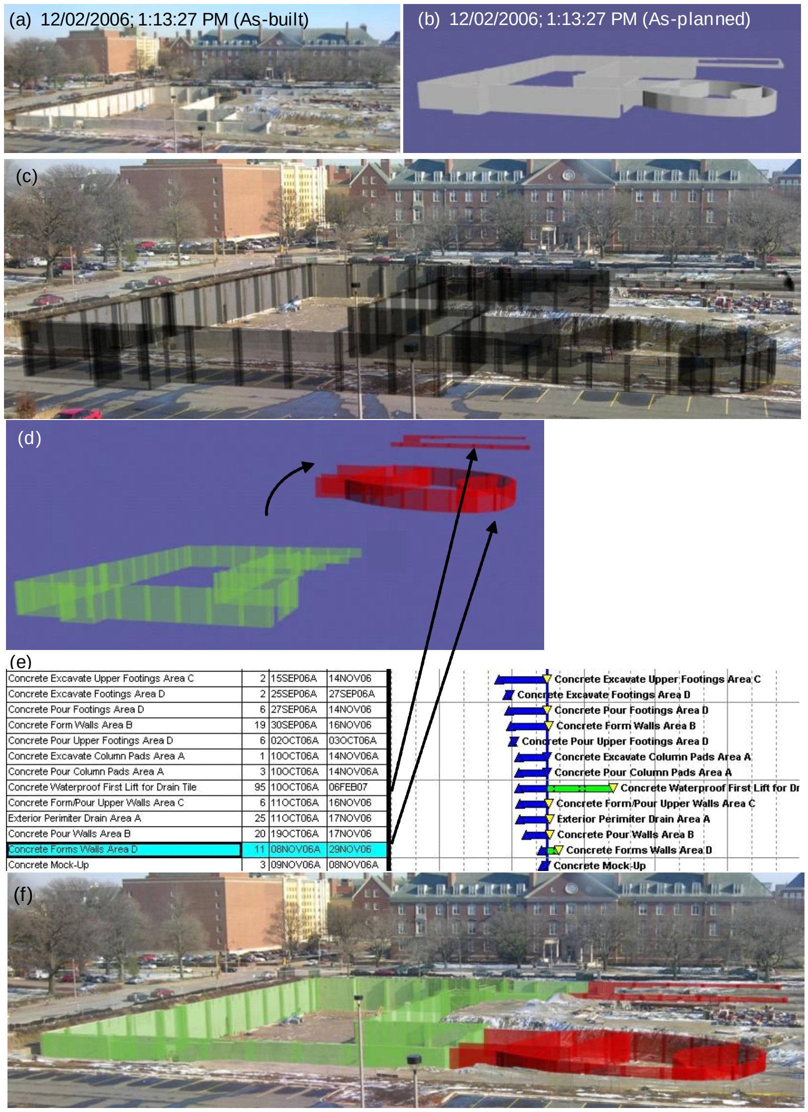

Figure 2.10. From Top to Bottom: (a) The site photograph taken on 12/02/2006; 1:13:27PM, (b) Snapshot of the 4D model at the same time as the photograph, (c) superimposed image, (d) schedule deviation detected and color coded according to the schedule in (e), and (f) color-coded superimposed 3D model on the site photograph (Photograph subject: College of Business Instructional Facility, UIUC; Source: Facilities and Services, UIUC.

It is clear that as more components are constructed or install on the site, the number of 3D model components in the 4D environment increases and as a result visual representation could potentially become more complex. Given the identified deviations, a consistent visual scheme is required to simplify and facilitate its interpretation. Therefore, in order to effectively and consistently use these visualization techniques, a single color spectrum ranging from dark red to dark green for all possible EVA monitoring and project performance metrics based on an underlying metaphor of a traffic light is proposed (Figure 2.11). This metaphor can manually or automatically visualize various project metrics with discrete values. For example it categorizes building elements based on their schedule deviations in three distinct categories: ahead of schedule, on schedule, and behind schedule (Figure 2.11).

Color Spectrum			
Performance	Poor	As Expected	Excellent
Time Deviation	Behind Schedule	On-Schedule	Ahead of Schedule
Cost Deviation	Cost Overrun	On-Budget	Cost Savings
Quality	Below Quality Requirements	Meet Quality Requirements	Exceed Quality Requirements
Conflicts	Claims	No-Conflicts	Excellent Work
Safety	Recordable Accident/ Injury	No Recordable	No Accident/ Injury
Productivity	Less than Expected	As Planned	More than Expected
Environmental Impacts	More than Expected	As Expected	Less than Expected
Social & Political Impacts	More than Expected	As Expected	Less than Expected

Figure 2.11. Critical information sets for project managers during construction phase and the color spectrum.

According to Figure 2.11, *light green* is used to represent those components that their performance is "as-expected," *dark green* for those components that are performing "above expectation," and they need the least management effort, while *red color* represents components that need corrective action. Once the status of progress for each building component is identified, these colors are assigned to the 3D components and the color coded 3D as-planned model is superimposed on the photograph. Figure 2.12 shows the site and superimposed photographs representing as-built and progress status respectively. As seen in Figure 2.12.b, behind schedule 3D entities that are color coded in red, on-schedule 3D entities in light green and ahead of schedule in dark green. In Figure 2.12.d, behind schedule steel members along with parts of the foundation components are color coded in red which represent that these components may need corrective actions in order for the project to be on schedule. The application of color gradients and color quadrangles to visualize multiple progress parameters together or ranges values for a progress situation has also been considered [please refer to Golparvar-Fard et al. (2007)]. Authors have implemented a "MouseOver" action on these augmented photos to make these imageries are interactive and provide progress status information associated with the colors. This potentially allows the user to also extract progress monitoring data from the visualization system.

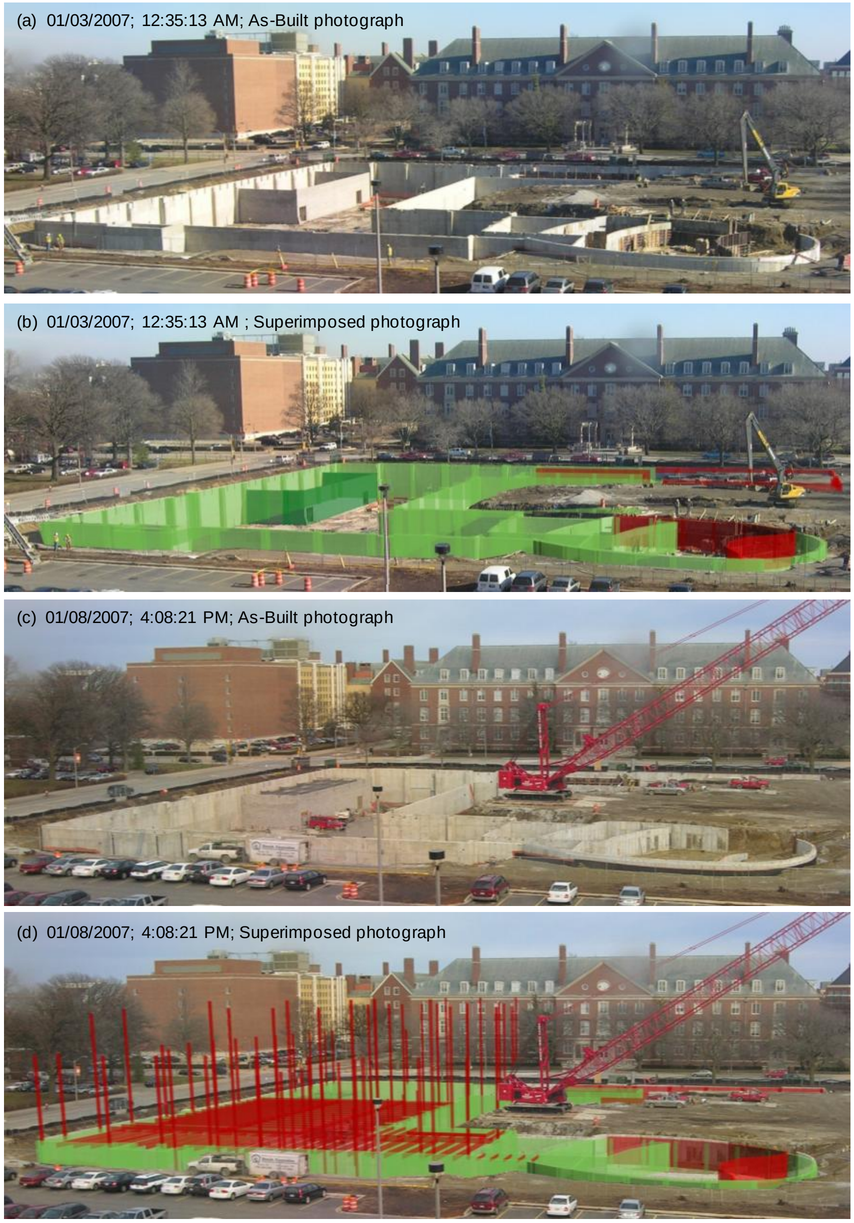

Figure 2.12. From Top to Bottom: (a) The site photograph taken on 01/03/2007; 12:35:13AM, (b) The color-coded superimposed photograph at the same time as the photograph a, (c) The site photograph taken on 01/08/2007; 4:08:21PM and (d) The color-coded superimposed photograph at the same time as the photograph (c). (Source of the photographs: Univ. of Illinois, Facilities and Services).

2.5.3 Feature extraction (occlusion removal techniques)

Once the augmented photographs are generated, in order to keep the realism of the scene and perspective integrity of the virtual and actual environments, the occluding objects needs to be placed on the original depth in which they appear from the perspective of the viewer (Figure 2.5, Figure 2.6.C). This requires two types of features to be extracted: (1) Static features and (2) dynamic features. These features are explained as follows.

Static Feature Extraction

Some visual features, such as excavation profile, fixed components on the site such as light towers and/or trees are static on the time-lapsed photographs, i.e., the shape or location of these features, do not change rapidly. Once the superimposition of the colored as-planned model on the site photograph is performed, some of these features are overlaid with the color coded 3D model, while in camera's line of sight, these features are located in front of the as-planned 3D model and should not be occluded by the model. Hence these features need to be extracted from the original site photograph and overlaid on the superimposed image. Since these static features do not frequently change throughout the period of construction, once they are recovered, the same process could be applied to the rest of the time-lapsed photographs. In computer vision, there are many different edge detection techniques that could help in finding these features within photograph. These methods include but are not limited to Canny, Sobel, Robert, Laplacian of Gaussian, and SUSAN (smallest univalue segment assimilating nucleus) edge detection techniques (Shin et al. 2001; Smith and Brady 1997). All these methods could be used to detect corners of the features and localize them. Among these methods, SUSAN edge detector had been applied in this research due to its good detection, localization, response, and speed to be usable for image processing systems compared to the rest of the mentioned edge detection techniques (Shin et al. 2001; Smith and Brady 1997). In this method, nonlinear filtering is used to define image parts that are closely related to each individual pixel. These pixels are associated with their local regions within the photograph that have similar brightness to that pixel. Feature detectors are based on minimization of local regions and noise reduction. The detail of this method is not scope of this chapter and could be found in Smith and Brady (1997); rather the applicability of the method to extract static features is described in the AR model. Figure 2.13 shows the result of applying the SUSAN edge detection in recovering the excavation line, light poles, and some machinery located on the construction site. The recovery of the information below excavation line in the photograph has been done in a supervised manner, i.e., the required recovery section is manually selected and it is automatically applied to subsequent time-lapsed photographs.

Another possible way to overcome static occlusion problem is to model the static occluding objects in 3D model and have them hide the geometry of the augmented images just as any real object hides the background in photographs. (The writer would like to acknowledge that this idea was suggested by one of the anonymous reviewers of a version of this work that was published in ASCE journal of Computing in Civil Engineering). However this method may increase the level of details required for 3D modeling and would not be suitable for cases where the occluding objects, themselves needs to be detected and/or tracked.

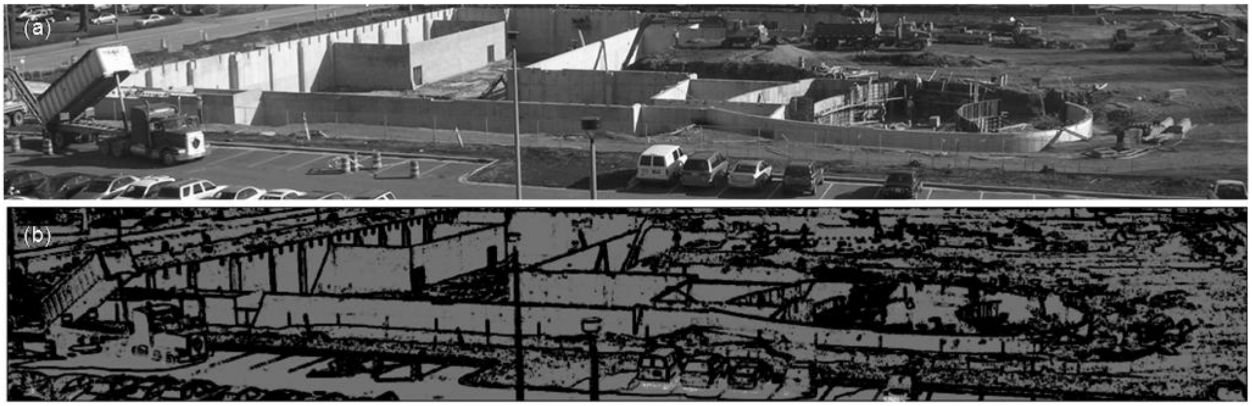

Figure 2.13. (a) Cropped portion of the photograph taken on 01/03/2007; 11:22:55AM and (b) the image after applying SUSAN Edge detection algorithm (Threshold=20); as seen the excavation line, lamp posts, truck on the left site of the photograph and the cars parked are recovered.

Dynamic Feature Extraction

Along with aforementioned static features, dynamic features also exist within photographs such as construction machinery, temporary structures, and work crew. These features also need to be extracted to be overlaid back on the photograph to preserve depth and perspective within the superimposed photograph. The same feature detection technique i.e., SUSAN are applied to dynamic feature extraction. As seen in Figure 2.13 the truck in front of the foundation wall is also recovered. This method required manual supervision and could be time consuming while other techniques such as identification of moving objects between consecutive images or using different points of view that do not have the machinery crossing their field of view could also be considered for future implementations to reduce such overheads. (The writer would like to acknowledge that this idea was suggested by one of the anonymous reviewers of a version of this work that was published in ASCE journal of Computing in Civil Engineering).

2.5.4 Visualized progress report

Figure 2.14 illustrates a visualized report of progress monitoring. In this figure, the photographs and 4D snapshots are presented and based on the work schedule and the comparison performed, deviations are identified and are color coded. The deviations are also quantified based on the number of days according to the schedule and are reported. Finally, based on the actual cost occurred and the planned costs, cost performance index (CPI) and schedule performance index (SPI) are calculated and presented (Figure 2.14.f). These forms of reporting can facilitate the coordination process by reducing the time to inform the participants as to what the situation is. Once the superimposed photographs are ready, the report table could be generated. This sort of representation does not require the observer to have any expertise or knowledge about construction operations.

Based on the positive feedback received from the professionals and executives of the five construction case studies in this research as well as other executives from leading construction companies, writers believe the visualization will facilitate progress monitoring process.

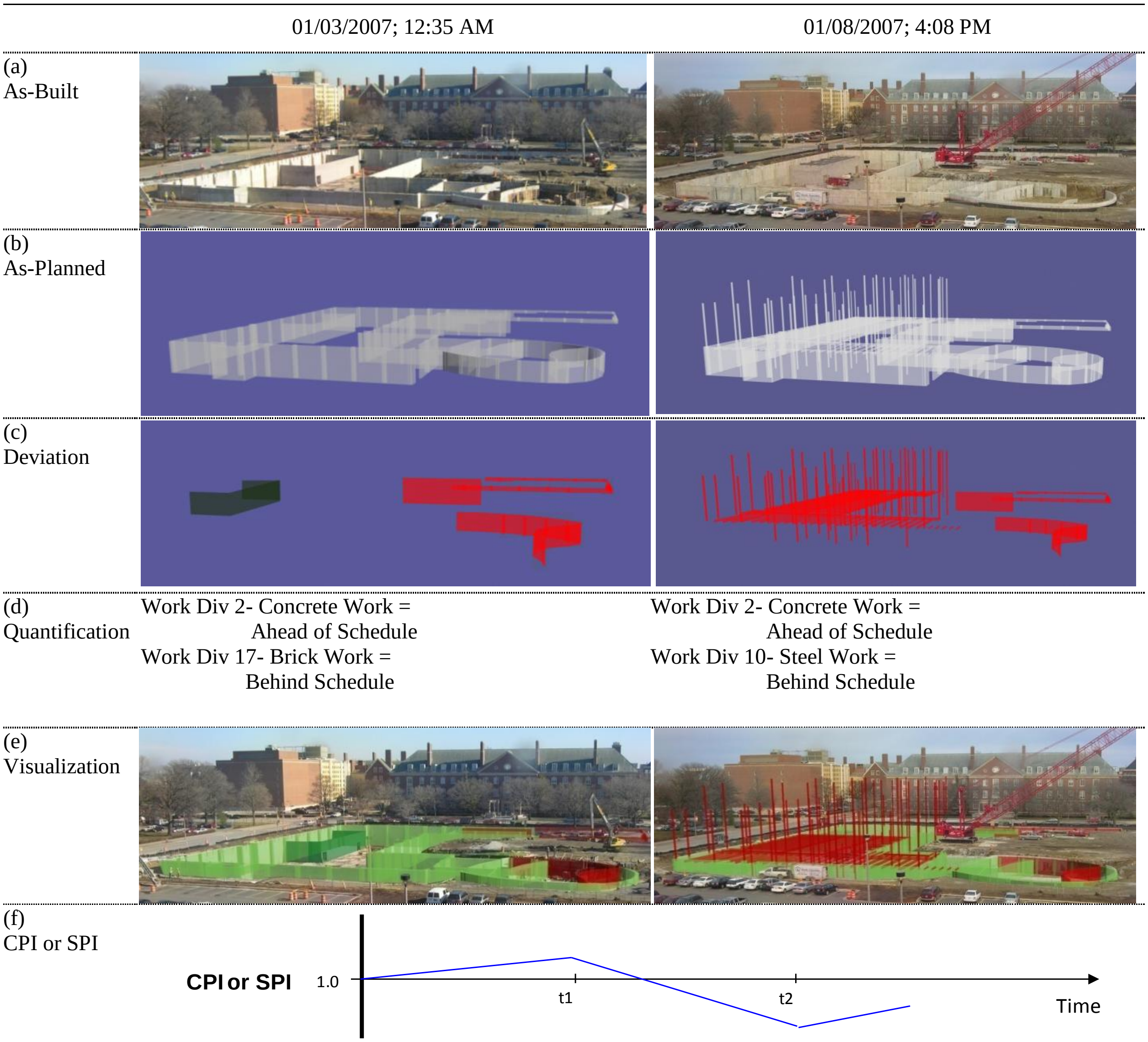

Figure 2.14. Visualized monitoring report: (a) As-built photographs, (b) 4D snapshots, (c) color coded virtual components, (d) quantification of the deviation, (e) augmented photographs and (f) measured EVA performance metrics (Cost performance metric (CPI) and Schedule performance metric (SPI)).

2.6 Conclusions

This preliminary method has shown that AR environment can successfully represent progress monitoring information in forms of as-planned, as-built information along with their comparison in a holistic manner. The superimposed images retain all the construction site information while the planned information along with the status of progress is enriching the contextual information within these photographs. The registration method gives the opportunity for image processing to be applied to specific regions within the photograph to assess the status of the progress based on material and shape recognition techniques. Color-coding metaphors give the end users of the superimposed photograph the opportunity of grasping progress status based only on a single representation form and could facilitate the communication of progress status within a coordination meeting, allowing more time to be spent on control decision making. Moreover preliminary results of applying feature detection technique preserves depth and perspective within the superimposed photograph allowing a more realistic picture of the progress status to be represented. The overall methodology and reporting addresses the issues related to data collection and reporting steps of a robust progress monitoring.

This work is part of a larger project that aims to automatically generate superimposed photographs for progress monitoring. Overall, the aim is to develop methods and processes within an AR environment that automatically and distinctively recognize visual construction content within site photographs, compare with the as-planned 4D model and visualize the status of progress using visualization and project management techniques. Considering application of time-lapsed photographs for visualization of as-built data collection, two major challenges are identified.

2.6.1 Challenges with time-lapsed photographs for visualization and assessment of the as-built data

Occlusion/Proximity Problems for Data Collection

Type of structures (e.g., steel, concrete, and composite), camera location for taking time-lapsed photographs (e.g., ground level versus upper levels, proximity of components to the camera), horizontal and vertical obstacles (e.g., static objects on site or blockage of the view of one element by the others), and outdoor versus indoor monitoring are all among the challenges of visualizing as-built data. Figure 2.15 shows two different scenarios on horizontal and vertical occlusions and the challenges of visualizing progress only on a single view. As seen in Figure 2.15.a and b, a column is occluded since there is another column which is blocking camera’s line of sight toward to the specific column under study. This situation has been solved by moving the camera to a new location. The vertical occlusion case is also shown in Figure 2.15.e where the slab has blocked the view toward the beam. There is a need for finding the optimum locations of a network of cameras both for outdoor and indoor progress monitoring to make sure all the elements could be monitored and data required for as-built progress is collected. In addition, authors suggest using an unordered set of registered photographs that are taken from various viewpoints to tackle the occlusion issue, and/or using a remote helicopter to capture photographs in order to avoid angle and line of sight issues for higher elevations.

Automatic Photograph Analysis for Progress Monitoring

Considering all the challenges with shadow and illuminations, a series of image processing and pattern recognition techniques is required to make sure progress of any type of element regardless of the material used or the texture of the surface could be detected under no severe noise in the photograph.

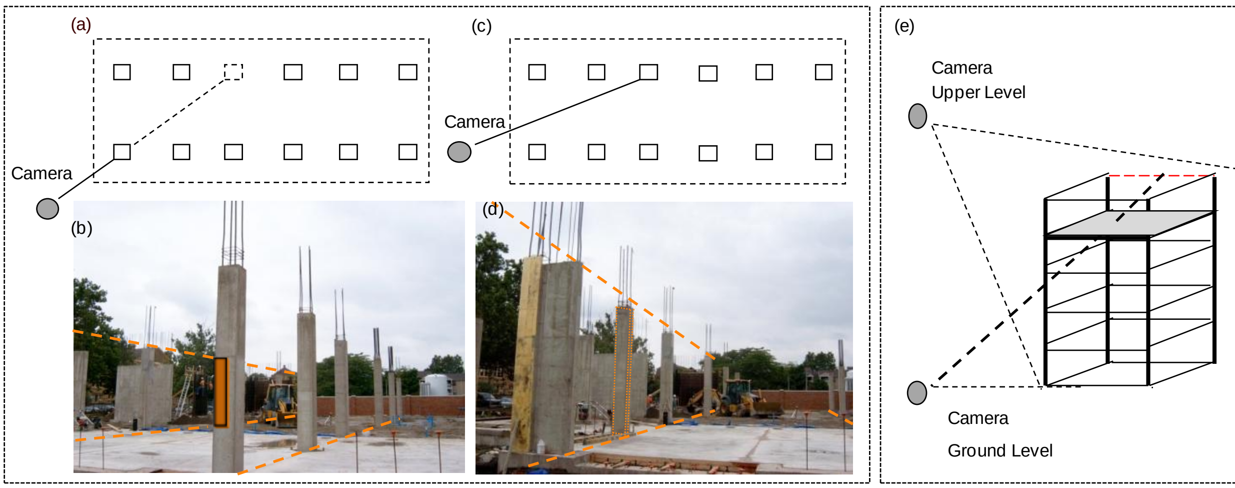

Figure 2.15. (a) Plan view of two column grids while one of the columns has occluded camera's point of view on the other column; (b) photograph of the occluded column; (c) position of the camera was changed and the column is not occluded; (d) photograph of non-occluded view and (e) camera pose problem in vertical situations, from ground level the highlighted beam is not visible (See color figure online).

2.6.2 Challenges with as-planned data

Although the baseline for progress monitoring would be the as-planned model, the correspondence between the schedule information and a product model on one side and the level of details within the 4D model on the other side, creates two major challenges for its application as a baseline for monitoring: (1) Activities with no correspondence in the 4D model: The 4D as-planned model does not represent all the information within the schedule. It may not show activities within schedule that do not have corresponding components. For example there is no way to communicate quality control activities within the current 4D models; and (2) Level of details in the 4D model: The major challenge with the as-planned data are mostly related to the level of detail for progress monitoring. Most of the 4D models can be viewed only in one level of detail. For example, it many only communicate schedule information within the general contractor's interest and it may not include all the shop drawing details, however for progress monitoring these details could affect the decision made on the progress observed. For instance, considering a steel structure, the level of details within joints between columns and beams could be modeled but it may not be possible to perform the comparison in that level of details. The applicability of a 4D model with such level of detail depends on the robustness of image processing techniques in overcoming data collection problems and considering the occlusions.

Based on these challenges, the future work and automation of the visualization falls in four categories: (1) exploring more visualization techniques and perform testability and applicability of these techniques in communication of progress monitoring information on concurrent representation of performance metrics and work sequence visualization; (2) exploring time-lapsed photographing for data collection, optimum locations for exterior and interior data collection considering all the challenges discussed; (3) addressing measurement, quantification, and assessment of progress status using effective image processing and computer vision concepts along with using edge detection techniques from one side and on the other hand, formalizing a database for the system based on IFC; and (4) applying the technique on various construction projects. Ultimately, an all-inclusive methodology will be developed that not only visualized progress status, but automatically collects data, analyses the photographs, compares them to as-planned model database and visualizes progress status.

CHAPTER 3. D^{4}AR- A 4-DIMENSIONAL AUGMENTED REALITY MODEL FOR AUTOMATING CONSTRUCTION PROGRESS DATA COLLECTION, PROCESSING AND COMMUNICATION

3.1 Overview

Early detection of actual or potential schedule delay in field construction activities is vital to project management. This entails project managers to design, implement, and maintain a systematic approach for construction progress monitoring to promptly identify, process and communicate discrepancies between actual and as-planned performances. To achieve this goal, this research focuses on exploring application of unsorted daily progress photograph logs available on any construction site as a data collection technique. The approach is based on computing- from the images themselves- the photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using daily progress photographs and superimposition of the reconstructed scene over as-planned 4D models. Within such an environment, progress photographs are registered in the virtual as-planned environment and this allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes superimposed over 4D models allow site images to be geo-registered with the as-planned components and consequently, location-based image processing technique to be implemented and progress data to be extracted automatically. The results of progress comparison between as-planned and as-built performances are visualized in the D^{4}AR (4D Augmented Reality) environment using a traffic light metaphor. This chapter presents preliminary results on three ongoing construction projects and discusses implementation, perceived benefits and future potential enhancement of this new technology in construction, in all fronts of automatic data collection, processing and communication.

3.2 Introduction

Early detection of actual or potential schedule delay or cost overrun in field construction activities is vital to project management (Halpin 2006). It provides the opportunity to initiate remedial actions and increases the chance of controlling such overruns or minimizing their impacts. Since schedule delays and cost overruns diminish profits of a project, it is easy to see why both project managers and project executives are perceptive to any deviation. This entails project managers to design, implement, and maintain a systematic and comprehensive approach for progress monitoring to promptly identify, process and communicate discrepancies between actual (as-built) and as-planned performances as early as possible. In this chapter, monitoring is defined as collecting, analyzing, recording, and reporting information concerning key aspects of project performance at the appropriate level of detail required by project managers and decision makers.

Despite the importance of progress monitoring, systematic implementation of such framework can be challenging because: (1) Current progress monitoring is time-consuming as it needs extensive as-planned and as-built data extraction (Navon and Sacks 2007). Every day, superintendents and field engineers study 2D as-planned drawings, construction details as well as project specifications, review progress perceived by that date and study schedule and work breakdown structure to detect the work to be performed. Subsequently, they perform, monitor and supervise site activities and for the work performed, they collect site photographs and document daily construction reports; (2) The excessive amount of work required to be performed may cause human-errors and reduce the quality of manually collected data and since only an approximate visual inspection is usually performed, makes the collected data subjective; (3) Existing methods for monitoring such as weighted milestones and budget-based monitoring are also non-systematic and create a tendency to let project as-planned inputs serve as proxy measures for performance outputs which affects the quality of the results (Meredith and Mantel 2003). They may also create a time-lag between the time progress is reported and the time that progress is actually accomplished; (4) In addition, progress reports are visually complex, and they do not effectively represent multivariable progress information (i.e., schedule, cost, and performance) nor do they intuitively reflect information pertaining spatial aspects of the construction progress and their associated complexities (Kymell 2008, Poku and Arditi 2006; Koo and Fischer 2000); and (5) Current reporting methods increase the time required to describe and explain the progress situation in coordination meetings and in turn could delay the decision making process (observed by authors and reported in Golparvar-Fard et al. 2006). In summary, with current methods, it may be not be easy to understand the progress situation clearly and quickly.

Most of the current techniques for automating progress data collection (such as laser scanners, RFID and embedded sensors) are promising if one wishes to eliminate labor-intensive and non-value adding tasks associated with manual progress data collection. A drawback is the necessity to add new tasks that need to be performed before, during, or after utilization of such technologies at a construction site (El-Omari and Moselhi 2008, Kiziltas et al. 2008, Akinci et al. 2006). Barcodes and RFID sensors are excessively time consuming to set up and costly for many projects. Additionally they cannot be attached to many types of components or capture progress of partially installed components. Laser scanners are also expensive, require experienced people for operation, could document excessive noise within dynamic scenes, and require manual data processing and selection as well as a preparation time for warming up (Kiziltas et al. 2008). In addition, laser scanners only provide Cartesian coordinate information of the scanned scene.

Working with such featureless data and without any semantic information of the scene (Kiziltas et al. 2008), geometric reasoning is challenging and induces estimation errors. Also none of these techniques (other than when site images are overlaid on laser scanners point clouds (El-Omari and Moselhi 2008) provide any reliable visual information about work sequence or site logistics. To address all these issues, in our approach we have taken all the aspects of progress monitoring into account: collection, analysis, communication and reporting. We have looked into the existing simple yet robust progress data collection and communication techniques available on any job site to see how we can effectively and efficiently build upon existing information and data collection techniques to address mentioned problems. Such information and techniques are categorized on two fronts:

(1) As-planned progress data: We consider using three-dimensional/ four-dimensional models as as-planned data repositories to facilitate accessing geometrical information, visualizing planned schedule and communicating progress. Visualization of the as-planned progress in 4D environment enables project participants and clients, regardless of their level of construction knowledge and expertise, to identify spatial layouts and explore construction processes (Hartmann et al. 2008, Hartmann and Fischer 2007, Woksepp and Olofsson 2006). In addition, 3D/4D models can provide a consistent visual base-line platform of as-planned information (Golparvar-Fard et al. 2009a, Song, Pollalis, and Peña-Mora 2005) and act as an underlying structure for monitoring progress where deviations between the as-planned and as-built progresses could be visualized.

(2) As-built progress data: Considering current technical inefficiencies of available data collection technologies i.e., laser scanners, bar codes and RFID tags we investigate the idea of processing daily progress photographs to enhance collection, analysis and communication of as-built data. Digital photography together with internet has enabled construction management companies as well as sub contractors, project owners and architects to share progress photographs on a truly massive scale. Nowadays it is a common practice for jobsite images to be gathered periodically, stored in central databases, and utilized in communication and coordination of project tasks (Soibelman et al. 2008). Site photographs not only have the advantage of being understandable to those who are not well-versed in studying written material or numerical data analysis or even those who question verbal or written reports (Oglesby et al. 1989), but also allow a large amount of progress data to be understood and absorbed quickly. Just as the Chinese proverb says “A picture is worth a thousand words”, it could be imagined how daily site photograph logs, which consist of many site images, can help as comprehensive sources of as-built data. Furthermore photographs provide a visual value in understanding large amount of information, and could be automatically processed and converted into information regarding construction progress (Brilakis and Soibelman 2008, Golparvar-Fard and Peña-Mora 2007, Navon and Sacks 2007,

Wu and Kim 2004, Abeid et al. 2003) and yet compared to other data collection techniques, do not burden efficiency of the project management processes by requiring significant data collection efforts.

In this chapter, we focus on the application of progress site imageries as well as 3D/4D models for progress monitoring. First we review current progress monitoring practice and its deficiencies in detail as well as the state-of-the art technologies for automatic progress monitoring data collection and associated visualization techniques. Then we present our work on combing daily progress images and 3D/4D models to create the 4 Dimensional Augmented Reality (D^4AR) models.

The D^4AR models consist of a new image-based modeling technique for visualizing progress monitoring wherein progress discrepancies between as-planned and as-built construction performances are visualized through superimposition of 4D as-planned models over site photographs using different visualization techniques such as a traffic light metaphor. Our approach is based on computing, from the images themselves, the photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built scene using daily progress photographs and superimposition of the reconstructed scene over the as-planned 4D model. Within such an environment, progress photographs are registered in the virtual as-planned environment, allowing a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes superimposed over 4D models allow site images to be geo-registered with the as-planned components and consequently, a location-based image processing technique to be implemented and progress data to be extracted automatically. The result of progress comparison study between as-planned and as-built performances can subsequently be visualized in the D^4AR environment. In such an environment, a construction project manager would be able to: 1) use the 4D as-planned model as a baseline for progress monitoring, compare it to daily construction photographs and study workspace logistics; 2) interactively and remotely browse and explore registered construction photographs in a 3D environment; 3) automatically analyze registered images and quantify as-built progress; 4) automatically measure discrepancies between as-planned and as-built performances; and 5) visually represent progress discrepancies through superimposition of 4D as-planned models over progress photographs, make control decisions and effectively communicate those with project participants.

Figure 3.1 shows a comparison between traditional representations of construction as-planned and as-built data and how D^4AR associates these two sets of information to visualize progress discrepancies and workspace logistics in single imagery. To that extent, we present reconstruction of the as-built scene, superimposition over as-planned model and visualization of the discrepancies, and discuss guidelines for automatic measurement of progress. The resulting system is robust and reliable in practice. Finally we have included preliminary results of generating these models for three ongoing construction projects, ranging from $32M to $62M for a period of two to two and a half years, and conclude with a discussion of limitations and future works.

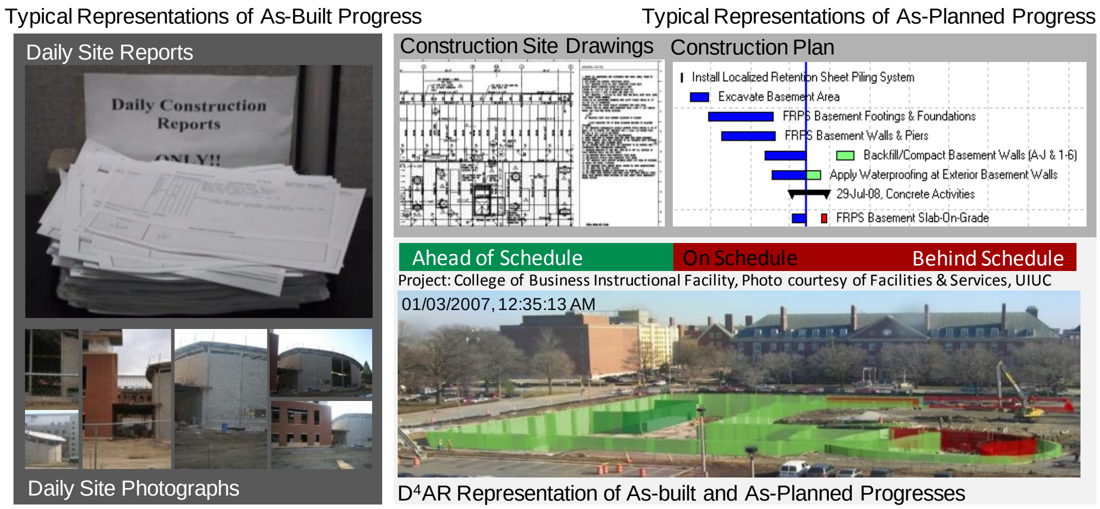

Figure 3.1. A comparison between traditional representations of construction as-planned and as-built data and how D^{4}AR associates these two sets of information to visualize progress discrepancies and workspace logistics in single imageries.

3.3 Progress Monitoring: Current Practice Challenges and Current Emerging Technologies

Well-depicted baseline, systematic data collection, rigorous comparison of the as-planned and as-built progress, and effective presentation of measured deviations are key ingredients for effective project control. Unfortunately many challenges undermine the ability to implement these objectives in practice. Next we examine some of these challenges:

3.3.1 Challenges in current practices

(1) Current progress monitoring is time-consuming and labor-intensive: Currently many construction projects are not systematically monitored, i.e., there is no monitoring plan for when and how to monitor progress, making it very difficult to take corrective actions on a timely basis. Current methods require manual data collection and extensive as-planned and as-built data extraction from construction drawings, schedules, budget information and field reports produced by superintendents, subcontractors, trades foremen and project managers (observed by authors and also reported by Navon and Sacks 2007). Occasionally, field personnel collect progress data from a construction site at certain time intervals, analyze and deliver them to project manager in different formats (e.g., as-planned data such as construction drawings, spreadsheets, bar charts, CPM or as-built data such as daily/weekly progress reports, progress graphs, site photographs and videos). Such discrete reporting does not explicitly convey problems in a timely manner, since project managers need to devote a significant amount of time and

effort to sort out, prioritize and interpret these data (Golparvar-Fard et al. 2009, Song, Pollalis, and Peña-Mora 2005). Figure 3.2 shows an example of existing mechanisms of reporting perceived progress in a coordination meeting at one of the projects under study.

(2) Quality of manually collected and extracted progress data may be low: Progress data– usually manually acquired by field staff– is dependent upon what they are able to measure on the construction site. Usually, the information collected tends to be based on their interpretation of what needs to be measured, the way it needs to be measured and the way it needs to be presented, and therefore it may not reveal the actual impact of site circumstances on the construction project. More importantly their approach may affect quality of the collected data and make it more susceptible to data error since the ability of measuring progress is based on the expertise of the field staff and the tools that are available to them. Figure 3.3 represents a sample of a daily progress report from one of the projects under study. As seen in this case, there is only a percentage documented per activity without further details.

Color Coding Scheme: Orange= Foundation and footings placed; Green = Foundation walls placed; Blue = Slabs placed; and Purple = Pipe installed.

Figure 3.2. An example of existing progress reporting techniques. Construction drawings and work schedules are hung on a construction site trailer's wall to communicate progress with contractors and subcontractors. Progress is visualized in two-dimensional drawings using annotations and color-coding. The date on which progress is made is also annotated on different sections. Different work plans are hung over each other.

(3) Existing methods of measuring progress are non-systematic and metrics are subjective: Accurate measurement of the progress performance usually poses the most difficult data gathering problem as there may be a tendency to let project inputs serve as proxy measures for output (Meredith and Mantel 2003). For example, a concrete subcontractor reports to the project manager that they have completed 60% of the

roof work. Does it mean 60% of the planned area/volume of concrete pouring is finished? Is it 60% of the planned concrete that has been used? Or is it 60% of the planned labor-hours that have been spent? Is it 60% of the originally planned work or the actual requirement that is complete? If the item being referenced is a small work unit, it may not have a significant difference. However, in the case where the references are to the whole task or project, assumption of input/output proportionality could be very misleading (Meredith and Mantel 2003). This issue is found in the most commonly used monitoring methods: (a) *Monitoring physical progress in percentile*: used in most construction fields and heavily reliant upon experience and knowledge of the project management personnel. This metric is subjective and inefficient in presenting progress due to its abstract nature of representing physical progress since the actual progress is determined by evaluation of the field staff; (b) *Budget-based monitoring*: based on the percentage of the budget paid to contractors according to the schedule-based inspections. This method of monitoring creates time-lag between progress estimations and schedule updates. In addition, judgments are often subjective and misleading, especially if field staff makes any erroneous decisions on the volumes of material consumed or the actual physical progress made. This in turn affects the robustness of the method (Shih and Wang 2004). Without a comparative analysis in the construction plan, resources, and cost data, inaccurate assumptions and measurements on the progress could be made. Consequently, mistakes such as over paying and overlooking of an expected delay might occur.

(4) Progress monitoring reports are visually complex: Control over the decision making for corrective actions and schedule revisions usually takes place in progress coordination meetings. A wide range of individuals (e.g., from the owners and architects to subcontractors and trades foremen) with different areas of expertise and interests often attend these meetings. In these face-to-face interactions, progress information needs to be easily and quickly communicated among the participants. However, none of the existing reporting methods (e.g., progress S curves, schedule bar charts, photographs, and textual reports) easily and effectively present multivariable information (e.g., schedule, cost, and performance) in a holistic manner nor do they intuitively reflect information pertaining to the spatial aspects of construction progress and their associated complexities (Poku and Arditi 2006, Koo and Fischer 2000). Existing representations cause a significant amount of information to be inefficiently presented in the coordination meetings; as a result, extra time needs to be spent in describing existing problems and explaining the context in which problems occurred rather than understanding the causes of the problems, evaluating alternatives to solve the problems and discussing corrective actions (based on field observations and as observed in Golparvar Fard et al. 2006). Therefore with the current methods, it is not easy to understand progress of a project clearly and quickly.

[redacted] **CONSTRUCTION INSPECTION REPORT**

Store No.	3374 New	**Schedule**	Site		Bldg.	
Store Name	[redacted]	Contract Time	141	days	187	days
Store Division	Midwest	Days Elapsed	175	days	84	days
Project Location						
Project Address	[redacted]					
City, State	Sugar Grove, IL.	Extensions		days		days
GO/GRO Date	3/29/2006	Days Left	-34	days	103	days
Date	11/28/05					
Time	8:00	Site Start	06/06/05	Building Start	09/05/05	
Report #	2	Site Complete	10/31/05	Building Complete	03/03/06	send to Arch. File clerks send to Arch. File clerks (new ~~or remodel~~)

WEATHER : Clear ____ Overcast X Rain X Temperature Range 50's

SITE CONDITIONS : Dry ____ Muddy ____ Snow ____

WORK FORCE :

Site	Refrig. / Fixt.	Msnry/Concrete	Electricians	Plumbers	HVAC	Ceiling
	X	X	X	X		
Iron	**Sprinkler**	**Stud / Drywall**	**Roofers**	**Carpenters**	**Painters**	**Flooring**
		X	CANCELLED		CANCELLED	

WORK PERFORMED

	Subcontractor	% Completed	Comments
1.	Site	95%	
2.	Foundation	100%	
3.	Masonry/Precast	80%	
4.	Iron	99%	
5.	Roof	70%	
6.	Sprinkler		
7.	Electrical	20%	
8.	Plumbing	35%	
9.	HVAC		
10.	Stud/Drywall	15%	
11.	Painting	10%	
12.	Ceiling		
13.	Refrigeration	10%	
14.	Fixturing		

MILESTONE EVENTS

	Event	Scheduled Compl Date	Actual Compl Date	Comments
1.	Pre-cast Start	10/6/05	10/18/05	
2.	Roof Start	11/17/05		
3.	Mechanical, Refrigeration & Electrical Rough-in Start	11/11/05		
4.	Slab Start	11/22/05		Non-colored concrete
5.	Deck Spray Start			
6.	Building Secured			
7.	VCT Start			
8.	Fixture Start			
9.	Energy Mgmt. Complete			
10.	Merchandising Start			

Figure 3.3. A sample of a real project progress/inspection report (some information is removed for confidentiality). As shown from the “Work Performed” section, it is very difficult to figure out how much real progress has been perceived or to figure out if schedule-based or monetary progress has been made.

3.3.2 Emerging field data capture technologies

For more than a decade, researchers have been pointing out deficiencies in current construction site data collection practices (e.g., manual data collection, need for systematic collection and processing of as-built data to produce useful and real-time progress information (Kiziltas et al. 2008, Bosche and Haas 2008, Navon and Sacks 2007, Navon 2006, Akinci et al. 2006; Chen and Wong 2002, Echeverry and Beltran 1997). According to (Navon and Sacks 2007) these research efforts have been motivated by: (a) an increasing need for real-time feedback and monitoring information, (b) rapid and cost effective technological development in automated data collection technologies for construction. The main technologies designed and implemented for automatic data collection are barcode and Radio Frequency Identification (RFID) tags, Global Positioning System (GPS), Laser scanners and embedded sensors:

- Barcode and RFID tags have been used to capture and transmit data from a tag embedded or attached to construction products (Kiziltas et al. 2008, Navon and Sacks 2007, Ergen et al. 2007, Jaselskis and El-Misalami 2003, Echeverry and Beltran 1997). Unlike barcodes, RFID tags do not require line-of-sight, close proximity, individual reading and direct contact (Kiziltas et al. 2008). Active RFIDs also have higher reading ranges and allow data to be stored on them; however their performances are reduced in proximity of metals and liquids in particular when RFID is used at higher frequencies (Kiziltas et al. 2008). Although RFIDs and barcodes potentially eliminate non-value adding tasks associated with project management processes, they require frequent installation and maintenance. Additionally they cannot be attached to many types of components and they do not capture progress of partially installed components.

- Laser scanners have been used for construction quality control (Akinci et al. 2006, Jaselkis et al. 2006), condition assessment (Gordon et al. 2004), component tracking (Bosche and Haas 2008, Teizer et al. 2005) and progress monitoring (El-Omari and Moselhi 2008, Bosche and Haas 2008, Su et al. 2006). Although laser scanners are promising to automate data collection, still they are expensive and there is a set of challenges in implementing such technology on construction sites. These limitations include discontinuity of the spatial information, mixed pixel phenomenon (Kiziltas et al. 2008) as well as scanning range and sensor calibration. For example, any moving object in line of sight of the scanner would not allow the point cloud of the under-study object to be captured. In addition, the moving object creates additional effort of the user to manually have the noisy point cloud fixed. Furthermore as the laser scanner gets away from the objects, level of details within the captured components are reduced. Laser scanners also require regular calibrations as well as warm up time. They are not easily portable and cannot efficiently be used for scanning indoors. These limitations are a part of time consuming process of data collection; nevertheless since the type of data they provide only contains Cartesian coordinate information of the scanned scene, processing such data is time consuming and also they do not carry any *semantic* information, such as which point belongs to what structural components. Working with this type of featureless data makes geometric reasoning based on this data tedious and error prone (Kiziltas et al. 2008). Also none of these techniques provide any visual reliable information about work sequence, site logistics or construction crews. Recently El-Omari and Moselhi (2008) presented a new approach for progress data collection by using 3D laser scanners and photogrammetry. The method was shown to be less time-consuming and has higher cost savings compared to single application of laser scanners. Their suggested approach minimizes access limitations of scanner placement but still the processing time required for each scan may considerably be high and the registration of images and 3D point cloud needs further adjustments. Also laser scanners may not give the possibility of aligning site images - taken from arbitrary viewpoints- with the 3D point cloud; yet in El-Omari and Moselhi (2008) the common points between laser scanner's 3D point clouds with images have been selected manually. Manual selection of common points between each image and point cloud (as experienced by the authors) makes such an approach difficult to use.

- GPS, Geographical Positioning Systems as a location tracking tool also need line-of-sight between the receiver and the satellite; therefore it cannot normally operate indoors, limiting the project context that could be monitored. Behzadan et al. (2008) suggests using WLAN technique as a tracking technique for indoor locations but they also report difficulties in using WLAN set ups on actual construction sites, and they relate these inefficiencies to ongoing works (i.e., changes in soil, structure, plant and equipment, site layout). These inefficiencies necessitate WLAN system to be calibrated after regular intervals to maintain a high level of accuracy. Such regular calibration requirements may make such a system difficult to manage.

- Other techniques such as wearable computers (PDAs) along with speech recognition and touch screens have also helped in capturing construction site data electronically (Reinhardt et al. 2000), but current systems still need full time observer(s) to input and process the information (Navon and Sacks 2007) and have not minimized the time required to process the data.

Also, none of these techniques besides (El-Omari and Moselhi 2008) - in which photographs are used to provide more information about the context of the scene- provide visual and reliable information about work sequence logistics, site layout or construction crew. Our approach addresses all the aspects of progress monitoring: *collection*, *analysis*, *communication* and *reporting*. We have looked into the existing simple yet robust progress data collection and communication techniques available on construction sites to see how we can effectively and efficiently use such information to address mentioned problems. Such information is categorized on two fronts: as-planned visualization as a baseline of progress monitoring, and as-built data collection and visualization techniques. In the section that follows some of the previous works which have led to this research are briefly introduced.

3.3.3 As-planned visualization as baseline for progress monitoring

Visualization technologies have been widely adopted in construction, from visualizing control data (e.g., Korde et al. 2005, Songer and Heys 2003) to visualizing building products, to facilitate constructability reasoning or workability of the operation methods selected for construction (e.g., Hartmann et al, 2008, Kamat and Martinez 2008). The three main categories of these technologies that have been implemented to contribute to visualization of progress information are:

4D models as a progress monitoring baseline for simulating as-planned progress

These models are mainly developed for detecting spatial and temporal conflicts, understanding construction logistics, coordinating construction with subcontractors and trades and visualizing planned progress to owners (Hartmann et al. 2008, Kamat and Martinez 2008, Hartmann and Fischer 2007, and Staub-French and Khanzode 2007). These kind of pre-construction time-based models enable project participants and clients, regardless of their construction knowledge, to understand spatial constraints and explore construction alternatives before construction starts. While these models may not take into account every incident that might occur to the building under construction, they could be used as proper baselines for as-planned information of a project in our proposed research. These 4D models not only provide a realistic visual platform of the as-planned database, but also will serve as an underlying structure for monitoring progress where deviations between the as-planned and as-built progress status could be visualized.

Color/tone variations and motions for visualization of progress discrepancies

In this context, Song, Pollalis, and Peña-Mora (2005) introduced a project dashboard wherein a 3D-model visual representation was used to represent progress. Multiple project data sets were applied to geometric attributes (e.g., shape, faces and edges) of a building model by means of color- tone variations and motion. The results of this study suggests that consistent application of colors allows progress metrics to be represented easily and also eliminates visual complexities which are caused by complexities associated with large-scale and sophisticated building product models. The preliminary results of using color-tone variations form a suitable baseline for visualizing progress metrics and we expand our proposed research methodology and system upon this concept.

Augmented reality for visualization of progress

Within this category, Lee and Peña-Mora (2006) suggested overlaying as-planned models on photographs and conceptually formed a method for visualization of construction progress where deviations between planned and as-built performance models were conceptually represented in an AR (Augmented Reality) environment (such as ones developed by Behzadan et al. 2008; Wang and Dunston 2005). Using traffic light and weather metaphors, progress was manually visualized in comprehensive single imageries. The findings from all these studies on as-built data collection, as-planned modeling and visualization of progress monitoring form a stepping stone (Golparvar-Fard et al. 2007, Golparvar-Fard and Peña-Mora

2007) upon which the proposed framework for interactive visualization of construction progress monitoring with the D^4AR model is developed.

3.3.4 Progress photography for as-built visual model

Site photographs are becoming valuable sources of accurate project information (Soibelman et al. 2008). Nowadays, it is a common practice among all parties involved in projects (from construction managers to subcontractors and from clients to architects) to take digital photographs from construction sites to create a complete progress photo-log and utilize the log for coordination, communication as well as supplementary documents to potential claims. Cameras, especially if equipped with zoom lenses, can cover extensive areas of a construction site. They also have the capability of providing real-time positioning information about multiple entities concurrently and are capable of self-calibrating and minimizing positioning errors when multiple cameras are installed (Brilakis and Soibelman 2008). All of these facts indicate that cameras and project photographs have evolved into a significant and irreplaceable part of project documentation and thus provide solid participations for their usage as visual, real-time as well as easy-to-obtain and low-price data capturing technology which does not need any expertise. The availability of such rich imagery of large parts seen under different viewing conditions presents enormous opportunities for progress monitoring, study of workspace logistics, quality assurance/ control, safety, as well as construction productivity. From the stand point of progress monitoring, these site photographs present the ultimate data set, which should give the ability to model a significant portion of as-built geometry at high resolution respective to conditions where enough photographs are being taken. This will also enable 3D visualization of as-built scene, progress data collection, localization, communication and recognition that can impact a construction project at large. Previous research efforts in using photographs for the purpose of progress monitoring goes back to Oglesby et al. (1989) wherein it was suggested that the application of site photographs allows analysts to focus on the details of the work face while being away from site tensions and confusions and perform time-studies on time-lapsed photographs for productivity improvement. However, lack of advanced technologies for automation, had made the process time-consuming and unattractive to some extent. More recently Abeid et al. (2003) presented Photo-Net II wherein time-lapse digital movies of construction activities were linked with critical path activities. In Photo-Net II, time-lapse photography has been used as a source of spatial as-built information; however, as-planned spatial information has not been integrated into the system. In addition, Golparvar-Fard et al. (2009a) also recently presented an Augmented Reality (AR) system wherein 3D models are superimposed over time-lapsed photographs. In that environment, 3D models were semi-automatically superimposed over one image using control points and same camera configuration was applied to all subsequent images, allowing progress deviations to be visualized over time-lapsed images. Figure 3.4 shows an example of such augmented photographs where the 3D model is superimposed over the photograph and different schedule deviations are visualized using a traffic light color spectrum.

Such images are fairly easy to obtain, are inexpensive and easily understandable; however, time-lapse photography has a series of limitations for progress monitoring. Time-lapsed photos only show what is not obstructed by objects such as construction machinery or scaffolding. Once the building envelope is placed, the application of time-lapsed images is limited, since it will be impossible to track progress inside the building. In addition they only show what is within range and field-of-view of the camera. Various illumination, shadows, weather and site conditions also make it difficult to use time-lapse photography for performing consistent image analysis on such imagery. Figure 3.5 shows some of these effects within a limited time-lapsed dataset. As shown in Figure 3.5.a, the slab has casted a shadow over interior structural components and have made it difficult to see inside. Also in Figure 3.5.b, the shadow casted by the adjacent building or the fog in Figure 3.5.c have almost made it impossible to understand the scene, and in turn make it very difficult to use a consistent image processing technique for all images or different parts within a single image. Even in normal conditions only a limited area of a time-lapsed photo will be associated with each construction component (may be even less than 50 square pixels). Developing image processing techniques that can operate on such limited-size patches is a major challenge.

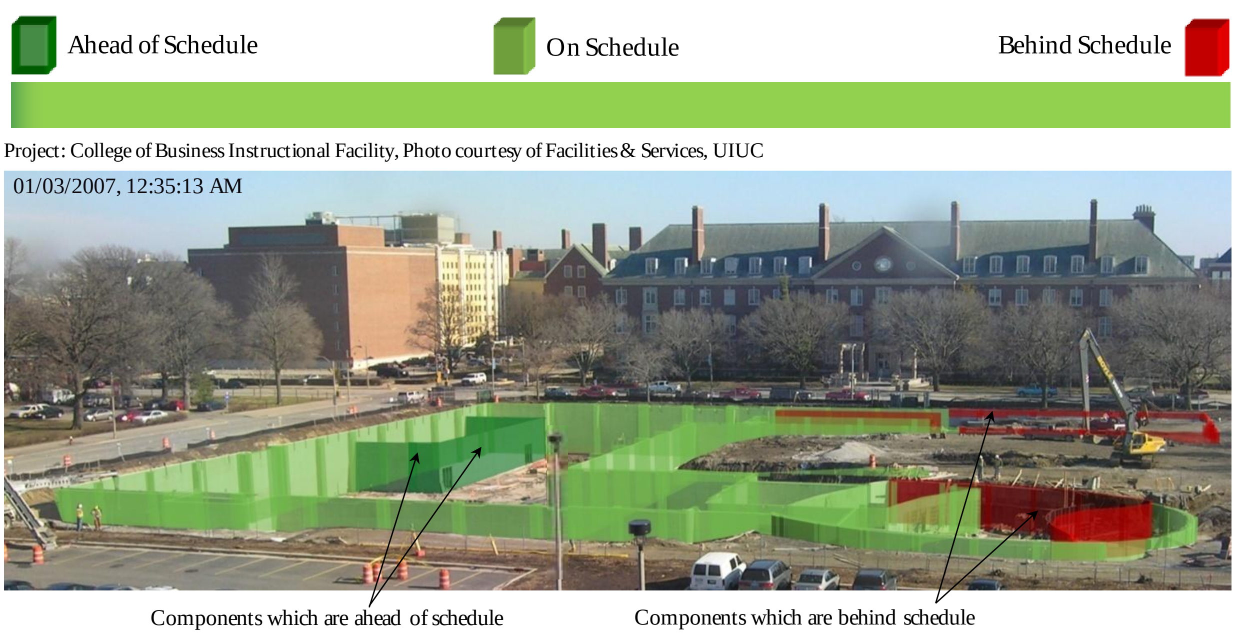

Figure 3.4. The as-planned 3D model of UIUC College of Business Instructional Facility project is superimposed over the site image, visualizing progress as of 01/03/2007 using traffic light metaphor color spectrum. Photo courtesy of College of Business, UIUC; used by permission.

In Golparvar Fard et al. (2009), Leung et al. (2008) and Abeid et al. (2003), installation of multiple cameras on a construction site is suggested; however again each camera will have the mentioned limitations and such a limited number of views cannot overcome limitations of occlusion, obstruction and weather conditions. Given the benefits and limitations of time-lapse photography even where multiple cameras are installed, comprehensive visualization of progress will not be possible. This motivated the authors to look into a larger visual dataset, i.e., the unordered set of progress imagery that is casually being taken on construction sites. These images are usually taken by construction managers, owner representatives, contractors and subcontractors and have the capacity to enable complete visualization of a construction site. Furthermore they have minimal redundant occlusions since photographers usually have the tendency of taking photos from particular components on the site as opposed to their potentially occluding peripheries. This makes site photo-logs even more attractive especially because such datasets can enable a more comprehensive 3D visualization of as-built scene, localization, communication and recognition that can ultimately impact a construction project at large.

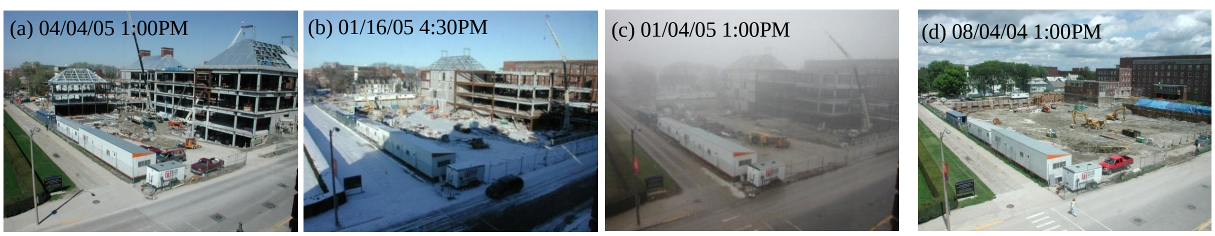

Figure 3.5. Time-lapsed progress Photographs taken during construction of Institute of Genomics Biology, UIUC; Photographs courtesy of Information, Tech & Communication Services, College of ACES; used by permission.

To date, the application of this site imagery for a complete as-built reconstruction and progress recognition is almost unexploited. Site photographs are usually not organized according to the locations they are taken from, are uncalibrated and are also widely variable and under various illumination, resolution, and image quality. Developing computer vision and image processing techniques that can effectively operate on such imagery is a major challenge. One key challenge is image registration, i.e., figuring out correspondences between images, and how they relate to one another in a common 3D coordinate system. This procedure is commonly called *Structure from Motion* (*SfM*). While substantial research has been done in these areas over the last decade (Snavely et al. 2008, Akbarzadeh et al. 2006, Brown and Lowe, 2005, Hartley and Zisserman 2004, Triggs et al. 1999) many challenging aspects are still unsolved. For instance, there is a necessity to work with images that are capturing sites whose appearance is constantly changing due to progress or excessive movement of objects (e.g., construction crew and machinery). Furthermore, progress photographs taken at a project are either from specific activities under progress and/or are taken in a panoramic manner and therefore they may not carry enough information about perspective (since panoramic images form a plane) for a more global reconstruction of the as-built construction scene. In the sections that follow, we first present some of the state-of-the-art steps towards solving this problem. Then we present our preliminary results in reconstructing and localizing the as-built scene and registration of progress images.

3.4 Overview of Research works leading to D^{4}AR Model

Within the last decade, there have been significant increases in capabilities of computer vision and image processing techniques in feature detection, localization and registration of images. One of the key issues has been to discover the presence of corresponding features across multiple views in the same scene. Once a set of feature correspondences are known between these images, camera positions and orientations could be calculated. These techniques are still under consistent developments in computer vision, computer graphics and multimedia applications domains. In the following, some of the works that have further inspired development of the D^{4}AR model are introduced:

3.4.1 Feature detection and correspondence

Image matching is a fundamental aspect for reconstructing a 3D (either sparse or complete) structure from multiple images in computer vision domain. First step for this task is extracting distinctive invariant features from images to be used to perform reliable matching between different views of an object or scene. These features should be invariant to image scale and rotation changes, and as shown by Moreels and Perona (2008), Tuytelaars and Mikolajczyk (2008), Mikolajczyk et al. (2005), Tuytelaars and Van Gool (2004) and Lowe (2004), allowing robust matching across a substantial range of distortion, change in 3D viewpoint, addition of noise, and change in illumination. The features need to be highly distinctive, in the sense that a single image can be correctly matched with high probability against a large database of images. Mikolajczyk et al. (2005) review some of these techniques and evaluated their performances. In our research, we have used Lowe’s SIFT features - Scale Invariant Feature Transforms (Lowe 2004)- which is widely used in the computer vision community and achieves good performances over an acceptable range of viewpoint changes. Recent methods have taken advantage of these properties (Savarese and Fei-Fei 2007, Snavely et al. 2007, Rothganger et al. 2006, Niebles et al. 2006, Brown and Lowe 2005). Figure 3.6 shows some of these features that are identified in a construction image.

3.4.2 Structure from Motion

Structure from Motion (SfM), aims to reconstruct the unknown 3D scene structure and estimate unknown camera positions and orientations from a set of feature correspondences among an image set (Ma et al.

2006, Akbarzadeh et al. 2006, Hartley and Zisserman 2004, Faugeras et al. 2004, Pollefeys 2004, Triggs et al. 1999, Tucco and Verri 1998, Tomasi and Kanade 1992). Bundle adjustment has been shown to be a critical tool for obtaining a robust 3D reconstruction from a large number of sparse images. Experiments conducted by Snavely et al. (2007) and Bown and Lowe (2005) show bundle adjustment is robust with respect to changes in image resolution, time, focal length variability, and illumination changes. While these techniques have been applied for image-based walkthroughs and virtual touring, our chapter marks the first successful demonstration of SfM technique being applied to geospatially photographs that are capturing a dynamic construction scene over the time span of its construction.

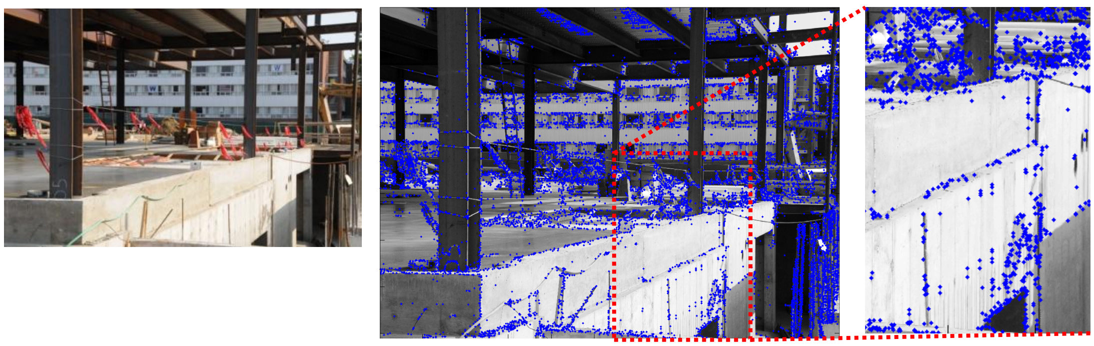

Figure 3.6. SIFT Features detected on a daily progress photograph (08/27/08), Student Dining Hall Project – Photograph is taken right after concrete was placed in the First Floor Slab; Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

3.4.3 Image based modeling and rendering

Image based modeling is the process of generating 3D models from a set of input photographs. In the computer graphics domain, SfM and model-based reconstruction are named under image-based modeling techniques. Notable examples of such works are the semi-automated Façade system of Debevec et al. (1996) which was used to create fly-through of University of California Berkeley campus and the Phototour of (Snavely et al. 2006) which was used to create virtual tours among thousands of online images. Image based rendering techniques can be used for synthesizing new views of a scene from a set of photographs (e.g., Avidan and Shashua 1997, Szeliski 1996, Seitz and Dyer 1996 and Chen and Williams 1993). Perhaps among the many works done in these areas, our approach needs to be closer to *Phototour* (Snavely et al. 2006) and *Sea of Images* (Aliaga et al. 2003) where a large collection of images are taken throughout architectural spaces. In our work, images are casually acquired on the site (as in Snavely et al. 2006), rather than being taken from fixed locations or on a guided robot (as in Aliaga et al. 2003). In our approach we do not need to render the complete scene structure (as in Debevec et al. 1996), rather we only need to render images on camera frusta. In this manner, we bypass the more challenging tasks of full photorealistic or non-photorealistic rendering of the as-built site.

3.4.4 As-planned models

The application of 4D technology in construction site simulation, for the purposes of process evaluation and communication, has been under development for some time. Forerunners to this field were the works of Williams (1996) and Collier and Fischer (1996). In a 4D system, combined description of schedules and geometries of a particular scheduled event in a chronological manner helps to visualize construction process (McKinney et al. 1998). Techniques such as (Kamat and Martinez 2008, and Behzadan and Kamat 2007) also exist where construction operations are simulated and visualized in 4D virtual or Augmented Reality (AR) environments. The latter techniques focus on visualization of construction operations and require location tracking techniques which is obtained either by GPS or WLAN (Behzadan et al. 2008). Because our approach does not require GPS or any other instrument for location tracking, it has the advantage of being applicable to the existing image databases that are already being collected on a daily basis on almost every construction site. Our proposed feature correspondence estimation and sparse reconstruction of the as-built scene goes beyond what is possible in mentioned location-based systems since it does not need any additional work (no setup or calibration time) from field superintendents as they usually take photos from ongoing construction on a daily basis.

3.5 Overview of the D^{4}AR model

Our system like other Augmented Reality (AR) applications requires accurate information about camera extrinsic parameters (i.e., *relative* location and orientation), and intrinsic parameters (i.e., focal length and distortion of the lenses) of each construction site camera. In addition the superimposition of the reconstructed scene over as-planned model requires *absolute* locations of the cameras. However in our system, we do not rely on the camera itself or any other equipment such as GPS or wireless location trackers for detecting location, orientation, or geometry. Rather, we compute such information from the images themselves using computer vision techniques. In this section, the steps towards reconstruction of the as-built scene and superimposition of 3D model over photographs are presented as follows:

3.5.1 Reconstructing cameras and sparse as-built scene

We first detect a set of robust features in each image, then match these features across images, and finally run a robust *SfM* procedure to recover camera intrinsic and extrinsic parameters. We use EXIF tag of image files to initialize our estimate on focal length. However using EXIF tag is not necessary when this information is inaccurate. This component of the system allows photographs being taken from any type of camera to be applicable for sparse reconstruction. In this system, *SfM* only provides the relative position of each camera, while we are interested in absolute coordinates. Therefore we calculate the transformation between as-planned and as-built models using a method similar to that of (Golparvar-Fard et al. 2009a). We registered an as-built 3D set of points to a set of as-planned 3D model points that minimizes the sum of squared residual errors between the set and the model. Each of these steps is described in the following subsections:

Keypoint detection and matching

The first step in reconstruction of the as-built scene and geo-registration of progress images is to find feature points in each image that could be used to estimate the initial structure of the scene. In our work, we use the SIFT keypoint detector (Lowe 2004), because of its good invariance to scale changes and view and illumination transformations as well as its widespread application in the computer vision domain. For a detailed study of feature detectors and descriptors, the reader can look into Moreels and Perona (2008), Tuytelaars and Mikolajczyk (2008), Mikolajczyk et al. (2005), Tuytelaars and Van Gool (2004) and Lowe (2004) wherein different feature detectors and descriptors are compared with each other. A small image of 500x500 pixels typically gives about 1,500 to 2,000 SIFT features. As a proof of concept for keypoint detection and matching, we run SIFT detection on a subset of 160 daily progress photographs. This data set of images was taken on the Student Dining and Residence Hall construction project of Turner Construction Company in Champaign, IL. A field engineer carried a high-resolution SLR camera (Nikon D300) for this task. The choice of a high resolution camera was only based on the possibility for further enhancement of the algorithm so the quality of the images could be synthetically reduced (in our experiment reduced to about 3 Mega Pixels) and the keypoint detection could be tested on synthetically lowered resolution images. Figure 3.7 shows these points on a subset of images on the same dataset.

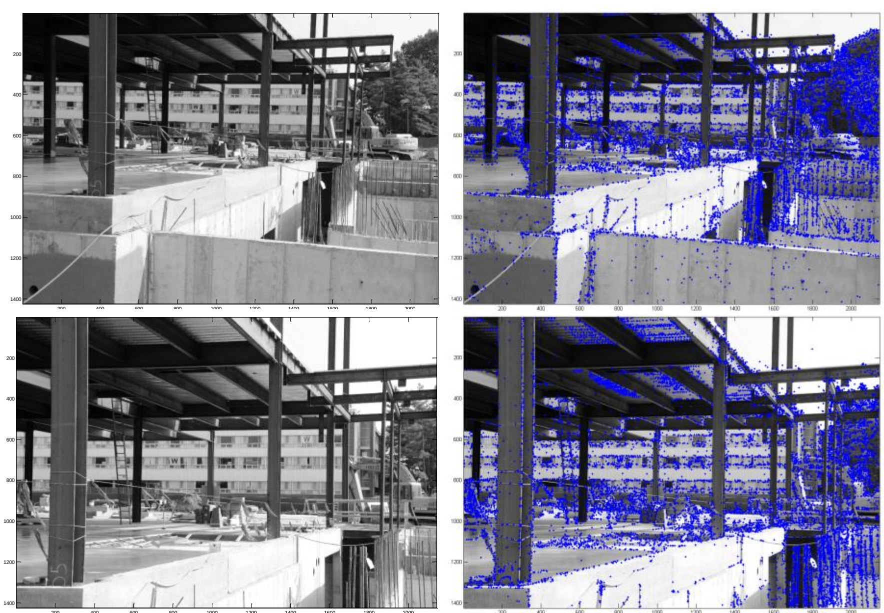

Figure 3.7. SIFT Features shown on two daily progress photographs taken on 08/27/08, Student Dining Hall Construction Project; Photographs are taken right after concrete was placed in the First Floor Slab; Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

Once the features have been detected over the dataset, we need to detect how many of these features are matched in each image pair. We use SIFT descriptors to match keypoint between each image pair. Each SIFT descriptor is a 128-dimensional feature vector. Using (Lowe 2004) approach, once keypoints are identified, the gradient of intensities is captured over a window of pixels centered around a keypoint. Then these pixels are categorized to a 4x4 sample windows wherein each sample window and histogram of intensity gradients are stored in 8 cardinal directions (4x4x8 directions = 128 dimensions). Descriptors are matched across two images by computing a distance function between corresponding histograms of intensity gradients. Features are matched by using a nearest neighborhood matching strategy. As experienced by Snavely et al. (2006), if the number of features is large enough a *k-d* tree matching scheme (Arya et al.1998) may be used instead; this is particularly effective when the dimension of the data is large (as in our case). Overall this improves the efficiency of the matching algorithm. To minimize computation load, we also use ANN's priority search algorithm and instead of classifying false matches by thresholding the distance to the nearest neighbor, we use the ratio test described by Lowe (2004): for a feature descriptor in image i, we find the two nearest neighbors in image j, with distances d_1 and d_2, then accept the match if $d_1/d_2 < 0.6$. If more than one feature in image i matches the same feature in image j, we remove both of such matches, as one of them is a false match. Figure 3.8 shows the keypoints across the same image pair used in Figure 3.8 and visualizes matches through connecting these features by solid lines. In this image pair, 2071 matches are found in which some false matches are also formed and visualized in lower image in Figure 3.8.

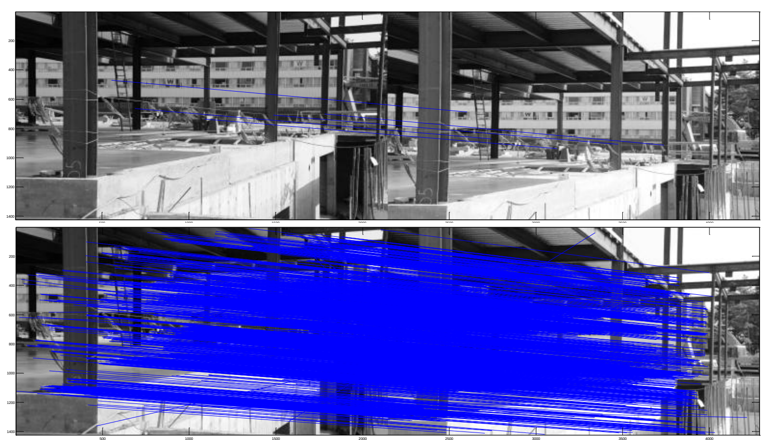

Figure 3.8. Detected SIFT features matched over the same image pair of Figure 3.8. The upper image shows the first 5 matches found (lines in blue color) and the lower images shows the overall 2071 matches found. If looked closely a couple of mismatches diagonal to the stream of matches are visible.

Due to the sensitivity of the reconstruction algorithm to false matches, we further refine our process to remove such false matches. In our approach, once the matching features are detected in an image pair, we robustly estimate a fundamental matrix for the pair using RANSAC (Fischler and Bolles 1981). Fundamental matrix helps remove false matches as it enforces that corresponding features have to be consistent under view point transformation, that is:

$$p_L^T F p_R = 0 \tag{3.1}$$

(p_L and p_R are point coordinates and F is the Fundamental matrix; See Figure 3.9). In our model, in each iteration of RANSAC, a fundamental matrix is computed using the eight-point algorithm of Hartley and Zisserman (2004), and then the problem is normalized to improve the robustness to noises (Hartley 1997).

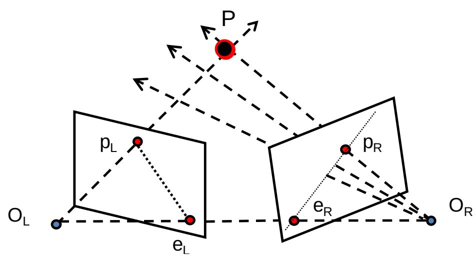

Figure 3.9. Epipolar geometry of an image pair. In this figure O_L and O_R are the origin of cameras.

As suggested by Snavely et al. (2007), we set the RANSAC outlier threshold to be 0.6% of the maximum image dimension, i.e., 0.006 maximum of image width or height) (about 12 and 9 pixels for two dimensions of a 2144x1424 image). The Fundamental matrix returned by RANSAC is refined by running the Levenberg-Marquardt algorithm (Nocedal and Wright 1999) on the eight parameters of the Fundamental matrix, minimizing errors for all the inliers to the Fundamental matrix. We remove outliers to the recovered F-matrix (false matches) using the above suggested threshold. Figure 3.10 shows the keypoint matches in the same image pair as of Figure 3.8 and shows how the false matches are pulled out.

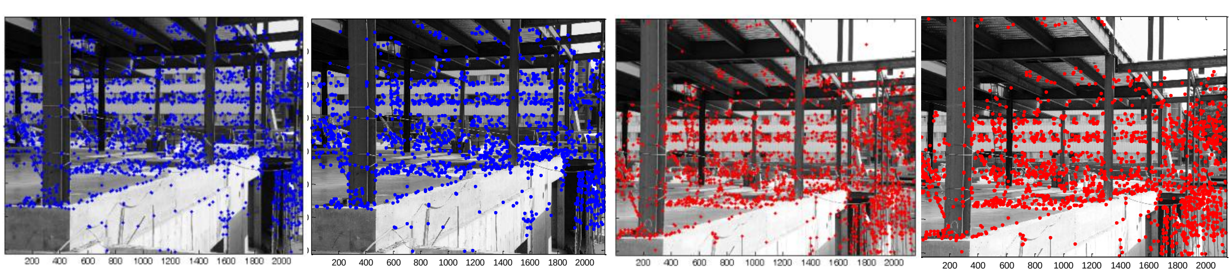

Figure 3.10. Left to Right: Visualizing keypoint matching between a pair of images shown as (a) Image1-BeforeRANSAC, (b) Image1-After RANSAC, (c) Image2-Before RANSAC, (d) Image2-After RANSAC, number of matches have dropped from 2079 to 1800 and show a more accurate matching.

Since for lower numbers of matches in an image pair, even after fitting a Fundamental matrix through RANSAC iteration, the possibility of getting false matches is still high, we set a threshold to remove image pairs with number of matches less than the threshold. We set this threshold to be twenty matches which seems reasonable to opt out false matches. After finding a set of consistent matches between all image pairs, we organize these matches into *tracks*. A track connects matching keypoints across multiple images (Snavely et al. 2006). We keep tracks with a minimum of two keypoints for the next phase of the reconstruction procedure.

Structure from Motion

Now, we recover camera extrinsic and intrinsic parameters (extrinsic: rotation, translation; and intrinsic: focal length and distortion) for each image and a 3D location for each keypoint. The recovered parameters should be consistent, in that the re-projection error, i.e., the sum of distances between the projections of each keypoint track and its corresponding image features, is minimized. Similar to other SfM approaches, in our experiment this minimization problem is formulated as a non-linear least squares problem and solved using bundle adjustment. Here we briefly describe the required steps but the reader is encouraged to look into Snavely et al. (2007) and Triggs et al. (1999) for more details.

First, we estimate extrinsic and intrinsic parameters of a single image pair. Since bundle adjustment as other algorithms for solving non-linear problems is prone to getting stuck in bad local minima, it is strongly suggested by many researchers (e.g., Nistér 2004) to start with a good initial image pair and good estimates for camera parameters in the chosen pair. This initial pair for *SfM* should not only have a large number of matches but also a large baseline, so that the initial as-built scene can be robustly reconstructed. An image pair that is poorly described by a homographic transformation satisfies this condition. A 2D image homography is a projective transformation that maps points from one image plane to another image plane (Hartley and Zisserman 2004). We find the homography between all image pairs using RANSAC with an outlier threshold of 0.4% of maximum of image width and height, and store the percentage of feature matches that are inliers to the estimated homography. We select the initial image pair as that with the lowest percentage of inliers to the recovered homography, but with at least 100 matches (As also noted by Snavely et al. 2007). The extrinsic camera parameters for this pair are estimated using Nistér's five point algorithm (Nistér 2004), and then the tracks visible in the image pair are triangulated. A two-frame bundle adjustment for this initial pair is performed. Next, we add another photograph camera to the optimization. We choose the camera that examines the largest number of estimated tracks, and initialize the new camera's extrinsic parameters using the *Direct Linear Transform* (DLT) technique (Hartley and Zisserman 2004) within a RANSAC procedure. For this RANSAC step, we use an outlier threshold of 0.4% of maximum of image width or height. As mentioned previously we use focal length from the *EXIF* - Exchangeable image file format- tags of JPEG images (file type of almost all digital cameras) to initialize the focal length of the new camera and estimate the intrinsic camera matrix (see Snavely et al. 2007 more details).

Starting from this initial set of parameters, while the model is kept fixed, we run the bundle adjustment algorithm allowing only the new camera and the keypoints it observes to change. Finally, we add points observed by the new camera into the optimization algorithm only if it is observed by at least one existing recovered camera, and if triangulating the point gives a well-conditioned estimate of its location. We estimate the conditioning by considering all ray pairs that could be used to triangulate that point, and finding the pairs with maximum angle of separation. If this maximum separation angle is larger than a threshold, then the point is triangulated. Once the new points have been added, another global bundle adjustment is run to refine the entire as-built reconstructed scene. In our experiment, the minimum error solution using the sparse bundle adjustment library of Lourakis and Argyros (2004). This procedure is continued for all cameras until no camera is remained which observes enough 3D points to be reliably reconstructed. With such an approach, the algorithm may only determine and reconstruct a subset of the used images. Figure 3.11 shows the reconstructed sparse scene from the set of 160 images used from Student Dining and Residence Hall Projects of Turner Construction in Champaign, IL. Interestingly not only the scene, but also its peripheral structures (e.g., Garner Residence Hall building) on campus of University of Illinois in Champaign-Urbana is sparsely reconstructed.

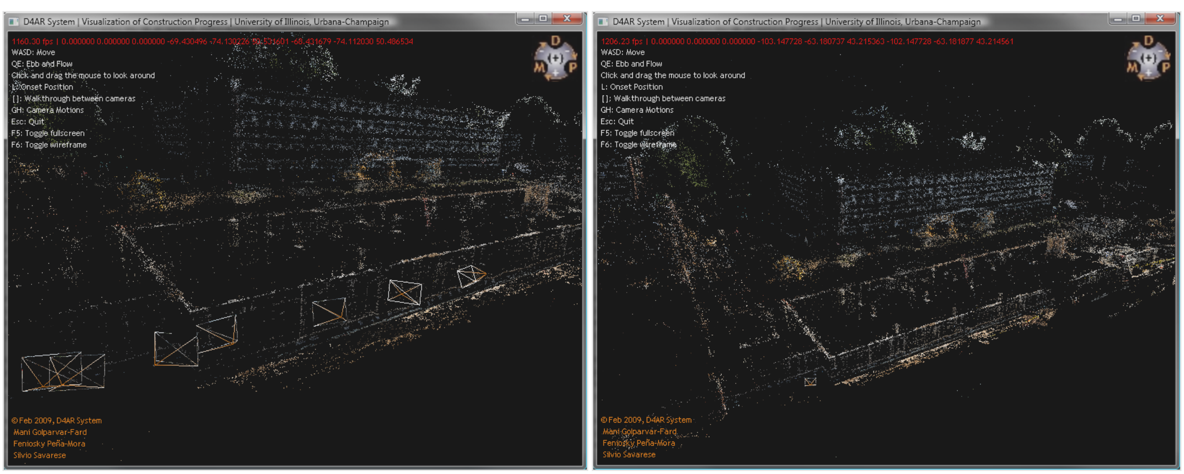

Figure 3.11. The reconstructed sparse scene of Student Dining and Residence Hall construction project in Champaign, IL. The right image represents 7 camera frusta for which their images were used for sparse reconstruction of the as-built site.

Geo-Registration

The *SfM* procedure estimates *relative* camera locations. The final step of the location estimation process is to align the reconstructed scene with the as-planned model to determine the absolute geocentric coordinates of each camera. Although the as-built scene browser can work with relative coordinates, for geo-registration of the scene with as-planned model, the absolute coordinates are required. The estimated camera locations are related to the absolute locations by a global translation, rotation, and uniform scale transform. To determine the correct transformation, we use the closed-form solution of absolute orientation using unit quaternions (Horn 1987) similar to that of Golparvar-Fard et al. (2009b) to register the as-built scene over the as-planned model. We register as-built 3D set of points to a set of as-planned 3D model control points that minimize the sum of squared residual errors between the set and the model. Figure 3.12 shows a screenshot of the expected alignment. In some cases the recovered as-built scene cannot be aligned to a geo-referenced coordinate system using a similarity transform. This can happen if the *SfM* procedure fails to obtain a fully metric reconstruction of the scene, or because of low frequency drift in the recovered point and camera locations. One way to rectify the recovered scene is to pin down a sparse set of ground control points or cameras to known 3D locations (acquired, from surveying instrument when visible location in some photographs before SfM step) by adding constraints to the *SfM* optimization (not tested yet by authors). Also a set of lines that are known to be orthogonal in the original model (self-calibration constraints) could be chosen to rectify the superimposition. In order to further refine the alignment, ICP-based (Iterative Closest Point) technique (Besl and McKay 1992) can also be used.

As-built Scene Representation

After the as-built scene is reconstructed and is superimposed over the 3D model, scene needs to be used for interactive explorations. The following data structure is used to represent the as-built reconstructed scene:

- A set of key points, in which each keypoint consists of a 3D location and a color that has been averaged out from all the site images that the keypoint is being observed from.
- A set of cameras, while the extrinsic parameters (translation and rotation), and intrinsic parameters (focal length and distortion in height and width directions) are known.
- A mapping between each point and all the cameras that observe the point. A list of number of cameras which observe the point, the location of the point in local coordinates of the image, and the SIFT keypoint index are all stored.

While this information is stored, cameras would be rendered as frusta. Once a camera is visited in this reconstructed scene, the camera frustum is texture-mapped with the full resolution image so the user can zoom in and thoroughly analyze progress, productivity as well as site logistics. Figure 3.13 shows two images of the reconstructed scene while the image under study is shown with respect to the reconstructed scene.

Figure 3.12. The alignment of the Student Dining and Residence Hall construction project 3D model with one of the construction progress images using Golparvar-Fard et al. (2009a) approach. As shown some of the foundations and foundation short walls as well as piers that are not yet constructed, are superimposed over the image. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.

Once the registration of the 3D model with the reconstructed scene is performed, the reconstructed sparse scene is masked and only images with respect to the as-planned model are visualized. Figure 3.14 shows two images from Student Dining and Residence Hall projects wherein the as-planned model as of the day image was taken is superimposed over the image.

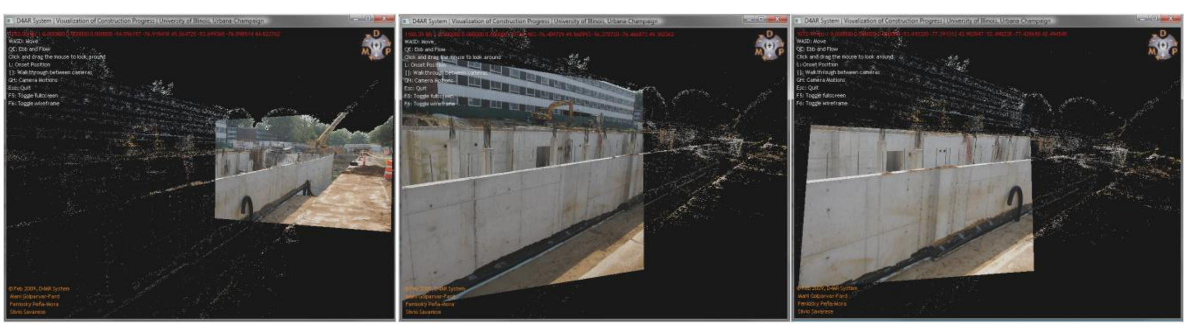

Figure 3.13. The registration of images within the sparsely reconstructed scene. Student Dining and Residence Hall construction project in Champaign, IL. Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

3.6 Application of D^4AR model for progress monitoring

In this research, D^4AR system was implemented in Microsoft C++ .NET using Microsoft DirectX9 graphics library. The D^4AR marks the first system that allows as-built construction spatial information to be visualized within the same framework of as-planned construction information. As shown, as-of-now, our system is only capable of reconstructing a sparse as-built scene and superimposition of the scene over a 3D model. As a proof of concept and to perceive how this model could be used in different aspects of the construction domain, many superimposed images have been generated and a set of them has been specifically used during the construction of two of our case studies. The first author of this chapter has been a part of the onsite Turner Construction team for both Dining Hall and Residence Hall construction projects in Champaign, IL and has been generating such images for the project. In this section, the experiences of the authors on current and perceived applications of D^4AR on those ongoing projects are discussed in full details.

Figure 3.14. The registration of images with the construction progress images. Student Dining and Residence Hall construction project in Champaign, IL. Images used are provided courtesy of Turner Construction (Used by permission).

3.6.1 Virtual walk through on the as-built scene

One of the major applications of this system is that it allows project managers, project executives, superintendents, subcontractors as well as owners and even architects to remotely access the under construction site (specifically if this system is offered through a web browser) and navigate through all the as-built scene, and browse through the collection of progress photographs in any given day. Such application can create significant benefits as follow:

1. *Remote Construction Control Decision Making*: It allows project managers, superintendents and other project participants to virtually walk on the construction site, as-of the time the scene has been reconstructed and position themselves in those positions that progress images have been taken. Such an interactive user walk-through allows progress to be discussed remotely without the need of any of those participants to be physically on the jobsite.

2. *Minimizes the time required to discuss the as-built scene*: Project managers and superintendents will spend less amount of time discussing or explaining progress. Rather, they can spend more time on how a control decision could be made, especially because the reconstructed as-built scene and geo-registered images allow workspace logistics, safety issues, progress and even productivity of workforce and machinery to be remotely analyzed. Such an as-built system could also be very beneficial in weekly contractor coordination meeting as the workspace could be navigated through the virtual world, especially once used in conjunction with large screen collaboration tools (e.g., such as smart board used in Golparvar-Fard et al. (2006) or even multi-touch screens (e.g., multi-touch interaction wall of Han (2006)))

3. *Significant cut in travel time and cost on project executives and architects* – Project Executives and architects can study the reconstructed scene and geo-registered images, instead of spending time and money to travel to the jobsite. The reconstructed scene with as-built progress images can be very beneficial, especially when the possibility of adding new photographs quickly to the system is considered. Even if a perspective of an interest is not registered within the reconstructed scene and is not present in geo-registered image dataset, the user in the case of being owner and project executives can request the scene to be photographed. Those photographs taken can also be quickly geo-registered allowing a significant progress communication problem to be resolved.

3.6.2 Visualizing progress deviations

The main motivation of authors behind developing the D^4AR system has been to come up with a system that geo-registers spatial as-built and as-planned models within the same environment allowing construction progress to be measured, analyzed and communicated. To that extent, authors have proposed the application of a traffic light color spectrum to be used for visualizing progress (Golparvar-Fard et al. 2009a and Golparvar-Fard et al. 2007). Figure 3.15 shows the application of the proposed color metaphor to visualize progress. As seen, the color spectrum (shown in Figure 3.4) has been used over the as-planned model to easily communicate deviations in progress. The presented image shows the actual progress made on construction of the College of Business Instructional Facility at the University of Illinois. As seen the concrete foundations have not been placed as of Dec 02, 2006 (the day photo was taken but schedule run date is November 13, 2006) and therefore forms for concrete walls are not set in place yet.

One of the other observed applications of visualizing deviation is to facilitate onsite discussions. In the Student Dining and Residence Hall project, the authors came up with a D^4AR superimposed image, highlighting the building foundation which was misinterpreted by the concrete subcontractor. This image has been used by the project manager to communicate the component under attention to concrete superintendent and foreman. The poor architectural/structural detailed-drawings respective to a continuous concrete footing miscommunicated the scope of work. The concrete subcontractor's foreman interpreted drawings in a way that a specific continuous footing is not a load-bearing component and therefore it does not need to be constructed along with the rest of the footings. Figure 3.16 shows the image where in the component which was not yet constructed as-of the day photo was taken (May 16, 2008) is highlighted. As seen, the strip footing highlighted in red (between two single footings) needs to be constructed while the foreman did not interpret it as a load bearing component from the drawing. After series of discussions using this image, concrete was placed and the strip footing was constructed.

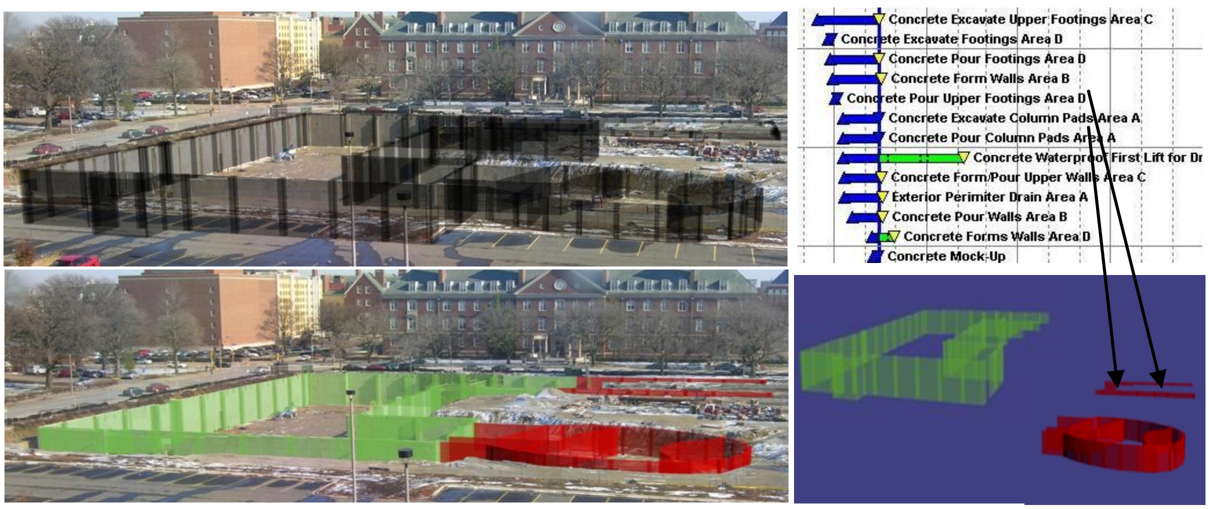

Figure 3.15. The superimposed photo has been color-coded based on actual progress on the jobsite. As seen the concrete foundations have not been placed yet and therefore wall forms are not put in place yet. Photograph from construction of College of Business Instructional Facility at University of Illinois's campus, courtesy of College of Agriculture, Communication and Education, UIUC and Gilbane Construction Co; used by permission.

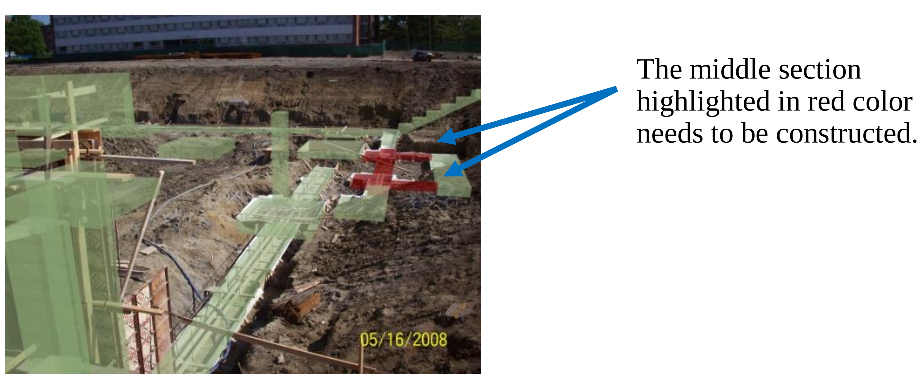

Figure 3.16. The superimposed photo visualizing the component which has been misinterpreted by the carpenter foreman. Student Dining and Residence Hall project, Champaign, IL. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.

3.6.3 Automatic progress tracking

The D^{4}AR system geo-registers construction site photographs with as-planned building components, and therefore serves as a rich baseline for automatic progress monitoring through consistent visual detection of progress and comparison with as-planned information. Figure 3.17 shows an IDEF-0 process model for automating progress monitoring through the D^{4}AR system. As shown, first the digital as-planned model will be combined with progress metrics to provide a progress monitoring baseline. In this case, Earned Value Analysis (EVA) as a robust monitoring mechanism is proposed. Although EVA has some limitations as referred in Kim and Ballard (2000), all the construction work is planned, scheduled and budgeted in time-phased planning value increment, so it can constitute a performance measurement baseline (Abba 1997) which is useful for comparison. As-planned model wherein progress monitoring baseline is set will be used for comparison with the reconstructed as-built model. Once site images are all registered, progress will be analyzed and according to the analysis perform, as-planned model will be color-coded and superimposed over site images.

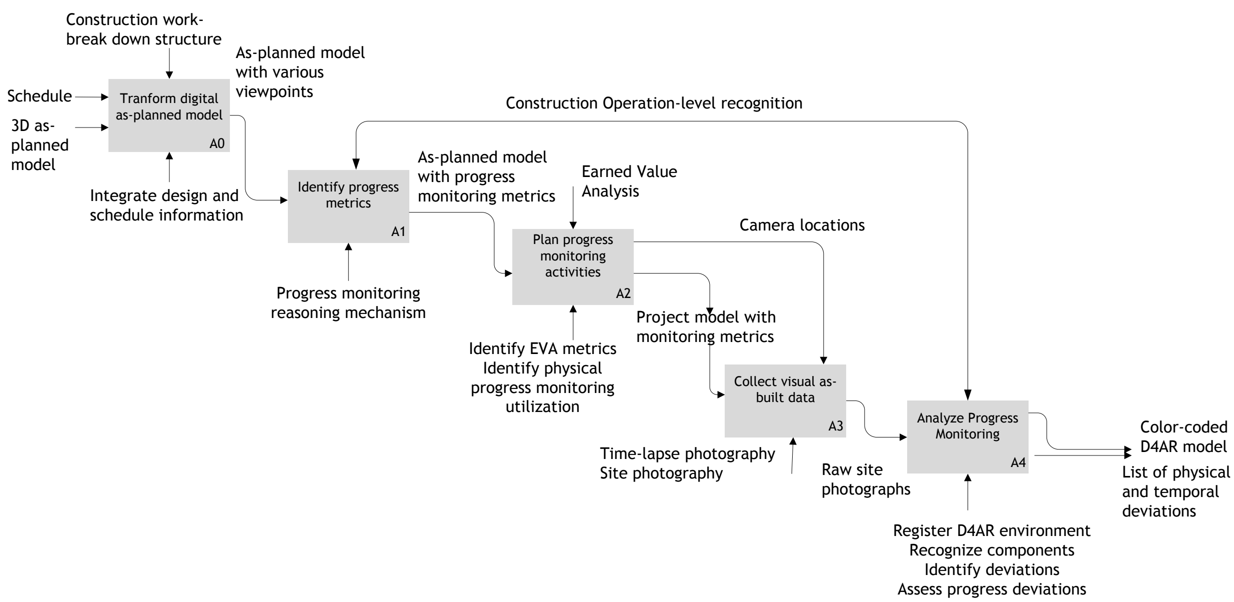

Figure 3.17. IDEF0 representation of automatic progress monitoring using the D^{4}AR model

Figure 3.18 presents step A4 of automatic progress monitoring system using the D^{4}AR model in detail. Once the images and the 3D model components are geo-spatially and temporally registered, deviations could be measured using image recognition or processing techniques.

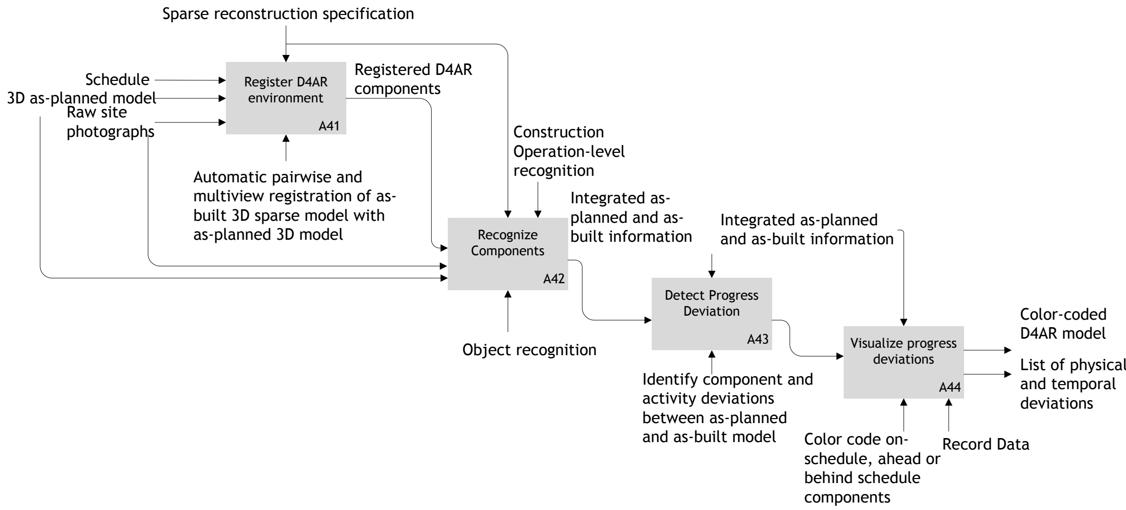

Figure 3.18. IDEF0 representation of analyzing progress monitoring (Step A4 of the overall IDEF-0 representation of proposed D^4AR system).

Figure 3.19 schematically visualizes how progress for a concrete wall given one geo-registered image could be analyzed. Now, one can imagine how a set of site images that contain photos of the same building component can minimize false-positive returns on any image processing technique. Furthermore, using a site photo-log minimizes redundant occlusion problems (which exists in case of using time-lapse cameras on a job site). Since these photos are normally taken closer to construction components, a larger patch containing more pixels would be available for analysis. This in turn boosts the accuracy of an automated progress detection system. The more number of image patches available for each component, the better the implemented image processing algorithm can be.

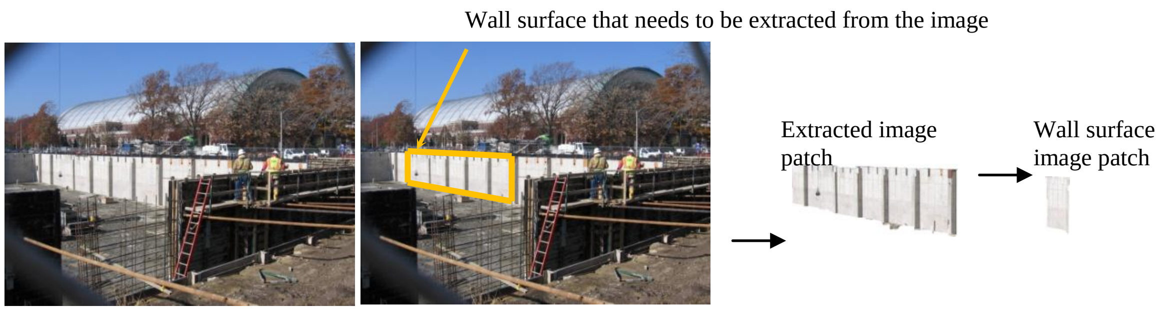

Figure 3.19. Proposed Method of extracting image patches and performing image analysis for detecting progress. Photograph of College of Business Instructional Facility construction project, Champaign, IL; November 08, 2007, Gilbane Construction Company.

3.6.4 Application of the D^4AR system for interior progress monitoring

One of the major applications of the D^4AR is for tracking progress of interior components. If enough photographs are taken to connect exterior photographs' path to those of interior, this system could be efficiently used for tracking interior as well. As such, visualizing progress of MEP/FP (Mechanical-Electrical-Plumbing/Fire Protection) systems will also become possible. For such application, we perceive using short focal length lenses or wide angle lenses to allow short distances to be captured as well. This component of the research is still ongoing.

3.6.5 Registering new daily site photographs

New construction progress photographs can be incrementally added to the reconstruction (the as-built model) so as to update the model without the need to redo the reconstruction from scratch. First, a user can open a set of progress images, and drag and drop each image onto its approximate location on the as-built model. After each image has been dropped, the proposed system estimates the location, orientation, and focal length of the new photo by running a version of the *SfM* algorithm. In a similar fashion first, SIFT keypoints are extracted and matched to the keypoints of the cameras closest to the initial location; then the existing 3D points corresponding to the matches are identified; and finally, these matches are used to refine the configuration of the new camera. After a set of photos has been dragged onto the environment, it generally takes in order of seconds to optimize the parameters for each new camera.

3.6.6 Augmented reality occlusion removal

One of the perceived applications of geo-registered photograph is for occlusion removal. Occlusion within augmented reality systems changes the perspective of the virtual model and real world possibly causing confusion. A practical example of how occlusion may cause misperception is presented in Figure 3.20. As seen, the footing and pier highlighted appear in front of the temporary electricity box on the jobsite, but in reality they should be located behind the box. Note that the registration error in this image is minimal, especially when the accuracy of registration of the virtual foundation walls over actual foundation walls is perceived. Such occlusions may create confusion. We suggest two solutions for such cases:

- Since in the D^4AR environment each component has the chance of being observed in a subset of images, user can study each component from different perspectives which will remove all potential confusions on depth and/or perspective.
- Since each image in the D^4AR is geo-registered and intrinsic and extrinsic camera parameters are known, cameras are all calibrated. This information helps to extract geospatial information of certain components and allows occlusions to be removed through rendering the image patch associated with that component over the 3D model.

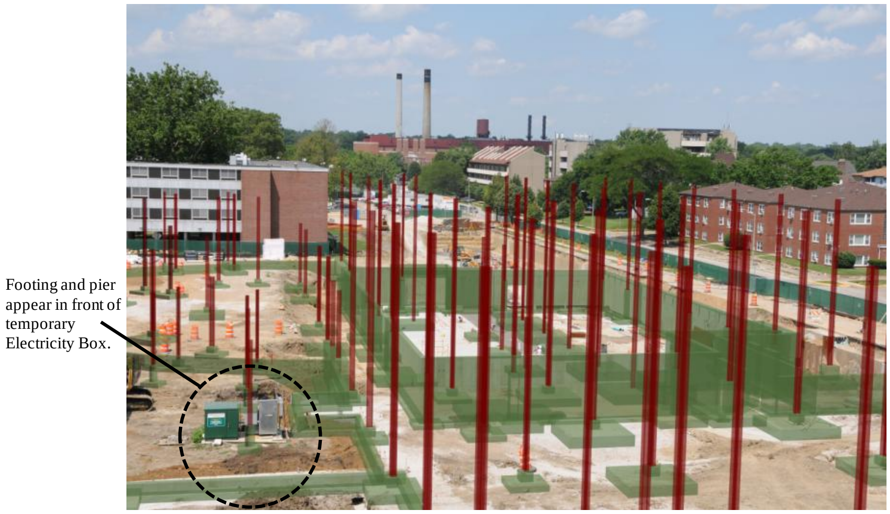

Figure 3.20. As-built model superimposed over the progress photograph. Student Dining and Residence Hall construction project in Champaign, IL. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.

3.7 Conclusions

Visualization of as-built and as-planned construction can enhance identification, processing and communication of progress discrepancies. To that end, D^4AR is proposed wherein application of unsorted daily progress photograph logs available on any construction site as a data collection technique is explored. Based on computing - from the images themselves - photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using daily progress photographs and superimposition of the reconstructed scene over as-planned 4D models will be possible. Within such an environment, progress photographs are registered in the virtual as-planned environment which allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes are superimposed over 4D models allowing site imagery to be geo-registered with the as-planned components and also allowing a location-based image processing technique to be used and progress data to be automatically extracted. The D^4AR system can perform as a robust tool for contractor coordination and communication purposes. This chapter's preliminary results show perceived benefits and future potential enhancement of this new technology in construction, in all fronts of automatic data collection, processing and communication. There are still many technical challenges in developing a full systematic progress monitoring system and these are explored in the following chapters.

CHAPTER 4. INTEGRATED SEQUENTIAL AS-BUILT AND AS-PLANNED REPRESENTATION WITH D^{4}AR – 4 DIMENSIONAL AUGMENTED REALITY - TOOLS IN SUPPORT OF DECISION-ENABLING TASKS IN THE AEC/FM INDUSTRY

4.1 Overview

The significant advancement in digital imaging and widespread popularity of digital cameras for capturing a comprehensive visual record of construction performance in Architecture/Engineering/Construction and Facility Management (AEC/ FM) industry have triggered an extensive growth in the rate of site photography, allowing hundreds of images to be stored for a project on a daily basis. Meanwhile collaborative AEC technologies centering around Building Information Models (BIM) are widely being applied to support various architectural, structural, as well as pre-construction decision-enabling tasks. These models, if integrated with as-built perspective of a construction, have great potentials to extensively add value during construction phase of a project. This chapter reports recent developments from research efforts in (1) automated acquisition of as-built point clouds from unordered site daily photo collections and geo-registration of site images; (2) automated generation of 4D as-built point clouds, as well as (3) semi-automated superimposition of the integrated as-built model over 4D (3D + time) BIMs to generate integrated 4D as-built and as-planned visualizations. The limitations and benefits of each modeling approach, the motivations for development of D^{4}AR - 4 Dimensional Augmented Reality - environments for integrated visualization of as-built and as-planned models, as well as perceived and observed applications and benefits in seven case studies are discussed. Not only does the D4AR visualize construction processes and performance deviations, but it can also be significantly used as a tool for automated and remote progress and safety monitoring plus quality control and site layout management, enabling enhanced coordination and communication.

4.2 Introduction

Over the last decade there has been a significant growth in digitography - capturing digital images and videos - in the Architecture/Engineering/Construction and Facility Management (AEC/ FM) industry. Nowadays it is common for owners, contractors as well as architects and engineers to take meaningful photographs of their work several times on a daily basis. In construction where time is a major factor of profit, it is easy to understand why practitioners started to adopt digital photography even before consumer market took off; Continuously taking snapshots, disseminating them within minutes over internet and finding ways to communicate through this medium and add value to work processes (ENR 2003). An extensive literature review on application of photography in AEC/FM industry and its value in identifying and solving various construction management programs (e.g., Ibrahim and Kaka 2008; Brilakis and Soibelman 2006; Abeid et al. 2003; Saad and Hancher 1998; Oglesby et al. 1989) as well as our observations on seven projects (9/2006- 9/2009) indicates construction images are mostly being used for:

1. Visualization of construction operations and their sequences. Images provide easy-to-understand and detailed visuals of construction operations serving as (1) powerful coordination and communication tools among project participants, (2) safety or construction methodology education tool for workers (in case of self-performing contractors) and for subcontractors (usually in case of construction management) and even as (3) marketing tools. The ability of annotating over these images enhances their application as flexible communication media.

2. Progress monitoring and tracking of construction crew and machinery. Photographs captured from different viewpoint on a daily basis or time-lapsed images serve as a powerful media for remote and quick analysis of construction performance and/or track construction entities. Availability of such visual data supports more frequent monitoring and as-observed reduces the time required for progress analysis.

3. Productivity measurements. Video streams and time-lapsed images allow contractors to manually measure and analyze productivity of their work force and machinery away from the jobsites and revise work processes or sequence of activities to improve productivity.

4. Accident investigation. Visual data provide powerful pieces of evidence for parties involved in an accident and also for project management to properly file accidents for safety referencing and documentation purposes.

5. Dispute resolution. The as-built report of a project is a common legal tool in support of a contractor's claim for compensable delay. These reports especially when compared to an as-planned, show the impact of other party's decisions and shortcomings on the active critical path activities. In different steps of such dispute resolution process or even in case of litigation, images and videos (especially in cases where software tools lock out images from tampering) serve as excellent compelling pieces of evidence documenting work as it progresses which significantly facilitates the resolution to disputes, supporting valid legal claims, adding creditability to the as-built as well as abolishing erroneous disputes.

6. Quality assurance/ quality control. If high resolution images are captured from proper view points with appropriate amount of lighting, quality of the finished surfaces can remotely be tracked, analyzed and controlled.

Currently, photography of a construction project with a 10-megapixel camera costs only about a few hundred dollars and it does not need much training. Instead of taking several pages of notes on a job sites, field engineers and superintendants can nowadays come back from construction sites with photo dairies with minimal notes where each photo is already stamped with the date and time it was captured. For these reasons, photography has evolved into significant part of documentation and further justifies growth of their application within the AEC/FM industry.

However, our observations from seven ongoing construction projects - daily construction photo collections plus time-lapsed photographs were collected [9/2006-9/2009] - as well as literature review reveals that although there is a great potential for new applications with these extensive sources of information, though such applications are adversely affected by the significance of the amount of data which needs to be organized, annotated, indexed (Digital Asset Management). Currently some contractors for example catalogue their images into subsequently numbered folders and later on, tag those images with metadata such as “Rodbuster” or “Ironworkers” (ENR 2006). When they need an image, they may need to search on the basis on location and content and this in turn induces a tedious and sometime error prone task. In addition it is time consuming and sometime difficult to sort these images chronologically as well as based on their geospatial locations; observing and studying construction operations and their sequences. All these challenges call for a more sophisticated approach to organize construction daily images allowing them to be interactively browsed within a geo-spatial configuration. Similar situations have been reported in other literature reviewed (Brilakis and Soibelman 2006, and Abudayyeh 1997) and techniques for automated classification and retrieval of visual data based on material, date and location are presented. However in these proposed methods images are retrieved based on their visual content (e.g., construction material or shape). Nonetheless knowledge databases that could be used as baseline for image queries are manually generated and fine tuned for specific databases. Location of different elements cannot yet be automatically figured out using these methods and needs to be manually tagged to photographs. More importantly none of these techniques automatically visualize the underlying as-built geometry, and geo-spatially register and sort images. Our observations further discloses that if these photographs are used to reconstruct 4D (3D + time) geometrical representation of the as-built scene, and images are geospatially and chronologically registered within a 3D virtual environment, they form powerful visualizations that could be used as a source for as-built data extraction, analysis as well as communication and coordination. Such an integrated environment allows photographs to be browsed and situated- on demand- based on their location and the time captured.

During the same period of time there also has been a significant growth in application of Building Information Models (BIM). BIMs as collaborative AEC technologies support architectural and structural perspectives while their application could be extended to preconstruction stages where schedule can be linked to the model and the 4D model to be used for constructability analysis, study of the work process as well as generating construction schedules. Currently the benefits of BIM models are well perceived by many AEC/FM companies and these models are being widely adopted. As an example currently General Services Administration (GSA) requires all AEC firms dealing with them to include BIM as a part of their work proposal (Goedert and Meadati 2008). The application of BIM is also a binding module in some recent AEC contracts as well. For example as of July 1, 2009 Wisconsin established itself as the first state requiring BIM on large public projects (Design and Construction 2009) and even American Institute of Architects (AIA) has established protocols as extensions to contracts on how BIM models could be developed and management throughout the course of a project (AIA 2008). Despite significant value these models provide in automated system clash detection, evaluation of time-space conflicts, studying integration of schedules and construction sequences, recent literature reviews and surveys demonstrates that their application has been mostly limited to the design and pre-construction stages and there has been less significant value experienced by practitioner from application of these models in support of field construction management and operations (Hartmann et al. 2008; Goedert and Meadati 2008; Kunz and Gilligan 2007). Limited research has been conducted on methods to augment these BIM models with other information and implement those models to gain value beyond pre-construction stage. There is still a substantial amount of information that is being collected on construction fields in forms of as-built, photographs, schedules, submittals, RFIs, or change orders which is transferred to project participants in file cabinets. There will be added benefits if this data is incorporated into BIM (Goedert and Meadati 2008, Caldas et al. 2005) and/or a photo-based 3D representation of as-built. Since success of every construction project is linked to the ability of accessing both as-built and as-planned project information in an efficient manner, integrated representation of these models becomes more attractive.

This chapter reports the latest developments of our ongoing research efforts in automated generation of integrated 4D as-built and as-planned models using photographs that are casually collected on construction sites as well as BIMs. The existing research efforts in automated acquisition of visual 3D models from images as well as geo-registration of those in a virtual environment both in construction and other industries and also a brief summary on the underlying principles are initially outlined. Following that, a brief overview on current status of application of BIM models as well as their potential for integrated visualization of as-built and as-planned models is presented. Subsequently, a new fully-automated approach for (1) reconstruction of 3D point cloud models from site images, (2) fully-automated registration of these models to generate 4D photo-based as-built models as well as (3) semi-automated registration of those with as-planned models, both based on their geospatial configuration as well as sequence of construction is presented. Subsequent to using a prototype implementation for testing over seven different cases from two ongoing construction projects, our results demonstrate that this all-inclusive integrated modeling approach provides flexibility in studying as-built, sorting and browsing daily site images geospatially and chronologically from a model-based perspective. While integrated with BIM models not only has a potential to overcome limitations associated with visualizing such models independently, but also create a window of opportunity for further extending the application of 4D (3D + time) BIM models within construction phase, facilitating analysis and revision of schedule, construction operations and their sequences and act as coordination media. Finally observed and perceived applications and benefits of these models for remote progress monitoring, revision of work schedules, as well as safety management, quality assurance/control and site logistics management are discussed.

4.3 Overview on Application of Images and Photo-based 3D Reconstruction in Construction

Application of photography and videotaping might seem to some practitioners as a peripheral activity within the AEC/FM industry, but in today's business environment, low cost of cameras, ease of use, as well as possibility of quick exchange of images over internet has evolved their applications to vital elements for communications and coordination. Nowadays site photographs are captured in two forms: (1) Still photographs casually captured from ongoing activities under different viewpoints; and (2) time-lapsed photographs and videos. Table Table 4.1 show a comparison in application of time-lapsed photos to daily photologs that are casually collected. A detailed discussion on of each approach is not in the scope of this chapter and readers are encouraged to look into (Golparvar-Fard et al. 2009b; Brilakis and Soibelman 2006). Instead here we introduce a new way of looking into how superintendents perceive construction performance and how application of unordered daily photographs can catalyze perception of various events that make up construction cycles.

Field engineers and superintendents perceive a lot of information about construction performance and geometrical configuration of components by moving through and around construction sites on a daily basis. When the field engineer moves and components around him/her move, progress information from the site is sensed over time. Through these observations, field engineers usually take many photographs and vary the composition to capture ongoing activities naturally with least amount of occlusion. We have observed this issue first-hand as the author has been actively involved in construction of two concurrent building projects. For example in these projects, field engineers take about 250 photographs per day. In addition, these two projects consist of 18 bid packages and for each package, contractors excluding their subs, take about 20-25 photos on a daily basis. Adding the photographs that the owner representatives take (about 20/day) in addition to other photos taken by executives and regional safety directors for each contract, it is easy to see the wealth of visual information which is available to be harvested. Since field engineers naturally find the best viewpoint to capture site images, these photographs have one great attribute in common: *Least amount of occlusion on documenting critical construction activities*. This wealth of visual information motivates application of techniques which allow both the underlying structure of the building components as well as the motion of the cameras (motion of the field engineer with camera) to be captured and represented in a virtual environment. Figure Figure 4.1.illustrates some of these images that are taken for progress monitoring, documenting quality and safety, site layout management as well as productivity analysis.

Table 4.1. Comparison of application of time-lapsed images with daily photologs and their conditions during construction phase of a project.

	Digital Asset Management (DAM)	
	Daily site photologs	Time-lapsed images
Ease of capturing images	• Almost at no cost	• Cameras and enclosures are expensive • Requires permission usually from the owners • Require frequent maintenance • Requires access to power and cable/ wireless transmission
View Range	• If a large set of images are used, they can capture everything that is not embedded (both at exterior and interior)	• Captures only what is in range or in the view • Can be equipped with Zoom/Pan/Tilt functionality at a cost to cover wider areas, but still only captures what is not occluded by static occlusions (e.g., natural progression of the progress) and dynamic occlusions (e.g., temporary structures, machinery) • Multiple cameras usually needed to cover wider areas • Monitoring interior is significantly challenging due to range issues
Remote Analysis	• Possible	• Possible
Weather and Illumination Conditions	• Many images captured over a short period of time usually captures consistent illumination • Weather conditions do not affect the camera itself but slightly affect quality of images	• Since the viewpoint is usually consistent, sever changes of illumination is observed throughout a day • Weather conditions severely affect the camera itself and quality of images making it impossible to see through during precipitations and cloudy days
Suitability for Progress Monitoring	• Remote and quick analysis if a large number of images are collected	• Remote and quick analysis if not obstruct by occlusion
Suitability for Productivity Analysis	• Static analysis of productivity is possible • Allows stop-motion analysis if significant number of images or video is collected	• Dynamic analysis of productivity is possible • Allows stop-motion analysis to be performed if small sequences of time are considered
Storage	• Requires significant amount of digital storage	• Require massive amount of digital storage specially if small time-steps are used

As observed from Table Table 4.1 if proper techniques for application of these daily photologs are used, significant benefits could be observed. One of the challenging research tasks is to automatically figure out the 3D geometry of the site from an unordered collection of photographs as well registering these images according to the geospatial location they were captured from.

Over the past decade, several research efforts began addressing concerns mostly with retrieval of images as well as applications of time-lapsed photographs. For example Abudayyeh (1997) proposed a method for manual linking of images/ videos to other types of data. Later on Brilakis and Soibelman (2006) developed a prototype for content-based retrieval of images from existing databases. These works stressed the importance of indexing but still the problems of (1) automated reconstruction of the as-built from these images and (2) geospatial registration of the images were not resolved. More recently the use of *PhotoModeler* (2009) was suggested by Dai and Lu (2008) for modeling of precast façades. Modeling with *PhotoModeler* requires two kinds of human interactions for calibrating cameras and measuring camera configuration: (1) marking and (2) referencing. Marking refers to using *manual* intervention to identify vertices in photographs and connect those vertices with edges. Second it involves referencing which is selecting a vertex and *manually* linking it to it corresponding vertices across other images. Using Ringed Automatically Detected Targets, more recent version of *PhotoModeler* allow visual targets to be detected and matched across multiple images. Still there is a substantial amount of human intervention; there is a cost and need for training and if seen throughout the time span of a construction phase may make such application time-consuming and less attractive. The following sections provide a brief overview on principles for photo-based reconstruction.

Figure 4.1. Various images that are captured on a daily basis. Images courtesy of Turner Construction; used by permission.

4.4. Overview on Photo-based Reconstruction and Principles of Structure-from-Motion

In the last two decades, there has been a dramatic increase in the capabilities of computer vision algorithms in finding correspondences between images that are subsequently captured, reconstructing 3D geometry of the scene they represent as well as calibration and registration of the cameras, a process formally known as Structure-from-Motion (SfM) (Hartley and Zisserman 2004). This process goes well back to early techniques in photogrammetry (Thompson 1959) however in more recent decades due to increase in performance of computers and digital imaging, automated collection and processing significant number of these images in reasonable time is becoming feasible. Substantial research progress was achieved when Triggs et al. (1999) presented *bundle adjustment* method which is a statistical optimization solution to the problem of finding geometrical location of feature points and orientation of the cameras.

Finding structure from motion is similar to perception of the field engineer in a sense that correspondence between images (the scenes field engineer observes) needs to be captured and the reconstruction of 3D components (geometrical configurations) to be found. To find correspondences between images, first a set of feature points (points that are potentially distinct enough that could be observed under different viewpoints, scales and lighting conditions) need to be independently found in each image and their motions from one image to another need to be computed. The trajectories of these feature points could be used to reconstruct their 3D geometrical positions and estimate motion of camera(s) used to capture those. A possible solution to understanding the underlying geometry of field activities using SfM solution involves the following steps: (1) Extract feature points from images; (2) Find an initial solution for the structure of the scene observed and motion of the cameras; (3) extract the 3D locations of these features points and calibrate camera matrices; (4) representing the scene with 3D geometrical locations of these points as well as cameras that observed those; (5) Inferring geometrical, textural, and/or reflective properties of the scene and interpret those as information regarding the construction site or ongoing activities. Early works on modern Scale Invariant Features detection (SIFT) and matching goes only a few years back to Lowe (2004) where now is being publically used within computer vision society. For a detailed comparison of the recent feature detection techniques readers are encouraged to look into Mikolajczyk et al. (2005). If these features and their correspondences are known, SfM technique could be implemented. Brown and Lowe (2005) presented one of the first automated SfM prototypes based on SIFT feature detection and matching which was later extended by Snavely et al. (2006) as an underlying mechanism for *Photosynth*, a system developed for Microsoft. Other approaches to the above mentioned global solvers are techniques such as Nistér (2004) wherein first robust calibration of image triples are formed and assembled and subsequently bundle adjustment is applied. The underlying SfM technique we propose in this work for reconstruction of as-built point clouds is similar to the work of Snavely et al. (2008) while the technique we use is extended to (1) specifically allow images that capture dynamic construction scene to reconstruct the as-built and be accurately registered, (2) automatically register daily point clouds over one-another as well as (2) register the 4D point clouds over as-planned models allowing remote navigation in such an augmented reality environment both in space and time. A detailed mathematical description of computer-vision steps is not within the scope of his chapter; instead, the steps that form the process will be detailed in the D^4AR model section.

4.5 Overview on As-planned Building Information Modeling

Building information models provide the ability of performing photorealistic renderings and allow design-development reviews and system clash detection be studied in virtual environment. BIMs also facilitate communication of design and coordination of working system, cost estimation and automated generation of bills of quantities. During construction phase of a project, these models can be helpful in analyzing construction operations by allowing project managers to determine site management strategies, facilitating contractor coordination, planning of site logistics or access routing, as well as studying integrity of schedule and construction sequences (e.g., site accessibility, trade coordination, temporal structures, lay-down areas use, different construction methods or means). Despite significant benefits of BIM during design and pre-construction stages, their value within construction phase of a project is not yet well perceived by the practitioners. Based on an investigation over a significant number of projects where BIM has been implemented, Hartmann et al. (2008) reports that only if these models are generated at the design phase, engineers can subsequently use them to generate design visualizations and later on construction managers can use them to plan construction of the facility. Application of these models during the construction phase can increase if difficulties in modeling detailed operations and site layouts are simplified and further potential added-values from integrating BIM with as-built are investigated. Not only does integrating BIM with rich as-built imagery can overcome these challenges in modeling, but it also allows benefits of each visual dataset to be augmented. In the following section, an overview on recent research efforts on integrated as-built and as-planned visualization is presented.

4.6 Overview on Integrated As-built and As-planned Visualization

Research in the area of integration of as-built and as-planned models during construction phase of a project goes back to early efforts in comparing laser scanning point clouds with CAD models. For example Gordon et al. (2003) suggested a method to compare laser scans of buildings to original 3D plans, in order to find and highlight elements deviating from accepted tolerances. Laser scanners only provide Cartesian information about the as-built. The sheer volume of the data that needs to be interpreted, the cost (about 100K USD) and need for expertise and other existing technical challenges makes application of laser scanners less attractive than techniques which extract point clouds from images. For a detailed comparison in terms of application and accuracy between laser scanner and daily site photographs in as-built reconstruction readers are encouraged to look into Golparvar-Fard et al. (2009c).

To the best of our knowledge, integration of BIM models with time-lapsed photographs for the purpose of *visualizing progress deviations* was first developed in Golparvar-Fard and Peña-Mora (2007) and Golparvar-Fard et al. (2007) where 3D BIM models were superimposed over time-lapsed images and a traffic light metaphor was used to color code progress deviations. Kim and Kano (2008) also suggests three methods for determining the 3D viewpoint and direction of a construction photograph to perform visual comparison of the construction photographs and corresponding VR images. Other works that have suggested such application are Ibrahim et al. (2009) wherein 3D model is overlaid on time-lapsed photographs wherein using vision-based techniques changes in appearances of objects within time-lapsed images are studied. Manual integration of daily site photographs and Industry Foundation Class (IFC) models have also been previously suggested in Brilakis and Soibelman (2006) and Goedert and Meadati (2008) however images were manually integrated with 3D models and no method for automated registration and visualization of as-built and as-planned was proposed. In the following section, our approach for integrated comprehensive representation of as-built and as-planned models is presented.

4.7 D^{4}AR – a 4 Dimensional Augmented Reality- Model for Integrated As-built and As-planned Visualization

Our objectives are (1) automated reconstruction of as-built point cloud models from unordered daily site photographs, (2) automated registration of point clouds to generate 4D as-built point clouds, and (3) semi-automated superimposition of 4D point clouds over 4D BIM models, and use the resulting integrated sequential augmented reality environment to facilitate remote and quick decision-makings. This section provides an overview on underlying concepts used throughout development of the continuing research on the D^{4}AR system (Golparvar-Fard et al. 2009a), which is the basis for the novel D^{4}AR model and is presented in the following modules. Our previous research revealed that the initial construction had to be further developed to take advantages of (1) daily photologs over the course of a project and use those to reconstruct 4D as-built models and (2) efficiently register those with 4D as-planned models. These modifications were mostly based on the following needs:

1. Generating point clouds from photos captured in one day and superimposing reconstructed point clouds at different days to allow a 4D as-built geometry + imagery model to be generated. This allows all images to be automatically registered with the 4D BIM model, allowing as-planned and as-built to be studied both in space and time.

2. Matching these point clouds in an effective way with the 4D models so no manual intervention will be required.
3. Forming the underlying framework on manual and automated extraction of information from the integrated model allowing different schedule sequences, operational details, logistics as well as safety and quality issued to be analyzed remotely.

Figure 4.2 shows an overview on data and processes in our D^{4}AR reconstruction and visualization system. As seen, this system is comprised of several modules. In the first module, photographs collected on a daily basis are used to reconstruct daily point clouds and have the images registered with respect to the point cloud. Second, have the 4D BIM model developed and updated to reflect the latest changes in geometry and schedule. Next, register as-built point clouds from different days over one-another using Iterative Closest Point (ICP) registration step. Finally superimpose the integrated as-built over the BIM model allowing all point clouds and all site photographs to be registered and visualized with the 4D as-planned model. In the following, an overview of each module is presented:

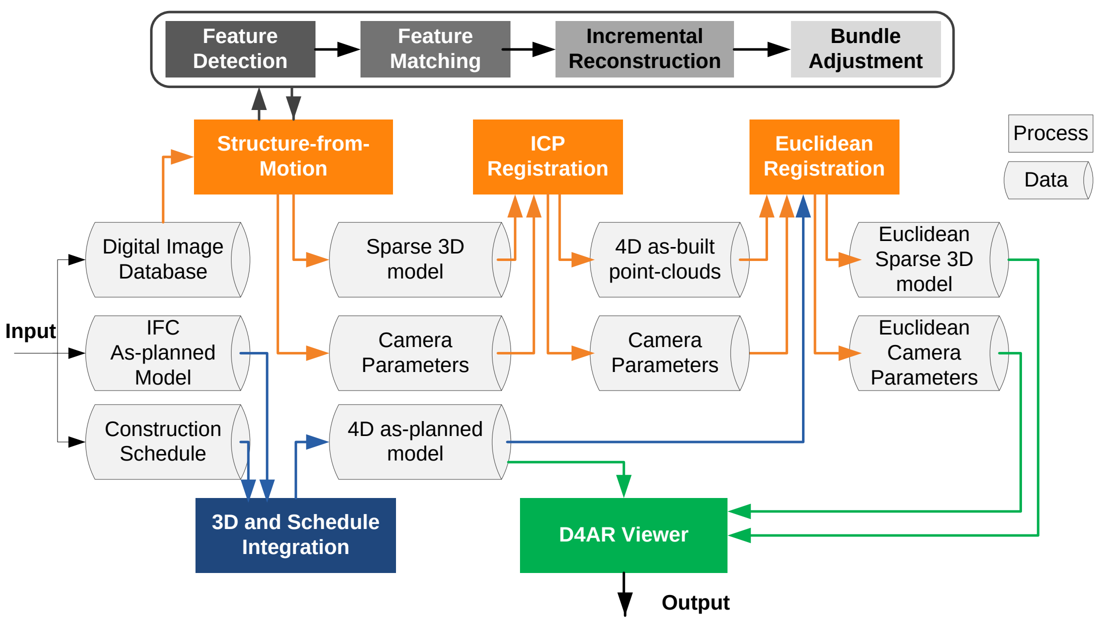

Figure 4.2. An overview of data and processes in the D4AR reconstruction and visualization system.

4.8 As-built Reconstruction Module

Several computer vision techniques can be used to reconstruct a point cloud from a series of photographs. For our application, we have used Structure-from-Motion (SfM) technique to reconstruct an as-built point cloud from a set of daily images. The choice among specific steps of the SfM is to make sure the system is fully automated and works with existing unordered daily photos. This module (As shown in Figure 2) consists of the following steps: (1) Analyzing images and extracting feature points from images; (2) Matching image feature across image set; (3) Find an initial solution for the 3D locations of these features points and calibrating cameras for an initial image pair and reconstructing the rest of the structure of the scene observed and motion of the cameras based on bundle adjustment and finally (4) Registering point clouds that are generated for each day to make a 4D as-built model. To present how these steps are formed, we exemplify two sets of 112 and 160 images that are taken on 8/20 and 8/27/2008 on Ikenberry Residence Hall project in Champaign, IL. In both cases, the field engineer causally walked along the sidewalk of the project and captured these images within a few minutes. Figure 4.3 presents a subset from these images which are shown to roughly illustrate the overlapping parts of these images. The SfM steps we use are as follows:

Figure 4.3. A subset of ten images represented from the 160 image set captured by the field engineer while monitoring the Ikenberry Residence Hall project on a walkthrough along the sidewalk. Images collected on 8/27/08 courtesy of Turner Construction; used by permission.

4.8.1 Analyzing images into distinct invariant features

The first step is to automatically and independently find distinct feature points in each image to be further used to estimate the initial structure of the scene. Since the underlying representation of the images used are unknown or the dataset could even include non-relevant images, a set of points that are stable under local and global changes in translation, scale, affine transformation, as well as illumination variations need to be found. These points need to be reliably computed with high degree of *reproducibility* in other images. This notion goes back to corner detection techniques (Harris and Stephens 1988), where corner points of objects were mostly used to track 3D CAD objects from 2D images. In practice, however, most corner detector are sensitive not only specific to corners, but to local image regions which have a high degree of variation in all possible directions. Therefore in our work, we do not track corners of objects, rather we use the SIFT keypoint detector (Lowe 2004), which (1) has good invariance to scale changes and view and illumination transformations, (2) is somewhat invariant to affine transformations, and (3) has standard application in the computer vision domain (e.g., Savarese and Fei-Fei 2007). SIFT feature detection technique does not limit the detection to corners of various objects on the construction site.

Rather it allows distinct feature points to be detected from surrounding environment (e.g., trees, machinery, or periphery of the construction site) as well. To verify that our approach works fine with low resolution images, we synthetically reduced the resolution of images captured to 2 to 3MPixels and used those for experiments. An image of 3MPixels typically gives about 9,000 to 11,000 features. An example of detected features and number of features detected are illustrated in Figure 4.4 and Figure 4.5 respectively.

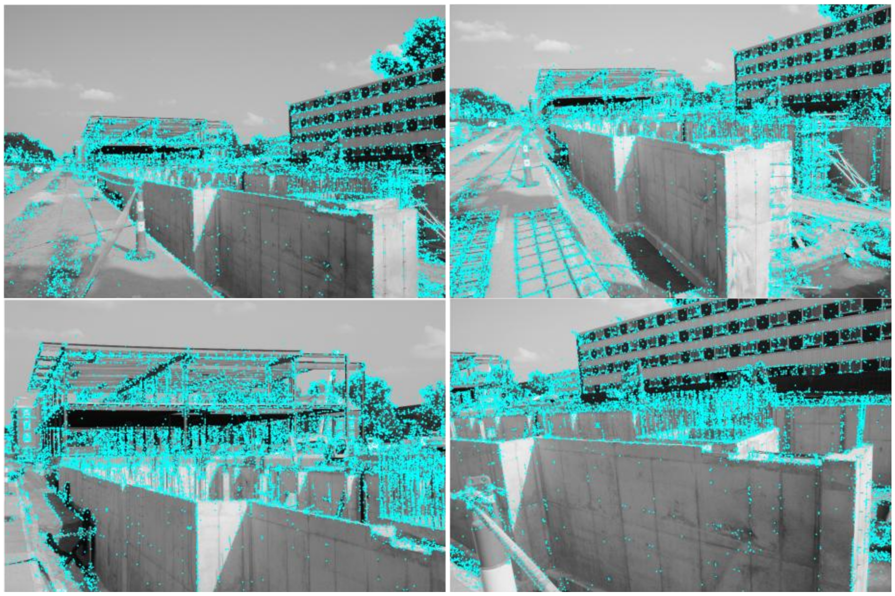

Figure 4.4. Four images taken on 08/27/08 from Ikenberry Residence Hall projects in grayscale with SIFT feature locations visualized in Cyan.

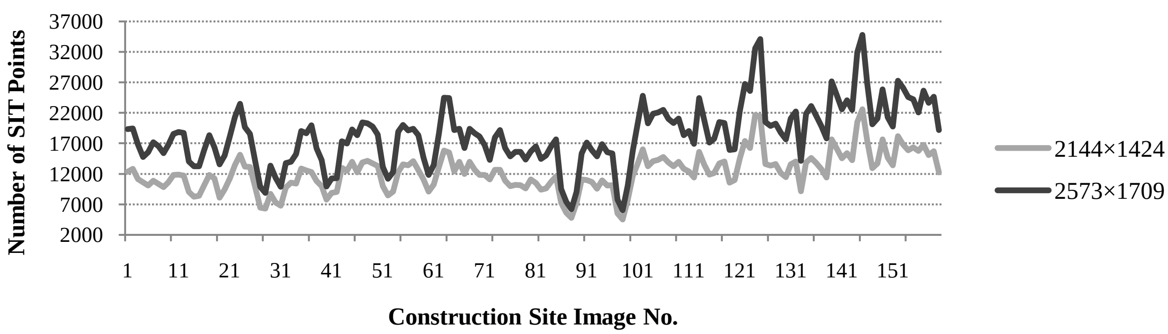

Figure 4.5. No. of SIFT features on the 160-image subsets taken on 8/27/09. Quality of images synthetically reduced to 36% and 25% of the original form (Image resolutions were 2573×1709 and 2144 × 1424).

As observed in Figure 4.5 the quality of the image dataset was synthetically reduced to 36% and 25% of the original resolutions to experimentally demonstrate the method we used is robust to work with low quality images. Yet, significant number of SIFT points are detected which allows a denser point cloud to be generated at later stages. It is worth noting that if lower resolution images are captured (as opposed to synthetic change in resolution), more SIFT points could be detected. This is due to interpolation techniques that are commonly used in down sampling an image and therefore it filters sharp gradient changes within the images.

4.8.2 Matching image features across image database

Once the features are detected, we need to detect the number of matching features in each image pair. To minimize computational speed, as experienced by Snavely et al. (2006), we use ANN's priority search algorithm and limit each feature point query to check a limited set. Furthermore, we use the ratio test described by Lowe (2004) for classifying false matches: for a feature descriptor in image *I*, a 128-dimension vector which is captured for each feature and ensures invariance to image location, scale and rotation for matching, we find the two nearest neighbors in *j*, with distances d_1 and d_2 (distances between feature descriptor vectors), then accept the match if $d_1/d_2 < 0.6$. Figure 4.6.a shows the number of matched SIFT features within the daily image dataset. Since SIFT features may not be completely distinct, there is a possibility that similar patterns especially located in façades of buildings (e.g., symmetrical patterns of façade, similar architectural columns, typical window details) may misleadingly match SIFT points in incorrect 2D locations in the image dataset. Due to the sensitivity of reconstruction algorithm to such false matches, we use an algorithm to remove such false matches. Our underlying assumption for refinement is that accurate matches will be consistent with the motion of the camera (the transformation of the image from one photography location to another). This assumption allows us to consider epipolar geometry between each image pair and consequently fit fundamental matrix. Therefore once the matching features are detected in an image pair, we estimate a fundamental matrix for the pair using RANSAC (RANdom SAmple Consensus) (Fischler and Bolles 1981). The fundamental matrix removes false matches as enforces corresponding features to be consistent under viewpoint transformation. In our model, in each iteration of RANSAC, a fundamental matrix is computed using the 8-point algorithm of Hartley and Zisserman (2004), and then the problem is normalized to improve robustness to noises (See Figure 4.6.b & c). If more than one feature in image *i* matches the same feature in image *j*, we also remove both of such matches, as one of them is a false match. As observed number of matching points in (c) is less than (b) since some matches are detected that are not consistent with the motion of the camera.

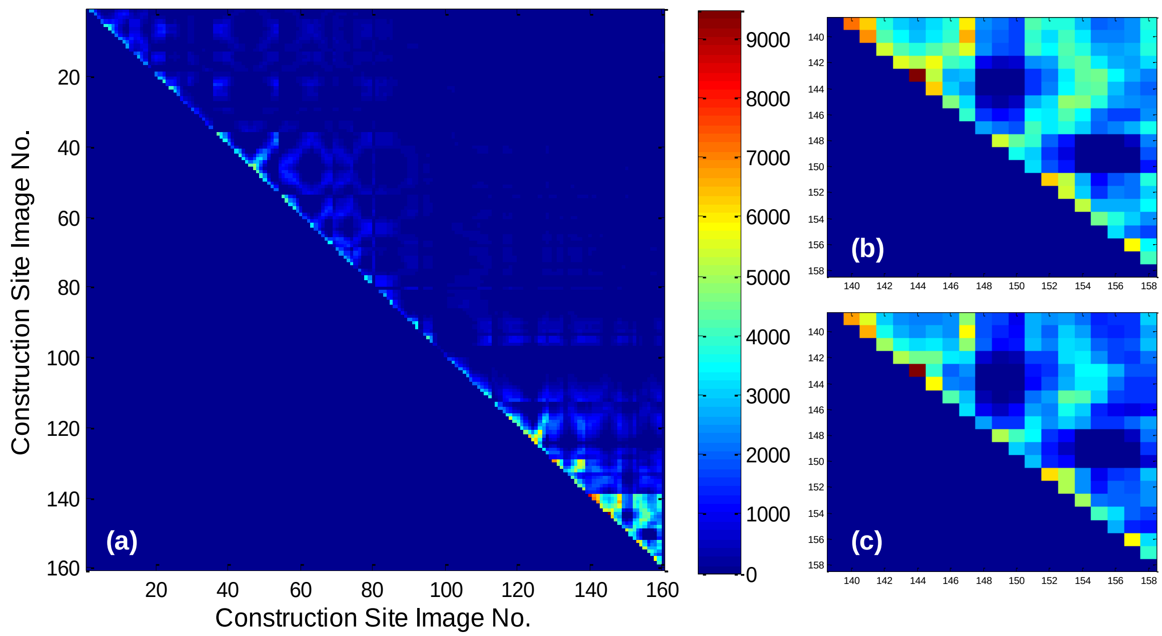

Figure 4.6. (a) Number of matched SIFT features between each image pair. Both axes show the camera indices and the colored dots visualize the number of SIFT features in image pairs. (b & c) show the close-ups of [140,160] subset before and after fitting Fundamental matrix in RANSAC loop.

Now, we recover camera extrinsic (rotation, translation) and intrinsic parameters (focal length and distortion) for each image and a 3D location for each feature point. The recovered parameters should be consistent, in that re-projection error; i.e., sum of distances between the projections of all 3D features and their corresponding image features, is minimized. This minimization problem can be formulated with the bundle adjustment algorithm (See Triggs et al. 1999 for more details). First, we estimate extrinsic and intrinsic parameters of a single image pair. Since bundle adjustment as other non-linear solvers may get stuck in bad local minima, it is strongly suggested by many researchers (e.g., Snavely et al. 2008, Pollefeys et al. 2004, Nistér 2004) to start with a good initial image pair and good estimates for camera parameters in the chosen pair. This initial pair for SfM should have a large number of matches, but also have a large non-homographic baseline, so that the initial scene can be robustly reconstructed. An image pair that is poorly described by a homographic transformation stratifies this condition. A 2D image homography is a projective transformation that maps points from one image plane to another image plane (Hartley and Zisserman 2004). We find the homography between all image pairs using RANSAC with an outlier threshold, and store the percentage of feature matches that are inliers to the estimated homography. We select the initial image pair with the lowest percentage of inliers to the recovered homography, but with at least 100 matches (As experienced by Snavely et al. 2007). The extrinsic camera parameters for this pair are estimated using Nistér's 5-point algorithm (Nistér 2004), and then the tracks visible in the image pair are triangulated. Finally a two-image bundle adjustment for this pair is performed.

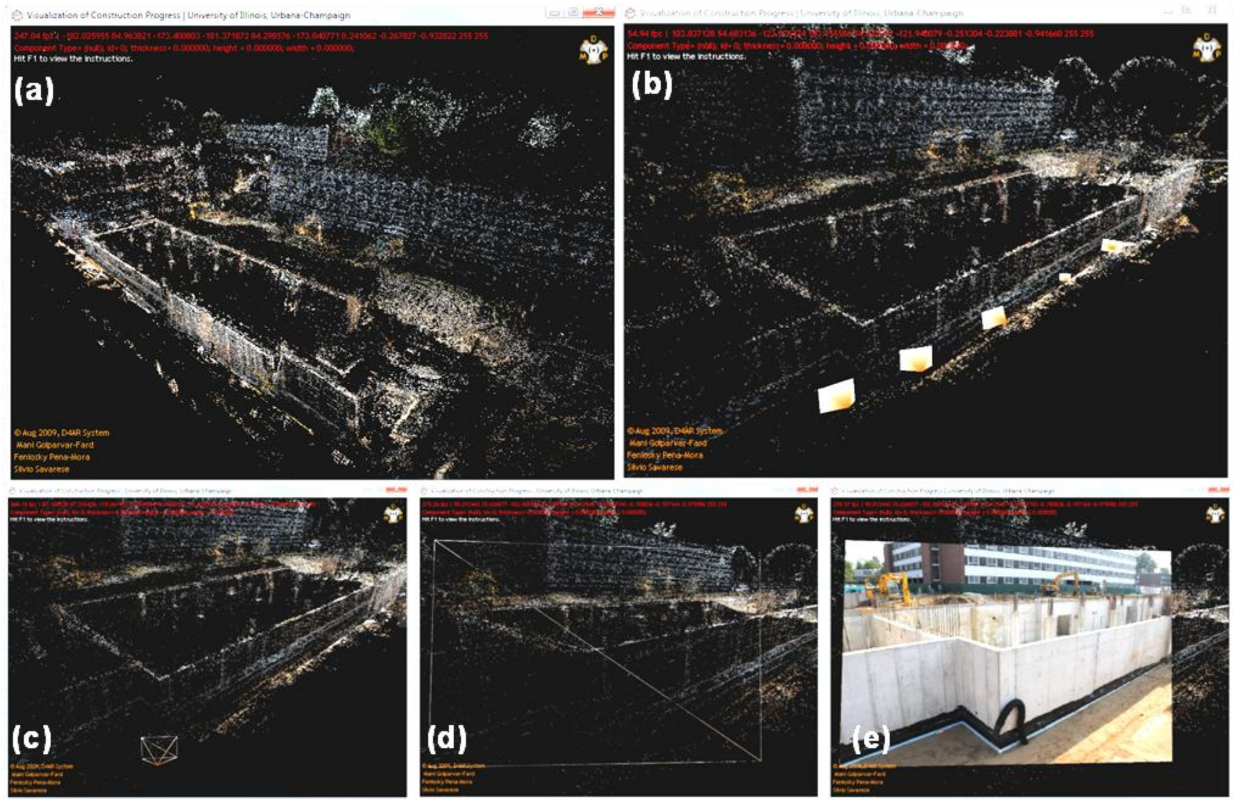

Figure 4.7. (a) Synthetic bird-eye-view of the reconstructed as-built point cloud; (b) Five camera frustra rendered, representing location/orientation of the superintendent when site photographs were taken; (c) One camera frustum is rendered and its location/orientation is visualized; (d) The as-built point cloud observed through camera frustum (same camera as (c)); and (e) camera frustum textured visualizing photograph registered over the 3D point cloud.

4.8.3 Incremental reconstruction

Next, we automatically add another camera to the optimization. A camera that examines the largest number of estimated points is chosen, and camera's extrinsic parameters are estimated using the Direct Linear Transform (DLT) technique (Hartley and Zisserman 2004) within a RANSAC procedure. For this RANSAC step, we use an outlier threshold of 0.4% image width or height. We use focal length from the EXIF - exchangeable image file format- tags of JPEG images (available in all digital cameras) to initialize the focal length of the new camera and estimate the intrinsic camera parameters.

Starting from this initial reconstructed scene, we run the bundle adjustment algorithm, allowing only the new camera and feature points it observes to change while the rest of the model is kept fixed. A feature point is added if it is observed by at least one recovered camera, and if triangulating the location gives a well-conditioned approximation. We estimate the conditioning by considering all pairs of rays that could be used to triangulate that point, and finding the pair of rays with the maximum angle of separation. If this maximum angle is larger than a threshold then the point is triangulated. Once the new points have been added, we run another global bundle adjustment to refine the entire as-built reconstructed scene. We use the minimum error solution with the sparse bundle adjustment library of Lourakis and Argyros (2004). This procedure is repeated for all cameras until no remaining camera observes enough reconstructed 3D points to be reliably reconstructed.

Overall only a subset of the images may be used for reconstruction of the scene. This subset is not selected beforehand, but is automatically determined by the SfM algorithm. After the as-built scene is reconstructed, the scene needs to be used for interactive explorations. We implemented an image-based rendering system in Microsoft C++ .NET using DirectX9 graphics library (D^4AR viewer in Figure 4.2). The following data structure is used to represent the as-built reconstructed scene: (1) A set of keypoints, in which each keypoint consists of a 3D location and a color that is averaged out from all the images that the keypoint is being observed from; (2) A set of cameras, while the extrinsic parameters and intrinsic parameters are estimated; and (3) A mapping between each point and all the cameras that observe the point. A list of numbers of cameras which observe the point, the location of the point in local coordinates of the image, and the SIFT keypoint index are all stored. While this information is stored, cameras would be rendered as frusta (camera pyramids). Figure 4.7.a & b show the reconstructed sparse scene from the same image subset of Figure 4.3and illustrate five of the registered cameras. Once a camera is visited in this reconstructed scene, the camera frustum is texture-mapped with a full resolution of the image so user can interactively zoom-in and acquire progress, quality, safety and productivity details as well as workspace logistics. Figure 4.7.c, d, e and f show the location of a frustum, the point cloud seen from that camera viewpoint, and finally the camera frustum textured while demonstrating how the image is geo-registered with the as-built point cloud.

4.8.4 4-dimensional as-built models

To extract time-varying 3D as-built models, we must perform inference about the position of cameras and as-built structure in both space and time. As mentioned, we use SfM techniques to deal with the spatial problem for a single day dataset, while here we focus on the temporal aspect of these models. First we run the SfM steps for each daily photo collection (it could also be a set of images taken from a series of days for which no significant change in construction is observed) and then register those over one-another. We formulate the task of registering generated point clouds for each dataset, as an iterative closest point (ICP) problem (Besl and McKey 1992), where we have ICP problem based on perspective transformation (unknown scale, rotation and translation). Since the SfM reconstruct the as-built point clouds with an unknown scale, we need to solve ICP problem based on general rotation and translation as well as scale. Using ICP with scale (Du et al. 2007) allows daily point clouds to be automatically registered and this in turn allows all images captures at different locations as well as different timing to be geo-spatially and temporally located within the same virtual environment.

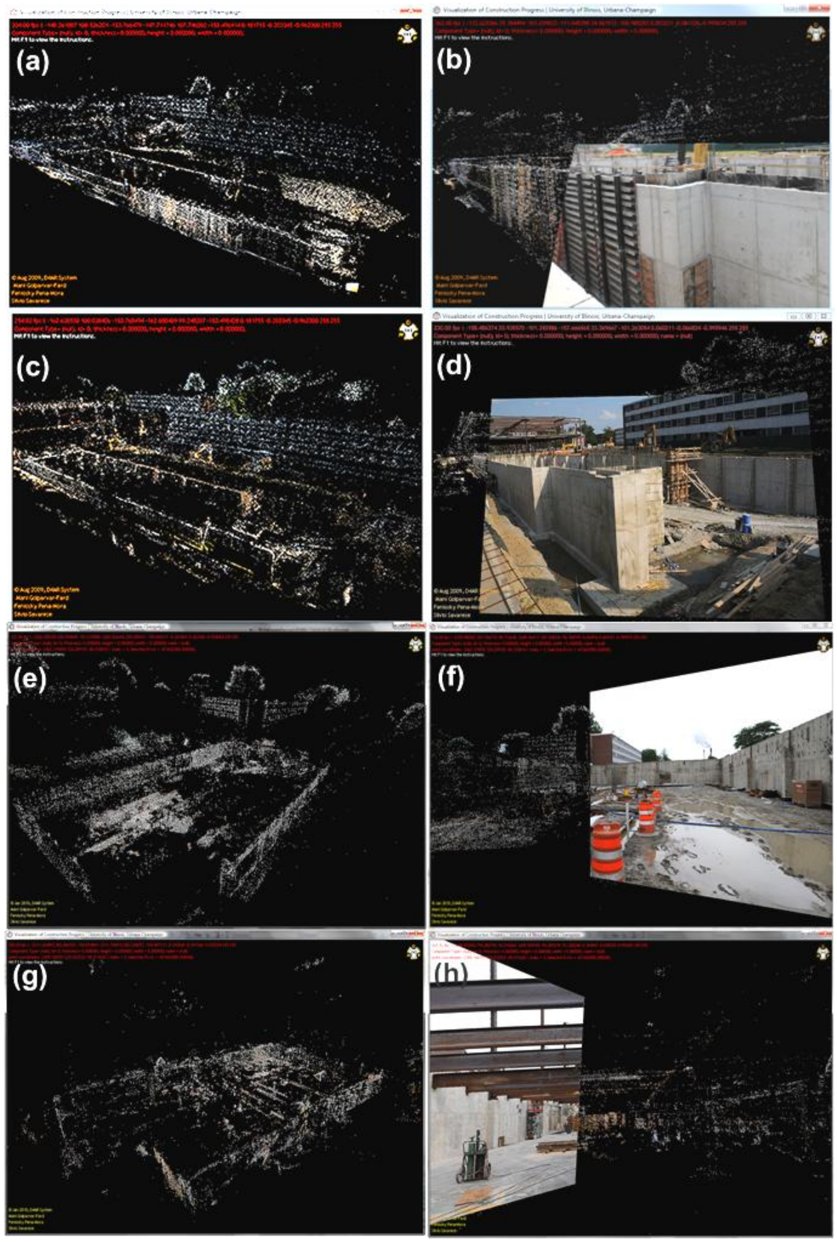

Figure 4.8. Visualization of point clouds as well as registered image for four datasets. (a) and (b) The point cloud and a registered image generated from 112 images taken on 08/20/08 from RH project; (c) and (d) The point cloud and a registered image generated from 160 images taken on 08/27/08 from RH project; (e) and (f) The point cloud and a registered image generated from 288 images taken on 07/07/08 from RH project. (g) and (h) The point cloud and a registered image generated from 118 images taken on 07/24/08 from RH project.

The resulting 4D as-built model allows project participants to select a specific location of a project and (1) study that location within a specific day using all images that have captured ongoing work in that area;

(2) study work processes and construction operations conducted in that location over time. Figure 4.8 presents four datasets from two different projects (Residence Hall = RH; Student Dining= SD): (1) 112 photos collected on 08/20/08 and (2) 160 photos collected on 08/27/08 from RH project; (3) 288 photos collected on 07/07/08; and (4) 118 photos collected on 07/24/08 from SD project. Using each dataset we generated the point cloud and registered all images used for that specific point cloud. Subsequently using ICP + scale algorithm we automatically registered these point clouds and generated a 4D as-built model of RH and SD projects where the ongoing activities could both be studied geo-spatially and temporally. As observed in Figure 4.8.b in the open area of the basement, foundation walls are formed, while in the subsequent week's observation (Figure 4.8.d) all those foundation walls are already placed and the forms are striped. Same situation is observed in Figure 4.8.e where in about 3-week time, some of the steel girders and columns are placed.

Figure 4.9.c illustrates the alignment of point clouds for the RH project depicted in Figure 4.9.a and Figure 4.9.b while Figure 4.9.g illustrates the same for the SD project point clouds depicted in Figure 4.9.e and Figure 4.9.f. Figure 4.9.d and Figure 4.9.h illustrate the registration of RH and SD BIMs over point clouds in (b) and (e) respectively.

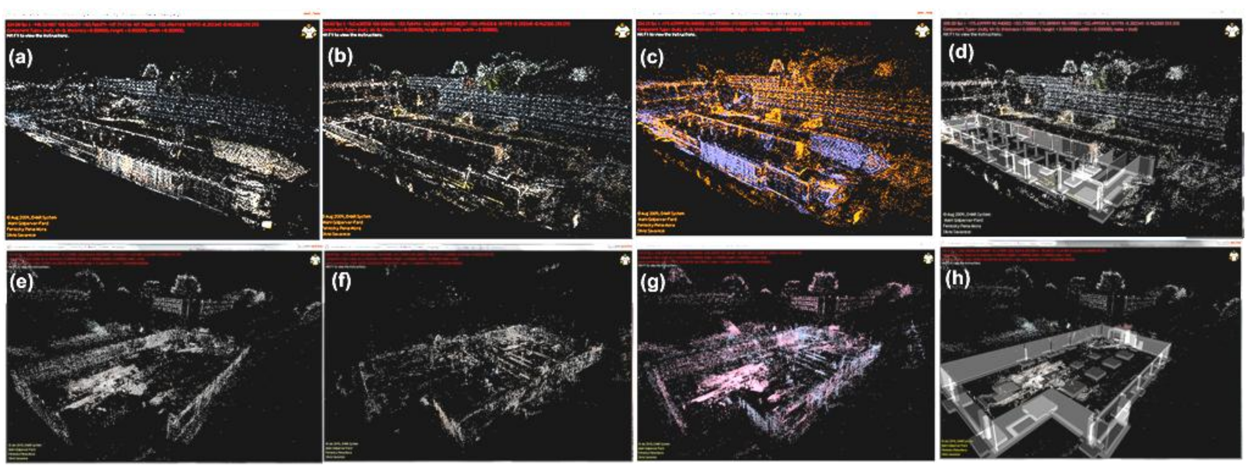

Figure 4.9. Point cloud/point cloud and Point cloud/BIM registrations. (a) point cloud reconstructed from 160 images from RH project (08/27/08); (b) point cloud reconstructed from 112 images from RH project (08/20/08); (c) violet point cloud is (a) and orange point cloud is (b); (d) registration of BIM with point cloud in (b); (e) point cloud reconstructed from 288 images from SD project (07/07/08); (f) point cloud reconstructed from 118 images from SD project (07/24/08); (g) red point cloud is (e) and blue point cloud is (f);(h) registration of BIM with point cloud in (e) (Images best seen in color).

4.9 4D As-planned Building Information Modeling Module

In order to represent the entirety of planned construction and query quantities and shared properties of materials, Industry Foundation Classes (IFC) is used as an underlying data model schema. This module consists of the following steps: (1) Generating an all inclusive as-planned model based on architectural and structural drawings at the pre-construction stage; (2) Linking the schedule to the as-planned model;

and (3) updating the model based on schedule revisions, approved RFIs, RPFs and change orders to continuously revise as-planned model based on changes made. The details animated within the 4D model needs to be at a level which allows a proper baseline for automating progress monitoring and model-based recognition to be generated. Here we base the level of detail at the construction schedule activity level. Our assumption is if a detailed progress monitoring (beyond what is already presented in the schedule) is required, a detailed schedule could be generated to properly set the baseline for comparisons. In our case studies, a third-level schedule (contractor-level) was used for the 4D model. For example, for placing basement foundation walls and piers, there was only one activity indicated in the schedule: “FRPS Basement Walls and Piers”. Therefore only the finished basement walls were visualized in the 4D model and operational details for placing the wall were not included. The 3D model for the project was modeled using a commercially available architecture and structural software and an IFC 2x3 file was exported. To visualize the 4D model, we extended the system to parse and visualize IFC-based models in the D^{4}AR viewer. Figure 4.10 shows four snapshots of the 4D models generated for the RH and SD projects. Choosing IFC file format is important as it allows (1) quantities and geometrical information of the as-planned model to be easily extracted; (2) earned physical progress to be compared with the planned values.

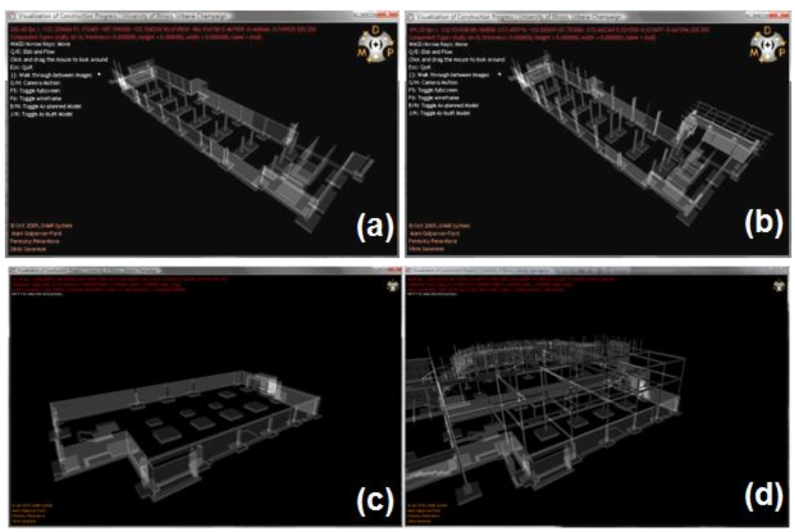

Figure 4.10. An illustration of the 4D models visualized in the D4AR environment. The interactive user interface allows the schedule to be reviewed over a revision period and information be queried from the as-planned model. (a and b) RH project; (c and d) SD project.

4.10 Registration of As-built and IFC-based As-planned Models Module

The final step of the D^{4}AR model is the global location estimation process which is to align the reconstructed scene with the as-planned model to determine the absolute geocentric coordinates of each camera. The SfM procedure estimates relative camera locations. In addition the point cloud gives us a significantly large number of points that do not belong to the building model itself (e.g., may form from the façade of surrounding buildings, machinery, or even people and plants on or around the site). Further the vertices extracted from the as-planned model are also very sparse and they may not be good representatives as the progress of as-planned model is not known at this stage. Therefore we allow users to select a set of corresponding control points from the integrated as-built point cloud and image-based model and have those associated with the as-planned model. These points could be surveying control points or a set of points that represent the geospatial location of the site. In our case, these points are mostly chosen from corners of the foundation walls and columns as their interactive detection and correspondence was visually easier.

Although the as-built scene visualization can work with relative coordinates, for geo-registration of the as-built scene with as-planned model, the absolute coordinates of the as-built scene are required. The estimated camera locations are related to the absolute locations by a global translation, rotation, and uniform scale transformation (7 DOF). Therefore three points known in both coordinate systems will be theoretically sufficient as they provide nine constraints (three coordinates each), more than enough to permit determination of these seven unknowns. However in practice, these measurements are not exact and if more than three points are used, greater accuracy can be sought. Therefore by adding additional points we do not expect to find the transformation that exactly maps the measured coordinates of points from one system into the other. Rather we minimize the sum of squares of residual errors. Let there be n points from as-planned and as-built model for registration. We denote the two coordinate system points by $\{r_{b,i}\}$ and $\{r_{p,i}\}$, respectively, where i is the number of corresponding points which ranges from 1 to n, $r_{b,i}$ and $r_{p,i}$ be the Cartesian coordinates of as-planned and as-built model respectively. We are looking for transformation of the form:

$$r_b = sR(r_p) + T \tag{4.1}$$

where s is a uniform scale factor, T is the translational offset and $R(r_p)$ is the rotated version of the planned model. Minimization of sum of square of the errors of such registration can be formulated as:

$$\sum_1^n \|e_i\|^2 = \sum_1^n \|r_{i,b} - sR(r_{i,p}) - T\|^2 \tag{4.2}$$

We use Horn (1987) to get a closed-form solution to the least square problem of absolute orientation. The error (Δe) can be measured in *mm*:

$$\Delta e_{mm} = \frac{\bar{w}_{pixels} \times \bar{f}_{mm}}{\bar{w}_{CCD,width}} \tag{4.3}$$

where $\bar{f}_{mm}$ is the focal length in mm, $\bar{w}_{pixels}$ is the image width in pixels and finally $\bar{w}_{CCD,width}$ is the CCD (Charge-Coupled Device) width of camera in *mm.* In our system, this process only needs to be done once for a project, since eventually as more photographs are taken, the new point clouds generated will be automatically matched with the initial reconstruction and nothing will be changed within the 4D IFC model.

Figure 4.11 and Figure 4.12 illustrate registration of the RH and SD 4D models over point cloud generated from 160 and 288 photos collected on 08/27/2008 and 07/07/2008. In both of these figures from left to right registration of the as-planned model over point cloud is visualized while registration from two cameras' perspective as well as a semi-transparent see-through visualization of the integrated system is represented subsequently.

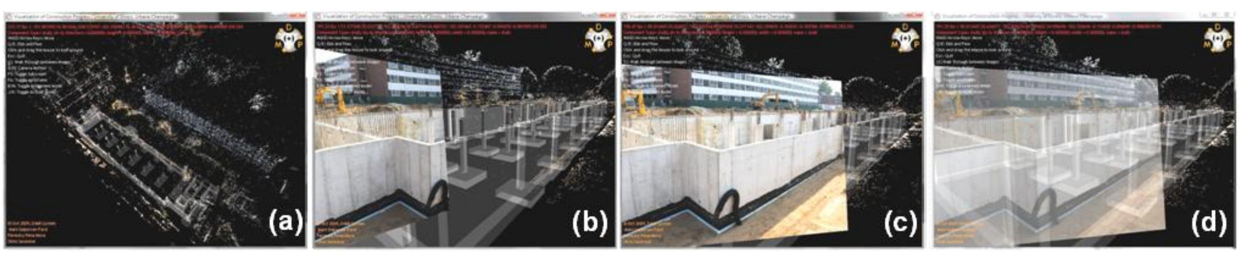

Figure 4.11. (a) Registration of the 3D IFC model over as-built point cloud; (b) The D^{4}AR model generated for RH project from an image point-of-view while the user has interactively yawed the viewing camera to the left; While scene is preserved, the accuracy of registration of 3D, pointcloud and image is illustrated; (c) another example of registration; (d) The same images as (c) is semi-transparent allowing a see-through of the construction site to be observed.

4.10.1 Performance metrics, factors and constraints

Overall, technical performance of the D^{4}AR tool is based on generality of images ($relevant\,reconstruction\,images / total\,daily\,construction\,images$) for reconstruction, accuracy of the reconstruction scene as a function of the conditions that the images are captured under, the density of the point cloud, ability of using low resolution images as well as accuracy in registration of the 4D IFC model over the point cloud. Based on these metrics, we have formulated a series of validating case studies.

Before such details are presented, implementation tools and architecture of the proposed system is discussed.

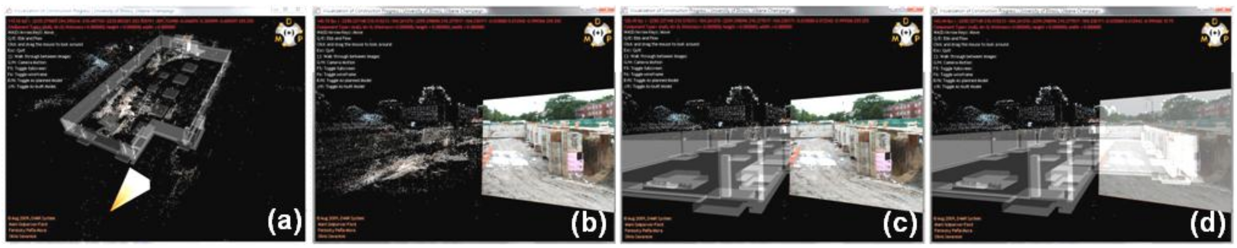

Figure 4.12. (a) Registration of the 3D IFC model over as-built pointcloud; (b) The D4AR model generated for SD project from an image point-of-view while the user has interactively dragged the image to the left; While scene is preserved, the accuracy of registration of 3D, pointcloud and image is illustrated; (c) another example of registration; (d) The same images as (c) is semi-transparent allowing a see-through of the construction site to be observed.

4.10.2 Implementation tools and architecture of the D^{4}AR system

A number of software packages and libraries were utilized for the development of the prototype that implemented the D^{4}AR system. Microsoft Visual C++ .Net along with DirectX 9.0 graphics library were used for coding all aspects of the visualization component, and MATLAB and Visual C++ was used to implement various steps in reconstruction of the scene from the images. The original SIFT implementation of Lowe (2004) as well as Sparse Bundle Adjustment package of Lourakis and Argyros (2004) were used for implementation of the reconstruction steps. The prototype's architecture comprises of three components: (1) first step takes place when daily site images are entered to the system. Our system analyzes each site image, reconstructs a point cloud and registers all images automatically. Once a point cloud is reconstructed, the reconstructed point cloud is geo-registered with the initial reconstruction through the ICP + scale algorithm (2) for the purpose of visualizing the IFC as-planned model; we used the IFCEngine.dll (TNO Building and Construction 2008) to parse the IFC file. A series of additional components are designed to allow as-planned as well as schedule information to be queried, ultimately providing a comprehensive as-planned model which can serve as a rich baseline for monitoring; (3) Finally the D^{4}AR model is generated and the 4D as-built point cloud is visualized as superimposed over the 4D IFC model.

4.10.3 Testing process for integrated visualization

A series of experiments were conducted on different subsets of daily construction site photographs collected on Student Dining and Residence Hall projects by Turner Construction Company. In total, these subsets were comprised of photographs taken mostly by the construction management team for the purposes of documenting as-built in the traditional way. From these comprehensive visual dataset, 7 different subsets ranging from 52 to 288 images were assembled for the experiments.

4.10.4 Results and validation

A summary of the conditions and accuracies under which D^4AR models have been formed are presented in Table 4.2. Experiments conducted for reconstruction of as-built point clouds from site images.. This table presents detailed information on these images, conditions they were taken under, as well as resolutions captured and resolutions used for experimentation. As observed, high generalities (percentage of successfully registered image/ used images) and reasonable densities are observed while computational times are practical. Table 4.3 presents accuracy of registration for case illustrated in Figure 4.8 as well as registrations shown in Figure 4.11 and Figure 4.12. As observed, the approach shows high accuracy in registration, though it should be noted that this measurement is based on how the control points are selected (in this case it is assumed that the user correctly selected the points) and it does not count for the inherent registration inaccuracies between the SfM point cloud and the images. Since usually more than the minimum number of control points (three) is selected, the selection error is minimized (the probability of incorrect selection of all correspondence points is very low).

Table 4.2. Experiments conducted for reconstruction of as-built point clouds from site images.

	RH #1[+]	**RH #2**	**RH #3**	**RH #4**	**SD #1**	**SD #2**	**SD #3**
Photos taken (#)	**52**	**112**	**198**	**54**	**288**	**118**	**130**
Experimented Photos (#)	52	112	160	54	288	118	130
Lighting Condition	Sunny, Bright	Sunny, Bright	Sunny, 5pm	Temporary lighting condition	Cloudy, rain runoff still on the side	Sunny, Bright	Sunny, Bright
Original Image Res.	4354×2848	4354×2848	4354×2848	3872×2592	4354×2848	4354×2848	4354×2848
Processed Image Res.	2144×1424	1715×1139	2144×1424	2323×1555	2144×1424	2573×1709	2573×1709
# of points recovered	22,261	43,400	62,323	1,293	61,638	31,661	15,100
# of images registered	52	112	160	22	286	118	123
Generality[++]	1.00	1.00	1.00	0.41	0.99	1.00	0.95
Computation time[†]	10 min	1 hr 49min	2 hr 36min	10 min	7hr 17min	3hr 20min	3hr 57min

[+] RH: 4-storey Concrete Residence Hall Project; SD: 2-storey Student Dining Steel/Concrete Project
[++] *total # of reconstructed images* / *total # of images used for experiments*
[†] Computational cost benchmarked on Intel® Core 2 Extreme CPU @ 2.93 GHz with 4.00GB of RAM.

Figure 4.13 also illustrates reasonable reconstructions that are generated from the dataset. These datasets contain images that show a wide-range view of the construction site as well as detailed images that are suitable for precise visual observations for quality control and safety. The interactive zooming technique implemented in the system allows these images to be thoroughly visualized in conjunction with the underlying 3D point cloud as well as the 3D expected as-planned model.

Figure 4.13. (a) The concrete circular column is manually colored with red as behind-schedule; (b) the column seen from a camera viewpoint while image is fully opaque; (c) same viewpoint as that of (b) while image is semi-transparently rendered allowing a see-through on the element.

Table 4.3. Registration error measured on reconstructions shown in Figure 8.

RH Project - RH#2 - RH#3	Test Case #	BIM + point cloud (9-a)	BIM + point cloud (9-b)	Point clouds (a) and (b)
	Image Size	2144×1424	1715×1139	--
	# of feature points	62,323	43,400	--
	# of corresp. Points	7	7	Randomly chosen by ICP
	Δe_{mm}	0.20 *mm*	0.65 *mm*	0.43 *mm*
SD Project - SD #1 - SD #2	Test Case #	BIM + point cloud (9-e)	BIM + point cloud (9-f)	Point clouds (e) and (f)
	Image Size	2144×1424	2573×1709	--
	# of feature points	61,638	31,661	--
	# of corresp. Points	9	9	Randomly chosen by ICP
	Δe_{mm}	0.73 *mm*	0.69 *mm*	0.70 *mm*

4.11 Discussion on Observed/Perceived Applications and Benefits of the D^{4}AR System

Our main motivation for developing the D^{4}AR system was to generate a system that geo-registers spatial as-built and as-planned models allowing construction progress to be *measured*, *analyzed* and *communicated*. However the availability of various perspectives of planned model, as-built cloud and site imagery and our preliminary observations on testing/utilizing D^{4}AR in our RH and SD case studies, implies a set of applications for the proposed system. Before discussing observed/perceived applications, it is worth noting that within the D^{4}AR system, new progress photographs can be instantly registered. First, the user can open a set of progress images, and position each image onto an approximate location on the as-planned model. After each image is added, the system estimates the location, orientation, and focal length of each new photo by running the *SfM* algorithm. In this case first key points are extracted and matched to the key points of the cameras closest to the initial location; then the existing 3D points corresponding to the matches are identified; and finally, these matches are used to refine the pose of the new camera. This by itself allows those areas that are not comprehensively photographed, to be further photographed on-demand and be quickly added to the overall reconstructed scene. Below is a list for observed and perceived applications of the D^{4}AR system:

4.11.1 Progress monitoring and revising work schedule

(1) *Remote monitoring of as-built construction*: The as-built visualization system allows project managers, superintendents and other project participants to virtually walk on the construction site, as-of the time the scene has been reconstructed and locate themselves in those positions that progress imagery has been taken. Such an interactive user walk-through allows progress to be perceived easily and quickly away from the hustle and bustle of the construction site activities. It also allows the as-built progress be compared with the as-planned 4D model, serving as a baseline for visualizing progress deviations. In this case, behind, on-schedule and ahead-of-schedule elements can be color-coded according to the color spectrum presented in (Golparvar-Fard et al. 2009a) (See Figure 4.13).

(2) *Facilitating schedule revisions*: The underlying basis of the system which visualizes the 4D-planned model allows prompt look-ahead schedule updating. Based on observations of as-built progress, completed construction process and the conditions under which they were completed, as well as the way resources were allocated can be understood. Comparing the as-built observations with the 3D planned model, allows different alternatives to be studied over the 4D model. It further allows constructability analysis to be performed in presence of the as-built imagery and this potentially enables better decision-making during schedule revisions by extending application of the 4D model.

4.11.2 Quality assurance/ Quality control

One of the observed applications of visualizing as-built model using point cloud along with imagery is to facilitate remote visual quality control. For example, in the case of Student Dining project, we were able to visualize the conditions of finished surface of the wall using one of the images. As shown in Figure 4.14 this area of the wall has suffered from a poor vibration during placement of the concrete and further finishing needs to be conducted to provide the acceptable quality of the exposed architectural surface. The availability of as-planned model as an underlying component allows specifications attached to the element be extracted and used for quality control purposes (not developed yet). Providing an interactive zooming ability in this D^{4}AR, allows project participants to not only study the quality from a very close range, but also to carefully count for provisional factors (perhaps something that may not be done extensively without such an easy-to-observe tool). Such imagery can also serve as a proper contemporaneous record for as-built that could be useful for coordinating reworks especially under remote conditions.

Figure 4.14. Illustration of interactive zooming. Capturing high resolution image along with the implemented interactive zooming allow the quality of the finished surface to be studied remotely. In addition safety issues (in this case rebar with no caps) could easily be observed from a very close range.

4.11.3 Safety management and education

Another observed application of visualizing as-built model using point cloud along with imagery is to facilitate offsite safety management and education. Figure 4.14 also illustrates an example, when rebar caps needed to be placed over wall reinforcement at the entrance of the jobsite. Such interactive zooming ability allows these cases to be remotely analyzed by safety inspectors and can potentially lessen frequency of on-site safety inspections. It could also be used as an effective safety education tool if enough photographs during safety irregularities are taken and those scenes are reconstructed. Another safety example is Figure 4.15.a wherein the trench area is reconstructed. In this case a safety inspector can remotely measure the depth of the backfill from the reconstructed point cloud and registered image and if is identified to be in excess of an unsafe depth, can report to the site to restrict access to the area with safety barriers.

4.11.4 Site layout management/ analysis of construction operation alternatives

The ability to observe a visual of the as-built scene together with animations of expected construction (either operational details or logistics of temporary resource locations as well as temporary structures) allows construction operations as well as site layout to be studied remotely. Although 4D models (Hartmann et al. 2008) or visualization of discrete event simulated operations (Kamat and Martinez 2008) by themselves are able to serve for such purposes, yet using imagery in conjunction with those models, not only allows photorealistic scenes to be rendered and studied realistically, but also minimizes the time and effort that needs to be put for making those models which consequently makes their application more attractive. Hence, it potentially increases usability of such analysis (not tested yet).

Figure 4.15. (a) Illustration of how trench depth can be measured; (b) Visualization of the foundation work. The section that needs to be formed for concrete placement is color-coded in red.

4.11.5 Remote decision-making and contractor coordination meetings

Other observed benefits of the D^{4}AR system in implementing the prototype of Student Dining and Residence Hall projects include:

(1) *Minimizing the time required to discuss the as-built scene*: Project managers and superintendents spent less time discussing or explaining progress. Rather, they spent more time on how a control decision could be made. Furthermore a reconstructed as-built scene and geo-registered images allow workspace logistics, and even productivity of workforce and machinery to be remotely analyzed. Such an as-built system was especially beneficial in weekly contractor coordination meetings as the workspace was navigated through the virtual world and consequently more time was spent on decision-making tasks as opposed to describing and explaining the situation using traditional 2D representation tools. An observed example of application of as-built for facilitating discussions in illustrated in Figure 4.15.b. In this case, a section of the foundation was not formed by the concrete contractor. In this case, such an augmented image was generated by the construction management team highlighting the foundations that need to be placed. The expectation was that this issue can potentially be a source of conflict but this simple visualization considerably facilitated the discussion to the extent that concrete foreman commented that "*I can clearly see it now*".

(4) *Significant cut in travel time and cost on project executives and architects* – Project executives and architects can study the reconstructed scene and geo-registered images, instead of spending time and money to travel to the jobsite. For example, Turner Construction project executives need to supervise several projects at the same time. Thus they need to frequently travel to these jobsites which might not be in close proximity to their main offices. Such remote interactive tool becomes very effective as it allows

them to stay in their offices, remotely walk through the site, and perform an overall visual supervision. It can also make such supervisory walk-through more frequent. The reconstructed scene with as-built progress imagery can be even more beneficial, when the possibility of quick adding of new photographs to the system is considered. Even if a perspective of an interest is not registered within the reconstructed scene and is not present in geo-registered image dataset, the user (i.e., owner, project executive, or the architect) can request the specific scene of interest to be photographed. Those photographs taken can be quickly geo-registered within the scene and this significantly facilitates progress communication.

4.12 Conclusions

Integrated visualization of as-built and as-planned construction can enhance *identification*, *processing* and *communication* of progress discrepancies and can serve as a powerful remote project management tool allowing all sorts of on-site observations (quality control, safety management, site layout management) to be performed remotely. To that end, D^4AR- 4 Dimensional Augmented Reality system - is developed wherein application of unsorted daily progress photograph collections available on any construction site as an easy and ready-to-use data collection technique is explored. Based on computing- from the images themselves- photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using progress daily photographs and superimposition of the reconstructed scene over as-planned 4D models is possible. Within such an environment, progress photographs are registered in the virtual as-planned environment which allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes are superimposed over each other, generating 4D as-built models. Such 4D as-built models are in turn superimposed over 4D models allowing site imagery to be geo-registered with the as-planned components allowing an all integrated sequential representation of construction to be generated; model-based computer vision recognition technique to be used and automatic extraction of progress/safety/quality data to be further explored. The D^4AR can serve as a robust onsite and remote tool for contractor coordination and communication purposes. Our preliminary results show observed and perceived benefits as well as future potential enhancement of this new technology in construction, in all fronts of remote onsite project management, automatic data collection, processing and communication.

Developing an automated progress monitoring system based on the D^4AR system and the proposed monitoring framework is presented in the chapter. Meanwhile automated linking of text-oriented information (daily construction reports, construction details, as well as request for information, request for proposals as well as architectural supplementary information) to daily site images using point cloud representation is being explored. Currently as the number of images increase for each dataset, computation time grows exponentially. This is mostly due to the pair wise matching step in our algorithm. In order to address this issue, future research will investigate application of GPS-camera photographs to tag photos based on their approximate locations and group them to minimize the number of pair wise matches and consequently decrease computational time. Finally, future research will focus on using D^4AR models for more case studies and further quantifying the added-values from application of D^4AR models.

CHAPTER 5. EVALUATION OF IMAGE-BASED MODELING AND LASER SCANNING ACCURACY FOR EMERGING AUTOMATED PERFORMANCE MONITORING TECHNIQUES

5.1 Overview

Accurate and rapid assessment of the as-built status on any construction site provides the opportunity to understand the current performance of a project easily and quickly. Rapid project assessment further allows the identification of discrepancies between the as-built and as-planned progress, and facilitates decision making on the necessary remedial actions. Currently, manual visual observations and surveying are the most dominant data capturing techniques but they are time-consuming, error-prone, and infrequent, making quick and reliable decision-making difficult. Therefore, research on new approaches that allow automatic recognition of as-built performance and visualization of construction progress is essential. This chapter presents and compares two methods for obtaining point cloud models for detection and visualization of as-built status for construction projects: (1) A new method of automated image-based reconstruction and modeling of the as-built project status using unordered daily construction photo collections through analysis of Structure from Motion (SfM) which was presented in Chapters 3 and 4; (2) 3D laser scanning and analysis of the as-built dense point cloud. These approaches provide robust means for recognition of progress, productivity, and quality on a construction site. In this chapter, an overview of a newly developed automated image-based reconstruction approach and exclusive features which distinct it from other image-based or conventional photogrammetric techniques is presented. Subsequently the terrestrial laser scanning approach carried out - which was carried out for reconstruction and comparison of as-built scenes by Jochen Teizer and Jeff Bohn as a collaborative project - is presented. Finally the accuracy and usability of both of these techniques for metric reconstruction, automated production of point clouds, 3D CAD shape modeling and visualization of the as-built scenes is evaluated and compared on eight different case studies. Compared to laser scanning point clouds, it is shown that for precise defect detection or alignment tasks, SfM point clouds automatically reconstructed from daily construction site photographs may not be as accurate and dense as those of the laser scanners nevertheless provide an opportunity to extract semantic information of the as-built scene (i.e., progress, productivity, quality and safety) through the content of the images, are easy to use, do not need add burden on project management teams by requiring expertise for data collection or analysis and automatically provide photo alignment and image-based renderings which can remarkably impact automation and visualization of the as-built scenes.

5.2 Introduction

Accurate and rapid assessment of progress, productivity, and quality control/quality assurance (QC/QA) is critical to successful project management. These assessments provide the opportunity to understand the current as-built status of a project efficiently, identify discrepancies between as-built and as-planned progress, and aid in deciding on remedial actions. Despite the importance of site assessment, within the Architectural, Engineering, Construction, and Facility Management (AEC/FM) industries, this process is not yet completely automated, nor has accuracy measurement benchmark been firmly established. Current manual practice for collecting data on as-built status of a project is still time-consuming and labor intensive (Cho et al. 2002). For example, on a 200,000 SF construction project with 11 bid-packages, on average 20-25 daily construction reports needs to be filled out and collected on a daily basis. Processing of such data is a difficult task due to its labor-intensive nature and the necessary level of competency with processing techniques required (Zhu and Brilakis 2007). In some cases a field engineer spends half to a full-day worth of work to process this data on a daily basis and have it compared with his/her own or superintendant's observations. Furthermore, techniques that are used to document and report the as-built status are visually complex and need to be improved to minimize the time required for describing them in contractor coordination meetings (Golparvar-Fard et al. 2009b). For example a drywall contractor may report in their daily construction report that *Framing* has been conducted on a particular day without explicitly indicating the location or the scope of the work. Such lack of accurate and detailed information occasionally requires more time to be spent in coordination meetings to discuss and explain the as-is status of a project. In addition, the formats of these reports (e.g., text-oriented daily construction reports, *S* progress curves, bar charts) may not accurately and visually represent the physical progress. There is a need for proper geometrical representations that facilitate control decision-making tasks. Overall, the large amount of data collected, processed and represented creates management issues in *reading*, *processing*, *visualizing* and *storing* the information in a seamless and an efficient way.

In recent years, significant progress towards automating detection and visualization of as-built status of a project has been achieved. These methods include visual sensing technologies (i.e., collecting large numbers of time-lapsed and daily site photographs using digital cameras) and 3D remote sensing technologies (i.e., robotic total stations, Global Positioning Systems (GPS), Radio Frequency Identification (RFID), bar codes, Ultra-Wide Band (UWB) and laser and distance ranging - LADAR). Among 3D remote sensing technologies, laser scanning has a high potential for applications in the construction industry as it can address all listed inefficiencies associated with current practice of progress monitoring. Despite high accuracy of laser scanners and dense reconstruction of as-built models as reported in several cases (Bosche and Haas 2008, Kiziltas et al. 2008, Teizer et al. 2005, and Jaselskis and

Gao 2003), a set of limitations and challenges in implementation may reduce the observed benefits by practitioners. These limitations include discontinuity of the spatial information, mixed pixel phenomenon (Kiziltas et al. 2008), scanning range, and sensor calibration. For example, moving objects in line-of-sight of an optical sensing instrument would create occlusions on the targeted object and create additional problems for the management team which must manually fix the superfluous noise. Compounding these issues, as the distance between the scanned objects increases, the level of details returned for the captured components can be reduced. Furthermore, the data collection process is time consuming and rigorous work, requiring sufficient knowledge of surveying theory, multiple individuals, and expensive and delicate components in an often rugged environment. The raw scanning data contains only *Cartesian coordinate information* of the scanned scene and does not carry any *semantic information*, such as knowing which point belongs to what as-built structural component.

Recent research efforts address these inefficiencies associated with stand-alone application of laser scanners. One example is presented in El-Omari and Moselhi (2008) wherein a new approach for progress data collection uses an integrated 3D laser scanning and photogrammetry technique. The method is shown to be less time-consuming with higher cost savings compared to the stand-alone application of laser scanners. The suggested approach also minimizes access limitations of scanner placement by integrating photogrammetry data with laser scanner point cloud; yet the processing time required for each scan is considerably high and the registration of images and 3D point cloud needs further adjustments. Also in this method, laser scanning does not allow site images taken from arbitrary viewpoints to be aligned with the 3D point cloud; nonetheless the *common points* between laser scanner's 3D points with images needs to be selected and matched *manually*. Manual selection and matching of common points between the data sources considering the large-size construction photo collections makes the system difficult to use by adding non-automated steps.

Bosche et al. (2009) and Bosche and Hass (2008) presented another example of such research efforts wherein a new approach for automated recognition of 3D CAD objects from 3D laser scanned scenes is presented. In their earlier work, the as-planned 3D CAD model is converted to a point cloud. Using point recognition metrics, correspondences between as-planned and as-built models are identified and recognition of the progress is returned. Recent work of Bosche et al. (2009) introduces an object surface recognition metric that shows high precision/recall on object recognition performance of a structural steel building.

However none of these methods take advantage of utilizing construction site photographs that are collected on a daily basis and are readily available on almost all construction sites. Even in more-recent photogrammetric or hybrid geometry and image-based reconstruction techniques such as (Debevec et al. 1996, Aguilera and Lahoz 2006, and Dai and Lu 2008), photographs are taken in supervised manners (e.g., calibrated cameras) and feature selection, stereo-matching and image-based modeling steps are all conducted in interactive ways, so significant manual interventions by a user is required to facilitate the reconstruction of the buildings. The frequency for site inspections and the amount of required supervision for these techniques makes their applications less attractive. Recent advancements in automated feature detection and matching techniques (Lowe 2004) allow photographs that are even randomly taken to be matched and used for reconstruction purposes [3], [14], [15], and [16]. These approaches such as [3] provide a potential opportunity to automatically reconstruct as-built scenes from construction photos that are randomly taken on construction sites and visualizing those through integrated representation of as-built point clouds as well as registered site photographs.

Before complete utilization of these emerging and automated image-based reconstructed point clouds for progress monitoring, their accuracy and usability needs to be evaluated against the laser scanning point clouds. A comparison of point clouds automatically generated from site photographs with point clouds from high precision laser scanners can provide such an evaluation. This chapter presents a comparison between two recent methods namely automated image-based reconstruction using Structure-from-Motion (SfM) techniques and terrestrial laser scanning for generating as-built models as an underlying basis for performance monitoring and defect detection. Eight sets of 3D spatial models, four from actual construction projects and four from laboratory testing are generated using (1) laser scanning point clouds, and (2) image-based reconstructed point clouds based on SfM using daily construction photo collections. In this chapter, daily construction photographs refer to uncalibrated images that are casually captured by field engineers with specific applications for management of progress, productivity or quality of the construction, while calibration information; i.e., intrinsic parameters (i.e., focal length, distortion) as well as extrinsic parameters (i.e., location and orientation) of the camera at the time images were captured are not known. Based on the experiments conducted, both approaches generated 3D CAD surfaces. For complete as-built model generation and progress monitoring, the 3D CAD models and their reconstructed surfaces are compared for accuracy and usability for generation and visualization of as-built status of a project.

This chapter begins by introducing the reader to the two techniques used in this research. First, we briefly overview the specific features which differentiates our developed image-based reconstruction based on SfM technique from other image-based modeling and conventional photogrammetry techniques. Subsequently the limitations associated with each of these methods are discussed. Next, the research methodology including experimental plan, data collection, and data processing is explained. Results of the conducted experiments for processing and visualization of as-built scenes as well as accuracy of each method are presented followed by conclusions and future work.

5.3 Background

In this section, previous works that have led to the application of daily construction photo collections and laser scanners for generating and visualizing as-built point clouds of construction sites are presented. Benefits and barriers of each of these approaches are then discussed next.

5.3.1 Image-based reconstruction using daily site photo collections and analysis of Structure from Motion (SfM)

The most widespread and easy-to-use method of obtaining data for monitoring project controls is simply having a project engineer or superintendant take photographs of construction progression using inexpensive and readily available digital cameras. A newer trend using automated time-lapse or videotaping construction cameras has also been useful in project management/controls and documentation of construction projects (Golparvar and Peña-Mora 2007, Bohn and Teizer 2010). Automated cameras allow users to know the current project status at customizable time intervals and field-of-view, taking advantage of remote controllable camera hardware via broadcast or cellular internet connection. Using these cameras, time-lapse videos of construction activities can be created and analyzed for post-action productivity. Although such images are easy to obtain, inexpensive, and easily understandable, automated or semi-automated detection of progress from site images is challenging [3]. Photographs only show activities that are (1) unobstructed by secondary activities or equipments (i.e., by machines, scaffolding) and (2) in the camera's field-of-view. These factors limit the application of time-lapse images, since once the envelope of the building is in place, it is impossible to track progress inside the building from the same camera's viewing point. In addition, different illuminations, shadows, weather, and site conditions make it difficult to use time-lapse photography for performing consistent image analysis (Golparvar and Peña-Mora 2007, Bohn and Teizer 2010). In such cases Golparvar Fard et al. (2009b) and Leung et al. (2008) suggest the installation of multiple cameras on the job site. Yet multiple fixed cameras come at greater expense and cannot overcome all limitations of occlusion, obstruction, weather, and dynamic and changing site conditions.

Given the benefits and limitations of time-lapse photography and webcams, this research suggests using unordered daily construction photo collections. As mentioned earlier, on a daily basis key project stakeholders (i.e., construction managers, owner-representatives, and subcontractors) collect large numbers of these images at almost no cost. The collection of these images can enable reconstruction and visualization of an entire site. Such large visual data sets would then allow for as-built visualization to increase communication among project stakeholders and recognize issues that may have high impact on the project at large.

However automated analysis of daily construction photographs is not easy. These images are usually not organized according to the locations they are taken from. They are not calibrated with respect to known coordinates and vary widely under various illumination, resolution, and image quality. These images typically focus on detailed activities that are constantly changing the work environment and/or may be taken in a panoramic manner. Therefore, they may not carry enough information from the perspective of tracking site progress which is essential for global reconstruction of the as-built scene. In addition to the problems mentioned, capturing progress on dynamic construction sites is difficult when objects such as construction work crews and machinery are moving. Hence, developing computer visualization and image processing techniques that can operate effectively with these data sets is a major challenge. Within the presented research scope, a key challenge is image registration (i.e., finding distinctive features within images and matching those within a common 3D coordinate system). Substantial progress has been done in this area by the computer vision community over the last decade (Debevec et al. 1996, Snavely et al. 2008, Hartley and Zisserman 2004, Pollefeys et al. 2004, Engels et al. 2006, Faugeras and Mourain 1995, and Triggs et al. 1999) but many challenges are still unsolved, specifically with respect to applications of SfM for fully automatically generating as-built construction point clouds. Many of such works still depend on using interactive methods for manual feature detection and matching (e.g., Aguilera et al. 2006, and Dai and Liu 2008) or calibrating cameras for data collection (e.g., Akbarzadeh et al. 2996 and Zhao et al. 2005). Although all these techniques can successfully reconstruct building models, however they add new tasks to the project management team by requiring manual supervision on the as-built reconstruction. Given the usual frequency of progress monitoring observations, application of these interactive techniques may become unattractive.

To address such inefficiencies, we looked into techniques that can automatically reconstruct as-built scenes from already available unordered construction photo collections. In section 3.1, we present the state-of-the-art steps towards automated image-based generation and visualization of as-built models using these images. Results of reconstructing and localizing the as-built scene and registering progress images with the as-built model are also presented.

5.3.2 Three-dimensional laser scanning

Laser scanning construction sites for progress monitoring has a number of unrealized benefits that are lacking in traditional methods (i.e., total stations, GPS). Laser scanning can be conducted in a number of ways including aerial, mobile, or more traditional, terrestrial based. This research focuses on terrestrial data capture due to the nature of the experiments, availability of technology, and ease of integration with current technology. Laser scanning is based on time-of-flight (TOF) measurements to collect range (x, y, z) and intensity (reflectivity) to distinct points in a scene. A laser scanner returns data as a point cloud, visualized through commercially available software. Users can interact and manipulate so called dense range point data allowing for construction of as-built conditions in a virtual environment (Jaselskis ad Gao 2003). A unique feature of laser scanning over traditional surveying is the ability to manipulate and view data in a full degree of freedom environment. Laser scanners allow for wide range measurements at high resolution, and are generally not limited by ambient conditions during operation (Jaselskis ad Gao 2003). Developing technology is focusing on semi/fully automated integration of laser scan data with CAD models and other visualization technologies (Kiziltas et al. 2008).

An observed characteristic of laser scanned scenes is the resulting density and standardization of the generated point clouds. Laser scanners can output extremely high resolution models, but at a much larger file size and processing time. The data is considerably accurate, though it is dependent on a number of factors including object distance from scanner, target surface reflectivity, and measurement angle (Akbarzadeh et al. 2006). More sophisticated laser scanners have higher accuracy, though at a much greater cost.

On the other hand, laser scanning has a number of limitations that impede implementing the technology alone in construction projects. Laser scanning takes significant time to complete a full scan, and depending on the size of the construction site, can take a crew of two people days (for large scale hi-resolution shots). Much like fixed automated cameras, laser scanners can only return data for objects that are within line-of-sight of the scanner and thus many occlusions occur, which is why multiple station locations are used (Jaselskis ad Gao 2003). Scanners cannot be utilized during inclement weather (e.g., rainfall). Laser scanners also require significant power, which is not always available on a construction site. According to Boehler and Marbs (2003), in certain cases laser scanning can be less accurate than photogrammetry, though the metric for this claim through comparison of point clouds automatically generated from SfM analysis and those of laser scanning will be established later in the chapter. Although laser scanning is currently cost prohibitive, though the technology is becoming less expensive and more widespread, in particular since commercial providers and government entities have begun to realize its return-on–investment (ROI) compared to conventional surveying methods. As the technology continues to grow, cost should decrease and adoption increase. For these reasons, comparison of their application to SfM point cloud is essential.

5.3.3 Combining site photographs with laser scanned scenes

The current status of remote sensing technology allows the argument that no single remote sensing method alone solves the needs of the AEC industry to build as-built models or to track construction progress. Instead, some studies such as Zhu and Brilakis (2007) recommend a combined approach of remote sensing technology. Photo collections and laser scanning are complementary technologies to use in combination because of the similarities in outputted data. Both can produce data in Cartesian coordinates (*x, y, z*) which can be easily modeled in a same virtual environment. Additionally, site photos allow capture of dynamic events on construction sites (i.e., moving crews and equipment) at high update rates which can be complementary to the detailed and static range data that laser scanners collect from fixed objects. Using site images does not add any burden or new tasks to project management, since daily construction photographs are already being collected. In addition, computer vision and/or image processing techniques that are applied on registered site photographs can add additional information that is essential to decision makers, such as information to work task progress, productivity, quality, site logistics, and safety. In contrary, laser scanning can capture a more comprehensive Cartesian-based data set that photo collections may not, since laser scanning collects many more point and creates much denser three-dimensional model.

5.4 As-built Data Capturing Methodology

In the following sections, SfM and laser scanning methods for capturing as-built conditions are explained more in detail.

5.4.1 Image-based as-built modeling using daily construction photo collections and Structure from Motion technique

This section briefly explains the steps that are required to generate as-built scenes using daily photo collections. The complete technical detail of this approach is not part of the scope of this chapter and is already covered in other works (Golparvar et al. 2009b, Snavely et al. 2008, Snavely et al. 2007, Brown and Lowe 2005, and Mikolajczyk et al. 2005), and (Golparvar et al. 2009c). A brief summary of the method follows. In the computer vision society, the described problem is defined as Structure from Motion (SfM). SfM studies both structure (i.e., three-dimensional structure of the environment) as well as the motion (i.e., motion of the camera within the scene). Such systems require accurate information of calibration information; i.e., both extrinsic (i.e., relative location and orientation), and intrinsic (i.e., focal length and distortion) parameters for each images taken on the construction site. The photo registration method used in this research approach relies on data extraction from digital images alone (Golparvar et al. 2009b). The approach neither relies on GPS or other wireless location tracker nor on pre-calibrated cameras for detecting location, orientation of the photographer and/or geometry of the photographed objects. Rather such information is automatically computed from the images themselves. Figure 5.1 represents the state-of-the-art steps that were implemented in this work towards solving this problem.

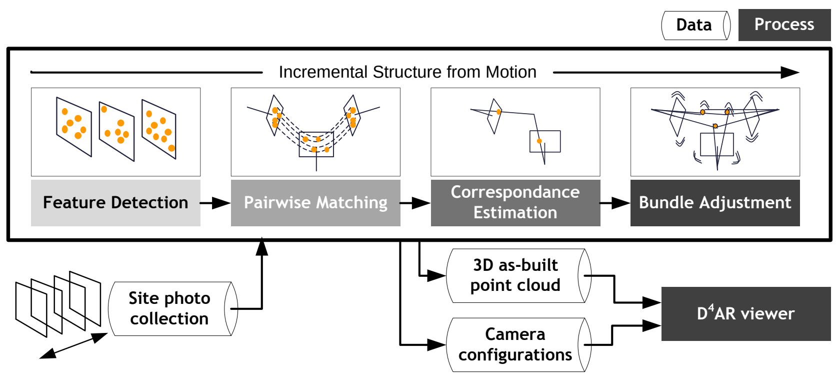

Figure 5.1. Schematic representation for steps of incremental Structure from Motion (SfM) followed from left to right (SfM graphics extended from [29], [38]).

5.4.2 Steps for image-based reconstruction

The steps towards reconstruction of the as-built scene are presented in the following:

Automated feature detection and correspondence

The first step to use site images for reconstruction is to find distinct features on each image, which can be automatically matched across a subset of images. Despite significant research on feature detection and matching, only recently have researchers implemented successful methods in extracting and detecting salient regions (in image/scale space) invariant with respect to scale, orientation and affine transformations. The features need to be highly distinctive, in the sense that a single image can be correctly matched with high probability against a large database of images. Mikolajczyk et al. (2005) reviewed recently developed view-invariant local image descriptors and experimentally compared their performances. In the system used in this research Lowe's SIFT features - Scale Invariant Feature Transforms (Lowe 2004), which is widely used in the computer vision community and achieves good performances over an acceptable range of viewpoint changes, is applied. Recent methods have taken advantage of these properties (Snavely et al. 2007, Brown and Lowe 2005, Niebles et al. 2006 and Savarese and Fei-Fei 2006). Figure 5.2 shows the SIFT features detected in the initial reconstruction image pair (explained later) from one of our experimental databases.

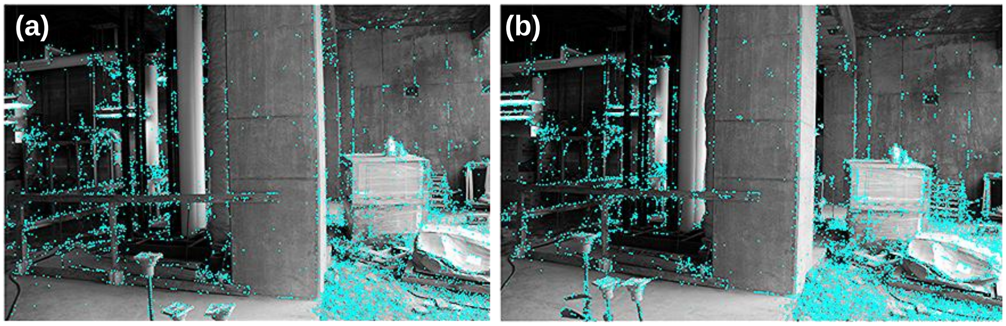

Figure 5.2. The SIFT (Scale-Invariant Feature) detectors shown over the initial reconstruction pair. A total of (a) 7,238 and (b) 9,745 SIFT features were detected.

Once features have been detected throughout the dataset, it is necessary to know how many of the detected features match in each image pair. In this work, features are automatically matched using a *nearest neighborhood* matching scheme. Since the number of features is large, a *k-d* tree matching scheme (Arya et al. 1998) is used to reduce the computation cost for matching. This is particularly effective when the dimension of the data set is large. Figure 5.3 shows the SIFT feature points across the same image pair used in Figure 5.2 and visualizes some of these matches through connecting these features by solid lines. Due to potential inaccuracies in feature matching especially because of similar or symmetrical appearance in building components, some false matches may also form. Due to the sensitivity of the reconstruction algorithm to these false matches, a fundamental matrix (Hartley and Zisserman 2004) within a RANSAC (random sample consensus) (Fischler and Bolles 1981) iterative method is fit to each matching image pair. The fundamental matrix helps remove false matches as it enforces corresponding features to be consistent under change in the view point.

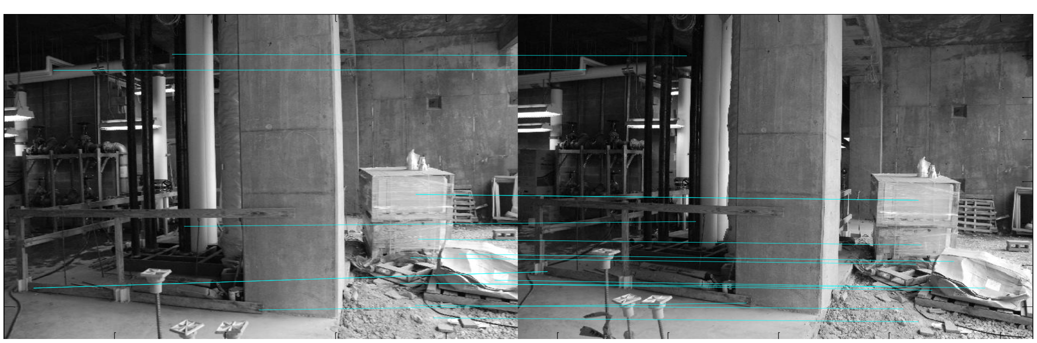

Figure 5.3. A total of 849 SIFT features were matched in this image pair. For visibility, only 14 of these matched features are shown.

Figure 5.3 shows 14 SIFT features (out of a total of 849) that are consistently matched after fitting a fundamental matrix. Figure 5.4 schematically presents the configuration of the image pair and the fundamental matrix that is used to remove false matches. The fundamental matrix F is a 3×3 matrix which relates corresponding points in a stereo image pair. In epipolar geometry with homogeneous image coordinates (the geometry of stereo vision), Q_L and Q_R, are corresponding points in a stereo image pair and FQ_L describes an epipolar on which the corresponding point Q_R on the other image must lie. This means that for all pairs of corresponding points holds $Q_R^T FQ_L = 0$. Fitting the estimated fundamental matrix for each image pair removes false matches that are not consistent with the estimated epipolar geometry.

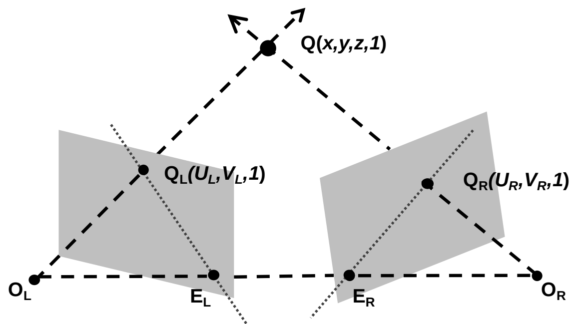

Figure 5.4. A schematic representation of the epipolar geometry for an image pair.

Structure from motion (SfM)

Once the correspondence between a set of feature points across a subset of daily site images are known, extrinsic (rotation, translation) and intrinsic (focal length and distortion) camera parameters for estimating the 3D location of each SIFT feature will be recovered. The recovered parameters should be consistent, in that the re-projection error (i.e., the sum of distances between the projections of each set of corresponding feature points and its corresponding image features) is minimized. This minimization problem can be formulated as a non-linear least squares problem and solved using bundle adjustment (Lourakis and Argyros 2004).

In this work, before formulating this non-linear least square problem, extrinsic and intrinsic parameters of a single image pair is estimated to initialize the reconstruction. Since bundle adjustment as other algorithms for solving non-linear problems is prone to fail by converging in local minima as opposed to global minima and hence it is strongly suggested by many researchers (e.g., Snavely et al. 2007, Nistér 2004) to start with a good initial image pair and good estimates for camera parameters in the chosen pair. This initial pair for SfM should have a large number of matches, but also have a large baseline, so that the initial scene can be robustly reconstructed. An image pair that is poorly described by a homographic transformation satisfies this condition. A 2D image homography is a projective transformation that maps points from one image plane to another image plane (Hartley and Zisserman 2004). The homography between all image pairs using RANSAC was found with an outlier threshold of 0.4% of the maximum of the image width and height. Stored was the percentage of feature matches that are inliers to the estimated homography. The initial image pair automatically selected was the pair with the lowest percentage of inliers, but with at least 100 matches (as experienced in Snavely et al. 2007). The camera parameters for this pair are estimated using Nistér's five point algorithm [36], and then the feature points visible in the image pair are triangulated. A two-frame bundle adjustment for this initial pair was performed. Next, all images that were taken by the cameras contribute to this optimization task. The camera that examines the largest number of estimated sets of associated correspondence across a subset of images was chosen, and initializes the new camera's extrinsic parameters using the Direct Linear Transform (DLT) technique (Hartley and Zisserman 2004) within a RANSAC procedure. For this RANSAC step, an outlier threshold of 0.4% of maximum of image width or height was applied. Focal length for each image was measured from the EXIF (Exchangeable Image file format) tags of JPEG images (file type of almost all digital cameras) and was used to initialize the focal length of the new camera and estimate the intrinsic camera matrix (Snavely et al. 2007).

Starting from this initial set of parameters, the incremental bundle adjustment algorithm allows any new camera and observed SIFT feature points to change while the rest of the model is kept fixed. Finally, points that were observed by the new camera were added into the optimization algorithm. A SIFT feature point is added if it is observed by at least one existing recovered camera, and if triangulating the point gives a well-conditioned estimate of its location. The condition is satisfied when considering all pairs of rays that could be used to triangulate that point, and finding the pair of rays with the maximum angle of separation. If its maximum angle is larger than a threshold, then the point is triangulated (Snavely et al. 2007). Once new points have been added, another global bundle adjustment refined the entire as-built reconstructed scene. The minimum error solution used the sparse bundle adjustment library Lourakis and Argyros 2004).This procedure is repeated for all cameras until no remaining camera observes enough reconstructed 3D points to be reliably reconstructed. Overall only a subset of the images that satisfy all constraints may be used for reconstruction. For example if images with significantly wide baselines or minimal overlaps are used or even cases where some none-related photos exist in the dataset, those images may not be used for reconstruction. Obviously this subset is not selected beforehand, but is automatically determined by the algorithm and the implemented system. The outcome of the implemented SfM algorithm is two folds: (1) 3D Cartesian coordinates of all 3D points reconstructed. Each 3D as-built point will be associated with a color which is averaged out from all images that this point falls into their view frusta; (2) A set of intrinsic and extrinsic camera parameters for each image. We use these two sets of information to visualize the as-built point cloud and camera frusta. For this purpose, camera parameters are used to render the location and viewpoint of each camera's frustum and superimpose the image texture on the frustum's frontal surface. The visualization component of the D^4AR (4D Augmented Reality) system is implemented in C++ using DirectX 9.0 graphics library. In this visualization system, users can navigate through the photos and observe the integrated photo and point cloud model both from real and synthetic perspectives. The results of experiments using the D^4AR system to visualize the sparse as-built site as well as the camera configurations are explained in the experiment section.

5.4.3 Laser scanning

For this research, four experiments were conducted to obtain eight datasets from different environmental settings, as both photographs and laser scanning data are affected by their surroundings (These experiments were not in scope of this thesis and were conducted by Jochen Teizer and Jeff Bohn at Georgia Tech). The experimental objects used include a single object cuboidal masonry block (scanned both indoor and outdoor) and two structural concrete columns (located on exterior and interior of the construction site). By scanning the same object both indoor and outdoor, the accuracy differentials can be calculated. All objects were scanned so that all visible faces were captured including sides and top (if possible). For each masonry block, $3'' \times 3''$ targets were affixed to the sides and top to be used in post-processing for scene reconstruction (only for laser scanning case) and determining three-dimensional accuracy. This method is more robust than previous research efforts from El-Omari and Moselhi (2008) that attempted to combine laser scans and photos from one face of an object. In addition, this research scanned objects on actual construction sites, allowing for realistic data collection in scenarios faced by surveyors. This experiment will allow the accuracy of photo generated point clouds vs. laser scanner generated point clouds to be measured and compared.

5.5 Description of Experimental Setup

To obtain digital images for the photo collection, a commercially available Nikon D-80 set at 10 megapixel resolution was used. Between 50 and 200 images were taken for each experimental object. Images were taken at a high speed exposure level to aid in fast photo image capture. A realistic scenario was created in which photo takers (e.g., superintendants, construction managers, owner's representatives) experience on walk-through on construction sites. All images were taken with an aperture (ISO) of 400 and a resolution of 3,872 horizontal pixels and 2,592 vertical pixels. Photos were taken immediately before the setup of the laser scanner in order to capture the “as-is” status of the under study site and its components. For each object, a circular path was traversed, with images being shot at approximately every meter. Depending on the size and location of the components, different numbers of pictures were needed. Technical data on the camera is shown in Table 5.1.

Table 5.1. Technical Data for Nikon D-80 (used in experiments).

Type of Camera	Single-lens reflex digital
Effective Pixels (millions)	10.2
Image Size (pixels)	3,872 × 2,592 [L], 2,896 × 1,944 [M], 1,936 × 1,296 [S]
Picture Angle (mm)	Equivalent in 35 [135] format is approx. 1.5 × lens focal length
Shutter Speed (sec)	Electronically-controlled vertical-travel focal plane shutter; 30 to 1/4000

A commercially available hi-resolution laser scanner (Leica ScanStation 2) was used to obtain laser range point data of the same scene. For each object, a 3-point survey traverse was used with scan data taken from each location. As in traditional surveying, each scan station includes both a foresight (following scan point) and backsight (previous scan point). Each location produces a standalone individual point cloud of a scene that, when combined with other point clouds from multiple field-of-views, can create a true 3D point cloud of a scene and the objects the scene contains. Although fully-automated registration methods become available to match individual point clouds of a scene to one scan world (a true 3D view of a complete scene), to obtain the highest possible accuracy, this research used highly reflective targets that were placed on the foresight and backsight. This was done in order to automatically register the scan stations during data analysis (this step was only used for laser scanned point cloud registrations). A typical experimental setup is shown in Figure 5.5. Technical data for the laser scanner that was used in this research is shown in Table 5.2.

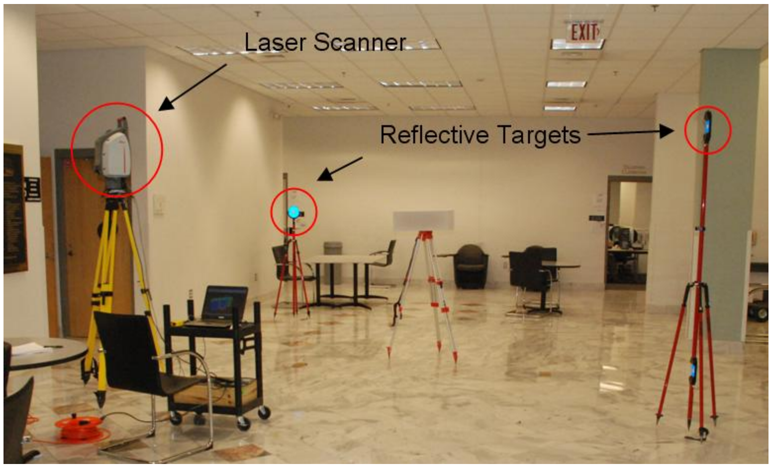

Figure 5.5 Experimental setup of scanning traverse.

Table 5.2. Technical data for Leica scan station 2.

Instrument Type	Pulsed, dual-axis compensated
Laser Type	Green
Scan Rate (points/sec)	Up to 50,000
Field of View (degrees)	H: 360°, V: 270°
Scanning Optics	Single mirror, panoramic
Modeling Surface Precision (mm)	2

Experimental data from four laboratory and field experiments are shown in Table 5.3. For each experiment, both hi-resolution and low resolution laser scans were performed at each station. For example, at all scan locations a low resolution scan was completed in 360° to capture the entire scene. Next, a hi-resolution scan focused specifically on the masonry block. Once the four experimental objects were scanned, the laser scanning point clouds were registered using commercially available software (Leica Geosystem Inc. Cyclone 6.0 and Cloudworx). The registration process is mostly manual, but algorithms in the software use the location of the reflective targets to tie scans together. The algorithms used to register the scene are propriety with Leica and are not in the scope of this research. Figure 5.6 shows the laser scanned columns both at exterior and interior.

Table 5.3. Laser scanning experimental data.

	Pictures taken (#)	Weather Conditions	Scans (#)	Number of points*	Time To complete (hrs)
1. Masonry Block (Indoors)	382	Indoor	3	961,793	2
2. Masonry Block (Outdoors)	376	Sunny, Bright	2	816,039	1.5
3. Column(Exterior at construction site)	80	Sunny, Bright	3	1,324,118	2
4. Column(Interior at construction site)	54	Indoor	3	719,320	2

* Number of references point specifically for the object, not entire scene.

5.5.1 Obtaining progress photo collection

During the conducted experiments, as mentioned, approximately 50 to 200 images with a resolution of 3,872×2,592 were taken. In order to prove that the algorithm works under different ambient conditions, two sets of photos from outdoor as well as two sets of photos from indoor were used for the purpose of reconstructing the scenes. These images were taken immediately before the setup of the laser scanner in order to capture the object unchanged. For each object, a circular path was traversed with images being shot at approximately every meter. Two of these subsets were taken on the mentioned masonry block at outdoor as well as indoor setup. To test the robustness of the SfM approach with respect to different resolutions in images, the resolution of indoors and outdoors images were synthetically reduced to 60% of the original resolution (2,323×1,555 and 1,936×1,296) (four experiments – total of eight datasets). The images in Figure 5.7 show some of the scenes that were taken from the masonry block under study in both indoor and outdoor configurations. The images in Figure 8 show indoor and outdoor construction site images used for each experiment.

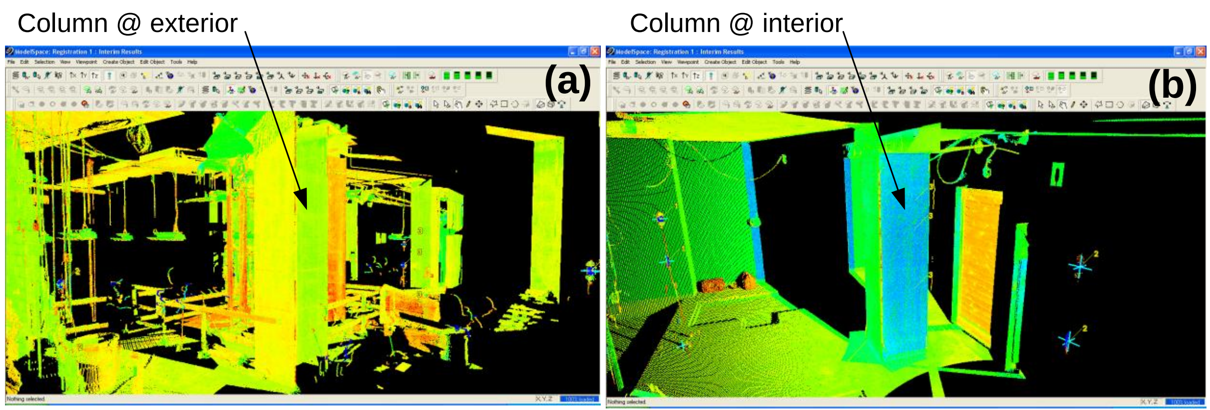

Figure 5.6. Laser scanned point clouds for (a) a column at exterior; and (b) a column at interior.

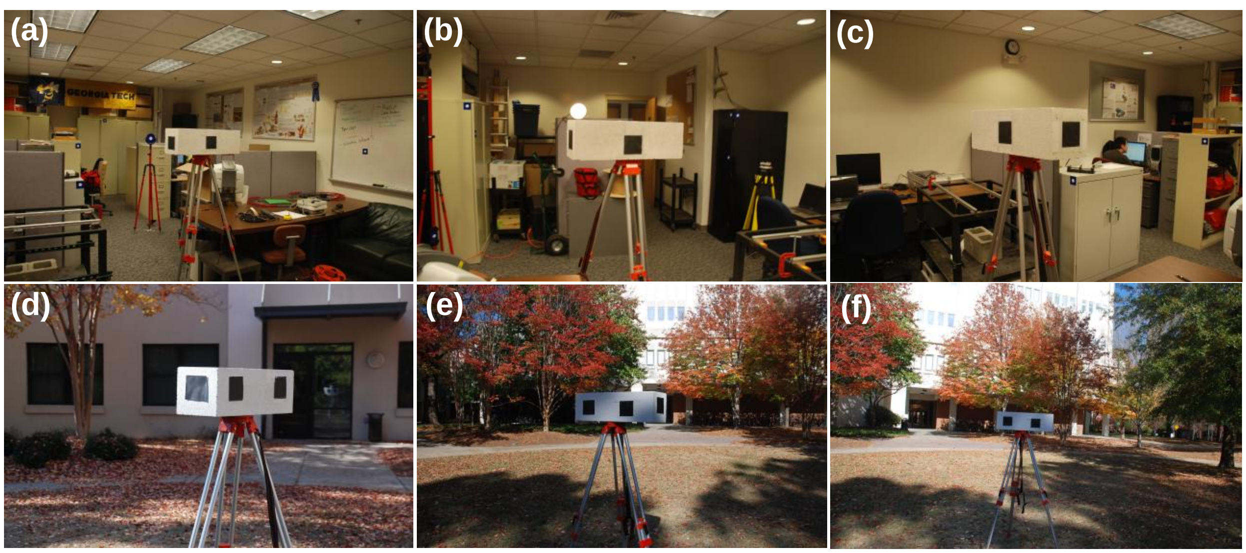

Figure 5.7. Experimental setup for photography of the block: image taken at an indoor laboratory environment (first row), Images taken outdoors (second row).

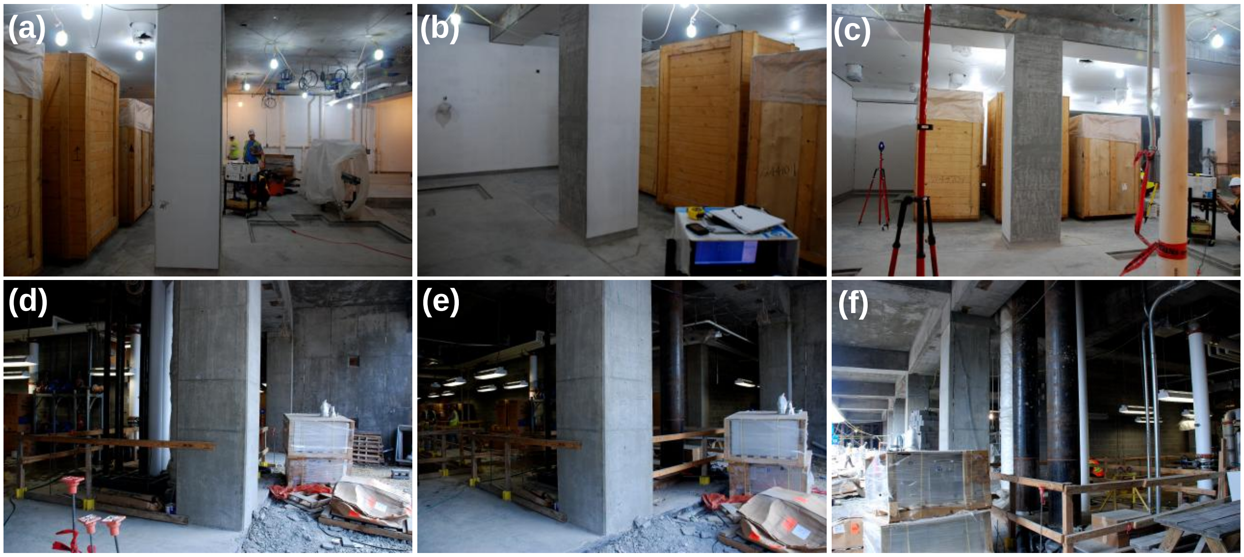

Figure 5.8. Two subsets of photographs taken from a column and its periphery at a construction site: Images taken indoors (first row), Images of column at the outdoor façade (second row).

Table 5.4 shows the results of the experiments conducted. For these experiments an Intel® Core 2 Extreme CPU @ 2.93 GHz with 4.00GB of RAM was used on a Windows 32bit platform. Figure 5.9, Figure 5.10, and Figure 5.11 show image-based renderings of the conducted experiments.

Table 5.4. As-built site photography and SfM experimental data and results.

	Exp. 1[+]	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**	**Exp. 6**	**Exp. 7**	**Exp. 8**
Total # of images	72	72	376	376	80	80	54	54
# of used images	53	53	242	242	80	80	54	54
Lighting Condition	Lab. lighting	Lab. lighting	Sunny, Bright	Sunny, Bright	Sunny, Bright	Sunny, Bright	Temp. lighting	Temp. lighting
Original Image Resolution	3872× 2592	3872× 2592	1936× 1296	1936× 1296	3872× 2592	3872× 2592	3872× 2592	3872× 2592
Processed Image Resolution	2323× 1555	3872× 2592	1162× 778	1936× 1296	2323× 1555	3872× 2592	2323× 1555	3872× 2592
# of points recovered	110,351	204,861	80,560	204,861	19,553	38,739	14,018	42,854
Generality[++]	1	1	1	0.94	0.71	0.71	0.41	0.41
Computation time	29*min*	45*min*	5*h* 12*min*	7*h* 03*min*	49*min*	1*h* 13*min*	10*min*	18*min*

[+] Experiments (1) & (2) Masonry block (interior); (3) & (4) Masonry block (exterior); (5) & (6) Concrete column (Construction Site– Outdoors); (7) & (8) Concrete column (Construction Site– Indoors)
[++] Generality = Number of images registered/ Number of images used.

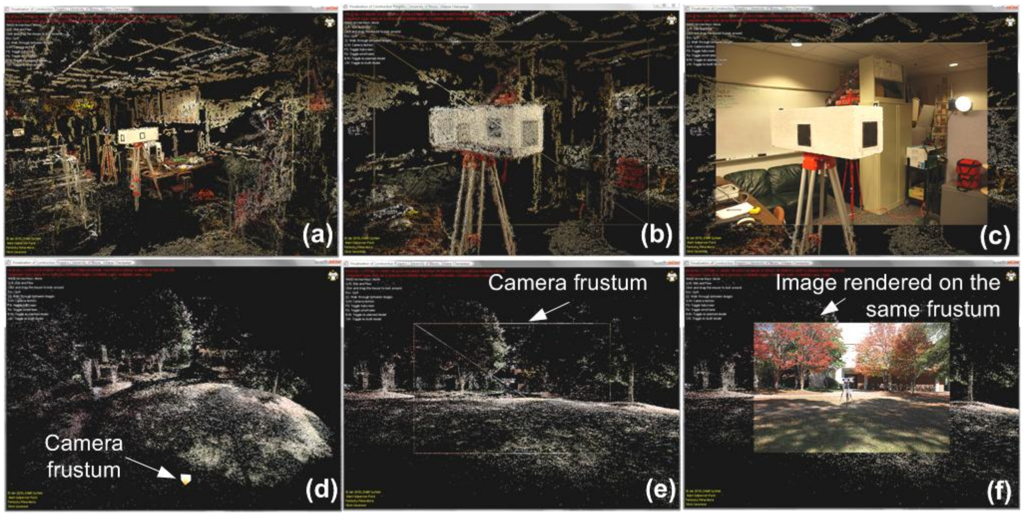

Figure 5.9. Snapshots of the D^{4}AR system – visualizing indoor laboratory setup as well as outdoor setup for photography of the masonry block at high resolution. From left to right, images show the reconstructed scene, the scene through a camera viewpoint (frustum) as well as the camera frustum rendered showing the image.

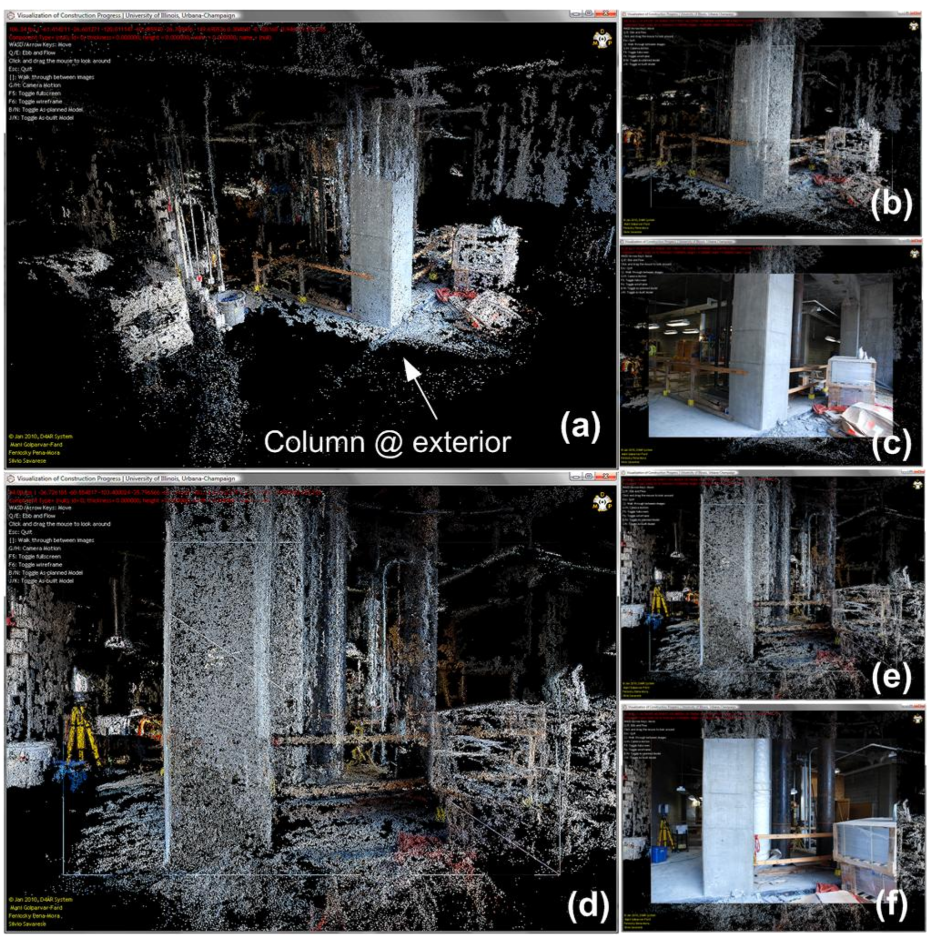

Figure 5.10. Snapshots of the D^{4}AR – visualizing the point cloud of a column and its periphery at the construction site (high resolution images were used and large points are used for rendering). (a), (c) Point cloud, (b), (e) point cloud visualized through two camera frusta and (e), (f) the same camera viewpoints of (b), (e) with images overlaid on the frontal surface of the frusta.

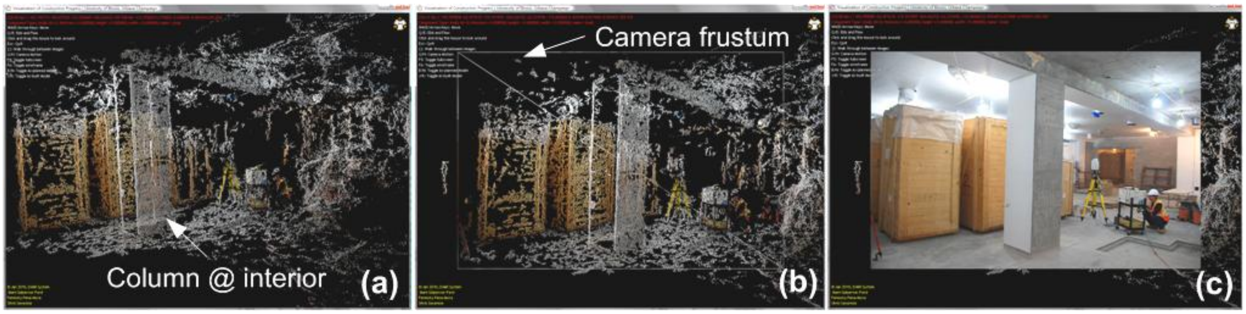

Figure 5.11. Snapshots of the D^4AR – visualizing the point cloud of a column at interior and its periphery at the construction site (high resolution images were used and large points are used for rendering). From left to right: (a) Point cloud, (b) point cloud visualized through one camera frustum and (3) the same camera viewpoint of (b) with the image overlaid on the frontal side of the frusta.

5.6 Accuracy Measurements and Methods

At this stage, both laser scanned data and photo data are modeled in individual environments. Registration of the laser scanned points took less than 10 seconds for each scene, since targets automatically reference each scan location to another. Registration will not be needed in case of image-based reconstructed point cloud as the complete point cloud is automatically generated in the last step of SfM. To compare the point cloud of the photo collection to point cloud of the laser scanner and to measure deviations, the next step included the manual extraction of the 3D laser point cloud of the masonry block as well as the exterior column from both point clouds (point cloud generated using photo collection and laser scanner). The laser scanned data as well as the photo collection point cloud overall returned minimal noise and thus the only modification to the model involved deleting points that were not on the masonry block or the column (i.e., the surrounding environments). Next, photo images taken by the laser scanner were overlaid on the laser scanner point clouds in order to create better realism. A semi-automated step selects the remaining points of the masonry block and forms a CAD object. This is done using a proprietary algorithm created by Leica Geosystems Inc. Currently this algorithm can automatically apply simple geometric shapes, such as columns, blocks, pipes, etc, if enough points are present. As this research focused on basic construction objects, this algorithm fits well into the scope of this work. Ongoing research is working on automating this task (Bosche and Haas 2008) and on optimizing the SfM point clouds for higher quality reconstructions (Goesele et al. 2007). Leica claims that the accuracy for fitting objects to point clouds is 2 millimeters which for general project progress monitoring seems to be sufficient. Three different views of the returned laser scanned data for the masonry block and three views of the return column (exterior case) are shown in Figure 5.12.a shows a digital photo of the masonry block. Targets have been placed on the block to aid in calibration and accuracy measurements. These targets have only been placed for the laser scanning scenario and the accuracy measurement and they were not used for calibration of the images in the photo collection. Figure 5.12.b shows a high density laser scan of the block and the resulting CAD object produced, while Figure 5.12.c shows the block with a photo overlay from the integrated camera of the laser scanner.

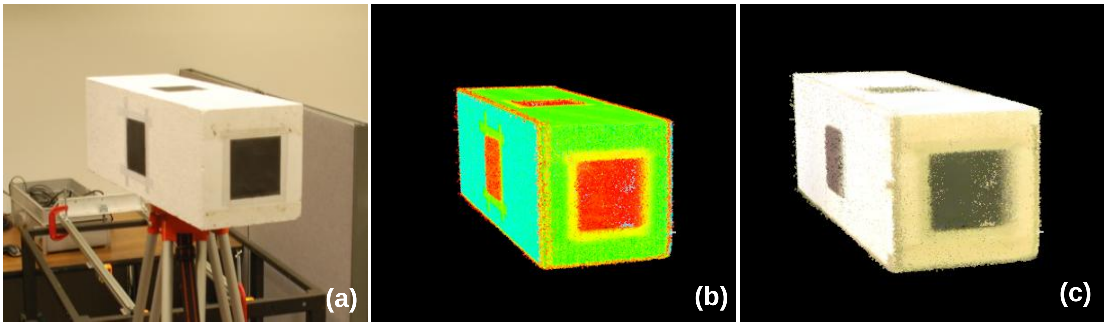

Figure 5.12. (a) Actual image of masonry block, (b) returned point cloud over fitted CAD object, (c) point cloud with masonry block images overlaid.

The same method was applied to the points created from photo collections stated in the preceding paragraphs. It is important to note that the number of points returned from both methods is different in terms of their density. This is intended, as only sparse points are needed for the scene construction using the photo collection. In order to automatically fit a single object to represent the block, a dense dataset was required; however in our experiment the returned points were not at the necessary density level required by the algorithm to automatically fit a single object to represent the masonry block and thus was not recognized as a single object by the system. Therefore, individual surfaces were created semi-automatically for each face of the block. The surfaces were then constrained to one another to create intersections, representing the block edges. From these lines, Cartesian distances were measured. Since the SfM reconstructed scene needs to be upgraded to the proper scale, in other words transformed from metric to a Euclidean reconstruction, the comparison of the ratios for each dimension (*x*, *y* and *z*) was used instead of a volumetric comparison. Using this ratio allows the linear accuracy (which is useful for alignment controls) to be evaluated and compared to the true measurements of the objects (obtained using standard tape measuring tools). Table 5.5 displays a comparison of the ratios for each dimension (*x*, *y*, and *z*).

Table 5.5. SfM and laser scanning accuracy ratio comparisons.

Object	Data Source	Measured values								
		X/Y	$\|\Delta\|$	$\|\delta\|^{*1}$	*Y/Z*	$\|\Delta\|$	$\|\delta\|^{*2}$	*X/Z*	$\|\Delta\|$	$\|\delta\|^{*3}$
Block	Actual	0.327	**--**	**--**	3.060	**--**	**--**	1.000	**--**	**--**
(outdoor)	Laser	0.322	0.004	**1.22%**	2.966	0.094	**3.07%**	0.956	0.044	**4.40%**
	Photolog #1	0.317	0.010	**3.05%**	2.743	0.317	**10.36%**	0.870	0.130	**13.00%**
	Photolog #2	0.320	0.007	**2.14%**	2.834	0.226	**7.38%**	0.921	0.079	**7.90%**
(indoor)	Laser	0.332	0.005	**1.53%**	3.010	0.050	**1.66%**	1.000	0.000	**0.00%**
	Photolog #1	0.330	0.003	**0.92%**	2.758	0.302	**9.86%**	0.909	0.091	**9.10%**
	Photolog #2	0.332	0.005	**1.53%**	3.010	0.050	**1.66%**	1.000	0.000	**0.00%**
Concrete Column	Actual	0.220	**--**	**--**	4.556	**--**	**--**	1.000	--	--
(outdoor)	Laser	0.223	0.004	**1.81%**	4.587	0.031	**0.68%**	1.025	0.025	**2.50%**
	Photolog #1	0.198	0.021	**9.54%**	5.085	0.530	**11.63%**	1.004	0.004	**0.40%**
	Photolog #2	0.214	0.006	**2.72%**	4.809	0.253	**5.55%**	1.001	0.001	**0.00%**
(indoor)	Laser	0.229	0.009	**0.04%**	4.530	0.026	**0.57%**	1.010	0.010	**0.01%**
	Photolog #1	0.233	0.013	**0.06%**	4.612	0.056	**1.22%**	0.997	0.003	**0.00%**
	Photolog #2	0.230	0.010	**0.04%**	4.570	0.014	**0.31%**	0.999	0.001	**0.00%**

* $|\delta| = |\Delta / \Phi_{actual}|$ Where in (1) $\Phi = X/Y$, in (2) is $\Phi = Y/Z$ or in (3) is $\Phi = X/Z$.

As observed neither of the used approaches (laser scanning or using photo collections) are completely accurate. The accuracy of these ratios in some of the cases when the SfM point cloud is used is less than the accuracy of the point cloud generated by the laser scanner. With the experienced accuracy, the applicability of this algorithm for fitting as-built CAD objects on SfM point clouds may be reduced. Especially for some cases where precise alignments are required, the application of the SfM point cloud may not be favorable. In contrary to this, within a certain tolerance of perpendicularity (e.g., during post-disaster rapid assessments), SfM point cloud can still be favorably used to measure deviations. It was also observed that the ratios in each experiment were slightly larger than the controlled ratio. In the case of laser scanner, this was most likely due to superfluous points that were not removed in the post-processing of data. Had these points been removed, the ratio difference would have been smaller. In the case of photo generated point clouds, this was most likely due to the synthetically reduced quality of the photographs, the small number of photographs used, the SIFT feature detection technique, as well as the thresholds used in feature detection and bundle adjustment steps. In a case where high resolution photographs and/or other feature detection methods are used and the thresholds are less penalizing, the number of detected SIFT features, as well as the quality and density of the photo generated point cloud are higher. Figure 5.13 and Figure 5.14 further show the resulting sparse point clouds of the masonry block and the concrete column (exterior) created by the photo collections and a semi-automatically reconstructed surface planes. Based on the photo collection sparse point clouds, the masonry block edges and concrete column edges are manually extracted from the CAD faces and visualized.

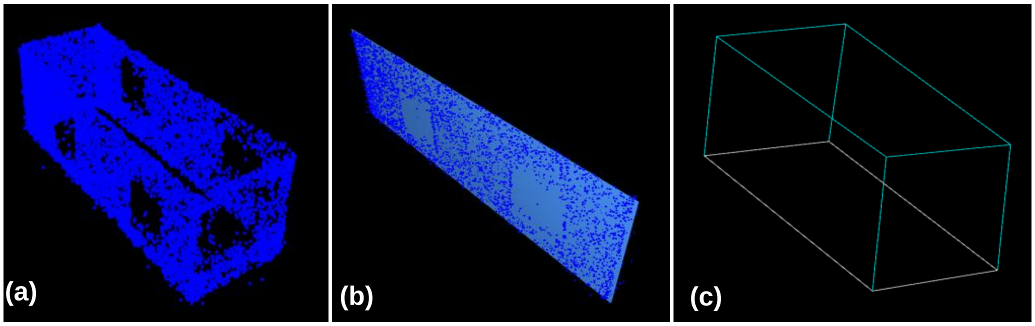

Figure 5.13. (a) Points of masonry block reconstructed from the photo collection, (b) reconstructed shape surface, and (c) reconstructed shape edges.

Figure 5.14. (a) Rendered photo of the column automatically registered with the point cloud; (b) point cloud from the same viewpoint without the image; (c) reconstructed shape.

Table 5.6 qualitatively summarizes the advantages/disadvantages associated with using SfM point clouds along with still photographs compared to and laser scanning point clouds. Overall it seems for high precision tasks such as measuring defects or precise alignment of a certain structural or mechanical elements [39], using laser scanners or conventional surveying methods offer valid and practical approaches. For applications where an overall knowledge of project status or even status of a post-disaster site is more important than detailed and accurate measurement, the use of SfM and site photographs becomes very handy. Although the SfM point cloud is less accurate compared to the laser scanning, it provides the opportunity of visualizing the as-built scene through geo-registered site photographs with much less effort and no cost. The joint representation of the point cloud with all registered images - in addition to the possibility of extracting semantic information through image processing over registered photographs- allows a site to be virtually represented in an integrated manner, providing a remote control decision making opportunity.

Table 5.6. Qualitative summary of comparing SfM cloud and still photographs vs. laser scanning point cloud.

		Laser Scanning Point Cloud	SfM Cloud + Still Photographs
Cost	**Data collection cost**	8~16 man-hours *	0~1 man-hour
	Data processing cost (Registration)	O**(sec)	O(min~hrs) on a single machine+ O(min) with parallel computing
	Technology implementation cost	O(10,000~130,000 USD)	Cost of a consumer camera O(100~500 USD)
Level of automation		Manual intervention for noise reduction/ removal	None
Storage space		Point cloud = 1~2 GBs per experiment	Point cloud = 1~100 MB(s) per experiment Photographs = 0.1~1 GB per experiment
Accuracy / Resolution		Very High / Dense	High / Sparse to normal ***
Applications		• Progress monitoring data collection • Quality Control • Alignment/Defect inspection • Static progress visualization • Comprehensive emergency building assessment • Static safety analysis	• Progress monitoring data collection • Quality Control • Remote visual inspection • Remote decision making • Static/dynamic progress visualization • Rapid/Comprehensive emergency building assessment • Site logistics visualization • Construction crew and machinery productivity analysis • Static/ Dynamic safety analysis
Need for training to operate		Yes	No
Add new project management task		Yes, both for collection and processing laser scanning data	No

* May require two workers simultaneously operating it.
** Order of
*** Could be dense if either number of photographs is increased or high resolution photographs are used.
+ Computation time on a single machine is an exponential function of the number of photographs used.

5.7 Conclusions

This chapter presented two methods for generating as-built models as an underlying basis for performance monitoring and defect detection as well as defining the accuracy of each method. Eight sets of 3D spatial models, four on actual construction projects and four in a laboratory were generated using (1) point clouds from laser scanning and (2) image-based point clouds reconstructed with daily construction photo collection using Structure from Motion (SfM) techniques. Using both data collection approaches, 3D CAD surfaces were generated. As a stepping stone for a complete as-built model generation and progress monitoring, these models were compared for accuracy and usability for generation and visualization of as-built status of a project. As demonstrated in laboratory and field experiments, the accuracy of using the

SfM point clouds is marginally less than point cloud generated by the laser scanner, while both approaches allow the as-built environment to be visualized from different viewpoints. In addition, the SfM approach allowed hi-resolution photographs to overlay site point clouds. Applying this technique and utilizing existing site photographs for progress monitoring, productivity measurement, as well as QC/QA and safety monitoring, provides project management with a remarkable opportunity on automation and visualization of as-built data. In order to make this approach fully automated, as-planned models need to be properly registered with the as-built scene. Such registration allows pose of the searched objects in the as-built model to be known *a priori* and may significantly improve progress monitoring. Particularly when registration of as-planned Building Information Models is considered, benefits are amplified. Such an augmented environment can be used for automatic data collection, processing and reporting. More questions remain to be addressed and additional research is required for algorithms that automatically extract conventional or parametric CAD objects from laser scanners or SfM point clouds. Optimizing the multi-view reconstruction algorithms for a higher-quality range clouds must be further investigated as well.

CHAPTER 6. AUTOMATED MODEL-BASED PROGRESS MONITORING USING UNORDERED DAILY CONSTRUCTION PHOTOGRAPHS AND IFC AS-PLANNED MODELS

6.1 Overview

Accurate and efficient tracking, analysis and visualization of as-built status of buildings under construction are critical components of a successful project monitoring. Such information directly supports control decision-making and if automated, can significantly impact management of a project. In this chapter, we describe a new automated approach for recognition of physical progress based on two emerging sources of information: (1) Unordered daily construction photo collections, which are currently collected at almost no cost on all construction sites; (2) Building Information Models (BIMs), which are increasingly turning into binding components of Architecture/Engineering/Construction contracts. First, given a set of unordered and uncalibrated site photographs, we present an automated approach based on structure-from-motion, multi-view stereo, and voxel coloring and labeling algorithms to calibrate cameras, photo-realistically reconstruct a dense as-built point cloud in 4D (3D + time), and traverse and label the scene for occupancy. This strategy explicitly accounts for occlusions and allows input images to be taken far apart and widely distributed around the environment. An IFC-based (Industry Foundation Class) BIM is subsequently fused into the as-built scene by a robust control-based registration-step and is traversed and labeled for expected progress visibility. Next, a machine learning scheme built upon a Bayesian probabilistic model is proposed that automatically detects physical progress in presence of occlusions and demonstrates that component-based progress monitoring at schedule activity-level could be fully automated. Finally, the system enables the expected and reconstructed elements to be explored with an interactive, image-based 3D viewer where deviations are automatically color-coded over the IFC-based BIM. To that extent, we present our underlying hypotheses and algorithms for generation of integrated 4D as-built and as-planned models plus automated progress monitoring. Experimental results are presented for challenging image datasets collected under different lighting conditions and sever occlusions from two ongoing building construction projects; marking our model to be the first probabilistic model for automated progress tracking and visualization of deviations that incorporates unordered daily construction photographs and BIMs in a principled way.

6.2 Introduction

Accurate and efficient tracking of the as-built status of buildings under construction has been repeatedly reported as a critical factor for success of project control (e.g., Bosché 2009, Bosché et al. 2009, Zhang et al. 2009 and Navon 2007). Such information directly supports progress monitoring and control and if automated can significantly impact management of a project. Despite the importance of progress monitoring, current methods for site data collection, processing and representation are *time-consuming* and *labor-intensive* (Bosché 2009, Golparvar-Fard et al. 2009a, Kiziltas et al. 2008, Navon and Sacks 2007). These methods require manual data collection and extensive as-planned and as-built data extraction from construction drawings, schedules and daily construction reports produced by superintendents, subcontractors and trades foremen. Quality of the daily progress reports also highly depends on the data collected by field personnel which tends to be based on their interpretation of what needs to be measured, the way it needs to be measured and the way it needs to be presented, and therefore it may not reveal the actual impact of site circumstances on the construction project (Golparvar-Fard et al. 2009a, Navon and Sacks 2007). For example in a daily construction report submitted by a drywall contractor, it may be reported that "framing" was conducted without specifying the amount of resources being used, the exact location of the work performed as well as the progression made. Even if progress is measured, it may be conducted in a *non-systematic* way and metrics may tend to be *subjective*. For example, a concrete subcontractor reports that 60% of the roof work is complete. Does it mean 60% of the planned area/volume of concrete is placed? Or is it 60% of the planned labor-hours that have been spent? Is it 60% of the actual requirement that is complete? If the item being referenced is a small work unit, it may not have a significant difference. However, in the case where the references are to the whole task, assumption of input/output proportionality could be very misleading (Meredith and Mantel 2003). Finally progress monitoring reports are *visually complex*. Typically decision-making for corrective control actions and revision of work schedule takes place in contractor coordination meetings. A wide range of individuals with different areas of expertise and interests often attend these meetings. In these face-to-face interactions, progress information needs to be easily and quickly communicated among the participants. However, none of the existing reporting methods (e.g., progress S curves, schedule bar charts) easily and effectively present multivariable information (e.g., schedule and performance) nor do they intuitively reflect information pertaining to the spatial aspects of progress and their associated complexities (Poku and Arditi 2006, Koo and Fischer 2000). Existing representations cause a significant amount of information to be inefficiently presented in coordination meetings. As a result, extra time needs to be spent in explaining the context in which problems occurred rather than understanding the causes of the problems, evaluating alternatives to solve the problems and discussing corrective actions. Therefore there is a need for effective monitoring which allows data to be collected easily and at almost no cost, processing the information automatically and reporting back in a format that could be used by all project participants.

Nowadays, cheap and high resolution digital cameras, low cost memory and increasing bandwidth capacity have enabled capturing and sharing of construction photographs on a truly massive scale. For example, on a 200,000 SF building project in Champaign, IL an average of 250 photos/day is being collected by the construction management team. Such a large and diverse set of imagery along with the photos contractors and their subs take (about 25 photos/day for each bid package) as well as the photos owner take (about 25-50 photos/day), enable the as-built scene to be fully observed from almost every conceivable viewing position and angle during construction of a project. The availability of such rich imagery - which captures dynamic construction scenes at minimal cost – may enable geometrical reconstruction and visualization of as-built models at high resolution which can have broader impacts for the Architecture/Engineering/Construction (AEC) community.

In the meantime, Building Information Models (BIMs) are also increasingly turning into binding components of Architecture/Engineering/Construction (AEC) contracts. For example as of July 2009, Wisconsin establishes itself as the first state requiring BIM models for public projects with minimum total budget of $5M (Building Design & Construction 2009). In a recent survey McGraw-Hill Construction (2009) reports that 49% of AEC companies are already using BIM (a growth of 75% from 2007). Gilligan and Kunz (2007) reports that while the application of BIM models are increasing, yet significant attention is placed towards project design and system clash detection. If linked with project schedules, BIMs can form detailed chronological models that allow 4D (3D + time) clash detection and schedule quality control to be conducted. Furthermore they can serve as powerful baseline for progress tracking as well as visualization of discrepancies. Application of these models during construction phase can be increased if further potential added-values from integrating BIMs with as-built models are investigated.

Nonetheless, linking unordered photo collections with as-planned models for the purpose of monitoring construction progress is challenging. First, such imagery is usually *unordered*, *un-calibrated*, with widely unpredictable and uncontrolled lighting conditions. Second, *visibility order* and *occlusions* need to be considered for successful alignment. In particular one needs to account for two types of occlusions: (1) *Static occlusions*: self occlusions caused by progress itself (e.g., a façade blocking observation of elements at interior) or occlusions caused by temporary structures (e.g., scaffolding or temporary tenting); and (2) *Dynamic Occlusions*: rapid movements of construction machinery and workers during the time photographs are taken. Developing computer vision techniques that can effectively work with such imagery to monitor building element changes has been a major challenge.

In this chapter, we address these challenges and introduce a new approach for monitoring as-built elements from unordered photographs based on *a priori* information (4D BIM). First using Structure-from-Motion (SfM) techniques, an as-built point cloud is generated and photographs are automatically registered. Subsequently the as-built point cloud is registered over the as-planned model and improved by Multi-View Stereo (SVM). At this stage a new voxel coloring algorithm is used to generate a volumetric reconstruction of the site, labeling different areas according to visual consistent observations while fully accounting for occlusions. Same labeling process is conducted on the as-planned model to identify occupied and visible areas to be monitored for progress. Finally a Bayesian probabilistic model is introduced to automatically recognize progress by comparing measurements of progress with dynamic thresholds learned through a Support Vector Machine (SVM) classifier. In addition, the algorithm automatically accounts for occlusions and recognizes if reconstructed building elements are missing because of occlusions or because of changes. This makes our model to be the first *probabilistic model for automated progress tracking and visualization of deviations that incorporates both as-planned models and unordered daily photographs in a principled way*. Our model is able to use existing information without adding burden of explicit data collection on project management teams. We have used this model to track and visualize progress on two building projects. In the following sections, we first review previous works on automated progress monitoring and subsequently present our automated detection model in details.

6.3 Previous Work

The last decade, capabilities of site data collection technologies have significantly increased. These technologies include Barcode and RFID tags (Kiziltas et al. 2008, Navon and Sacks 2007, Ergen et al. 2007, Jaselskis and El-Misalami 2003, Echeverry and Beltran 1997), Laser scanners (Bosché 2009, Bosche and Haas 2009, El-Omari and Moselhi 2008, Su et al. 2006, Akinci et al. 2006, Jaselkis et al. 2006) and wearable computers (Reinhardt et al. 2000). In this section, we particularly review recent works on terrestrial laser scanning and photography (conventional photogrammetry and vision-based) techniques for progress monitoring as recent works on these two types of technologies can potentially automate all steps of *collecting*, *analyzing*, and *representing* progress and its deviations from the plan.

6.3.1 Laser scanning based systems

A popular trend to automation of progress monitoring is to acquire multiple depth maps with a laser range scanner, register them using Iterative Closest Point (ICP) algorithm (Besl and McKay 1992), and merge them into a single 3D model (Bosché 2009, Huber and Hebert 2003, Levoy et al. 2000) and finally have it compared with the as-planned model (Bosché 2009, Bosché et al. 2009, Gordon et al. 2003, Huertas and Nevatia 2000). Recent examples on application of laser scanners for construction data collection and analysis include construction quality control (Akinci et al. 2006, Jaselkis et al. 2006, Shih and Wang 2004), condition assessment (Gordon et al. 2003), health monitoring (Park et al. 2007) and component tracking (Bosché 2009, Bosché et al. 2009, Teizer et al. 2005).

High-end laser scanners can acquire 3D data with high accuracy (at about 3*mm* at 50*m* spot size scan resolution and single point position accuracy of about 12*mm* at 100*m* – Reported by Bosché 2009), yet their cost is in the $100K range (Bosché 2009, Furukawa and Ponce 2006). Despite significant research on automated spatial data collection using laser scanners in various research fields, spatial and temporal resolutions are still limited (Furukawa and Ponce 2006). Other limitations include discontinuity of the spatial information (which requires frequent and sometimes manual registrations); mixed pixel phenomenon (Kiziltas et al. 2008), short scanning range, the need for regular sensor calibrations as well as slow warm-up time. For example, any moving object in line of sight of the scanner would not allow the point cloud of the under-study component to be captured. In addition the moving machinery and personnel by themselves create additional effort for the user to manually have the noisy point cloud improved. Even if the laser scanner is transformed to a new location, the new scanned point cloud still needs to be registered. Once the laser scanner gets away from the building components, level of detail within the captured components is reduced. Since they are not easily portable, they cannot efficiently be used for scanning indoor environments. For these technical reasons, we believe the value from application of laser scanner is not yet significantly observed by the AEC industry.

In a recent study, Bosché (2009) relates this issue more to the low level of automation and poor efficiency observed from majority of cases where application of laser scanners have been reported: "*only a few elements can be investigated in day*". Yet, Bosché (2009) and Bosché et al. (2009) proposes the first quasi fully automated systems for tracking 3D CAD model of a steel structure in site scans. In their early algorithms (Bosché et al. 2009), a CAD element is converted to a point cloud representation. Subsequently using a point-to-point comparison, range of as-built and as-planned models is evaluated and if this range is less than a manually set threshold, the CAD element is recognized. Such approach may not be robust to different angular resolutions of scans and depends on scanner–building component distances. It also depends on accuracy of registration (in their experiment 50*mm*). In a recent work (Bosché 2009) registration accuracy is improved and instead of point-to-point comparison, a surface is recognized for each element and then this surface is compared with a minimum recognizable surface. The results of their recognition performance are improved yet precision of such proposed method are not yet fully verified and the approach still is susceptible to partial occlusions (as reported by the authors themselves). More research is to be done on efficient automated application of laser scanners.

6.3.2 Photograph based systems

Over the past decade, advancement in digital photography and techniques that process such visual data has led significant amount of research to be reported on potential and observed application of site photographs for various construction management tasks and techniques that can manually, semi-automatically and automatically interpret them (e.g., Cordova and Brilakis 2009; Ibrahim et al. 2008, Soibelman et al. 2008, Ordonez et al. 2008, Shih et al. 2006, Trupp et al. 2004, Abeid et al. 2003, Abeid and Arditi 2002, Nuntasunti and Bernold 2002, Everett et al. 1998, Abudayyeh 1997). As the digital photography is advancing, the prices for cameras are significantly falling down (about a few hundred dollars), yet they are able to capture several high-resolution (10Mpixel) images or medium-resolution (2Mpixel) videos at 60fps. Of course prices for laser scanners will drop, yet it is unlikely to catch up cameras in near future since their manufactures do not respond to competitive mass-market of digital cameras (Furukawa and Ponce 2006) and for these reasons many recent computer-vision works have focused on their application (Furukawa and Ponce 2009, Agarwal et al. 2009, Snavely et al. 2008). Nonetheless here we mostly focus on several photo-based techniques that are proposed for monitoring of construction projects.

One of such early techniques is the use of *conventional photogrammetry*. Photogrammetric techniques use conventional high-resolution cameras and do provide high accuracy site models comparable to that of the best laser scanners but their spatial resolution is even more limited, mostly about a few hundred scattered points (Furukawa and Ponce 2006) and they may require application of markers (Uffenkamp 1993). Their analogue instruments have many limitations which do not affect their application in production of maps and plans (Moore 1992), yet restricts their application for non-topographic subjects. Examples of such issues are restriction in camera rotations, range of the focal length, and analysis of the orientation data. Their application due to such technical issues is almost out of date (Moore 1992) and especially given the repetitive nature of progress monitoring, makes their application unattractive. Over the past few years, with the advancement in SfM techniques, some of those techniques are revived and are being used to automatically generate structure and capture motion of the cameras (Will be discussed later).

More recently several vision-based systems have been proposed for tracking progress (Ibrahim et al. 2009, Zhang et al. 2009, Golparvar-Fard et al. 2009b, Lukins and Trucco 2007, Podbreznik and Rebolj 2007, Golparvar-Fard and Peña-Mora 2007, Alves and Bartolo 2006, Jung et al. 2004, Wu and Kim 2004). The general process for tracking in these systems is to first capture time-lapsed photographs from a fixed location, register digital site photographs to 3D CAD/ BIM models in a common coordinate system using camera pose estimation techniques (e.g., Golparvar-Fard et al. 2009b, Song 2007, Golparvar-Fard and Peña-Mora 2007) and then have the site 2D photograph image processed and compared with the as-planned model (Golparvar-Fard and Peña-Mora 2007). Ibrahim et al. (2009), Zhang et al. (2009) and Lukins and Trucco (2007) propose similar semi-automated techniques with difference in the recognition step. In these works, pre-calibrated photographs are compared with previously taken photographs and progress is tracked only on concrete columns located on the closest structural frame of buildings. This is done by searching specific regions of interest and recognizing progress as regions of images which observe significant changes from the previous image (through computing changes in pixels and by using Adaboost detector (Freund and Schapire 1999)). Then theoretically the changes are compared to a 3D model to calculate the percentage completion of each building components. The approach seems to be the promising given the nature of time-lapsed images and has the most level of automation reported so far, yet it has several limitations intrinsic to application of time-lapsed images: (1) since the camera is fixed, small registration errors over the distance will significantly affect registration and minimizes allocated image area for each element making the task of recognition drastically challenging (Golparvar-Fard et al. 2009b); (2) the sensitivity of the region of interest and detectors to changing lighting conditions, particularly in the presence of sever shadow lines affects the image processing; (3) dynamic occlusions (movement of machinery and personnel) which are common on construction sites and may result in false detection of regions of interest, ultimately resulting in false object detection (extreme clutter is reported by Zhang et al. 2009 and Golparvar-Fard et al. 2009b) and finally (4) static occlusions (progress itself) which will make it difficult to analyze elements farther to the camera (Golparvar-Fard et al. 2009b). In their work, similar to (Golparvar-Fard et al. 2009a, Leung et al. 2008) application of a network of cameras is suggested, yet installation costs, security and privacy issues compared to the gained value make their application less attractive. Other shortcomings are related to proposed vision-based approach: (1) A considerable amount of preparatory work occurs both around and within the construction area of the final component, yet the actual progress can occur very quickly (i.e., an entire prefabricated column lowered into place). Variations in the shape of the structure may not actually occur very frequently; rather it is often the effects of exterior modification that gives visible indication of change. Relating such changes to particular type of events to the completion of the component is challenging. Zhang et al. (2009) also argues that Work Breakdown Structure (WBS) in their as-planned models significantly affects results and make their approach less practical as particularly suggests AEC professionals to manually decompose the as-planned model to the appropriate level of detail. In our previous work, Golparvar-Fard et al. (2009b), we suggested application of multiple sources of images which is one of the underlying motivations of this work.

Recently Quiñones-Rozo et al. (2008), Dai and Lu (2008) and Kim and Kano (2008) reported on application of close-range digital photogrammetry and imaging techniques to track construction activities or model machinery. Their works (Quiñones-Rozo et al. 2008 and Dai and Lu 2008) still need to use manual detection and manual matching of feature points (Dai and Lu 2008), placement of special targets Quiñones-Rozo et al. (2008) or manual application of surveying equipment which substantial amount of human intervention make such applications time-consuming and less attractive for repetitive progress monitoring tasks. In addition their image processing technique reported in Quiñones-Rozo et al. (2008) still need to have a clear view of the site to detect excavation work and the pattern detection and comparison is highly sensitive to lighting conditions and needs images to be taken under similar lighting conditions.

6.3.3 Unordered daily construction photography

Golparvar-Fard et al. (2009a) proposed application of unordered daily site photographs and IFC-based BIMs for the purpose of automated data collection, processing and visualization of progress monitoring. The focus is on large sites and capturing entirety of as-built model from images that are randomly taken in and around a construction site. The proposed algorithm work builds upon a set of SfM algorithms where the objective is to reconstruct the scene without any strong prior (Agarwal et al. 2009, Furukawa et al. 2009, Pollefeys et al. 2008, Schindler et al. 2008, Sinha et al. 2008, Snavely et al. 2008; Zebedin et al. 2008, Cornelis et al. 2007, Snavely et al. 2006, and Debevec et al. 1996). In some of these techniques such as Zebedin et al. (2008), aerial images are used for reconstructing building models. In others such as Agarwal et al. (2009) entire city is reconstructed from unordered photographs collected from Internet, or as in Cornelis et al. (2009), and Pollefeys et al. (2008) building façades are reconstructed from car-mounted videos, and in Sinha et al. (2008) photorealistic architectural surfaces are interactively reconstructed. In Golparvar-Fard et al. (2009a) once the underlying structure and the motion of the camera are captured, the reconstructed point cloud is registered over an IFC-based BIM and deviations between as-planned and as-built model is visualized both in 3D as well as 2D augmented reality views. In that work, we describe how given a set of daily site images, a sparse representation of the site can be generated. Observed and perceived applications of the D^4AR system are discussed and potential automated progress monitoring algorithms are also roadmapped. However, no implementation for the automated detection was proposed. In this chapter, we first introduce a new approach for volumetric reconstruction of the as-built scene. Our work in photo-based reconstruction is closest to Furukawa et al. (2009) in which a stereo algorithm is designed for building interiors which predominantly consist piece-wise planar surfaces. However, compared to Furukawa et al. (2009), our images are collected for monitoring progress while the focus is to capture images that are of immediate importance to AEC professionals. Therefore our images can be taken far apart and be widely distributed in the scene.

Furthermore, quality of reconstruction is not the focus; rather we focus on detecting changes in elements given partial occlusions.

6.4 Contribution

The first contribution of this chapter is a significantly improved algorithm for dense reconstruction and robust registration for 4D as-built models from daily site photo collections. Compared to (Golparvar-Fard et al. 2009a), a more robust vision-based method comprised of SfM, MVS and voxel coloring algorithms is used for reconstruction. Furthermore registration is enhanced allowing point clouds to be registered automatically generating a 4D as-built point cloud model and have it semi-automatically registered over 4D IFC-based BIM. Our observations and experiments show that the resulting D^4AR visualization has the following ability:

Data collection: The approach is fully dependant on the daily photo collections; does not have any cost or a need for any manual intervention beyond uploading images into the system and works even with low quality images taken from a cell phone.

As-built modeling automation and visualization: This process is fully automated, i.e., once images are deposited into the system, features are fully automatically identified and matched to visualize the underlying as-built point cloud. The camera configurations are automatically identified as well.

Occlusion handling: Since unordered daily photographs are usually taken with least amount of occlusions, their application is very desirable for automated as-built modeling. Nevertheless the underlying SfM automatically removes inconsistent representations, so there is no need for manual fixing of the point cloud (the case in laser-scanning point clouds). In addition, moving objects in the scene are not fully removed from the point clouds; rather they are dynamically captured in registered images.

As-built processing efficiency: Each point cloud can be generated in a few hours (computational cost at this stage). Once the underlying model is generated, adding new photographs to the system is processed in order of seconds.

Augmented reality registration: Registration of the 4D IFC-based BIM is still semi-automated as it needs a set of initial control-points to be selected and matched. This only needs to be done once in the start of the project. Registration of point clouds over one another will be automatically done using iterative closest point (ICP) algorithms by selecting a subset of points that has consistent visual appearance in point clouds (e.g., an existing structure which is reconstructed in consecutive point clouds).

The foremost contribution of this chapter is the automated progress monitoring model and the SVM machine learning approach. It is shown that to the extent that the project is photographed, physical progress can be fully detected and compared to an IFC-based BIM. It allows range images for each photograph to be generated, segmenting images based on observed progress as well as dynamic occlusions (A significant progress with 2D segmentation of observed objects on site images). It is shown through multiple experiments that the proposed automated detection has the following characteristics:

Progress monitoring automation: Monitoring physical progress is fully automated; only detection of progress operational details (e.g., differentiation of concrete from formwork) is not yet included; nevertheless the statistical model explicitly introduces such detection into the model which makes extension of our algorithms easy.

Progress monitoring accuracy: The metrics shown in the experiments seem to be satisfactory given the formation of this progress tracking model for the first time.

Robustness to occlusions: The conditional statistics model for automation of monitoring seems to be superior to other detection techniques (Bosché 2009, Zhang et al. 2009). It fully takes occlusions into account and detects most of the components even with partial occlusions.

Computational efficiency: The progress is detected over a few hours at this stage, yet the fully automated component makes its application feasible.

6.5 Underlying hypotheses on automated physical progress detection engine

Our suggested model detects progress based on *a priori* information (4D as-planned model) using daily construction photographs. Suppose we need to monitor progress on "FPRS basement concrete columns" (FPRS = form/pour/strip) activity. In our approach, the Work Breakdown Structure for the 4D model is governed by the level of detail presented in the schedule; i.e., if FPRS of all the basement concrete columns are linked to this activity, all those elements will turn into base-line for tracking progress and progress for those will be reported in a *mutually independent* fashion. Secondly, in our approach, progress is defined as the observation on the day the element is expected to be placed and operational details (e.g., forming stage of columns) is not considered but is accounted for at this stage. Currently a superintendant or a field engineer walks around the site all day every day to observe progress from all possible viewpoints, compares it with paper-based plan information (e.g., construction drawings and schedules), measures deviations and reports back to project manager. We assume at several stage of this observation, images are captured to visually document progress. Since these images are collected from different viewpoints and lighting conditions, they challenge any vision-based system by: (1) Generating swift intensity changes within a short distance of the image; and (2) Generating two types of occlusions: (2.1) Static occlusions: self-occlusions caused by progress itself (e.g., a façade blocking observation of progress at interior) or occlusions caused by temporary structures (e.g., scaffolding or temporary tenting); and (2.2) Dynamic Occlusions: Rapid movements during the time photographs are taken (e.g., movement of construction machinery and crew). Figure 6.1 highlights the technical challenges of a vision-based progress monitoring system.

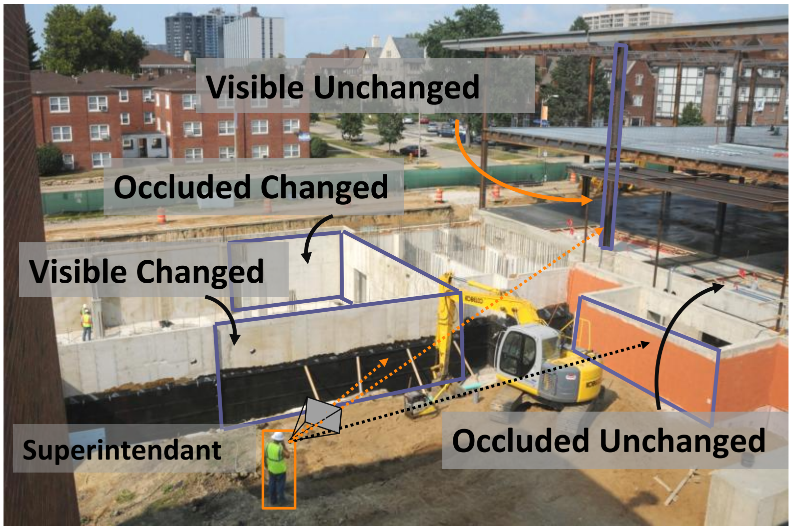

Figure 6.1. Progress monitoring and the challenges, Student Dining Hall construction project, Champaign, IL. (8/27/2008). Image Courtesy of Turner Construction (Image best seen in Color).

For the *as-planned model* we assume (1) an IFC-based BIM is generated based on the most updated construction drawings. ASIs, RFIs, RFPs or change order are reflected in the model as of the last time project schedule is revised; (2) the most updated project schedule is used as baseline for the 4D model. For *the as-built model*, we assume photographs are *all* collected on one specific day or in a short period of time where not significant progress in construction is made. In our approach there is no need to infer temporal order from images. Rather that information is automatically extracted from EXIF tag of JPEG images (available in all cameras). Finally for *registration of as-planned and as-built models*, we assume at least three distinct control points are known so that the as-planned model could be superimposed over the as-built sparse point cloud. We assume there will be an error in registration and we consider that error in our model.

6.6 Overview on the D^{4}AR progress visualization and detection engine

In this section, we provide an overview for the specific features of our system. As shown in Figure 6.2 our work is based on the joint application of daily construction photographs, IFC-based BIM as well as construction schedule to generate the D^{4}AR model and automatically measure progress. First we combine schedule with the IFC-based BIM by manually linking the elements to activities to create a 4D baseline for progress monitoring. Next using SfM techniques, we generate an underlying 3D geometry for the as-built scene and set a baseline for visual navigation based on automatic registration of the photographs in the scene. This is completed by calculating camera pose (i.e., location, orientation, and field of view) and sparse 3D Cartesian coordinate information of the as-built scene (Golparvar-Fard et al. 2009a).

Subsequently the 3D IFC-based BIM is superimposed over the integrated as-built point cloud and camera model. The Euclidean point cloud as well as the camera parameters is fed into MVS algorithm (Furukawa and Ponce 2009) to improve reconstruction. The results are subsequently placed into an as-built voxel coloring and labeling algorithm developed in this research to get a dense reconstruction of the as-built site and label scene for as-built occupancy. Using a similarly structured voxel-coloring algorithm, as-planned is also labeled for occupancy and visibility. These two labeled as-built and as-planned spaces are fed into a novel *Bayesian model* and monitored by dynamically classifying the results through a Support Vector Machine (SVM) classifier. Finally, detected as-built, camera configurations plus 4D BIM are fed into the D^{4}AR viewer to visualize as-built, as-planned and progress deviations in an integrated fashion. In the following sections, the SfM and other steps designed for progress tracking are presented.

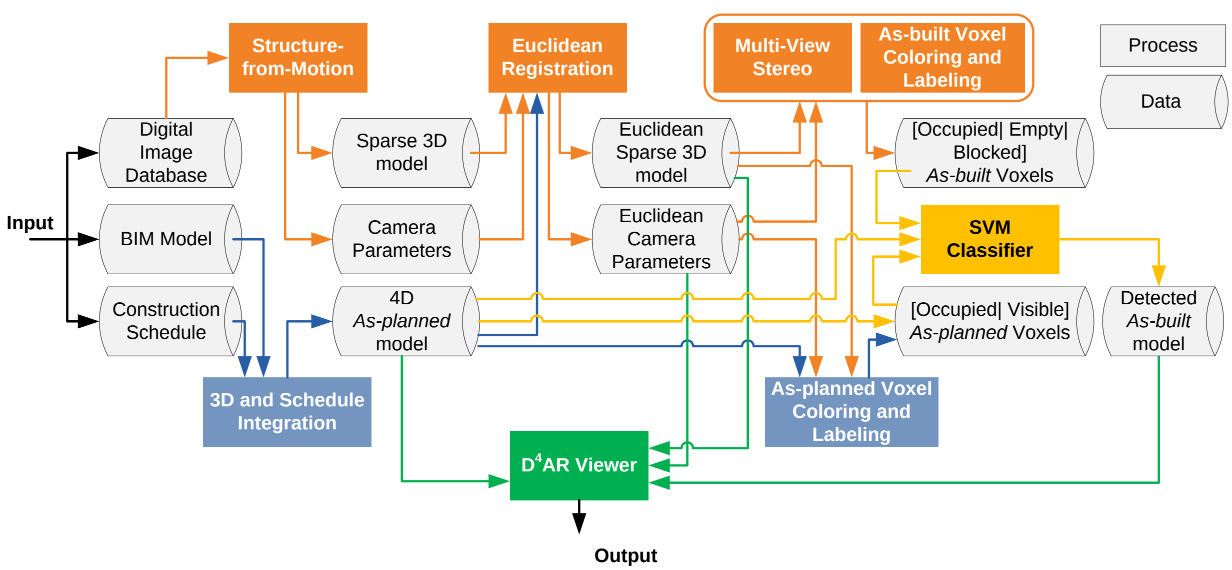

Figure 6.2. An overview of data and processes in our tracking, analysis and visualization system.

6.6.1 Reconstructing an underlying as-built representation using structure-from-motion

Recently Golparvar-Fard et al. (2009a) sparsely reconstructed and visualized the as-built scene from unordered daily photographs. The work is based on SfM technique similar to (Snavely et al. 2008) to automatically reconstruct an as-built point cloud from a set of images (no manual intervention at any stage). This module consists of the following steps: (1) Analyzing images and extracting SIFT feature points (Lowe 2004) from images; (2) Matching image feature across image set (Hartley and Zisserman 2004); (3) Find an initial solution for the 3D locations of these features points, calibrating cameras for an initial image pair and reconstructing the rest of the observed scene plus estimating motion of the cameras based on bundle adjustment (Nistér 2004; Triggs et al. 1999) and finally (4) Registering point clouds that are generated for each day to build a 4D as-built model (new concept developed in this chapter). To present how these steps are formed, we choose two sets of 112 and 160 images that are taken on 8/20 and 8/27/2008 on Residence Hall (RH) project in Champaign, IL. In both cases, field engineer causally walked along the sidewalk of the project and took images within a few minutes. Figure 6.3.a and b represents reconstructed sparse scene from the same image subset and illustrate five registered cameras in the D^4AR visual environment. Once a camera is visited, the camera frustum is texture-mapped with a full resolution of the image so user can interactively zoom-in and visually acquire information on progress, quality, safety and productivity as well as workspace logistics. Figure 6.3.c shows location of a camera frustum; 3d shows the site through the same camera; and 3e demonstrates the image textured on camera's viewing plane.

6.6.2 Aligning the as-built model to the as-planned model

In order to align the as-built point cloud with the as-planned model, transformation between these two Cartesian coordinate systems needs to be found. In this case, given an as-built point cloud that is reconstructed from photos collected at a time (t), we use the as-planned model that is updated up to time (t_0) ($t_0 \leq t$); i.e., the as-planned model shows progress up to time (t_0). The alignment transformation can be formed as a rigid-body motion and hence can be decomposed into rotation and translation. However in SfM, the scale may not be known. In addition the point cloud gives us a significantly large number of points that do not belong to the building model itself (e.g., may form from the façade of surrounding buildings, machinery, or even people and plants on or around the site). Further the vertices extracted from the as-planned model are also very sparse and they may not be good representatives as the progress of as-planned model is not known at this stage. Therefore we allow users to select a set of corresponding control points from the integrated as-built point cloud and image-based model and have those associated with the as-planned model. These points could be surveying control points or a set of points that represent the geospatial location of the site. In our case, these points are mostly chosen from corners of the foundation walls and columns as their detection and correspondence was visually easier.

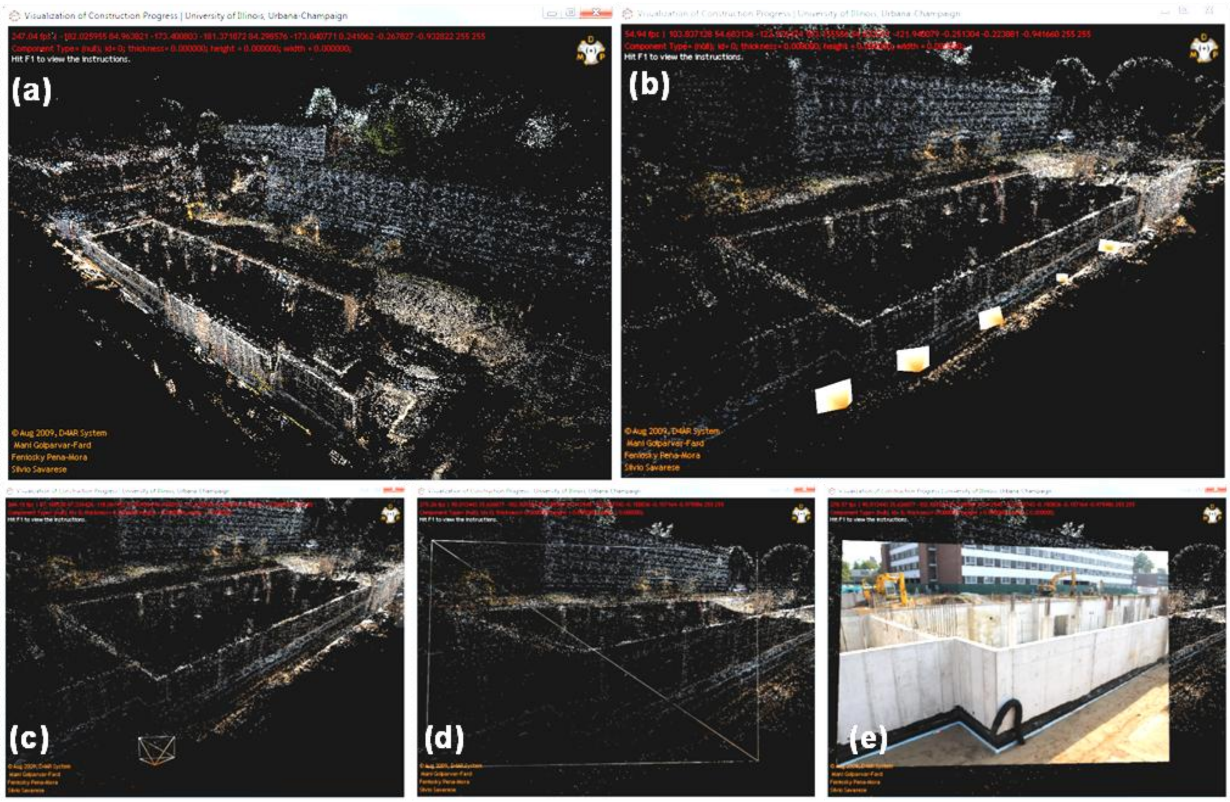

Figure 6.3. (a) Synthetic bird-eye-view of the as-built point cloud reconstructed; (b) Five camera frustra representing location/orientation of the superintendent when site photographs were taken rendered; (c) One camera frustum is rendered and its location/orientation is visualized; (d) The as-built point cloud observed through camera frustum (same camera as (c)); and (e) camera frustum textured visualizing photograph registered over the 3D point cloud.

The unknown uniform scaling adds one more degree of freedom to the original transformation problem (overall 7 DOF). Therefore three points known in both coordinate systems will be theoretically sufficient to permit determination of these seven unknowns. However in practice, these measurements are not exact and if more than three points are used, greater accuracy can be sought. Therefore by adding additional points we do not expect to find the transformation that exactly maps the measured coordinates of points from one system into the other. Rather we minimize the sum of squares of residual errors. Let there be *n* points from as-planned and as-built model for registration. We denote the two coordinate system points by $\{r_{b,i}\}$ and $\{r_{p,i}\}$, respectively, where *i* is the number of corresponding points which ranges from 1 to *n*, $r_{b,i}$ and $r_{p,i}$ be the Cartesian coordinates of as-planned and as-built model respectively. We are looking for transformation of the form [Eq.6.1]:

$$r_b = sR(r_p) + T \tag{6.1}$$

s is a uniform scale factor, T is the translational offset and $R(r_p)$ is the rotated version of the planned model. Minimization of sum of square of the errors of such registration can be formulated as:

$$\sum_1^n \|e_i\|^2 = \sum_1^n \|r_{i,b} - sR(r_{i,p}) - T\|^2 \tag{6.2}$$

We follow Horn (1987) which gives a closed-form solution to the least square problem of absolute orientation, one that does not require iteration and does not need a good initial guess. The error (Δe) can be measured in mm using the following form [Eq.6.3]:

$$\Delta e_{mm} = \bar{w}_{pixels} \times \bar{f}_{mm} / \bar{w}_{CCD,pixels} \tag{6.3}$$

where $\bar{f}_{mm}$ is the focal length in *mm*, $\bar{w}_{pixels}$ is the image width in pixels and finally $\bar{w}_{CCD,pixels}$ is the CCD (Charged Coupled Device) width of camera in *mm*. In our system, this procedure needs to be done only once to have the initial point cloud registered to the 3D model. From then after, we only need to register the point clouds that are generated from new photographs to the underlying point cloud. For this purpose, under the condition that in our photolog we have a set of photographs that are showing part of the scene which is not significantly changed from one-day to another, we use an ICP algorithm (Besl and McKay 1992) that can solve for scale as well (Du et al. 2007). This method automatically finds a random set of points from each point cloud and automatically aligns the new point cloud to the former one, in turn having the new point cloud registered with the as-planned model. This allows 4D as-built point clouds to be generated wherein user can navigate the as-built scene both spatially and chronologically. The 4D as-built point clouds registered with the 4D as-planned model allows expected and the actual schedule of the project to be compared as well. Figure 6.4 shows eight snapshots from RH and SD (Student Dining) construction project case studies. In each row, first two separately reconstructed point clouds are shown while in the third image, the two point clouds are registered and mutually visualized. Finally in (d) and (h), registration of IFC-based BIM with point clouds in (b) and (e) is visualized. In cases (a) and (b), reconstructions are based on 112 and 160 photographs collected from outside of the RH basement along the side-walk and in cases (e) and (f) reconstructions are based on 288 and 118 photographs collected from inside and around the SD basement. Table 6.1 reports the accuracy of registration for point cloud/point cloud and point cloud/BIM. As observed high accuracies are achieved, though the accuracy is not sensitive to how the control points are selected. Since usually more than the minimum number of control points (three) is selected, such interactive selection error is minimized.

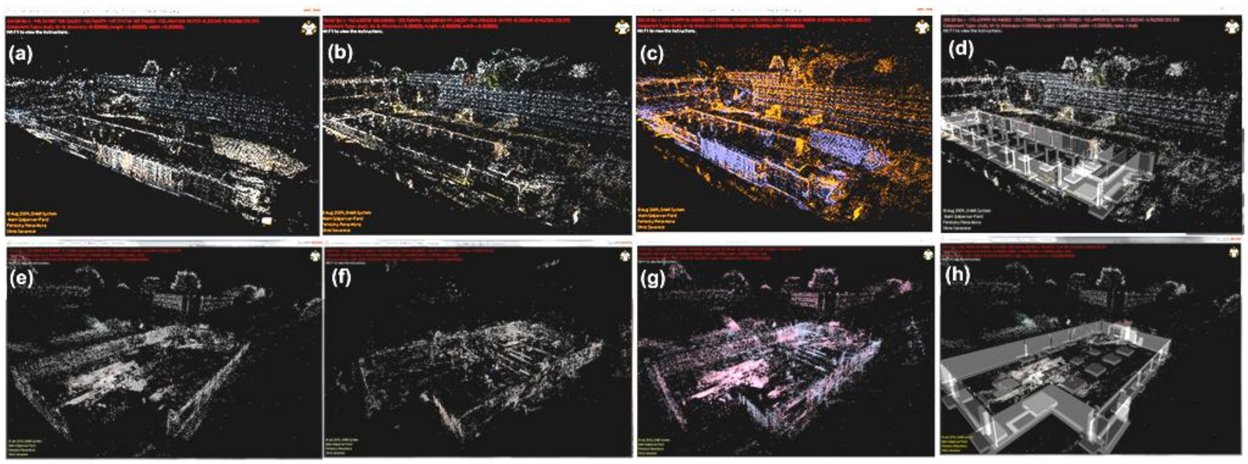

Figure 6.4. Point cloud/point cloud and Point cloud/BIM registrations. (a) point cloud reconstructed from 112 images from RH project (08/20/08) ; (b) point cloud reconstructed from 160 images from RH project (08/2/08); (c) violet point cloud is (a) and orange point cloud is (b); (d) registration of BIM with point cloud in (b); (e) point cloud reconstructed from 288 images from SD project (07/07/08); (f) point cloud reconstructed from 118 images from SD project (07/24/08); (g) red point cloud is (e) and blue point cloud is (f);(h) registration of BIM with point cloud in (e) (Images best seen in color).

Table 6.1. Registration errors measured on reconstructions shown in Figure 6.4.

RH Project - RH#2 - RH#3	Test Case #	BIM + point cloud (4-a)	BIM + point cloud (4-b)	Point clouds (a) and (b)
	Image Size	2144×1424	1715×1139	--
	# of feature points	62,323	43,400	--
	# of corresp. Points	7	7	Randomly chosen by ICP
	Δe_{mm}	0.20 *mm*	0.65 *mm*	0.43 *mm*
SD Project - SD #1 - SD #2	Test Case #	BIM + point cloud (4-e)	BIM + point cloud (4-f)	Point clouds (e) and (f)
	Image Size	2144×1424	2573×1709	--
	# of feature points	61,638	31,661	--
	# of corresp. Points	9	9	Randomly chosen by ICP
	Δe_{mm}	0.73 *mm*	0.69 *mm*	0.70 *mm*

6.7 Automated Progress Monitoring Problem Setup and Notation

In order to detect progress, we first discretize the integrated as-built and as-planned scene Ω into a finite set of opaque voxels (volume element in space) along dominant Euclidean axes in form of $n_x\delta_x\times n_y\delta_y\times n_z\delta_z$ wherein each voxel (v) occupies a finite homogenous volume of the scene ($\delta_x\delta_y\delta_z$) and has a consistent visual appearance. This approach allows us to reason about progress in small elements within the space. In our model, voxels are assumed to be equilateral; therefore resolution of the voxel grid is determined by δ. Given an image Π_i, $proj_i(v)$ is used to denote the reprojection of the voxel (in form of a set of pixels) over image i and is measured with:

$$\ni k=1,2,...,8 \rightarrow \begin{bmatrix} u & v & 1 \end{bmatrix}'_k = K_i[R_i \mid T_i]\begin{bmatrix} x & y & z & 1 \end{bmatrix}'_k \tag{6.4}$$

$$proj_i(v) = [\min(u_k, v_k)..\max(u_k, v_k)] \tag{6.5}$$

wherein k is the index of the voxel corners, K_i is the intrinsic camera parameters, R_i and T_i represent camera rotation and translation. Since we analyze all images during the SfM step, the intrinsic and extrinsic camera parameters for all cameras are known at this stage.

6.8 Voxel Traversing and Labeling

The next step is to traverse the scene and assign two sets of labels (as-built and as-planned) as well as a color to each voxel. This step allows expected and actual progress in each voxel of the scene to be sensed. It is critical to traverse the voxels in a certain order otherwise the reconstruction results will not be unique. In order to address this issue, we introduce *an ordinal visibility constraint* similar to that of (Seitz and Dyer 1999) allowing certain invariant voxels whose colorings are uniquely defined to be found. Rather than only using this constraint to address uniqueness of the solution, in our approach we find areas within the space that are occupied and visible (i.e., observable progress).

First we transform the integrated scene to a new coordinate system wherein the axes are aligned with the dominant axes of the as-planned site. This will minimize search space, since we can only reason about areas in which progress is expected to be observed. Then we start traversing the scene from the closest voxel to the convex hull of the cameras (rough approximation of the scene boundaries) in a plane normal to the convex hull and eventually in a front-to-back order (See Figure 6.5- axis 1 to 3 directions). As we march through the voxels, we verify the visibility constraint. The labeling process is as follows: For every voxel ($\upsilon_{i,j,k}$) in the scene, we define two sets of labels $l(\upsilon_{i,j,k})$: [1] As-built and [2] As-planned labels.

6.8.1 As-built labeling

For the as-built, we first check if a voxel already contains 3D SIFT or MVS points. In this case, we label that voxel as *Occupied* (O_b), have that voxel reprojected back on all images that observe that voxel [Eqs. 6.4 and 6.5] and if the boundaries of reprojection fall into the boundaries of the image surface, then the reprojected pixels will all be marked [See Eq. 6.6].

$$\forall i \in C_1, \ldots, C_n, \exists(proj(v_k) \in \left\{\begin{bmatrix} -w/2 \\ -h/2 \end{bmatrix} - \begin{bmatrix} w/2 \\ h/2 \end{bmatrix}\right\}) \rightarrow \forall m,n \in proj(v_k), Mark_{m,n} = 1 \tag{6.6}$$

This allows us to automatically generate segmented range images while accounting for complete and partial occlusions. If the voxel does not contain SIFT or MVS points (which is more often the case), we check for visual consistency. In such cases if voxel reprojections on the image-set do not overlap with masked pixels i.e., is not fully occluded from all images, and it happens to contain *a* part of the as-built scene (without considering noise or quantization effects), it needs to have equal radiance reprojections. In presence of these effects, we evaluate correlation of pixel colors to quantify voxel consistency:

$$\lambda_v = \frac{(n-1)SD^2}{\sigma_0^2} \leq thresh \tag{6.7}$$

Where *SD* is the standard deviation of color values, and σ_0^2 is the accuracy of irradiance measurement (sensor color measurement error), and finally *n* is number of all images that observe the voxel. If λ_v is less than a maximum allowable correlation error (*thresh*), we label that voxel as visually consistent (O_b) and have that reprojected on all observing images and mark their image marking-boards accordingly. In our experiments there is a minimum allowable number of reprojected pixels for each voxel from all images ($n > 20$ pixels). Given this condition, if consistency is not satisfied, we label the voxel as *Empty* (E_b) and finally if the minimum allowable number of pixels is not satisfied, it means the voxel is occluded from all views and we denote that voxel as *Blocked* (B_b). In our experiments we have chosen *thresh*=1 by analyzing completeness vs. accuracy for as-built reconstruction. This process will have two significant outputs: (1) Labeling all voxels in the as-built as $[O_b \mid E_b \mid B_b]$, allowing reasoning to be made in presence of full and partial occlusions (both static and dynamic); and (2) creating as-built range images based on observations. Figure 6.6.a shows a plan-view of voxel labeling while in 6b reprojected voxel shown in 6a is marked on the image as $proj_1(v)$. In Figure 6c unchanged vs. progress observation concept is visualized. Figure 6.7 summarizes the as-built occupancy/visibility labeling and marking algorithm.

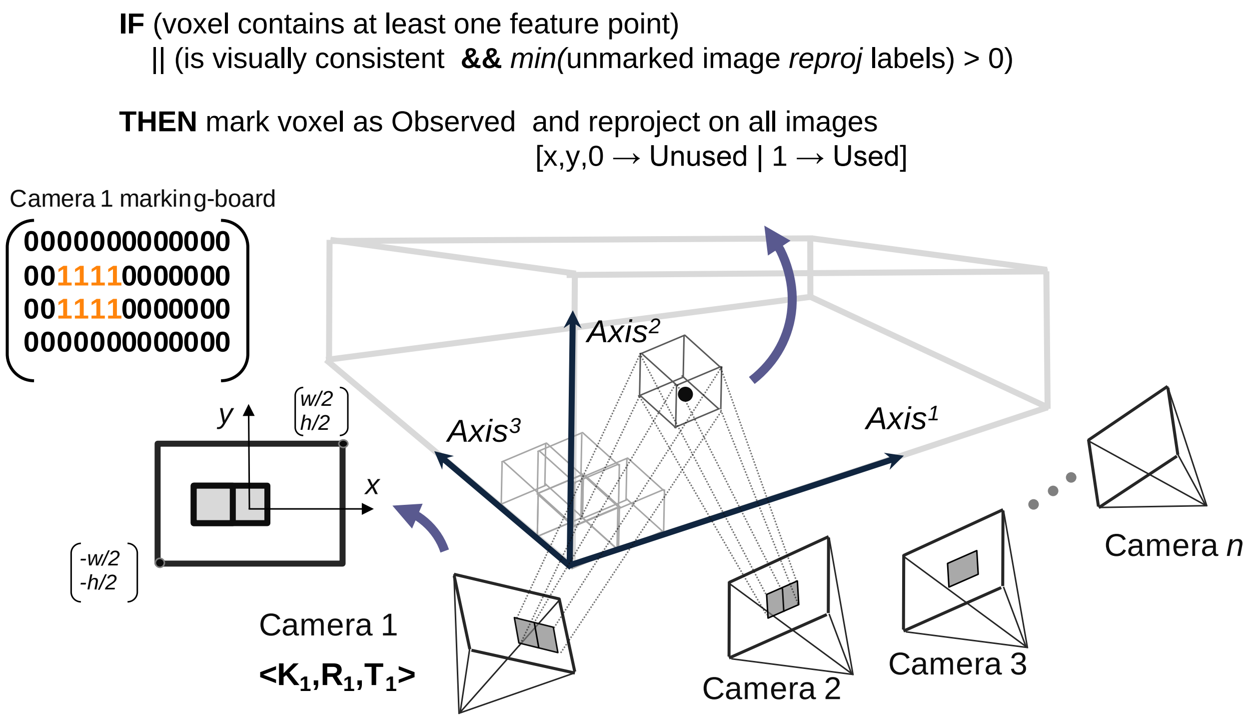

Figure 6.5. A representation of the as-built site and camera configurations; Reprojections of the voxel are shown on camera frusta 1 and 2. Marking for camera-1 is also shown on the left side. In this case voxel is detected as Occupied; therefore all pixels belonging to reprojection of the voxel on all images are marked "1".

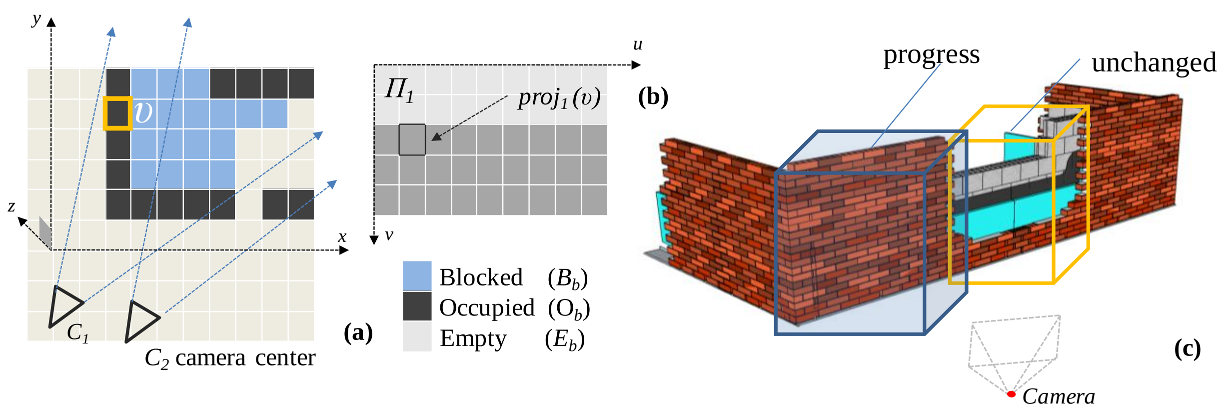

Figure 6.6. (a) Plan view of discretization of the scene to voxels along dominant axes. Each voxel with respect to shown camera configuration is either Occupied (O_p), Blocked (B_b) or Empty (E_b). (b) Image 1 (Π_1) from camera configuration in (a) is shown here wherein $proj_1(\upsilon)$ shows the projection of voxel (υ) from (a) over Π_1 which is marked (color coded different from unmarked voxel reprojections). (c) progress vs. unchanged observations.

Algorithm 1: *As-built voxel labeling and image marking*

Input: $\{C_i | i=1,2,\ldots,N\}$ camera list, point cloud model

Output: $\sum_{x,y,z}\left[\sum_3 l(v_{i,j,k})\right]$ where

$\sum_3 l(v_{i,j,k})$ is $[O_b | E_b | B_b]$ labeled with $[0 | 1]$

```
Start with δ, C.
Set Nx, Ny, Nz;
while (0<j< Ny) && (0<k< Nz) && (0<i< Nx)
    while 0<c<size(C)
        if ~[proj(c[i,j,k]) = 1]
            add(c) to list
            if [Ob(i,j,k) = 1] or [ λv ≤ thresh ] then
                Ob (i,j,k) = 1;
                for c← 0,1,2,…, camera list
                    proj(c[i,j,k]) = 1
                end
            else
                Eb (i,j,k) = 1;
            end
        else
            Bb (i,j,k) =1;
        end
    end
end
```

Figure 6.7. As-built voxel labeling and image marking. If a voxel contains at least one feature point or has consistent visual appearance, it will be labeled as occupied.

6.8.2 As-planned labeling

The as-planned model by itself accounts of static occlusions, though by placing the non-overlapping areas of the as-built scene (e.g., reconstruction of excavators, temporary structures) over the as-planned, we induce the dynamic occlusions to the model. Now we march the scene in a similar fashion to that of the as-built. This time, if a voxel has at least one of its corners inside an IFC element, we label that as *Occupied* [O_p]. Subsequently we will have a voxel reprojected back on all images that observe that voxel and mark the reprojected pixels. In this case, we keep the depth value of the voxel as another marking layer for the image. This will allow us to automatically generate as-planned segmented images based on location and depth of all IFC elements. In case of non-overlapping as-planned and as-built areas, we check the consistency from the as-built marking and have visually consistent voxels reprojected back on all images for marking pixels. This allows us to count for occlusions as well since if the reprojections contain the minimum unmarked pixels, we can label the voxel as *Visible* [V_p]. In our model, all labels are independent from one another and are marked with binary values (either 1 or 0). In addition to labeling voxels, image pixels are also marked so that if a pixel is observed, the pixel is labeled with 1 and if not observed, remains as 0 (See Figure 6.5 left side). Such labeling for visibility allows us to reliably and consistently reason about progress in full and partial visible areas. Figure 6.8 summarizes the as-planned occupancy/ visibility labeling and marking algorithm.

Algorithm 2: *As-planned occupancy/ visibility labeling and image marking*

Input: IFC model, $\{C_i | i=1,2,\ldots,N\}$, non-overlapping parts of the point cloud model

Output: $\sum_{x,y,z}\left[\sum_{3} l(v_{i,j,k})\right]$ where $\sum_{3} l(v_{i,j,k})$ is $[O_p \mid V_p]$ and is labeled with [0 | 1]

Start with δ, C.
Set N_x, N_y, N_z;
while $(0 < j < N_y)$ && $(0 < k < N_z)$ && $(0 < i < N_x)$
  while $(0 < E_i <$ size(Elements))
    if $[v(i,j,k)$ is_Occupied by $E_i]$ then
      $O_p\ (i,j,k) = 1$;
      while $0 < c <$ size(C)
        if $\sim[proj(c[i,j,k]) = 1]$
          add(c) to list
          for all c in list
            $proj(c[i,j,k]) = 1$
          end
          $V_p\ (i,j,k) = 1$;
        else
          $V_p\ (i,j,k) = 0$;
        end
      end
    end
  end
end

Figure 6.8. As-planned voxel labeling and image marking; If a voxel is filled by an IFC element, it will be labeled as occupied and if it is observable at least from one camera is marked as Visible.

6.9 Probabilistic Model for Progress Detection and Discriminative Learning

Now that the scene is labeled for as-built and as-planned occupancy, visibility and occlusion, we can form our progress detection engine. We formulate progress (observation per expected as-planned element i) as a binary value (E^i): $E^i = 1$ if progress is detected and $E^i = 0$ if not. First, we break the IFC-based BIM into independent elements given the existing desirable level of detail for progress monitoring and reporting. Let's go back to the example on "FPRS basement concrete columns" activity. In this case we first need to check for observation of each of these expected columns attached to this activity (all Elements i as E^i).

Let's assume that each element E^i attached to this activity consists of n voxels. We introduce a set of probability events: Within a given volume in the scene (ω_i): Let η be the event of observing an occupied as-built element (any tangible physical element), θ_P be the event of observing as-planned element, θ_T be the event that an as-planned element is occupied and finally s the expected level of construction status from the 4D as-planned model. We define probability of observing progress for element E^i associated with a given schedule activity (duration = n days) as a conditional probability of the form:

$$P(\eta^i \mid \theta_T^i) = \frac{P(\theta_T^i \mid \eta^i)P(\eta^i)}{P(\theta_T^i)} \tag{6.8}$$

Where $P(\theta^i{}_T|\eta^i)$ is the probability of observing expected as-planned element given some evidence of occupancy; $P(\eta^i)$ probability of the expected as-built element observation (a function of confidence in coloring and labeling the voxel; occupancy within element belonging to the expected as-built) and $P(\theta^i{}_T)$ probability of observing expected progress. Each element can be computed as follows:

For as-built:

$$P\left(\theta_T^i \mid \eta^i\right) = \left[\frac{\sum O_b}{\sum O_b + \sum E_b}\right]_{\theta p} \tag{6.9}$$

For the as-planned:

$$P\left(\theta_P^i\right) = \left[\frac{\sum V_p}{\sum O_p}\right]_{\theta^i p} \tag{6.10}$$

$$P(\theta_T^i) = (\frac{t}{d})V \tag{6.11}$$

where $P(\theta^i{}_T)$ is the expectation of observable progress (percentage of visibility from the camera set), d is the total duration of construction activity, and t represents the t_{th} day within this duration (d) and finally V is the volume of expected as-built element. We use $P(\eta^i|\theta^i{}_T)$ to estimate E^i (progress) with a threshold Γ^i. Choosing an optimal value for the threshold for each element is problematic. For example given a 10% visibility [$P(\theta^i{}_p)$] and 25% accuracy of reconstruction [$P(\theta^i{}_T|\eta^i)$], the $P(\eta^i|\theta^i{}_T)$ may be susceptible to noise and inaccuracy in reconstruction. Therefore it may not be reported as *detected*. This selection is particularly difficult, because (1) to achieve a desired accuracy, for different element types with different materials, different thresholds need to be used; (2) Progress monitoring task with partial visibility is subjective by nature and needs an expert's opinion as to whether it has taken place or not. Thus we use a machine learning model to estimate such dynamic thresholds in a principled way. We can express the threshold (Γ^i) as:

$$\Gamma^i = f(\theta_p(t), p(\eta \mid \theta_T), t/d, T_i, \Psi(t), \delta, thresh, \varepsilon_{Reg}, \varepsilon_{\mathrm{Rec}}) \tag{6.12}$$

Where t is construction activity duration from t=0 to d, T_i is the element type (e.g., column, beam, foundation), $\Psi(t)$ is the surface visual appearance of the element i (e.g., concrete, formwork, steel), δ voxel resolution, *thresh* the voxel consistency threshold and finally ε_{Reg} and ε_{Rec} are the accuracy in registration of as-planned model over point cloud and the accuracy of underlying reconstruction pipeline. For sake of simplicity at this stage, as shown in Table 6.1, we assume there is minimal error in registration and the underlying mechanisms of as-built reconstruction. The threshold Γ^i can be learnt by casting the problem into linear classification problem. That is by learning the hyper-plane that separates the two classes in a multi-dimensional feature space. The feature space is defined by $P(\eta^i|\theta^i_T)$, $\theta_p(t)$, t/d, T_i, $\Psi(t)$, δ, and *thresh*. The two classes are *progress=1* and *no-progress=0*. The optimal hyper-plane that separates the two classes can be learnt in a supervised fashion using a linear support vector machine (SVM) (Fan et al. 2008). Once the classifier is learnt, given a new observation (that is a measurement of progress $P(\eta^i|\theta^i_T)$) along with the measured features ($\theta_p(t)$, t/d, T_i, $\Psi(t)$, δ, and *thresh*) we can establish whether the progress has occurred or not by feeding observation into the classifier and retain the output.

Following to measuring expected progress for each element, we need to measure progress for the given schedule activity. Progress for a given schedule activity which is linked to n mutual independent elements in the IFC-based BIM can be formulated as:

$$P\left[\bigcap\nolimits_n P(\eta^i \mid \theta^i_p)\right] = P\left[\left\{\eta^i; i = 1 \ldots n \mid \theta^i_p; i = 1 \ldots n\right\}\right] \tag{6.13}$$

$P\left[\left\{\eta^i \mid i = 1 \ldots n \mid \theta^i_p \mid i = 1 \ldots n\right\}\right]$ is the probability of observing progress for a schedule activity, given its mutually independent sequence conditions (e.g., construction of column–slab; column–column and column–wall are considered mutually independent). In this case, we can formulate progress as [Eq.6.14].

$$P\left[\bigcap\nolimits_n P(\eta^i \mid \theta^i_p)\right] = \frac{\sum_n E^i \times V^i_p}{\sum_n V^i_p} \tag{6.14}$$

Figure 6.9 summarizes progress detection process for each schedule activity.

Algorithm 3: *Physical progress detection per construction schedule activity- n elements linked.*

Input: $\sum_{x,y,z}\left[\sum_{3} l(v_{i,j,k})\right]_p$ where $\sum_{3} l(v_{i,j,k})_p$ is $[O_p \mid V_p]$ and $\sum_{x,y,z}\left[\sum_{3} l(v_{i,j,k})\right]_b$ where $\sum_{3} l(v_{i,j,k})_b$ is $[O_b \mid E_b \mid B_b]$

Output: $P\left[\bigcap_n P(\eta^i \mid \theta_p^i)\right]$

Start with δ *and* Set N_x, N_y, N_z as inner voxels of all elements i *to n*
for i=1:n
    Define $t/d, T_i, \Psi(t)$ from IFC element i
    Calculate $P(\theta_p^i)$, $P\left(\theta_T^i \mid \eta^i\right)$, and Γ^i
    $\forall i, P(\eta^i \mid \theta_T^i) \geq \Gamma^i \rightarrow E_i = 1$
end
Calculate $P\left[\bigcap_n P(\eta^i \mid \theta_p^i)\right]$

Figure 6.9. Tracking physical progress for an activity in the work schedule.

6.10 Experiments and Results

In order to verify effectiveness and robustness of the proposed reconstruction pipeline as well as the automated progress detection over arbitrary set of daily photographs and in presence of occlusions, we performed experiments on three different photo collections. These image datasets were collected under different viewpoints and lighting conditions and were used for evaluating this task. These datasets are two photo collections of 112 and 160 images from RH project and a 288 image dataset from Student Dining (SD) project. The images are all taken at the basement level of project with significant amount of occlusion observed in both RH cases as the images were not taken from inside the basement area. Rather they were all taken along a side walk of the project (See locations of the camera frusta in Figure 6.3.b). We synthetically reduced the resolution of these images to about 2Mpixels to test robustness of our approach to the quality of images. We have initially set the voxel resolution to 1/5 foot (~0.06*m*). The 4D IFC-based BIMs for RH and SD projects have relevant schedule activities that are connected to 152 and 321 elements respectively (See Figure 6.15 for the relevant part of the RH project schedule). Figure 6.10.a to d illustrates the results of dense reconstruction for the case presented in Figure 6.4.b (RH 160) as well as the SD project (10e to h). All the snapshots in this case are taken from synthetic views in 3D virtual environment (none of these views exist in image dataset; rather each is a result of synthetic 3D visualization). Comparison of Figure 6.10 with Figure 6.3 further visualizes the contribution of MVS +

as-built voxel coloring to that of SfM (reported in Golparvar-Fard et al. 2009a) used for reconstruction of the as-built.

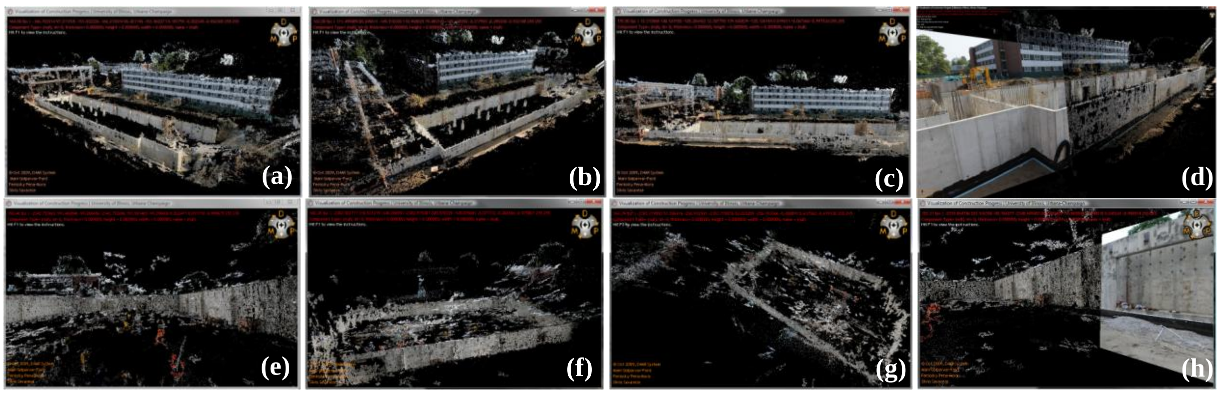

Figure 6.10. (a, b, c and d): Illustrates dense as-built reconstruction for the same RH dataset presented in Figure 4-b. (e, f, g, and h) represent the dense reconstruction of the SD dataset.

Figure 6.11 shows the results of traversing, labeling and re-projecting detected areas of as-built and as-planned spaces. For the same image plane shown in Figure Figure 6.11.a, range images for both as-planned and as-built scenes are generated (from the same camera plane viewpoint). In Figure 6.11.b IFC elements occupied by as-planned voxels are all reprojected back according to the depth from the camera plane. In order to visualize the depth, a color-coding scheme is represented where depth is visualized in relationship to the furthest elements from the camera plane (in this case, the rear foundation wall). In Figure 6.11.c, the consistently observed as-built voxels are reprojected back. Combination of Figure 6.11.b and c allows specific areas within each image where IFC-elements are supposed to be observed to be automatically segmented and visualized. This robustly takes occlusions into account as all the elements that are located closer in the line-of-sight to the camera will be detected first (ordinal visibility constraint). This will further allow a texture recognition system to be implemented to detect P(η^i) and account for progress details accordingly. For example, consider a concrete foundation wall which will be further prime-coated and insulated. Since the system is based on an IFC as-planned platform and is linked to the schedule, expected progress information can be queried easily and given the timing of the image (extracted from the EXIF tag) the type of visual surface to be observed will be known. This marks our system superior to all previously suggested techniques in construction site tracking as it fully accounts for occlusions and is relying on robust *priori* information.

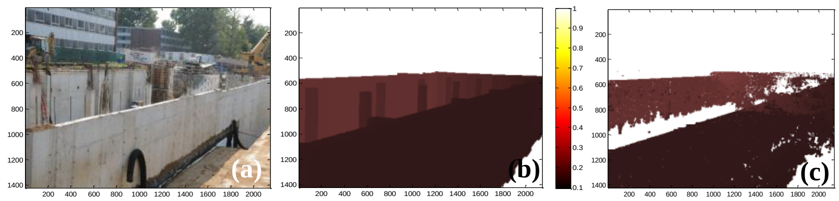

Figure 6.11. (a) An image taken on RH project dated 08/27/08. (b) Range image generated for the expected IFC elements. Color-coding shows the ratio of depth compared along the camera line-of-sight based on the back foundation wall; (c) the expected as-built progress voxels detected and projected back on the image plane.

6.11 Discussion on Automated Detection Accuracy

In our experiments, we analyze performance of detection engine by a number of common object recognition metrics. Particularly we use the following: (1) *Recall*: The fraction of truly recognized IFC-model elements (*TP* = true positive) relevant to the total number of model elements that are used for our detection engine (*TP* + *FN* = true positive + false negative). This parameter will show the *sensitivity* of our detection engine. (2) *Precision*: The fraction of truly recognized IFC-model elements relevant to the total number of model elements that are recognized with progress in our detection engine (*TP* + *FP* = true positive + false positive). This parameter will show the *accuracy* of our detection engine. In our approach, the SVM kernel machine classifies progress with a binary value (progress/ no progress).

We train the SVM model over the RH 112 photo dataset. The hyper-plane is dynamically learned though it can be roughly reported (from experiments) that if the expected observable area is less than 20% of the observable surfaces of the as-planned element and the volumetric reconstruction is only able to reconstruct the expected areas up to 50%, this element should not be recognized by the detection. The performance of the training is cross-checked by asking two field engineers and a superintendent to label the classification results. The accuracy of training was experienced to be 87.50%. Table 6.2 shows an example of how SVM classification has been accounted for two classes of concrete columns and foundation walls. In this example, the detection feature vector values are shown. In our approach, the accuracy of classification is automatically increased and more objectively formed as more experiments are conducted and are automatically added to the SVM linear classifier. We tested performance of the classifier on RH 160 and SD 288 photo datasets. The results of average accuracy for our experimental datasets are presented in Table 6.3.

Table 6.2. Supervised SVM learning of the detection threshold for T_i=(i=0 column; i=1 wall) and $\Psi(t)$=concrete.

Γ	$\theta_p(t)$	$p(\eta\|\theta_T)$	d/n	T	δ	th	Γ	$\theta p(t)$	$p(\eta\|\theta_T)$	t/d	T	δ	th	Γ	$\theta_p(t)$	$p(\eta\|\theta_T)$	t/d	T	δ	th	Γ	$\theta_p(t)$	$p(\eta\|\theta_T)$	t/d	T	δ	th
-1	0.16	0.16	1.00	0	0.20	1	-1	0.36	0.24	1.00	0	0.20	1	-1	0.43	0.21	1.00	0	0.20	1	-1	0.52	0.25	1.00	0	0.20	1
-1	0.24	0.84	1.00	1	0.20	1	+1	0.36	0.71	1.00	1	0.20	1	+1	0.46	0.89	1.00	1	0.20	1	-1	0.57	0.43	1.00	1	0.20	1
+1	0.32	0.75	1.00	0	0.20	1	+1	0.37	0.80	1.00	0	0.20	1	+1	0.49	0.88	1.00	0	0.20	1	+1	0.63	0.75	1.00	0	0.20	1
+1	0.35	0.84	1.00	1	0.20	1	+1	0.41	0.79	1.00	1	0.20	1	+1	0.51	0.85	1.00	1	0.20	1	+1	0.71	0.89	1.00	1	0.20	1

Table 6.3. Average accuracy of SVM binary detection for training and testing datasets.

	Dataset	# of images	# of IFC elements	Detection accuracy
Training	RH #2	112	152	87.50%
Testing	RH #1	160	152	82.89%
	SD	288	321	91.05%

We also investigated the ratio of progress which is expected to be detected, P(θ_T^i| η^i) to the expected observable regions, P(θ_p^i). Figure 6.12.a shows the results of the experiments on the RH 112 dataset. As observed, majority of false detections happen for below 20% observable progress P(θ_p^i). This further justifies the underlying learning step for SVM for which in presence of sever occlusion and poor reconstruction, no decision on progress should be drawn from such observations. To further investigate the sensitivity of our detection engine to presence of occlusions, we investigate the relationship between the accuracy to the percentage of visibility. As observed from Figure 6.12.b, there is no direct relationship between the percentage of occlusion to the accuracy. Rather the relationship between observed P(θ_T^i| η^i) and observable P(θ_p^i) which accounts for occlusions should control how decision of detection needs to be made. In this figure, vertical bars represent the measured standard deviations over detection accuracy.

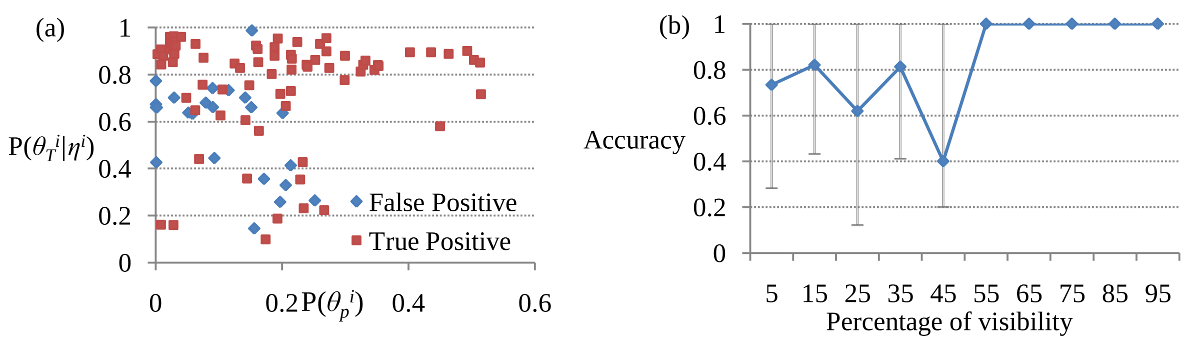

Figure 6.12. (a) The ratio of expected progress P(θ_T^i | η^i) to the expected observable regions, P(θ_p^i) for a subset of results from RH #1 experiment. (b) The ratio of accuracy of detection to the percentage of occlusion.

In order to examine the accuracy and sensitivity of our detection engine, we studied precision-recall and true-positive/false-positive graphs. Figure 6.13 illustrates the results over our experimental datasets. These graphs are only drawn for the elements that were expected to be detected and not for those elements that are fully occluded. Given the formation of this approach, the results of accuracy seem very promising, yet it shows our approach is not sensitive to formation of the hyper-plane.

(a) Precision-Recall graph

(b) True-Positive/ False-Positive graph

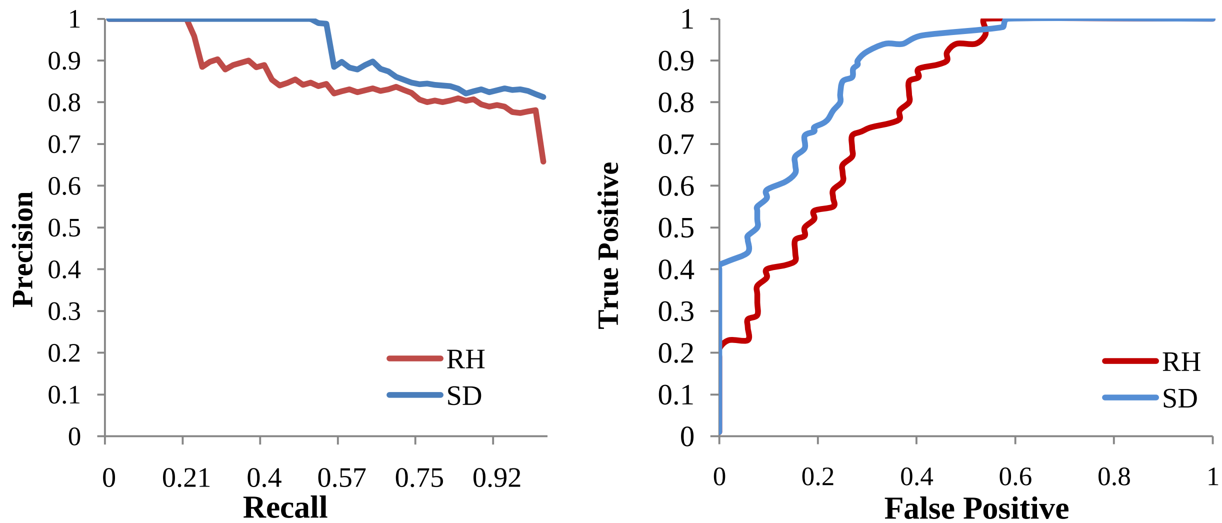

Figure 6.13. (a) Precision-Recall graph and (b) the True positive/False positive graph for our progress detection engine.

Finally to represent progress, we use the D^{4}AR model platform reported in (Golparvar-Fard et al. 2009a) and the color-coding scheme presented in (Golparvar-Fard et al. 2009b) to represent changed, unchanged with red and green. Figure 6.14 shows the results of visualizing the result of our progress detection engine. In these cases, the IFC elements that are behind or are on-schedule are color-coded with green and red colors accordingly. For those elements that progress is not reported, we color them in gray. Such color-coding scheme makes it easy to observe accuracy of progress detection, yet allows corrections to be made on a case-by-case basis.

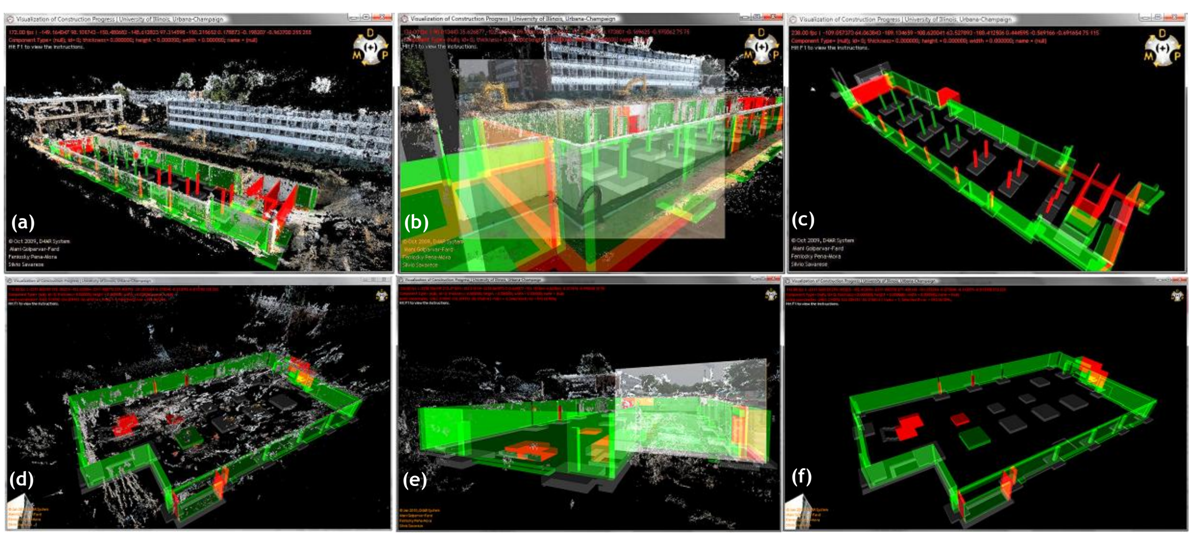

Figure 6.14. (a) Visualized progress for RH project over the D4AR environment. (b) Semi-transparent view of RH progress from a camera view point. (c) RH progress detection results color-coded over the IFC-based BIM. (d) Visualized progress for SD project over the D^{4}AR environment. (e) Semi-transparent view of SD progress from a camera view point. (f) SD progress detection results color-coded over the IFC-based BIM.

Figure 6.15 illustrates examples of false positives and missed positives (false negative in statistical terms) in our detection. As observed, since our model does not contain operational details (e.g., forming stages), the formwork is falsely detected as finish of a concrete element construction. In Figure 15c the wall highlighted should be detected, but due to occlusions, it is not properly reconstructed and consequently not detected.

Figure 6.15. (a, b) False Positive – the formwork should not be detected as evidence of progress; (c, d) Missed Positive (False Negative) – the wall should be detected for progress though it is severely occluded.

Finally, according to Eq.6.14, detected progress $P(\eta^i \mid \theta_T^i)$ and based on simple knowledge of sequences queried from the IFC-based BIM and the linked schedule(i.e., Supported by sequence relationship), progress will be reported back on elements. Figure 6.16 present a part of the RH project schedule and illustrates what activities are tracked for progress. As observed, given the accuracy of the detection engine (as this stage) progress can still be reported at schedule activity level. Since the exact timing of each operational stage (e.g., forming/ pouring) is not known, progress cannot be reported in finer levels of detail. Rather only if $P(\eta^i)$ is measured in Eq.6.8, progress can be reported in finer levels of detail without a need for a more detailed WBS (In our experiments for this chapter, $P(\eta^i)$ =1).

								Jul-08							Aug-08							Aug-08			
					28	29	30	31	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Visibility	**progress**		**Scheduled Start**	**Scheduled Completion**	M	T	W	R	F	S	S	M	T	W	R	F	S	S	M	T	W	R	F	S	S
		SITE																							
		Perform Interim Survey Control and Monitor Set-Up	**8/6/2008**	**8/6/2008**										X											
		RH BUILDING FOOTPRINT																							
		Install Perimeter Subsoil Drain Piping at North Wall	**7/28/2008**	**8/1/2008**	X	X	X	X	X																
		Construct Rebar Mats & Structures	**7/28/2008**	**10/31/2008**	X	X	X	X	X			X	X	X	X	X			X	X	X	X	X		
1	60%	FRPS Basement Walls & Piers+	**7/28/2008**	**8/15/2008**	X	X	X	X	X	X		X	X	X	X	X	?		X	X	X	X	X		
0.5	52%	FRPS Basement Perimeter Foundations+	**7/28/2008**	**7/29/2008**	X	X																			
		Apply Liquid Membrane at Perimeter Footings	**7/28/2008**	**8/1/2008**	X	X	X	X	X																
		Perform Elevator Drilling at NW Elevator Shaft	**7/29/2008**	**7/30/2008**		X	X																		
0	--	FRPS Basement Interior Foundations+	**7/30/2008**	**8/5/2008**	X	X	X	X	X			X	X												
1	86%	FRPS Interior Columns+	**8/1/2008**	**8/8/2008**	X	X		X	X			X	X	X											

? Pending owner-permit the contractor was allowed to work on that non-working day to catch-up with lost progress.
+ Critical activities in the work schedule.
++ Visibility is the percentage of elements that are not fully occluded.

Figure 6.16. Progress reported on RH construction schedule.

6.12 Conclusions

An automated approach for tracking, analysis and visualization of progress using daily site photographs and 4D IFC-based BIMs is presented. In the presented approach, images can have low qualities, yet robustly generate dense as-built point clouds. Subsequently the underlying point cloud is registered with other point clouds as well as the as-planned model, generating an integrated 4D as-built and as-planned model for progress visualization. The as-built and as-planned voxel coloring and labeling algorithm demonstrates high accuracy in labeling of a construction scene for occupancy and visibility. The SVM kernel machine shows promising results in detecting progress. This overall marks the presented approach to be the first of its kind to fully take advantage of already available daily site photographs and 4D IFC-based BIMs for automated progress tracking and analysis. Application of our system is perceived to minimize the time required for as-built data collection and as-planned data extraction; removing subjectivity of progress detection through an automated systematic detection; and finally the interactive visualization to minimize the time required for discussions on coordination of progress possibly leading to a better decision-making for project control. We need to perform more experiments for the underlying technique presented and conduct further research on three fronts:

1. 4D volumetric reconstruction: The proposed reconstruction pipeline show great accuracy but is not yet fully verified. More experiments need to be conducted for reconstruction of indoor environments and steel frameworks as specifically indoor areas are texture-less which potentially makes application of SIFT feature points more challenging. We also need to test the photorealistic reconstruction pipeline on modeling Mechanical/Electrical/Plumbing components of building, given the reflectivity of the surface of some of these elements as well as minimal volume they occupy. The scalability of the algorithm (tradeoff between *thresh* / voxel size) and accuracy of the suggested as-built pipeline to the number of photographs used need to be further investigated.

2. Progress monitoring detection: The model needs to be further enhanced by incorporating surface recognition techniques to detect progress according to operational details. By properly forming P(η^i) (As shown in Figure 15c), we would be able to report progress in finer levels of detail compared to underlying WBS of the IFC model. Stochastic components of error in registration and reconstruction need to be further examined.

3. Progress sequence knowledge: This model does not consider any formalized schedule sequence rationale for monitoring of construction. We will develop a formalized monitoring sequence knowledge based on existing literature (e.g., Koo et al. 2007; Echeverry et al. 1991). Instead of assuming mutually independence between elements for a given construction schedule, we intend to extend our progress detection model to incorporate such sequencing rationale to further count for proper measurement of earned progress given existing dependencies in the actual nature of construction progress.

CHAPTER 7. CONCLUSIONS

7.1 Summary and Contributions

Early detection of actual or potential performance deviation in field construction activities is critical to project management as it provides an opportunity to initiate proactive actions to avoid them or minimize their impacts. This entails project managers to design, implement, and maintain a systematic approach for progress monitoring to *identify*, *process* and *communicate* discrepancies between as-built and as-planned performances as soon as possible. Despite the importance, (1) current monitoring methods require manual as-built data collection and extensive as-planned data extraction; (2) due to extensive workload, observations are sometimes conducted infrequently and progress is measured with non-systematic metrics; and (3) current reporting techniques are also visually complex which requires more time to be spent on communicating the status of a project. Therefore there is a need for a systematic approach allowing data to be collected easily, processing the information automatically and reporting back in a format useful for all project participants.

This research addresses these challenges by introducing D^4AR – 4D Augmented Reality – models as integrated as-built and as-planned environments. These models generated for automated tracking and visualization of construction performance deviations, take advantage of two emerging sources of information: (1) Unordered daily construction photo collections, which are nowadays collected at almost no cost on all construction sites; and (2) Building Information Models (BIMs), which are increasingly turning into binding components of Architecture/Engineering/Construction (AEC) contracts and if linked with construction schedule, can serve as powerful baselines for tracking and visualization of performance deviations. To that extend the main contributions of this research through generating D^4AR models and using the integrated as-built and as-planned environment for automation and visualization of construction performance deviations are as follows:

7.1.1 Integrated visualization of progress monitoring metrics

The augmented reality environment introduced in **chapter 2** can successfully represent progress monitoring information in forms of *as-planned* and *as-built* information along with their *comparison* in a holistic manner. The superimposed images retain all the construction site information while the planned information along with the status of progress is enriching the contextual information within these photographs. The registration method introduced for time-lapse imagery gives the opportunity for image processing techniques to be applied to specific regions within the time-lapsed photograph to assess the status of the progress based on material and shape recognition techniques. Color-coding metaphors give the end users of the superimposed photograph the opportunity of grasping progress status based only on a single representation form and could facilitate the communication of progress status within a coordination meeting, allowing more time to be spent on control decision making. Moreover preliminary results of applying feature detection technique preserves depth and perspective within the superimposed photograph allowing a more realistic picture of the progress status to be represented.

7.1.2 Automated generation of as-built point clouds and supervised registration with building information models

Given a set of unordered and uncalibrated daily construction photographs, a modeling approach based on structure-from-motion is presented which automatically computes- from the images themselves- the photographer's locations and orientations, and generates a 3D point cloud representation of the as-built site. Within such an environment, images are registered in a virtual 3D environment, allowing large unstructured collections of daily photos to be sorted, interactively browsed and explored. Subsequently, 4D BIMs are fused into the as-built point cloud models by a control based registration-step and generate D^4AR models. In these models, all daily construction site photographs are automatically registered with the BIM model, allowing both expected and actual performance to be observed and visualized from all possible angles and viewpoints. The details of this modeling approach are provided in **Chapters 3 and 4**.

7.1.3 Automated registration step for generating 4D as-built point clouds

In order to generate 4D as-built point cloud, an automated approach based on iterative closest point algorithm is presented which automatically registers multiple as-built point clouds over one another. The task of automated registration is particularly challenging since structure from motion techniques are only capable of reconstructing as-built point cloud models up to a certain scale. Such ambiguity in reconstruction requires the registration to incorporate scale as part of transformation as well (7 DOF). Furthermore, since construction photo collections are assumed to be unordered and casually collected, reconstructed point clouds from different point clouds will represent different parts of the construction site with densities. Therefore they may not have consistent parts for automated matching purposes. In addition construction progress changes the appearance of the site and consequently the way point clouds are formed. Therefore as-built point clouds may not have enough overlap. In this research the presented method for automated registration reports high accuracy in automated generation of 4D as-built point clouds. The details of this automated registration step are provided in **Chapter 4**.

7.1.4 Visualization module for integrated representation and exploration of 4D BIMs, photo collections as well as 4D as-built point clouds

In this research, a D^{4}AR viewer is developed which enables as-planned 4D BIM and as-built 4D point clouds models along with their photos to be jointly explored with an interactive, image-based 3D viewer. In such an environment, construction performance metrics are interactively or automatically color-coded over the BIM using a simple traffic-light metaphor.

In this case, all cameras are rendered as frusta. If the user is observing the site through a camera, the back face of the frustum is texture-mapped with full resolution version of the photograph, so that the user can zoom in and observe construction operation in detail. The scene itself is rendered with points where in the color of each point is obtained from all images that observes that point. The viewer also allows transparency of the images to be changes. This function particularly allows see-through from camera frusta which enables the BIM to be observed along with the photo and the point cloud. The as-built data representation introduced in this research allows 3D points in the as-built point clouds to be connected with their re-projections. This further allows new algorithms for automated registration of (1) daily construction reports and (2) construction specifications with site photographs to be developed.

Since an IFC-based BIM schema for representation of as-planned models is used, users can query as-planned information and this further adds value by providing as-planned semantics. This feature enables earned value analysis for progress monitoring as physical progress along with cost and schedule information can be interactively or automatically extracted from BIM. The details of this rendering approach and viewer are provided in **Chapter 4**.

7.1.5 Evaluating application of image-based point clouds for automated progress monitoring techniques and comparing them with laser scanning point clouds

This research presented and compared image-based reconstruction and 3D laser scanning methods for obtaining point cloud models for detection and visualization of as-built status for construction projects. The accuracy and usability of both of these techniques for metric reconstruction, automated production of point clouds, 3D CAD shape modeling and visualization of the as-built scenes were evaluated and compared on eight different case studies. Compared to laser scanning point clouds, it was shown that for precise defect detection or alignment tasks, SfM point clouds automatically reconstructed from daily construction site photographs may not be as accurate and dense as those of the laser scanners nevertheless provide an opportunity to extract semantic information of the as-built scene (i.e., progress, productivity, quality and safety) through the content of the images, are easy to use, do not need add burden on project management teams by requiring expertise for data collection or analysis and automatically provide photo alignment and image-based renderings which can remarkably impact automation and visualization of the as-built scenes. The details of this analysis are provided in **Chapter 5**.

7.1.6 Automated model for tracking, analysis and reporting of physical progress at construction schedule's activity level based on D^4AR models

An automated approach for tracking and analysis of physical progress built upon D^4AR models is presented. In the presented approach, images can have low qualities, yet robustly generate dense as-built point clouds. Subsequently the underlying point cloud is registered with other point clouds as well as the as-planned model, generating an integrated 4D as-built and as-planned model for progress visualization. The as-built and as-planned voxel coloring and labeling algorithm demonstrates high accuracy in labeling of a construction scene for occupancy and visibility. The SVM kernel machine shows promising results in detecting progress. The automated progress monitoring scheme built upon the D^4AR is *the first probabilistic model for progress tracking and visualization of deviations that fully takes advantage of already available daily site photographs and 4D IFC-based BIMs and incorporates both as-planned models and unordered daily photographs in a principled way.*

Unlike other methods that focus on application of laser scanners (Chapter 5 in this dissertation, Bosche 2009) or time-lapse photography (Chapter 3 in this dissertation, Zhang et al. 2009, Ibrahim et al. 2009), this approach is able to use existing information without adding burden of explicit data collection on project management and reports competitive accuracies compared to those reported with laser scanners especially in presence of sever occlusions. The details of this automated progress detection approach along with dense reconstruction are provided in **Chapter 6**.

Overall the experiments conducted in this dissertation demonstrate that D^4AR models report (1) high accuracies in registration; (2) are fully automatically generated; (3) can handle various exterior and interior reconstructions; (4) reasonably work under static and dynamic occlusions; (5) allow interactive color-coding for visualization of different performance metrics; and (6) allow as-planned and as-built information be queried. The automated progress detection model reports competitive accuracies in detecting progress compared to state-of-the-art application of laser scanners (Chapter 5 in this dissertation, Bosche 2009) or time-lapse photography (Chapter 2 in this thesis, Zhang et al. 2009, Ibrahim et al. 2009).

7.2 Practical Implications

In this research, D^4AR models have been generated for seven ongoing construction projects, ranging from 18 to $326 million, spanning over one to three years while geographically spread from Chicago area to Kansas City. These projects are briefly overviewed as an appendix to this dissertation. Observed and perceived implications of these models in overcoming challenges of current progress monitoring practice are as follows:

7.2.1 Virtual walk-through on the as-built scene

D^4AR models allow project managers, project executives, superintendents, subcontractors as well as owners and even architects to remotely access the under construction site and navigate through the as-built scene, and browse through the collection of progress photographs in any given day. Such application can create significant benefits as follow:

1. *Remote Construction Control Decision Making*: It allows project managers, superintendents and other project participants to virtually walk on the construction site, as-of the time the scene has been reconstructed and position themselves in those positions that progress images have been taken. Such an interactive user walk-through allows progress to be discussed remotely without the need of any of those participants to be physically on the jobsite.

2. *Minimizing the time required to discuss the as-built scene*: Project managers and superintendents will spend less amount of time discussing or explaining progress. Rather, they can spend more time on how a control decision could be made, especially because the reconstructed as-built scene and geo-registered images allow workspace logistics, safety issues, progress and even productivity of workforce and machinery to be remotely analyzed. Such an as-built system could also be very beneficial in weekly contractor coordination meeting as the workspace could be navigated through the virtual world, especially once used in conjunction with large screen collaboration tools (e.g., such as smart board used in Golparvar-Fard et al. (2006) or even multi-touch screens (e.g., multi-touch interaction wall of Han (2006))).

3. *Significant cut in travel time and cost on project executives and architects* – Project executives and architects can study the reconstructed scene and geo-registered images, instead of spending time and money to travel to the jobsite. The reconstructed scene with as-built progress images can be very beneficial, especially when the possibility of adding new photographs quickly to the system is considered. Even if a perspective of an interest is not registered within the reconstructed scene and is not present in geo-registered image dataset, the user in the case of being owner and

project executives can request the scene to be photographed. Those photographs taken can also be quickly geo-registered allowing a significant progress communication problem to be resolved.

7.2.2 Visualizing performance deviations

The early motivation behind developing the D^4AR models has been to come up with a mechanism that geo-registers spatial as-built and as-planned models within the same environment allowing construction progress to be measured, analyzed and communicated. To that extent, this dissertation proposed the application of a traffic light color spectrum to be used for visualizing progress (Golparvar-Fard et al. 2009a and Golparvar-Fard et al. 2007). In various case studies conducted and presented in **Chapters 3 and 4**, applications of visualizing performance deviation in forms of progress, productivity, safety, QC/QA and their role in facilitating onsite and remote control decision makings are discussed.

7.2.3 Automated progress tracking

The automated progress tracking presented in this research is promising to automatically track progress with already available information on constructions sites. To that extent, the main problems associated with extensive data collection and analysis for progress monitoring is perceived to be minimized. Furthermore, application of a systematic method for detection of progress removes any subjectivity in the way construction progress is measured and reported. The automated progress detection algorithm reports progress at the construction schedule activity level and this further enables earned value analysis for analyzing construction performance to be conducted. Compared to application of laser scanners (Chapter 5 in this dissertation, Bosche 2009) or time-lapse photography (Chapter 2 in this dissertation, Zhang et al. 2009, Ibrahim et al. 2009) the presented approach reports competitive accuracies, is cheaper, does not need for expertise for operation, does not add new task for project management and captures dynamics of work progress without a need for dealing with mixed pixel phenomena (Kiziltas et al. 2008). Compared to the application of photogrammetric techniques, all steps in the presented system are automated. Considering frequency of monitoring observations and the need for real-time tracking and analysis of progress, application of D^4AR models for automated progress monitoring becomes more attractive.

7.2.4 Application of the D^4AR models for interior progress monitoring

One of the major applications of the D^4AR is for tracking progress of interior components. If enough photographs are taken to connect exterior photographs' path to those of interior, the presented modeling approach could be efficiently used for tracking interior spaces as well. As such, visualizing progress of MEP/FP (Mechanical-Electrical-Plumbing/Fire Protection) systems will also become possible. For such application, short focal length lenses or wide angle lenses are perceived to be used further allowing short distances to be captured as well.

7.2.5 Registering new daily site photographs

New construction progress photographs can be incrementally added to the reconstruction (the as-built model) so as to update the model without the need to redo the whole reconstruction. First, a user can open a set of progress images, and drag and drop each image onto its approximate location on the as-built model. After each image has been dropped, the proposed system estimates the location, orientation, and focal length of the new photo by running a version of the structure from motion algorithm. In a similar fashion first, SIFT keypoints are extracted and matched to the keypoints of the cameras closest to the initial location; then the existing 3D points corresponding to the matches are identified; and finally, these matches are used to refine the configuration of the new camera. After a set of photos has been dragged onto the environment, it generally takes in order of seconds to optimize the parameters for each new camera.

This functionality particularly becomes handy as project managers, project executives or site inspectors can request particular locations on the construction site to be photographed in proper details enabling them to conduct various decision making tasks remotely without the need to spend extensive time on processing information.

7.2.6 Augmented reality occlusion removal

One of the perceived applications of geo-registered photograph is for occlusion removal. Occlusion within augmented reality systems changes the perspective of the virtual model and real world possibly causing confusion. A practical example of how occlusion may cause misperception was presented in Figure 3.20. As seen in Figure 3.20, the footing and pier highlighted appear in front of the temporary electricity box on the jobsite, but in reality they should be located behind the box. Note that the registration error in this image is minimal, especially when the accuracy of registration of the virtual foundation walls over actual foundation walls is perceived. Such occlusions may create confusions. This dissertation suggests two solutions for such cases:

- Since in the D^4AR environment each component has the chance of being observed in a subset of images, user can study each component from different perspectives which will remove all potential confusions on depth and/or perspective.
- Since each image in the D^4AR is geo-registered and intrinsic and extrinsic camera parameters are known, cameras are all calibrated. This information helps to extract geospatial information of certain components and allows occlusions to be removed through rendering the image patch associated with that component over the 3D model.

7.3 Future Work

The research presented in this research contributed to developing the conceptual and mathematical foundations necessary to generate augmented reality imagery which combine unordered construction site photographs with Building Information Models. More specifically a 4-dimensional augmented reality environment for joint representation of as-built and as-planned models as well as automated progress tracking is developed in this research. This is an important contribution in the fields of visual sensing of construction operations and building information modeling as for the first time, it allows all site photographs captured from different angle and perspectives to be automatically registered with building information models. This in turn forms consistent perspectives from which as-planned and as-built models to be jointly analyzed. This in particular enhances application of building information models during the construction phase as it reduces the amount of work required to generate as-built models and site periphery. In the meantime, joint representation of as-built and as-planned models enables various semantics to be queried from underlying building information models, and model-based recognition systems for improving productivity, safety, quality and even measurement of carbon footprint of construction operations be developed. The conducted research uncovered several issues that needed to be addressed with respect to construction progress monitoring for interior spaces as well as MEP/FM elements. Integrating development and consistent application of D^4AR models by project participants is also unexplored. Thus, some of the future research plans are presented here below.

7.3.1 Automated operation–level progress monitoring using D^4AR models

The D^4AR model is currently able to measure physical progress, however it does not recognize materials and therefore, it cannot differentiate operation processes beyond level-of-detail presented in construction schedule or the Work-Breakdown-Structure (WBS). It is also not fully tested at interiors and is not tested for MEP components. Nonetheless, in early works with time-lapsed images (Chapter 2 in this dissertation), the focus was on recognition of materials given their appearance changes, which is a function of the construction site layout as well as position of the observer. Furthermore, progress tracking beyond the schedule or the underlying WBS of the BIM has an intrinsic ambiguity that might be resolved by high level reasoning. Nonetheless, we can take advantage of pattern recognition techniques to classify observations, identify materials, extract features that allow small-size or reflective components (e.g., MEP and curtain wall elements) to be detected. It consequently synthesizes such information with physical progress detection. One future research direction will be to unveil the mechanism that allows computer vision to recognize and interpret progress for all types of elements and at finer level-of-details than the underlying WBS + Schedule.

The main hypothesis for this proposed research is that extracting semantics from visual imagery can enhance the level of detail that could be tracked with the current D^4AR models. The current automated progress detection model can be further enhanced by incorporating surface recognition techniques to detect progress according to operational details. By properly forming $P(\eta^i)$ (As shown in Chapter 6 of this dissertation), we would be able to report progress in finer levels of detail compared to underlying WBS of the Industry Foundation Class (IFC)-model. The following questions particularly need to be answered: *(i)* How and to what extend we can recognize progress given unordered daily photologs?; *(ii)* What is the role of observation proximity to accuracy of detection?; *(iii)* How can we transform the underlying BIM to consequently form a robust model-based recognition?; *(iv)* How can we integrate appearance-based visual features with D^4AR models and consequently form more accurate construction progress detection models?

7.3.2 Integrating progress sequence knowledge to the automated progress detection model

The presented model for automated progress detection does not consider any formalized schedule sequence rationale for monitoring of construction and therefore in cases with low visibility and significant occlusion cannot perform well. Further research should focus on developing formalized monitoring sequence knowledge based on existing literature (e.g., Koo et al. 2007; Echeverry et al. 1991). Instead of assuming mutually independence between elements for a given construction schedule (as in Chapter 6 of this dissertation), the proposed progress detection model in this research needs to be extended to incorporate such sequencing rationale to further count for proper measurement of earned progress given existing dependencies in construction progression.

The main hypothesis for this proposed research is that construction sequencing constraints can be represented along with building information models to enable progress rationale to be described accurately. This research should focus on describing formalized process that utilizes the representation and classification mechanism to generate a rationale model and consequently report progress for occluded and low-visibility elements correctly and accurately.

7.3.3 Improved reconstruction of as-built sites including civil infrastructure systems, building interior spaces as well as Mechanical/Electrical/Plumbing components

The proposed reconstruction pipeline in this research reports high accuracy in reconstructing exterior and non-reflective construction elements but is not yet fully verified. More experiments need to be conducted to address the following needs and challenges:

(1) Photorealistic reconstructions of indoor environments and steel frameworks as specifically indoor areas and steel frameworks are texture-less and in cases have reflective surfaces which potentially make application of SIFT feature points used in this study more challenging.
(2) The current algorithms developed for D^4AR modeling, as the number of images increase for each dataset, computation time grows exponentially. This is mostly due to the pair wise matching step in the proposed structure-from-motion matching algorithm. In order to address this issue, further research needs to investigate using GPS-camera photographs to tag photos based on their *approximate* locations and group them to minimize the number of pair wise matches and consequently decrease computational time.
(3) In reconstructing a complete construction site with all details, one key challenge will be *scalability* of the developed algorithms. In particular, how reconstruction algorithms can be devised to generate D^4AR models for large civil infrastructure systems or building projects and operate with thousands of images?

In this future proposed research the reconstruction pipeline will be further tested for modeling civil infrastructure systems with particular application in asset management; interior spaces given their texture-less surfaces and finally Mechanical/Electrical/Plumbing components of building, given the reflectivity of the surface of some of these elements as well as minimal volume they occupy. The scalability of the algorithm (tradeoff between *thresh* / voxel size) and accuracy of the suggested as-built pipeline to the number of photographs used will be further investigated.

The main hypothesis for this proposed research is that more robust feature detection and matching algorithms could enable reconstruction of reflective and texture-less surfaces, aligning images through significant progress changes in seasons and weather conditions, registering architectural renderings with actual photographs of the site as well as robust matching using low-quality (e.g., cell phone camera) devices. Introducing parallel computation to the structure-from-motion stage of reconstruction algorithm can significantly lessen the computational time and allow large scale civil infrastructure systems as well as buildings to be constructed. Finally, introducing Manhattan-world assumption (Coughlan and Yuille 1999) which states that majority of finished architectural surfaces are aligned with 3-dominant axes can provide strong prior for robust reconstruction of interior spaces.

7.3.4 As-built shape modeling for automated generation of as-built BIMs

The latest as-built reconstruction pipeline developed in this dissertation results in promising dense point-clouds that can be further processed with parametric shape modeling techniques to generate as-built CAD models. These models augmented by materials sensed through pattern recognition and trained with machine learning techniques can form as-built BIMs. Currently only a few constructed facilities have a complete record of their as-built information. This line of research can automatically generate entirety of the as-built BIMs. The major contribution in this work will be to automate several processes that need currently need manual human operations.

In addition to application of as-built BIM models for generating records of buildings, similar to point cloud presentation in D^4AR models, these models allow expected and actual observations to be compared. This has particular application for rapid disaster managements. In disaster situations, information needs to be rapidly collected. Building upon current research with Mobile Workstation Chariot (MWC) (Golparvar-Fard et al. 2010b), the feature research will focus on devising a systematic approach to collect and transmit visual data in real-time and communicate those with remote servers for post-disaster site reconstruction and damage assessments. Within context of critical physical infrastructures, this research particularly will focus on a scientific approach for *(i)* generating post-disaster BIM models and *(ii)* automatically *compare pre* and *post-disaster structures* for stability and rescue operations.

The main hypothesis for this proposed research is that using spatial and visual data collected through construction site imagery, as-built parametric BIMs can be generated. Analyzing (1) geometric of construction surface and texture information simultaneously against an established taxonomy of construction materials, shapes and forms as well as (2) relationship of construction elements to one another, is likely to generate representations that can be used for classification of common building components into corresponding object categories.

In the context of disaster management, the main hypothesis for this proposed research is that using spatial and visual data collected with mobile workstation chariot allows post-disaster models to be rapidly generated. These models can be compared with pre-disaster models and automatically identify missing/ damaged element, further facilitating response and recovery operations.

7.3.5 Automated integration of textual construction reports and specifications with site imagery

In chapters 3 and 4 of this dissertation, it was indicated that the correspondence between 3D reconstructed points and their reprojections over site imagery is currently preserved in the proposed as-built data representation. Using such information, further research investigates automated linking of text-oriented information (daily construction reports, construction details, as well as request for information, request for proposals as well as architectural supplementary information) to daily site images using point cloud representation.

The main hypothesis for this proposed research is that linkage between construction reports and site imagery provides spatial information to be accompanied with textual information. Such integrated environment can significantly facilitate on-site data collection and analysis. It can further benefit facility management as it allows operation information to be automatically associated with imagery and in turn facilitate documentations on operation and management of large and complex facilities.

7.3.6 Immersive visualization of D^4AR models

Throughout this dissertation, theory, design and evaluation of D^4AR model were presented. AEC professionals can use D^4AR models to improve current capabilities in progress monitoring and overcome limitation of work processes. However potential of such interactive graphics in support of decision-making tasks needs to be well studied. Another future research approach will focus on integrating D^4AR models into immersive automatic virtual environments (CAVEs), allowing as-built and as-planned models to be jointly represented in real-dimensions. Currently many AEC professionals need to be collaborating on projects while they are geographically spread in different locations. This affects the frequency by which they will be able to inspect projects for safety, quality, and compliance with architectural and structural details. Virtual walk through in immersive caves and cubes not only allows AEC professionals to bring projects to their workspaces, but also navigate through them both spatially and temporally.

The main hypothesis for this proposed research is integrating D^4AR models into CAVEs increases the frequency by which on-site inspections for progress, productivity, safety and quality can be conducted. Expending formal decision-making assessment frameworks such as (Golparvar-Fard et al. 2006) allows the value-added of these technologies to be practically assessed.

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APPENDIX I: CONSTRUCTION PROGRESS MONITORING CASE STUDIES

In this appendix, the application of D^4AR system is demonstrated in seven different case studies. These case studies formed proper test beds for experimentation of this innovative technology for progress monitoring and allowed rigorous, practical and replicable tests to be performed and the innovative technology to be validated. These case studies also demonstrate the integration of education, research and industry tiers and demonstrate how academic and industry can mutually benefit from such partnerships. These case studies/ test beds include (1) Student Dining Hall Project- Champaign, IL, (2) Residence Hall-A Project – Champaign, IL, (3) College of Business Instructional Facility – Champaign, IL, (4) Kauffman Center of Performing Arts, Kansas City, MO, (5) Micro and Nanotechnology Extension Laboratory, Urbana, IL, (6) Institute of Genomics Biology, UIUC Campus, Champaign, IL, and (7) Jewel Osco Market Store located in Sugar Grove, IL.

Availability of different projects allows the developed system in this research to be tested on various types of structures from steel to concrete as well as sophisticated joint steel-concrete structures. These projects range from $ 18 million to $326 million which are constructed over a span of a year to two and a half years. Here, from practical implications point-of-view, it is shown how these site photograph logs present an ultimate data set for progress monitoring, giving the ability to model a significant portion of as-built geometry at high resolution respective to conditions where enough photographs are being taken. In the sections that follow each project will be briefly introduced, the types of collected data in forms of as-planned and as-built representation are discussed. Furthermore the application of the D^4AR model is demonstrated and the benefits and challenges of generating and using the innovative D4AR model are shown.

Case Study 1- Student Dining Hall Project- Champaign, IL

Project description

This new facility will replace two existing dining facilities on the campus of the University of Illinois at Urbana-Champaign. The project consists of a 139,327 S.F. 2-story masonry and curtain-wall building with a partial basement. This project is $36M steel frame with composite decking for about 25 month of scheduled work. The facility will feature a marketplace dining concept incorporating multiple food stations that provide a variety of cuisines and late-night dining options. It will be flexible enough to meet future dining trends and accommodate special student programs and events. This facility has been programmed to address the varied needs of 3,600 students. It will be the largest dining facility on the

UIUC campus and one of the largest university dining facilities in the country. Work includes connections to site utilities as indicated on drawings, including steam and condensate, sanitary and storm, chilled water, telecommunications, and electrical service. Work on this project is required to coordinate with work of Residence Hall – a separate project located on the same construction site - “link” stair enclosure, which is completely under separate contract. The project is required to be LEED certified with a Silver rating.

As-Planned and as-built progress data collection

The Data required and collected for progress monitoring and application of D^4AR model in this project falls into two categories:

(1) As-Planned Data: In order to properly set the baseline for progress monitoring, the building drawings, their cost estimates and construction schedule have all been collected. Based on the architectural and structural drawings, the as-planned 3D model was generated and link to the construction schedule to visualize the as-planned progress. Figure 1 shows two snapshots of the complete 3D model demonstrating how the building would look like when the project is complete.

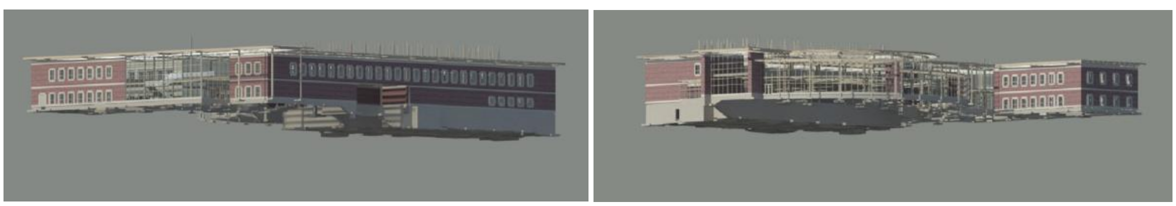


Figure 1. Snapshots of the IFC-based 3D model generated for the Student Dining Hall Project. Drawings used to generate the 3D model courtesy of the University of Illinois, Urbana-Champaign’s Facilities and Services; Used by permission.

(2) As-Built Data: The field engineer has constantly tracked the actual progress on the site. In order to thoroughly and systematically track design related issues RFIs (Request for Information), RFPs (Request for Proposals) as well as ASIs (Architects Supplemental Instructions) have all been collected and studied. To track the actual cost, CSVs (Contractor Schedule of Values) as well as all the contractor billings have been thoroughly collected and studied as well. Furthermore, the field engineer has actively been in charge of daily, weekly, and monthly progress reports. Based on all the reports collected and the actual progress observed, construction schedule has been revised on a monthly basis and all the revisions of the schedule are monitored and collected as well. The actual physical progress has been constantly estimated using the 3D model generated during the preconstruction stage and used for checking concrete billings as well as an appendix to Daily Construction Reports to the owner. Figures 2 and 3 demonstrate snapshots of

the 3D model highlighting concrete placements as well as an exemplary appendix to the Daily Construction Reports.

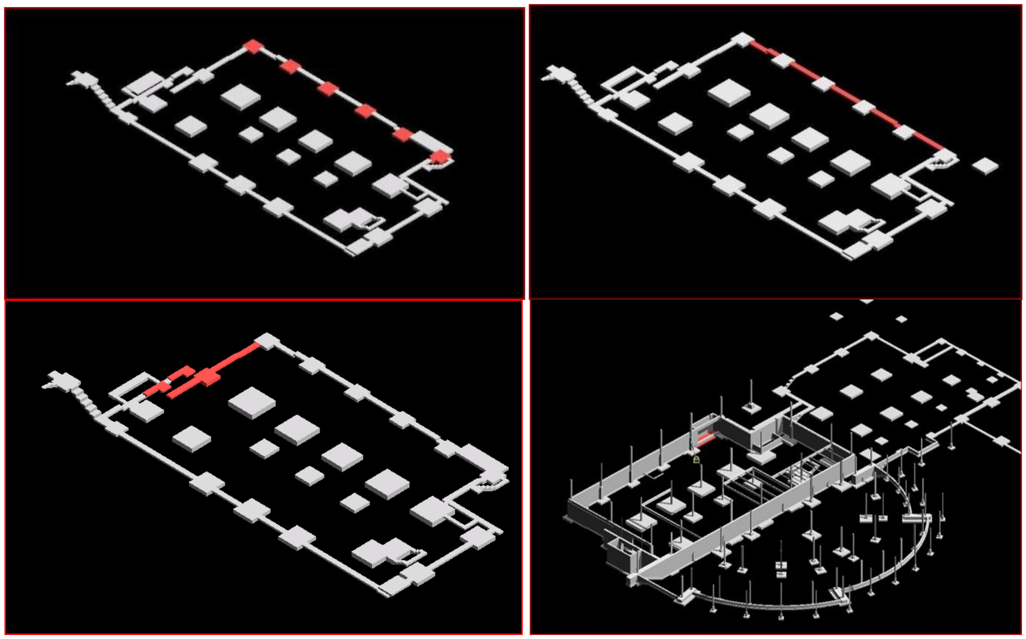
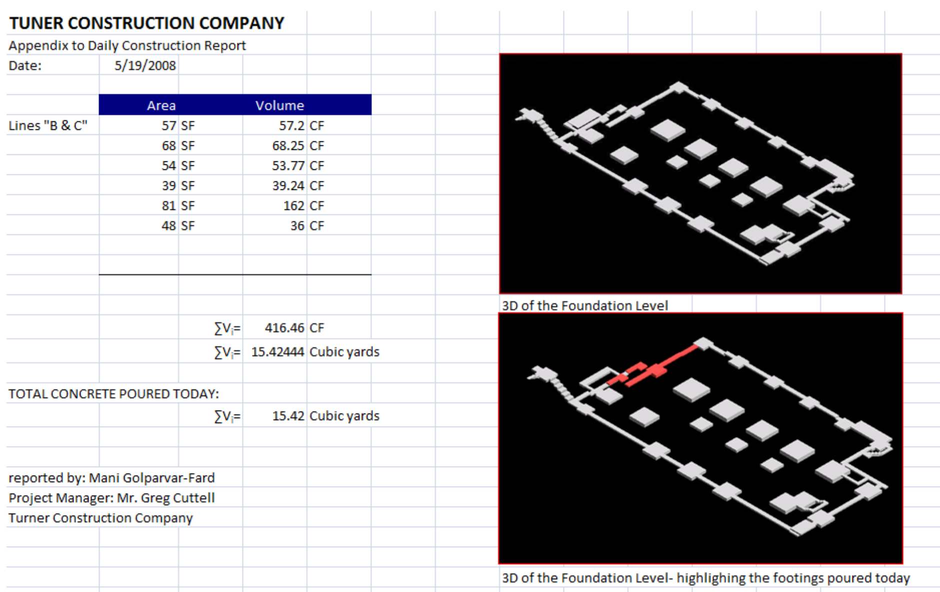


Figure 2. Snapshots of the IFC-based 3D model generated for the Student Dining Hall Project demonstrating the concrete placements: On a clockwise order placements made on 05/01/08, 05/06/08, 05/12/08, as well as 05/19/08.



TUNER CONSTRUCTION COMPANY

Appendix to Daily Construction Report

Date: 5/19/2008

	Area		Volume	
Lines "B & C"	57	SF	57.2	CF
	68	SF	68.25	CF
	54	SF	53.77	CF
	39	SF	39.24	CF
	81	SF	162	CF
	48	SF	36	CF

$\sum V_i =$ 416.46 CF

$\sum V_i =$ 15.42444 Cubic yards

TOTAL CONCRETE POURED TODAY:

$\sum V_i =$ 15.42 Cubic yards

reported by: Mani Golparvar-Fard
Project Manager: Mr. Greg Cuttell
Turner Construction Company

3D of the Foundation Level

3D of the Foundation Level- highlighting the footings poured today

Figure 3. Snapshot of an appendix to the Daily Construction Reported generated for concrete placement on 05/19/08. As demonstrated the placement was estimated to be 15.42 cubic yard. This report was used for double checking the placement reported by the concrete bid-package contractor.

As mentioned, photographs have also been collected on a daily basis for progress and safety monitoring, constructability analysis, as well as site logistical purposes. Rather than only taking photos from specific locations or progress within the day, scenes that capture overall depiction of the construction site are captured as well. During the experiment a high-resolution SLR camera was carried. The choice of a high resolution camera was based on the possibility for further enhancement of the algorithm so the quality of the images could be synthetically reduced and the keypoint detection could be tested on synthetically lowered resolution images. To assure the availability of data for further analysis, a larger number of photos than average (about 200/day) have been collected to allow more commonalities between images to be detected. Figure 4 shows a subset of daily progress photographs taken on 07/01/08 from the Student Dining Construction Project. Figure 5 shows the existing tools of reporting perceived progress in a coordination meeting at Student Dining Hall project under study.

Figure 4. A Subset of daily progress photographs taken on Student Dining Construction Project. Photos Taken on 7/1/2008. Images courtesy of Turner Construction Co., used by permission.

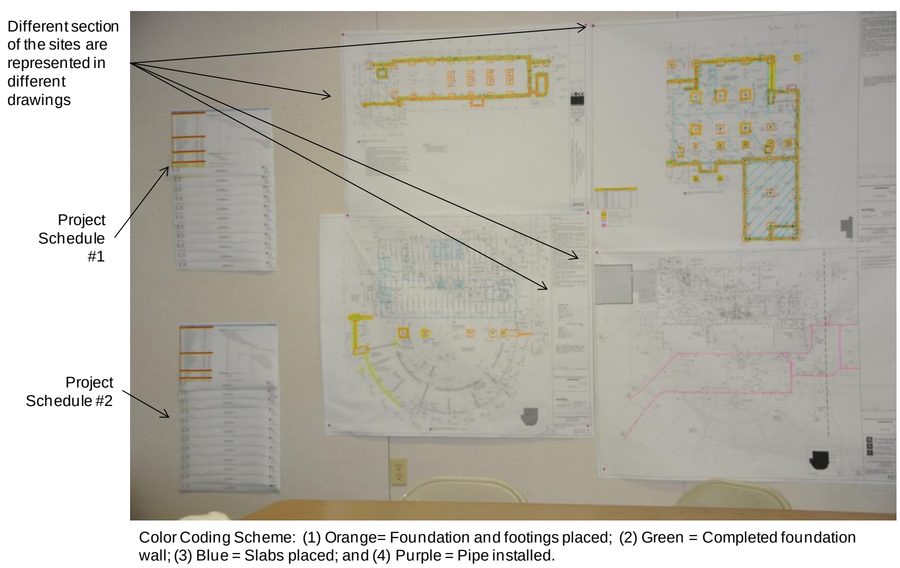


Figure 5. Existing progress reporting and visualization; Construction drawings and work schedules are hung on a wall in a construction site trailer to communicate progress with contractors and subcontractors. Progress is visualized in two-dimensional drawings using annotations and color-coding. The date on which progress have been completed on each component set is also annotated. The different level plans are hung over each other.

In the section that follows, the application of D^{4}AR model is presented. In the proposed system, a sparse 3D geometric scene of the site is reconstructed and progress photographs are geo-registered in a virtual environment. This allows project managers to interactively and remotely browse and explore as-built scene and geo-registered site construction photographs in a 3D environment. We show from the stand point of progress monitoring, how these site photograph logs present an ultimate data set, giving the ability to model a significant portion of as-built geometry at high resolution respective to conditions where enough photographs are being taken. Within the proposed platform, automatic 3D recognition techniques could be developed to quantify as-built progress from the geo-registered images. We present our results on Student Dining Hall project and further discuss benefits of implementing this new technology for generating and visualizing as-built scenes.

Application of D^{4}AR environment for progress monitoring

The main motivation of involvement in this project was to gather required data for developing D^{4}AR system and come up with a system that geo-registers spatial as-built and as-planned information within the same environment allowing construction progress to be measured, analyzed and communicated. To that extent, Figure 6 shows the sparsely reconstructed scene of Student Dining Hall project where 288 images with 25% of image qualities were used for the reconstruction of the as-built scene. As shows six camera frusta are rendered and geo-registered.

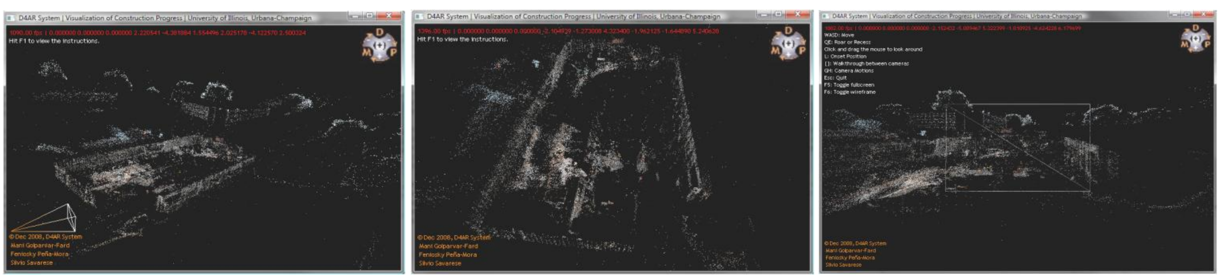


Figure 6. Sparsely reconstructed scene of Student Dining using 288 images with 25% of image qualities. Six camera frusta are rendered and geo-registered.

The availability of various perspectives of planned model, as-built cloud and site images brings a new set of application for the proposed system:

(1) *Facilitating Schedule Revision*: The underlying basis of the system which visualizes the 4D-planned model allows look-ahead schedule to be studies seamless of special configurations. Based on the observation of progress performance (form the cloud and image perspective), control decisions can be made, schedule be revised and look-ahead revised schedule to be further analyzed. Figures 7 and 8 demonstrate the application of 4D model and the superimposed model over an image visualizing progress and the foreseen work sequence.

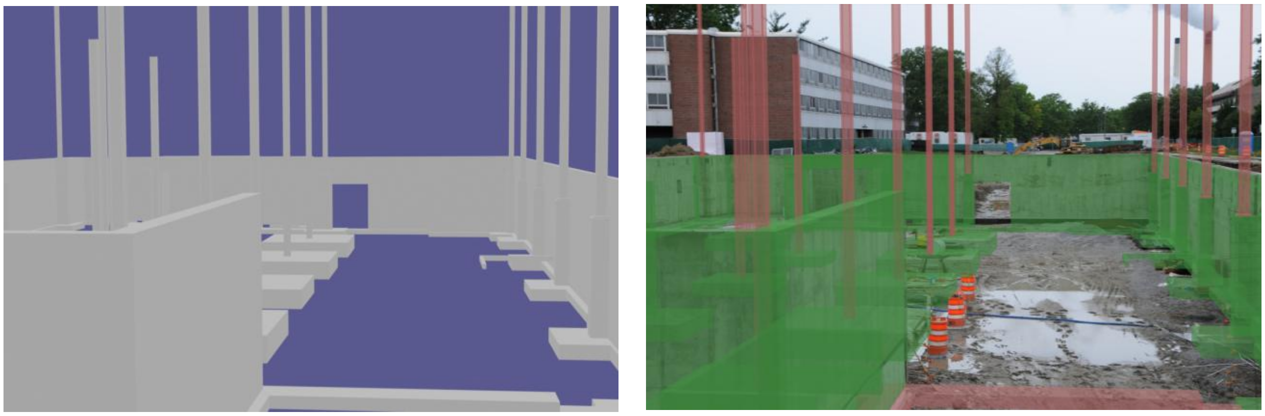


Figure 7. The snapshot of the 4D model and the superimposed model over an image visualizing progress. (Image taken on 7/7/2009, Student Dining Hall Project, Turner Construction Co.). Due to excessive precipitation over summer, the project was behind schedule and this affected the progression.

Figure 8. Snapshots of the 4D model superimposed over site images visualizing basement construction components as well as steel columns. (Images are courtesy of Turner Construction Co., used by permission).

(2) *Remote Monitoring of As-Built Construction*: The system without the planned model allows project managers, superintendents and other project participants to virtually walk on the construction site, as-of the time the scene has been reconstructed and position themselves in those positions that progress images have been taken. Such an interactive user walk-through allows progress to be discussed easily and quickly.

(3) *Minimizes the time required to discuss the as-built scene*: Project managers and superintendents will spend less amount of time discussing or explaining progress. Rather, they can spend more time on how a control decision could be made. Furthermore reconstructed as-built scene and geo-registered images allow workspace logistics, safety issues, progress and even productivity of workforce and machinery to be

remotely analyzed. Such an as-built system could also be especially beneficial in weekly contractor coordination meeting as the workspace could be navigated through the virtual world.

(4) *Significant cut in travel time and cost on project executives and architects* – Project Executives and architects can study the reconstructed scene and geo-registered images, instead of spending time and money to travel to the jobsite. The reconstructed scene with as-built progress images can be beneficial, especially when the possibility of adding new photographs quickly to the system is considered. Even if a perspective of an interest is not registered within the reconstructed scene and is not present in geo-registered image dataset, the user in the case of being owner and project executives can request the scene to be photographed. Those photographs taken can also be quickly geo-registered and this allows a significant problem of progress communication to be resolved.

(5) *D^4AR System- 4 Dimensional Augmented Reality Tool* - This system could also be used as an Augmented Reality tool wherein geo-registers spatial as-built and as-planned information within the same environment allowing construction progress to be measured, analyzed and communicated. To that extent, authors have proposed the superimposition of 3D model over point cloud and using traffic light color spectrum to be used for visualizing progress (Golparvar-Fard et al. 2009). One of the other observed applications of visualizing deviation of progress is to facilitate onsite progress discussion. In the Student Dining and Residence Hall project, the authors came up with a D^4AR superimposed image (Figure 9), highlighting the building foundation which was misinterpreted by the concrete subcontractor.

This image has been used by project manager and superintendent to communicate the component under attention to concrete superintendent and foreman. The poor architectural/structural details respective to this element miscommunicated the scope of this foundation and the foreman interpreted construction drawings in a way that it was not required to be constructed.

(6) *Automatic progress tracking*- Since this model geo-registers construction site photographs, it could serve as a rich baseline for automating progress monitoring through consistent visual detection of progress and comparison with as-planned information. Authors' have tested the system for automatic tracking but this component is not in scope of this chapter.

(7) *Registering New Progress Images*- New progress photographs can be instantly registered within the system. First, the user can open a set of progress images, and drag and drop each image onto its

approximate location on the as-planned model. After each image has been dropped, the system estimates the location, orientation, and focal length of each new photo by running a reduced version of the SfM algorithm. First, keypoints are extracted and matched to the keypoints of the cameras closest to the initial location; then the existing 3D points corresponding to the matches are identified; and finally, these matches are used to refine the pose of the new camera.

The middle section highlighted in red color needs to be constructed.

Figure 9. The superimposed photo visualizing the component which has been misinterpreted by the carpenter foreman. Student Dining and Residence Hall project, Image courtesy of Turner Construction Co., Used by permission).

(8) *Augmented Reality Occlusion Removal*- One of the perceived applications of geo-registered photograph is for Occlusion removal. Occlusion within Augmented Reality systems changes the perspective of virtual model and real world and may cause confusion. A practical example of how occlusion may cause misperception is presented in Figure 10. As seen, the footing and pier highlighted appear in front of the temporary electricity box on the jobsite, but in reality they should be located behind the box. Note that the registration error in this image is minimal, especially when the accuracy of registration of the virtual foundation walls over foundation walls in the photograph is studied. Such occlusions may bring misperception for however studies this single image. We suggest two solutions:

- Since in D^4AR environment each component has the chance of being visualized in a couple of images, user can study the element from a couple of different vantage points and that will correct depth understanding.

- Since each image in D^4AR is geo-registered and intrinsic and extrinsic camera parameters are known, camera is calibrated. This information helps to extract geospatial information of certain objects and allows occlusion removal through replacing objects back on the image.

Figure 10. As-built model superimposed over the progress photograph. Student Dining and Residence Hall construction project in Champaign, IL. Images used are courtesy of Turner Construction (Used by permission).

Case Study 2- Residence Hall-A Project – Champaign, IL

Project description

The Residence Hall Project includes construction of a new 58,000 SF four-story Residence Hall-A with basement. The building is of cast in place concrete frame with brick and curtain wall enclosure. This project is scheduled to be performed within a 21 month period and the construction cost is approximately $15M. Work includes connections to site utilities as indicated on drawings including sanitary and storm, chilled water, telecommunications, and electrical service. Work on this project is required to coordinate with the work on the Student Dining and Residential Programs building and site development work under separate contract (introduced in the previous section). Work on this project is also required to coordinate with work of the Site Utility Relocation project under separate contract (The third project happening on the same time affecting both Student Dining Hall as well as Residence Hall projects. When completed, the Residence Hall A will be occupied, in part, by students enrolled in UIUC's Beckwith Program, a residential support program for students with severe physical disabilities. The project is required to be LEED certified with a Silver rating.

As-planned and as-built progress data collection

As mentioned previously the author of this dissertation has been working on this project as a field engineer with the construction management team and had full access to all progress and productivity information. The Data required and collected for progress monitoring and application of D^{4}AR model falls into two categories:

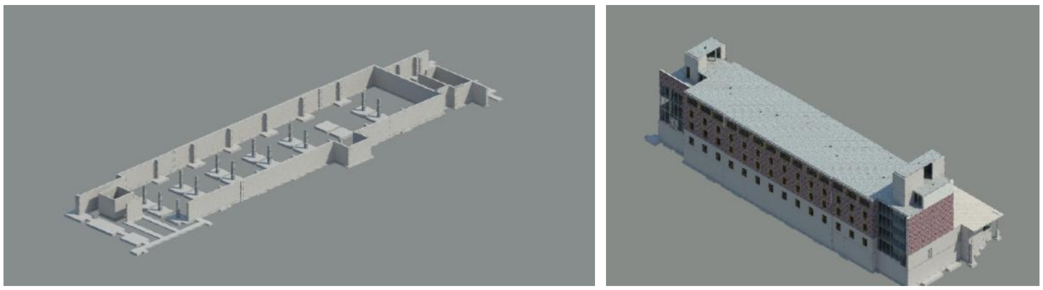


Figure 11. Snapshots of the IFC-based 3D model generated for the Residence Hall Project. Drawings used to generate the 3D model courtesy of the University of Illinois, Urbana-Champaign's Facilities and Services; Used by permission.

(1) As-Planned Data: In order to properly set the baseline for progress monitoring, the building drawings, their cost estimates and construction schedule have all been collected. Based on the architectural and structural drawings, the as-planned 3D model was generated and link to the construction schedule to visualize the as-planned progress. Figure 11 shows two snapshots of the complete 3D model demonstrating how the building would look like when the project is complete.

(2) As-Built Data: The same as Student Dining Hall project, field engineer has constantly tracked the actual progress on the site. In order to thoroughly and systematically track design related issues RFIs (Request for Information), RFPs (Request for Proposals) as well as ASIs (Architects Supplemental Instructions) have all been collected and studied. To track the actual cost, CSVs (Contractor Schedule of Values) as well as all the contractor billings have been thoroughly collected and studied as well. Furthermore, the field engineer has actively been in charge of daily, weekly, and monthly progress reports. Based on all the reports collected and the actual progress observed, construction schedule has been revised on a monthly basis and all the revisions of the schedule are monitored and collected as well. The actual physical progress has been constantly estimated using the 3D model generated during the preconstruction stage and used for checking concrete billings as well as an appendix to Daily Construction Reports to the owner. Photographs have also been collected on a daily basis for progress and safety monitoring, constructability analysis, as well as site logistical purposes. Rather than only taking photos from specific locations or progress within the day, scenes that capture overall depiction of the

construction site are captured as well. During the experiment a high-resolution SLR camera was carried. The choice of a high resolution camera was based on the possibility for further enhancement of the algorithm so the quality of the images could be synthetically reduced and the keypoint detection could be tested on synthetically lowered resolution images. To assure the availability of data for further analysis, a larger number of photos than average (about 200/day) have been collected to allow more commonalities between images to be detected. Figure 12 shows a subset of daily progress photographs taken on 07/01/08 from the Student Dining Construction Project.

Figure 12. A Subset of daily progress photographs taken on Residence Hall-A Project. Photos Taken on o7/1/2008. Images courtesy of Turner Construction Co., used by permission.

Figure 13 demonstrates a series of snapshots of the reconstructed as-built scene for the Residence Hall project. Figure 13- a & b show the reconstructed sparse scene from the same image subset and illustrated 6 of the registered cameras. Once a camera is visited in this reconstructed scene, the camera frustum is texture-mapped with a full resolution of the image so user can zoom in and acquire progress and productivity details as well as workspace logistics. Figure 13 – c, d, e and f show the location of a frustum textured while demonstrating how the site image is geo-registered with the as-built point cloud.

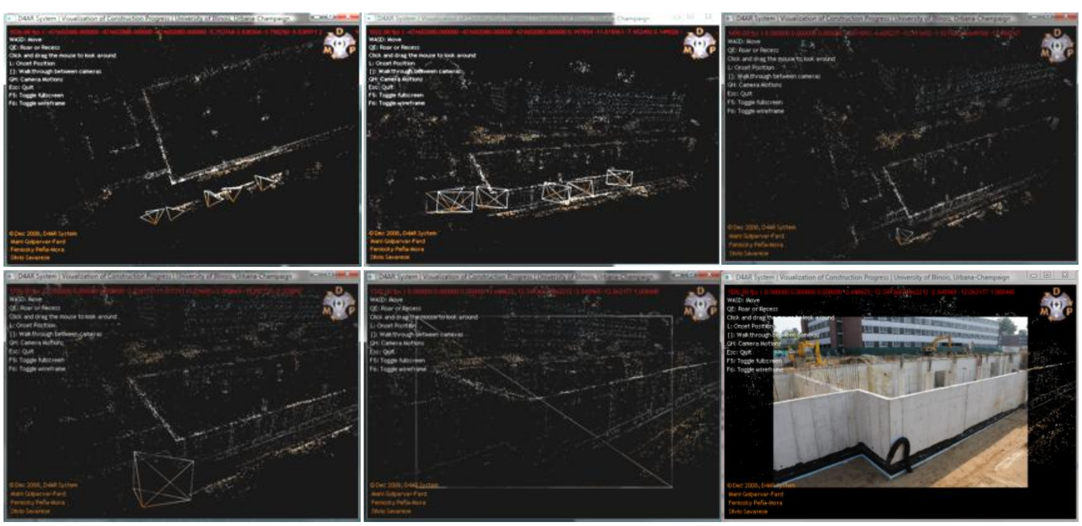


Figure 13. Sparsely reconstructed scene of Residence Hall using 52 images with 25% of image qualities. Six camera frusta are rendered and geo-registered.

Case Study 3- College of Business Instructional Facility – Champaign, IL

Project description

College of Business Instructional Facility is designed by Cesar Pelli and Associates. This Silver LEED facility provides 160,000+ SF of space to accommodate state-of-the-art classrooms, career development and academic counseling centers, student program offices, a recruitment suite, a 300-seat auditorium, as well as a space for students to meet and study. The estimated project budget was $62 million and the design and construction started on 14 Jan 04 scheduled to be finished by 13 Apr 08. The building was officially inaugurated on 24 Aug 08 while minor construction work was yet left to be done. Here is the design and project team:

- *Design Architect:* Cesar Perlli and Associates,
- *Architectural/Structural/Civil:* PSA - Dewberry
- *Mechanical/ Electrical Engrg:* KJWW Engineering Consultants
- *Environmental Engineer:* Atelier Ten
- *Landscape Architects:* Wolff Landscape
- *Acoustical Engineers:* Acentech Incorporated
- *Lighting Design:* Clanton & Associates
- *Construction Manager:* Gilbane Construction

As-planned and as-built progress data collection

The author was involved in this project from the very beginning with contacting the construction management team. The Data required and collected for progress monitoring and application of D^4AR model falls into two categories:

(1) As-planned Data: In order to properly set the baseline for progress monitoring, the building drawings, their cost estimates and construction schedule have all been collected. Based on the architectural and structural drawings, the as-planned 3D model was generated and link to the construction schedule to visualize the as-planned progress. Figure 14 shows two snapshots of the complete 3D model demonstrating how the building would look like when the project is complete.

Figure 14. Snapshots of the IFC-based 3D model generated for the Residence Hall Project. Drawings used to generate the 3D model courtesy of the University of Illinois, Urbana-Champaign's Facilities and Services; Used by permission.

Figure 15 also visualizes two snapshots of the 4D model generated for this project which are overlaid on time lapsed photographs taken from a fixed location during the construction.

Figure 15**.** Two snapshots of the 4D model overlaid on time lapsed photographs during the simulated construction, UIUC College of Business Instructional Facility.

(2) As-Built Data: In order to thoroughly and systematically track design related issues RFIs (Request for Information), RFPs (Request for Proposals) as well as ASIs (Architects Supplemental Instructions) have all been collected and studied. To track the actual cost, CSVs (Contractor Schedule of Values) as well as all the contractor billings have been thoroughly collected and studied as well. The revised construction scheduled (23 revisions) have all been collected and used for progress analysis.

Photographs have also been collected on a daily basis for progress and safety monitoring, constructability analysis, as well as site logistical purposes. For this project, photographs have been collected in two different methods: (1) from a fixed location close to the site, an installed camera had constantly taken photos (1 picture/minute) during the regular working hours (7AM to 6PM). All these photos completely visualize the project progress from the excavation stage to the completion of the project. Figure 16 shows three time-lapsed photographs that were collected during the project.

Figure 16**.** The time-lapsed progress photographs of college of Business Instructional Facility taken form a fixed camera installed on the site.

In addition to taking photos from a fixed location, daily construction progress photographs taken by the contractors were all collected. The research team at the University of Illinois visited the job site on a weekly basis and a series of images from various angles on the perimeter of the building were collected. Figure 17 shows a series of the images taken from different locations close to the auditorium under construction. It also shows the rendered image of the as-planned model demonstrating the architect's vision in conjunctions with the images taken on the site.

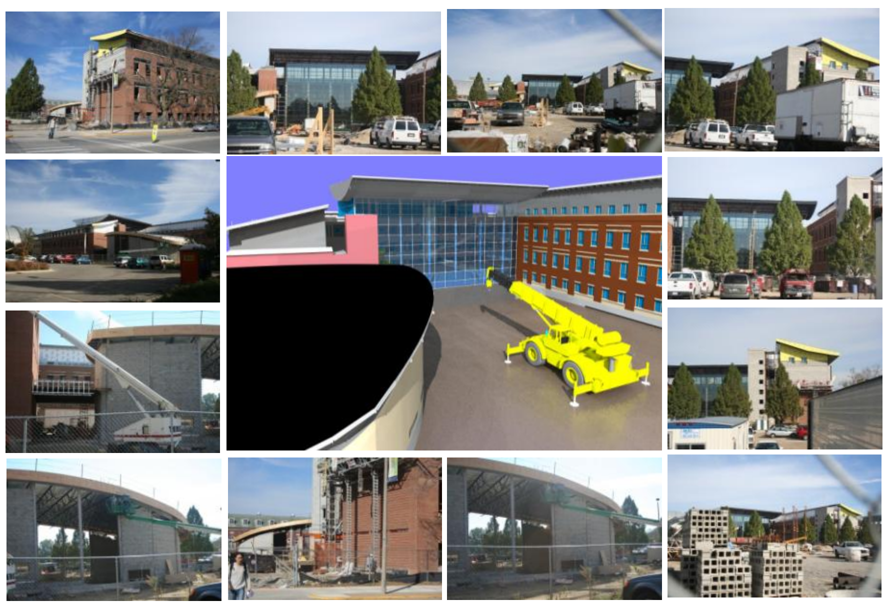


Figure 17**.** Progress Images of the construction of the College of Business Instructional Facility in conjunction with a snapshot of the 3D model generated for this project.

Result of visualization of progress monitoring

In the following figures (Figures 18, 19, 20 as well as 21) a series of progress images with their augmented equivalents are all shown. These images were made during the conceptual stages of D^{4}AR development and therefore were not actually used for coordination purposes.

Figure 18**.**Time-lapsed photograph of the construction site and the superimposed photograph representing progress status, 12-02-2006, 1:13PM, UIUC College of Business Instructional Facility.

Figure 19**.** Time-lapsed photograph of the construction site and the superimposed photograph representing progress status, 01-03-2007, 12:35PM, UIUC College of Business Instructional Facility.

Figure 20**.** Time-lapsed photograph of the construction site and the superimposed photograph representing progress status, 01-08-2007, 11:10AM, UIUC College of Business Instructional Facility.

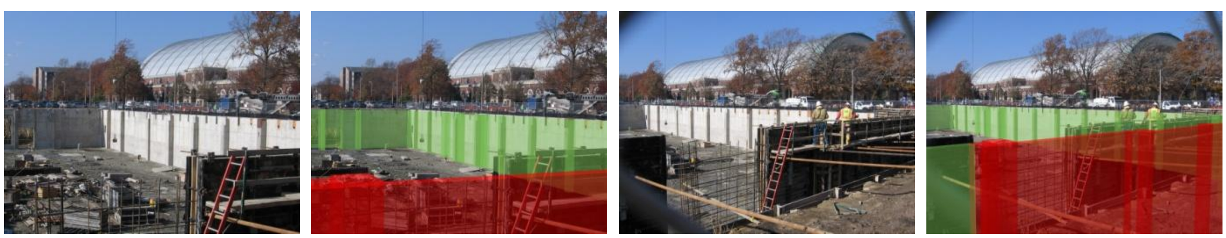


Figure 21**.** Randomly taken photograph of the construction site and the superimposed photograph representing progress status: From Left to Right: First two photographs: 11-07-06, 10:00AM, Second Two photographs, 11-08-2007, 11:20AM, UIUC College of Business Instructional Facility.

Case Study 4- Kauffman Center of Performing Arts, Kansas City, MO

Project description

Kauffman Center of Performing Arts is a two shell-shaped performing arts center which basically is a concrete hall and ballet opera house – dramatically crown a southern-facing opening onto a terrace garden below. As the world renowned architect, Mosh Safdie and Associates describes this vast glazed foyers make the most of the city views while also revealing the inner programmatic workings of each space to the exterior. Curvilinear vertical spines comprise the structure of the halls' segmented northern walls, sheathed in silvery stainless steel and glass; tensile forces are counteracted by cables anchoring the structure at the entrance level. This building will resident a 1,800 seat proscenium theater, home to the Kansas City Ballet and the Lyric Opera; as well as other national and international acts, including contemporary artists, country and western, some light rock and comedians . The proscenium hall will feature suites adjacent to box seats. Furthermore this building will home the multi-use "Celebration Hall" for performances, educational programs and banquets, with retractable seating for 250, a café to offer meals and refreshments to guests and theater goers and a 600-space parking garage connected to the Center with an additional 1,000-space garage directly across the street. The estimated project budget was $326 million and the design and construction started on 02 Oct 04 and is scheduled to be finished by 01 Sep 10. Here is the design and project team:

- Architect - Moshe Safdie of Moshe Safdie & Associates, Boston; Jerusalem; and Toronto.
- Architect - BNIM, Kansas City office
- Acoustics - Yasu Toyota of Nagata Acoustics, Los Angeles and Tokyo
- Theater Planning - Richard Pilbrow of Theatre Projects Consultants, South Norwalk, Connecticut; London, UK; and Singapore
- General Contractor - J.E. Dunn Construction Company
- Project Manager - Land Capital Corporation
- Construction Manager - MC Lioness Realty Group, LLC

As-planned and as-built progress data collection

The authors were involved in this project from the very beginning with contacting the construction management team. The Data required and collected for progress monitoring and application of D^4AR model falls into two categories:

(1) As-Planned Data: In order to properly set the baseline for progress monitoring, the building drawings, and construction schedule have all been collected. Based on the architectural and structural drawings, the as-planned 3D model was generated and link to the construction schedule to visualize the as-planned progress. Figure 22 shows two snapshots of the complete 3D model, wherein the architect demonstrates how the building would look like when the project is complete. Figure 23 further visualizes our detailed IFC-based 3D modeling which has been done to generate a proper baseline for monitoring to be used during the construction phase.

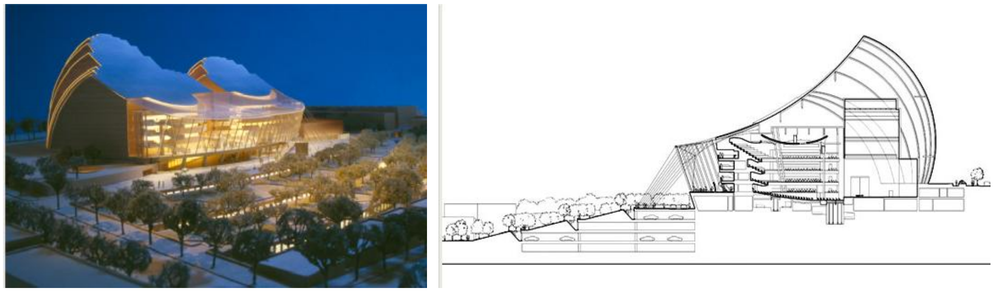


Figure 22. Kauffman Center of Performing Arts architectural rendering and section drawing

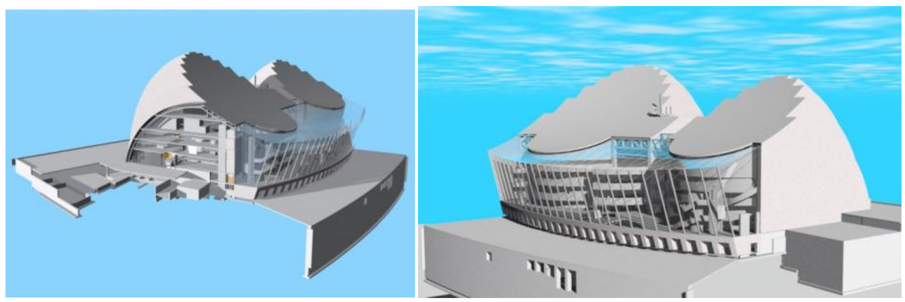


Figure 23. Snapshots of the IFC-based 3D model generated for the Kauffman Center of Performing Arts Project. Drawings used to generate the 3D model courtesy of the BNIM Architects as well as Mosh Safdie and Associates; Used by permission.

(2) As-Built Data: In order to thoroughly and systematically track physical progress, photographs have also been collected on a daily basis for progress and safety monitoring, constructability analysis, as well as site logistical purposes. For this project, photographs have been collected in two different methods: (1) from a fixed location: A camera was installed on a tower crane which constantly videotapes (1 picture/minute) the project. All these photos completely visualize the project progress from the excavation stage to the completion of the project. In addition to taking photos from a fixed location, daily construction progress photographs taken by the contractors as well as Arial photos taken during the construction were all collected. Figure 24 demonstrates an image of the Kauffman Center of Performing Arts construction site taken on a jobsite visit on Feb 2007 (Image taken from the 28th Floor of an adjacent building where the Architect's office is located in. Furthermore Figure 25 demonstrates a series of images taken from different locations.

Figure 24**.** The site of Kauffman Center of Performing Arts, Site visit on Feb 2007, From the 28th Floor of an adjacent building (Architect's office).

Figure 25**.** The Kauffman Center of Performing Arts images; The top image demonstrates the site from an Arial point of view while the lower images from left to right are taken from a tower crane and from an interesting point of view using a regular digital camera.

Case Study 5- Micro and Nanotechnology Extension Laboratory, Urbana, IL

Project description

This project was programmed for expansion of an existing building, Micro and Nanotechnology laboratory, on Urbana campus of the University of Illinois to accommodate more research space. The north extension is about 10,000 SF and the south extension is about 38,500 SF. The total project budget was $19.5 million and the design started on Jun 2005 and the construction was finished by October 2006.

As-Planned and as-built progress data collection

The same as previous cases, the majority of visual information required for visualization of progress monitoring was collected on this job site. Figures 26 and 27 represent a series of snapshots from the 4D model simulation as well as the daily construction images.

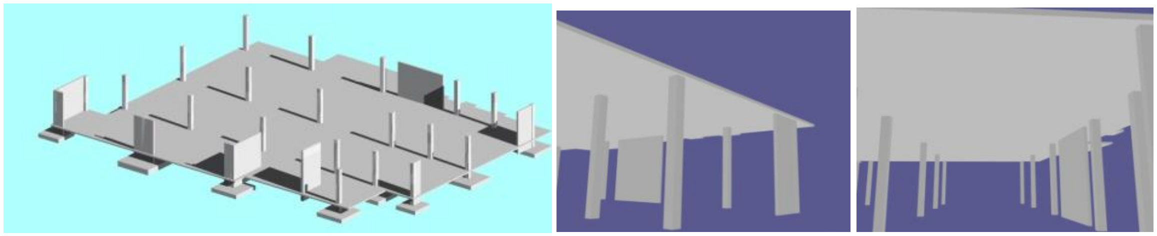


Figure 26**.** Snapshots of Simulated 4D model for Micro and Nanotechnology lab; South-east view and walk-through views: South-east.

Figure 27**.** Photographs taken form demolition phases to the end of the construction phase from different angles and point-of-views, Micro and Nanotechnology Lab Extension Project

Preliminary result of visualization of progress monitoring

Figure 28 visualizes some of the preliminary results of construction progress monitoring. These images were automatically generated to represent the concept of visualizing progress using a traffic light metaphor over the 3D model.

Figure 28. Randomly taken photograph of the construction site and the superimposed photograph representing progress status: From Left to Right: First two photographs: 11-07-06, 10:00AM, Second Two photographs, 11-08-2007, 11:20AM, UIUC College of Business Instructional Facility.

Case Study 6- Institute of Genomics Biology, UIUC Campus, Champaign, IL

Project description

This state of Illinois funded project was a building project with approximately 95,000 SF to house biotechnology facilities and research teams. The total project budget was $70.5 million and the design started on Feb 2004 and the construction was finished by May 2006.

As-planned and as-built progress data collection

The same as previous cases, the majority of visual information required for visualization of progress monitoring was collected on this job site. Figure 29 represents a series of snapshots from the 4D model simulation.

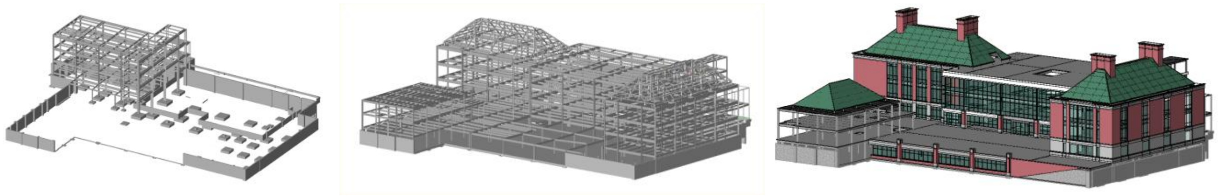


Figure 29**.** Snapshots of Simulated 4D model for Institute of Genomics Biology.

Similar to College of Business Instructional Facility project, daily construction photographs were taken both from a fixed location and from various locations around the site using a digital camera. The 6time-lapsed images (shown in Figure 30) were taken on a daily basis.

Figure 30**.** Photographs taken during construction of Institute of Genomics Biology, Champaign, IL.

Preliminary result of visualization of progress monitoring

Figure 31 visualizes a preliminary result of construction progress monitoring for Institute of Genomic Biology project. These images were generated during the development of registration of the 3D model with the time-lapsed photographs.

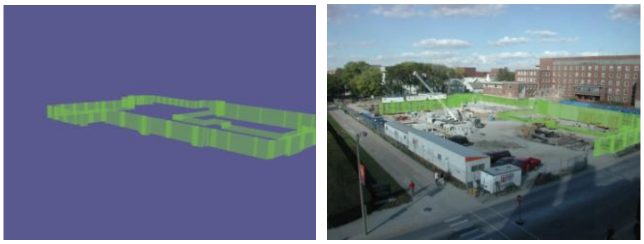


Figure 31**.** Snapshot of the IGB 4D model and a superimposed photograph visualizing the progress status, Institute of Genomics Biology, UIUC, Champaign, IL.

Case Study 7- Jewel Osco Market, Sugar Grove, IL

Project description

This Jewel Osco Market is located in Sugar Grove, IL. This project was contracted to *Novak Construction and was started on 22 Aug 2005 and was completed by 17 Feb 2006.*

As-Planned and as-built progress data collection

The same as previous cases, the majority of visual information required for visualization of progress monitoring was collected on this job site. Figure 32 represents a series of snapshots from the 3D created for this project.

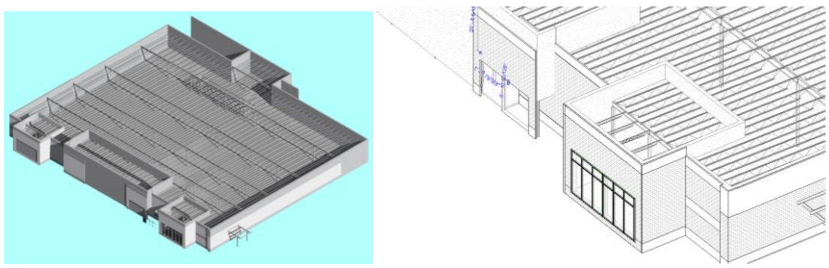


Figure 32**.** Snapshots of 3D model created for Jewel Osco Project.

Similar to the College of Business Instructional Facility project as well as Institute of Genomic Biology, daily construction photographs were taken both from a fixed location and from various locations around the site using a digital camera. The time-lapsed images (shown in Figure 33) were taken on a daily basis using a web-camera on the job site.

Figure 33**.** Time-lapsed photographs taken during construction of Jewel Osco, Sugar Grove, IL

Preliminary result of visualization of progress monitoring

Similar to that of the Institute of Genomic Biology project, a series of augmented images were generated during the development of registration technique of the 3D model with the time-lapsed photographs. Figure 34 visualizes three snapshots where the 3D model of the building is superimposed over the image. Red color used shows the installation of the pre-case concrete walls was behind schedule.

Figure 34**.** Snapshot of the Jewel Osco 4D model and a superimposed photograph visualizing the progress status, Jewel Osco, Sugar Grove, IL.

AUTHOR'S BIOGRAPHY

Mani Golparvar Fard graduated from Iran University of Science and Technology with a Bachelor of Science degree in Civil Engineering in 2002 and a Master of Science in Civil Engineering with focus on Hydrostructures in 2005. Subsequently he moved to Vancouver, Canada to pursue a Master of Applied Science in Civil Engineering with focus on Project and Construction Management at University of British Columbia where he graduated in 2006. Upon graduation he moved to Champaign-Urbana to pursue Ph.D. in Civil Engineering with focus on Construction Management. He also completed a Master of Computer Science degree at the University of Illinois at Urbana-Champaign in 2010. For several years, Mani has also worked as project engineer with Tehran-Berkeley Engineers and Consultants, Tarahane Darya Sahel, Talan Saze Design and Construction Co. and lately with Turner Construction. Following the completion of his Ph.D., Mani will begin work for Virginia Tech as Assistant Professor of Civil Engineering with focus on Construction Engineering and Management.