Joint Bluetooth/Wifi Scanning Framework for Characterizing and Leveraging People Movement on University Campus

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ABSTRACT

Collecting the real human movement has drawn significant attention from research community since a better understanding of human movement could provide new insights in network protocol design and network management for wireless networks. However, previous projects have only collected either location trace or the ad hoc contact trace. A comprehensive trace of real human movement, in which both the location information and ad hoc contacts are collected, has been still missing.

This paper presents a novel framework called UIM[1], which collects both location information and ad hoc contacts of the human movement at the University of Illinois campus using Google Android phones. Each UIM experiment phone encompasses a Bluetooth scanner and a wifi scanner capturing both Bluetooth MAC addresses and wifi access point MAC addresses in proximity of the phone. Then, Bluetooth MAC addresses are used to infer contact information and the wifi MAC addresses are used to infer physical location of the phone. Using the contact and location information, we investigate first the sensitivity analysis on contact duration and inter-contact duration. Then, we characterize the regularity of people movement, visit duration of people at locations, and the popularity of locations. We also study the social graph formed by ad hoc traces and find that the graph exhibits a small-world network in structure. Finally, we present the Hybrid Epidemic data dissemination protocol, which uses both wifi access point and ad hoc contact to expedite the data forwarding. We evaluate Hybrid Epidemic protocol with our collected ad hoc and wifi traces and find that in comparison with Epidemic data dissemination protocol, the Hybrid Epidemic protocol improves data forwarding delay considerably.

1. INTRODUCTION

Understanding the correct movement of mobile users is crucial to the design of efficient data dissemination protocols and to the network resource planning for Infrastructure-based wireless networks, Mobile Ad hoc Networks (MANET), and Delay Tolerant Networks (DTN). As a result, collecting the real movement trace of mobile users has drawn significant attention and effort from research community. However, obtaining an accurate human movement trace has remained challenging due to the lack of (1) the portable device that the experiment participants can carry for a prolonged experiment period, (2) a light-weight, power-efficient scanning protocol that can capture the movement trace and conserve the battery, (3) a device that can be programmed and debugged to capture both location information and ad hoc contacts. Nevertheless, there have been several efforts in collecting the human movement trace.

The first type of movement traces was collected by GPS-enabled devices carried by experiment participants [24, 16]. For this type of traces, the geographical coordinates of the experiment devices were obtained together with the timestamp. However, these devices could not collect the accurate geographical traces when the experiment devices were indoor, which resulted in the wrong movement pattern. More importantly, the collected geographical locations can not be used to infer the connectivity between two geographically closed nodes since there might be obstacles between them. Meanwhile, connectivity is a crucial and fundamental characteristic used to evaluate the performance of protocols for wireless networks.

The second type of movement traces was collected from WLAN environments where the association between the laptop/PDA and the wifi access points was captured with the corresponding time stamps [7, 8]. The information collected from these traces included the wifi MAC addresses of the laptops and the MAC addresses of their associated wifi access points. Since the laptop had a good battery capacity and laptop users usually charged their laptops when using the wireless network, the collected traces from WLAN provided a rich set of continuous data. Also, since the laptops were popular in corporate environments and university campuses, the trace collection experiment was easily scaled up to the entire corporate [4] or campus [8] environments. This offered a comprehensive set of wireless usage and detailed associations of the laptop devices and the wifi access points [12]. Previous work used these WLAN traces to infer the location of the experiment devices, derived various mobility models [8, 10], and used these derived mobility models to

[1]UIM stands for University of Illinois Movement

validate performance of network protocols for MANETs and DTNs. However, there was a fundamental weakness of these trace collection methods. The reason was that the collected trace did not always represent the real movement of people and this might result in the wrongly derived mobility models. Obviously, the laptop user did not always turn on the laptop and did not carry it with her all the time. Moreover, a normal laptop user usually turned on her laptop and left it on her office desk when she was doing other things (e.g., had lunch with friends, had meetings with colleagues, or went to exercise at the gym). Therefore, the location information inferred from the WLAN trace may not be the needed fine granularity. So, the collected associations of laptops and the wifi access points could be used to understand the wireless usage rather than the real movement of people.

The third type of movement traces was collected by using portable (experiment) devices such as PDA, iMote, cell phone. These portable devices were assigned to participants so that they would carry the devices all the time when they were walking. The collected information included the Bluetooth ad hoc contacts between the experiment devices and external Bluetooth-enabled devices, or among experiment devices only. The collected data had the list of scanned Bluetooth MAC addresses with the corresponding time stamps [22, 6, 5, 9, 13, 20, 17]. Due to the limitation of battery and the hardware capability of the experiment devices, only the Bluetooth ad hoc contacts were collected. Moreover, the scale of these experiments is much smaller in the number of participants and shorter in the experiment duration than those of WLAN experiments. It is clear that this method of trace collection captured more realistic movement trace since with high probability, the experiment devices were carried by the participants. However, this method of the movement trace collection did not collect the location information of the people movement, a critical factor to understand the movement behavior of people. Except [6], all previous works [22, 5, 9, 13, 20, 17] did not capture the location information of the movement. For [6], the location was inferred from the cellular ID associated with the experiment phone. However, since the transmission range of the cellular base station was ranging from several hundred meters (e.g., 500 m) to kilometers (e.g., 30 km), the location information inferred from the cellular ID did not provide the needed fine granularity.

From our observation, the wifi MAC address of the wifi access point could be used to represent the location [2] since a wifi access point usually is associated with a physical building or geographical location. Hence, this motivates us in designing new scanning and trace collection methods to obtain both Bluetooth ad hoc contacts and wifi MAC addresses of wifi access points and then use the wifi MAC address to infer the physical location. Table 1 compares the trace collected at the University of Illinois [2] with previous Bluetooth/Wifi traces. As shown in Table 1, to the best of our knowledge, we are the first to collect the ad hoc contacts and location information in a comprehensive movement trace. Moreover, our Bluetooth scanner can collect the ad hoc contact with the highest frequency compared to other data sets in the University Campus category.

In summary, this paper has the following contributions:

[2]We call the University of Illinois movement scanning system UIM.

1. We present a novel methodology to collect both ad hoc contacts and location information of the people movement in university campus using Google Android phones. Our system can run on the phone as a background service, thus it can be used to collect the movement trace as long as we wish. This offers a new opportunity to collect the rich set of data (ad hoc contacts and location) for a long period and overcome the battery limitation when doing the experiment with other devices such as iMotes, PTMR [22, 5, 9, 13, 20, 17].

2. We present new insights about contact sensitivity analysis, which has not been investigated in the literature before. We find that the contact duration, inter-contact duration distribution, number of contacts depend fully on how one defines the contact from the scanning frequency and the accepted number of missing scans.

3. We characterize the regularity of location visits, visit duration at locations, inter-visit duration at locations, and location popularity.

4. We characterize the social graph formed by ad hoc contacts of our data set and find that the graph exhibits the small-world network in structure.

5. We present and evaluate the performance of the Hybrid Epidemic Data Dissemination protocol on our collected data set. We find that the Hybrid Epidemic data dissemination protocol considerably improves the forwarding delay compared to the Epidemic data dissemination protocol [23].

This paper is organized as follows. We first present a new methodology of collecting the movement trace on the Google Android phone in Section 2. Then, we present the analysis of ad hoc contact distribution and location visit in Section 3 and Section 4, respectively. Section 5 presents our findings of the social graph formed by ad hoc MACs in our data set. In Section 6, we compare the performance of Hybrid Epidemic Data Dissemination protocol and Epidemic Data Dissemination protocol based on our ad hoc and wifi traces. Finally, we conclude the paper in Section 7.

2. UIM: JOINT BLUETOOTH/WIFI SCANNING FRAMEWORK

In this section, we introduce a novel user movement trace collection system called UIM. Our aim is that UIM satisfies the following objectives:

1. The system should ensure that user movement is scanned accurately

2. The system should conserve battery usage to scan the user movement for a long period

3. The system should incur no interference to the other applications of participants when participants carry and use the experiment devices

We find that the open nature of Android platform on Google phones enables us to investigate UIM and its novel methodology to efficiently collect more accurate user movement. In this section, we present the design and implementation of UIM.

	PMTR	Intel	Cam-City	Infocom	Cam-U	Reality	UIM	Toronto	UCSD	Dartmouth
Environment	**Workplace**	**Corp.**	**City**	**Conf.**	**University Campus**					
Duration (day)	19	3	10	3	5	246	19	16	77	114
# of Devices	49	8	36	41	12	97	28	23	273	6648
δ_B(second)	1	120	600	120	120	300	60	120	N/A	N/A
Ad hoc Trace	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Location Trace	No	No	No	No	No	CellID	AP	No	AP	AP
Device Type	PMTR	iMote	iMote	iMote	iMote	Phone	Phone	PDA	PDA	Laptop
# of In- contact	11895	1091	8545	22459	4229	54667	30385	2802	195364	4058284
# of Ex- device	N/A	92	3586	197	159	N/A	9015	N/A	N/A	N/A
# of Ex- contact	N/A	1173	10469	5791	2507	N/A	82091	N/A	N/A	N/A

Table 1: Comparison among collected Bluetooth/Wifi traces

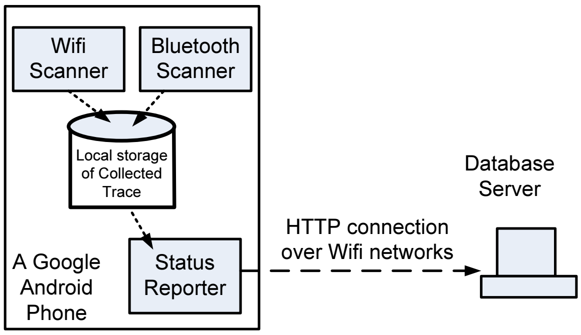


Figure 1: UIM System Architecture

2.1 UIM System Architecture

As shown in Figure 1, UIM has two main components: the database server and the Google Android phone. The former hosts a relational database management system, which accepts and stores the scanning status updates from the experiment phones. The latter has three subcomponents: the Bluetooth scanner, the wifi scanner, and the Status Reporter.

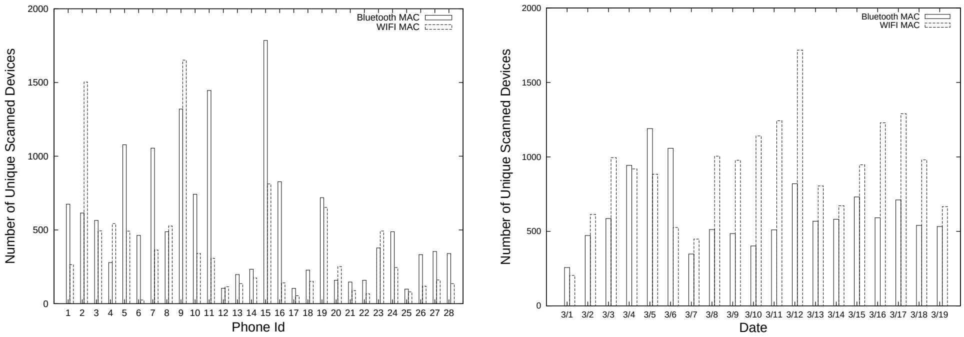
The *Bluetooth scanner* periodically (e.g., every 60 seconds) scans the Bluetooth-enabled devices in the phone's proximity [3]. The scanned results include the MAC addresses of the Bluetooth-enabled devices and the corresponding scanning time stamps. In this paper, we use δ_B to denote the scanning period of the Bluetooth scanner (e.g., $\delta_B = 60(s)$) and "ad hoc MAC" to denote the scanned MAC addresses of the scanned devices. Notice that the ad hoc MAC can be an experiment phone or a scanned device, which is not in the set of experiment phones. So, we use "external ad hoc MAC" to denote a scanned device, which is not in the set of experiment phones. The trace collected by the Bluetooth scanner is called the "ad hoc trace". We set the Bluetooth scanning period $\delta_B = 60(s)$ to conserve the phone battery. With $\delta_B = 60(s)$, our Bluetooth scanner provides the highest scanning frequency compared to previous ad hoc scanners in the University Campus category (see Table 1). Notice that UIM makes the experiment phones discoverable in the Bluetooth channel so that an experiment phone can scan other experiment phones in its proximity.

The *wifi scanner* periodically (e.g., every 30 minutes) scans the wifi access points in the phone's proximity. The scanned results include the MAC addresses of the wifi access points and the corresponding scanning time stamps. In this paper, we use δ_W to denote the scanning period of the wifi scanner (e.g., $\delta_W = 30(minutes)$) and "wifi MAC" to denote the scanned MAC addresses of the wifi access points. The trace collected by the wifi scanner is called the "wifi trace". There are two reasons we set the value of $\delta_W = 30(min)$. First, in the campus environment, people usually do not move too far and stay in the offices or buildings for a long time period (e.g., a class session is usually 50 minutes). Second, performing wifi scan on the cell phone is energy-consuming.

The collected movement trace, including ad hoc trace and wifi trace, is stored at the local disk of the phone. The *Status Reporter* updates the scanning status of the phone (e.g., how the scanning works, how many trace files have been created) to the server via the HTTP connection when the wifi connectivity is available. Due to the battery constraint, we only enable *Status Reporter* at several phones. We find that *Status Reporter* works smoothly if enabled.

UIM system achieves the *design objectives* as follows. For the *first objective*, UIM provides more accurate movement trace than previous works. Particularly, the Bluetooth scanner of UIM scans every 60 (s), which is the highest scanning frequency compared to previous works in the University Campus category as presented in Table 1. So, UIM can scan more accurate ad hoc MACs. Moreover, since UIM has the wifi scanner, the wifi MACs obtained by the wifi scanner can be used for location specification (see Section 4) to enrich the data set and infer missing movement information of the participants. For the *second objective*, since we tune the scanning frequency of Bluetooth and wifi scanners carefully, the phones can be used by participants as daily cell phones for about 2 days before running out of battery. Moreover, since most of our participants put their cell phone simcards into our experiment phones, participants recharge the phones and keep the phones on. Furthermore, we configure our scanners to run from 6AM to 11PM everyday, instead of running the entire day. After 11PM, the scanners pause to conserve battery and wake up at the 6AM the following day. Using this scanning configuration, we obtain most of the movement activity of the phone carriers and save the battery for the phone usage. For the *third objective*, we implement the UIM system so that UIM runs as a background process of the phone and is transparent to the phone user. We carefully implement and configure UIM so that it does not interfere with other services and applications of the phone users. Moreover, anytime the user turns on the phone, the scanners start and scan the devices in proximity periodically. This ensures that UIM remains robust to the usage of the phone and can starts running itself whenever

[3]In this paper we use "participant", "phone", "user", and "experiment phone" interchangeably.



(a) Scanned Device Distribution Over Devices (b) Scanned Device Distribution Over Time

Figure 2: Number of Unique Scanned Devices in the Collected Trace

the phone is on.

2.2 Overall Characteristics of UIM Trace

We have 28 participants who carry 28 phones for 19 consecutive days in March 2010. The participants include faculties, staff, grads, and undergrads as shown in Table 2. The CS faculties, staff, grads usually work inside our department building named Siebel Center. Meanwhile, CS undergrads may take classes in different buildings throughout the university campus. ECE and ABE (e.g., Department of Agricultural and Biological Engineering) grads stay in different buildings from Siebel Center. In this paper, we use D to denote the collected movement trace (including both ad hoc and wifi traces) from 28 phones in our experiment.

Table 2 shows the overall statistics of the UIM trace. In this table, for two phones p_1 and p_2, we say that p_1 and p_2 have an "internal contact" if p_1 sees p_2 in its Bluetooth scanned results or vice versa. For a phone p and an external ad hoc MAC address e, we say that p and e have an "external contact" if p sees e in its Bluetooth scanned results.

Overall Characteristics	
# of Internal Devices (participants)	28
Experiment Period (days)	19
Bluetooth Scanning Period (sec, δ_B)	60
Wifi Scanning Period (min, δ_W)	30
# of Internal Contacts	30385
# of External Scanned Devices	9015
# of External Contacts	82091
# of Scanned wifi Access Point MACs	6951
Participants	
# of CS faculties	2
# of CS staff	1
# of CS grads	14
# of CS undergrads	8
# of ECE grads	2
# of ABE grad	1

Table 2: Overall Characteristics of the UIM Trace

2.2.1 *Comparison of UIM and other traces*

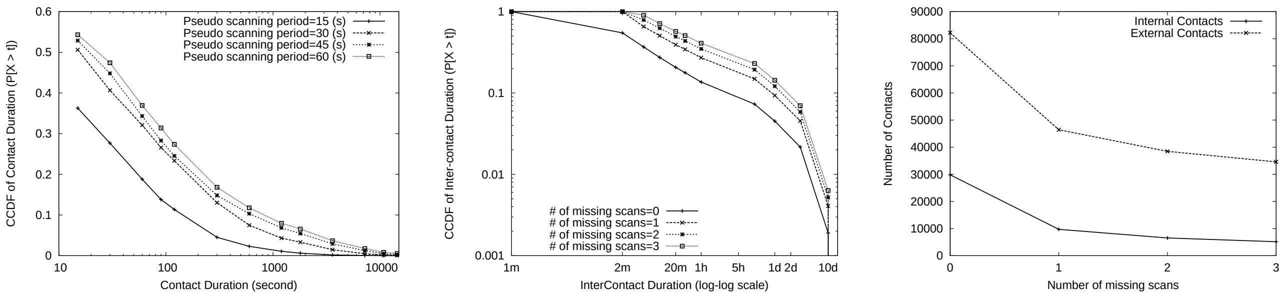
Table 1 compares the overall characteristics of UIM trace and other previously collected Bluetooth/wifi traces. UIM trace falls into the University Campus category trace and has the highest scanning frequency of the Bluetooth scanner. Thus, we obtain more detailed and accurate ad hoc contacts (see Section 3). For all traces, only Reality [6] can offer some level of location by inferring the cellular ID associated with the experiment phones. However, as we discuss in the Introduction section, the cellular base station transmission range varies significantly and thus can not be used for the fine granularity of the physical location. In UIM, we collect the wifi MACs of the wifi access points in the proximity of the phone. The wifi MACs are used to infer the physical location of the phone. To the best of our knowledge, we are the first to obtain the location trace and ad hoc trace in one comprehensive movement trace. Combination of ad hoc MACs and wifi MACs offers a rich set of movement traces and the appearances of people at diverse locations. These two pieces of context information will be exploited in our future work for the design of a new content distribution protocol.

2.2.2 *Distribution of Number of Scanned Devices*

Figure 2(a) shows the total number of unique scanned devices each phone obtains for the entire experiment period. We see that the numbers are considerably different among phones. This is because some participants move much more than others. Also, some locations may have more Bluetooth-enabled devices than other locations. Figure 2(b) shows the total number of unique scanned devices (both ad hoc MAC and wifi MAC) over 19 days of experiment. During our experiment, there are two weekends (03/07 and 03/14). These two days have slightly less number of scanned devices than other days. The first day of experiment (03/01) has the least number of scanned devices since we assigned the phones to participants in the late afternoon. Interestingly, in many days during the experiment period, the number of scanned wifi MACs is more than that of ad hoc MACs.

3. CONTACT ANALYSIS

Contact duration and inter-contact duration are two important metrics used to design data forwarding protocols for DTNs. In this section, we analyze the contact duration and inter-contact duration to provide more insights about these two metrics, which have not been provided in the previous studies [6, 5, 9, 13, 17]. Notice that the terms "contact duration" and "inter-contact duration" are the same as the terms "contact time" and "inter-contact time" used in previous studies. We use these two new terms in this paper



(a) Contact Duration Distribution (b) Inter-contact Distribution (c) Contact Number Distribution

Figure 3: Contact Sensitivity

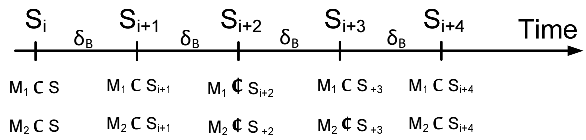


Figure 4: Contact Definition

since we believe the word "duration" represents properly the meaning of time period while the word "time" does not.

3.1 Contact Definition

In our context, a phone p and an ad hoc MAC M are said to have a contact if M exists in the Bluetooth scanned result of p. Let T_C denote the contact duration between a phone p and an ad hoc MAC M. T_C could be calculated by using the scanning period δ_B. For example, let N be the number of p's consecutive scans where M appears in the scanned results, $T_C = N \times \delta_B$. However, due to the hardware limitation of the Bluetooth driver at the phone and the unreliable wireless communication channel, it is possible that p does not receive M in its scanned result even when M is inside the Bluetooth sensing range of p. Therefore, in previous works [6, 5, 9, 13, 17], people accepted the missing scans in contact definition as follows: for p and M, although p does not see M in its scanned result for a certain number of scans, p and M are still considered in contact if the number of missing scans is acceptable. Figure 4 shows an example of contact definition. Let S_i denote the scanned result of p at time t_i. M_1 and M_2 are two ad hoc MACs scanned by the phone p. If the accepted number of missing scan for this figure is 1, from t_i to t_{i+4}, p and M_1 have one contact with the duration of $4\delta_B$ while p and M_2 have two contacts with the durations of $2\delta_B$ and δ_B respectively.

The accepted number of missing scans depends on the trace collection procedures. For example, in [5, 9, 13], the number of missing scans is one (with $\delta_B = 120(s)$); however, in [17], this number is 60 (with $\delta_B = 1(s)$). To generalize this, we define Δ_B as the *accepted number of missing scans* in the definition of contact. The contact duration T_C then depends on δ_B and Δ_B. Notice that Δ_B defines the boundary between the two consecutive contacts of a node pair.

3.2 Impact of δ_B on Contact Duration

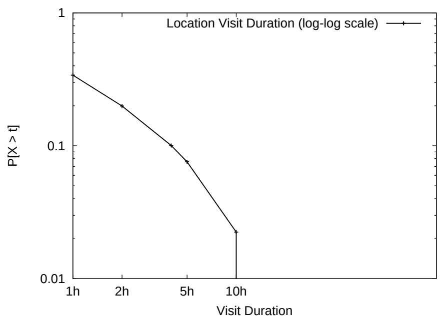
Figure 3(a) shows the sensitivity of contact duration when we vary value of δ_B. To obtain this plot, we have 6 students carry phones for 1 week, we set $\delta_B = 15(s)$ for the Bluetooth scanner. Notice that the lower bound (hardware limitation) of Bluetooth scan frequency for Google phone is 12 (s) [1]. We have tried the Bluetooth scan every 10 (s) and most of the time the scanned results are empty. Thus, we set $\delta_B = 15(s)$. Let here D_1 denote the data set obtained from these 6 phones with $\delta_B = 15(s)$. Each element in D_1 is the results obtained by one scan of any phone in the set of 6 phones. Since $\delta_B = 15(s)$, we can derive D_2 data set from D_1 using pseudo $\delta'_B \in [15, 30, 45, 60]$ as follows: if $\delta'_B = 30(s)$, D_2 is the set of odd or even scans in D_1. With $\delta'_B = 45(s)$, we take i^{th} scan from D_1 and put into D_2, and skip the $(i+1)^{th}$ and $(i+2)^{th}$ scans. Figure 3(a) is obtained from these D_2 sets of corresponding pseudo δ'_B and $\Delta_B = 0$. Notice that this figure is in log-log scale. The figure shows that with different values of δ'_B, we obtain different curves. More importantly, although the curves look similar in shape, the difference between them is significant, ranging from 15% to 20%. That means, the Bluetooth scanning period δ_B has important impacts on calculating contact duration. This has not been investigated in previous studies [6, 5, 9, 13].

Figure 3(a) also shows that a large amount of contacts (from 35% to 55%) are short contacts (less than 15(s)). Previous studies [6, 5, 9, 13] have not studied the short contact distribution due to their low scanning frequency (see Table 1). Except one study in a workplace environment [17], we are the first to study the distribution of short contact in university campus. As shown in [17], the short contact has an important role in data forwarding protocol in a workplace environment. In the future, we will investigate the impact of the short contact on data forwarding in the university campus environment.

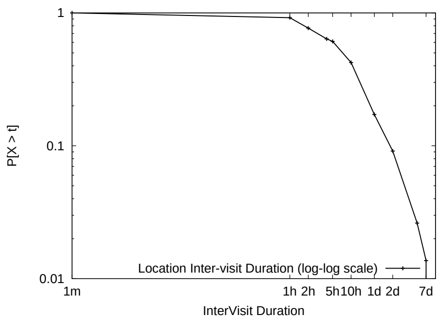
3.3 Impact of Δ_B

Besides δ_B, Δ_B has an important role in defining the contact duration T_C. This section studies the impacts of Δ_B on inter-contact duration and total number of contacts. Notice that the plots in this section are obtained from entire data set D with $\delta_B = 60(s)$.

As defined in previous studies [5, 9, 13], inter-contact duration is the time duration between the two consecutive contacts of a given node pair. It is well-known from the previous studies that the inter-contact duration follows the power law [6, 5, 9, 13, 17, 11]. Figure 3(b) shows that overall the inter-contact duration follows the power law and about 60%-80% of inter-contact duration is less than 1 hour. That means, if a pair of nodes meets at time t, this pair will meet again within one hour after time t with high probability. This figure also



(a) Location Visit Duration



(b) Location Inter-Visit Duration

Figure 5: Location Analysis 1

shows that when Δ_B varies from 0 to 3, the inter-contact duration varies up to 15%, although the shapes of the curves are similar. So, the value of Δ_B has a clear impact on the inter-contact duration distribution.

Figure 3(c) shows that when Δ_B varies, the number of external contacts and internal contacts in the entire data set changes significantly [4]. For the greater value of Δ_B, the definition of contact is more "robust" to missing scans and thus the contact lasts longer; thus, we have less number of contacts. For example, when Δ_B increases from 0 to 1, the number of external contacts decreases more than 30% from about 80000 to about 50000, while that of internal contacts decreases more than 60% from about 30000 to 10000. Similarly, when Δ_B increases from 1 to 2, the number of external contacts decreases 20% and that of the internal contacts decreases 30%.

In conclusion, the definition of contact depends on δ_B and Δ_B. So, when using the (inter-)contact duration distribution reported in previous studies [5, 9, 13], the readers should carefully consider the corresponding values of δ_B and Δ_B since they have significant impacts on (inter-)contact duration distribution.

4. LOCATION ANALYSIS

4.1 Definition of Location

As we described in Section 2, UIM collects wifi access points MAC addresses. The collected set of wifi access point MACs includes not only the wifi MACs associated with buildings in the University of Illinois campus but also ones at the residential homes/apartments where the participants stay with the experiment phones. So, the overall scanned wifi MACs give us the wifi access point map of the university campus and the surrounding areas where the students and faculties live.

Our wifi scanner obtains a list of wifi MACs in the proximity of the phone every 30 minutes, we use the list of wifi MACs to approximate the locations of the participants. The basic motivation for this analysis is that each wifi access point is associated with a physical building or physical location. In reality, the wifi access point usually stays inside its associated physical location. So, we can assume that the wifi access point is the "landmark" of the physical location. Since our phone can obtain the wifi MACs, we basically obtain the landmarks of the locations, or the locations themselves [2].

[4]Definitions of internal and external contact can be found in Section 2.2.

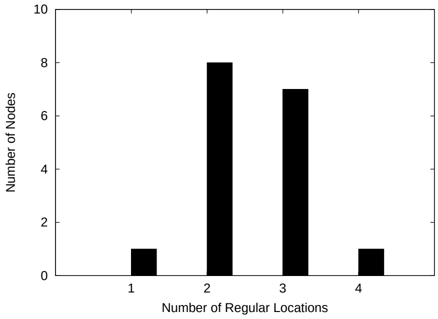
4.2 Obtaining Locations from wifi MACs

Due to the design of its hardware, anytime a Google Android phone performs a wifi scan, the phone receives multiple results, each of which consists of a list of wifi MACs. These results may not have exactly the same set of wifi MACs, but these results are usually highly overlapped. We, thus, aggregate all returned results from one scan and get the unique set of wifi MACs as the representative returned result of that scan. We also merge partial lists of wifi MACs if there exist multiple phones arriving at the same location from different directions. For example, a location L has a set of wifi access points. If there are two phone carriers heading to L from two different directions and these two phones are very closed to L, each phone may scan a partial list of the entire set of wifi access points at L. If these two scanned results are highly overlapped, we merge these two partial lists of wifi MACs to obtain the unique set of wifi MACs for L. This simple merging process works well for our data set and can identify locations from wifi MACs. Henceforth, we use the terms "wifi trace" and "location trace" interchangeably.

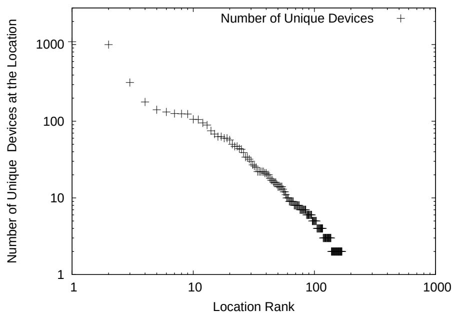
4.3 Characterizing the Location Visit

4.3.1 Location Visit Duration and Location Inter-Visit Duration

In our context, we consider a phone p has a "location visit" with a location L if L appears once in the location trace of p. Notice that the definition of "visit" between a phone and a location is similar to the definition of contact between a phone and an ad hoc MAC. We first calculate the "location visit duration", which is the duration the phone stays at a particular location. Similar to the contact definition, the definition of location visit depends on wifi scanning frequency δ_W and the accepted number of missing scans Δ_W. In Figure 5, we have $\delta_W = 30(min)$, $\Delta_W = 0$, and we use the entire data set D. Figure 5(a) shows that about 60% of location visits is less than 1 hour and the longest location visit is 10 hours. Since we have $\delta_W = 30(min)$, the result from this figure relies on the following assumption: for two consecutive wifi scans, if p scans the same set of wifi MACs, that means p stays at the same location during the last 30 (min). This might not be true if the phone carriers move to another location and then come back to L within the last



(a) Location Visit Regularity



(b) Location Popularity

Figure 6: Location Analysis 2

30 (min). However, this is the common limitation of existing trace collection methods since we only can obtain the "discrete" rather than "continuous" scanned result.

For a pair of phone p and location L, the inter-visit duration is the time duration between the two consecutive visits of p at L. Figure 5(b) shows the inter-visit duration distribution of our data set. This result differs from the association time between a laptop and its wifi access point [5], which was a heavy-tailed distribution as presented in previous study [10]. From this figure we see that the longest inter-visit duration is one week and for a pair of phone p and location L, if p visit L at time t, it is unlikely that p will return to L after one hour.

The next two questions are: (1) how regular is the location visit pattern in people daily movement?, and (2) what is the popularity of locations? To answer these questions, we select a data set D_3 from D with 17 phones for 15 days. D_3 has 170 unique locations. The reason we select D_3 is that several phones, out of 28 phones, have broken traces. We then divide a day time into 4 time slots ([6AM:10AM), [10AM:2PM), [2PM:6PM), [6PM:11PM]). This time division works for our data set since in the morning people come from home to work/class, then they may stay at work/school for lunch. In the afternoon, faculties may change the location to other offices for meetings or students change class rooms, then in the late afternoon, people come back home. Notice that we do not have a time slot from 11PM of one day to 6AM of the next day since our scanners do not work during that period to save energy. So, for 15 days a phone has 60 time slots. In each time slot, we aggregate all locations the phone visit and thus have a record in the format of ([time slot];[list of visited locations]). The next step is to find the *regular location*.

4.3.2 Regular Locations

In our context, for a phone p, **a location L is the "regular location" of p if p visits L at the same time slot for a certain number of days during the 15-experimental days**. This definition borrows the notion of "regular pattern" in Frequent Pattern Mining [3].

For each phone p, we apply the Frequent Pattern Mining with Vertical technique [3] to find the regular locations for p. Basically, we count, for each time slot, the number of appearances L_C of L over the 15-day period. If $L_C > 6$, L is a regular location. We select 6 as the threshold since from 15 days we have 2 weekends and thus we have only 11 working days. Moreover, the movement pattern of the weekday and weekend is different. We expect that the participant visits a regular location for at least 6 days during the 15-day period.

Figure 6(a) shows that 16 phones out of 17 phones have more than 1 regular location. 15 phones have from 2 to 3 regular locations while one phone has 4 regular locations. This confirms that the daily movement pattern of people is regular and predictable. The research on mobility models for mobile wireless networks thus need to take this regular movement pattern into account. Next, we present the *location popularity*.

4.3.3 Location Popularity

In our context, **the location L_1 is more popular than the location L_2 if there are more ad hoc MACs scanned by phones at L_1 than at L_2.**

To obtain the popularity of locations in data set D_3, we combine the ad hoc trace and wifi trace according to scanning time. Notice that our wifi scanner scans the wifi MACs (e.g., the location) every 30 minutes. If at time t the phone p appears at the location L in the data set D_3, we look into all ad hoc MACs scanned by p in the ad hoc trace during the period of 10 minutes (e.g., $[t - 5(min), t + 5(min)]$), aggregate these ad hoc MACs, and assign them as scanned ad hoc MACs at time t at location L. After repeating this for the entire data set D_3 and for all locations from 170 locations, we then aggregate all ad hoc MACs of the same location L into a unique set, which represents the set of ad hoc MACs scanned at L. Figure 6(b) shows the location popularity in terms of number of scanned ad hoc MACs at the locations (Notice that the figure is in log-log scale). This figure shows that location popularity exhibits a heavy-tailed distribution. Particularly, when location rank is greater than 10, the location popularity follows a Zipf distribution.

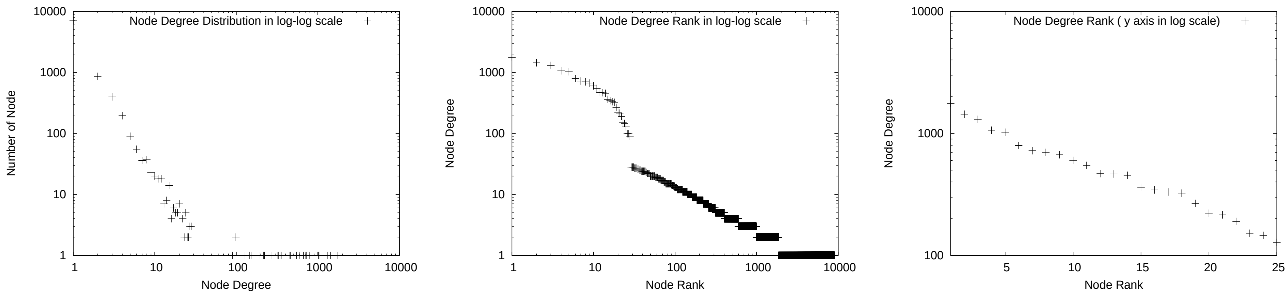
5. MINING THE SOCIAL GRAPH

In this section, we investigate the social graph formed by our ad hoc trace.

5.1 Social Graph

The social graph $G =< V, E >$ is an undirected graph, which is defined as follows. V is the set of nodes, including experiment phones and external ad hoc MACs. For a pair of nodes $v_1, v_2 \in V$, if v_1 is a phone and v_2 appears in one scanned result of v_1, then the edge $(v_1, v_2) \in E$. Notice

[5] A wifi access point was a physical location in previous study.



(a) Node Degree Distribution (b) Node Degree Rank (c) Top 25 of Node Rank

Figure 7: Node Degree of the Connectivity Graph $G =< V, E >$

that, if v_1 is a phone and v_2, v_3 exist in one scanned result of v_1, then in our context, $(v_1, v_2) \in E$, $(v_1, v_3) \in E$, but $(v_2, v_3) \notin E$.

5.2 The Small-world Structure

Figure 7 shows that the node degree distribution of the graph G follows a Zipf distribution with a heavy-tailed cut-off at the node degree of equal to or greater than 35 (this figure is in log-log scale). To further investigate the node degree distribution of G, we plot the node rank in terms of node degree in Figure 7(b). It shows that for the node rank greater than 25, the node degree follows the Zipf distribution. We then focus on the first 25 nodes in Figure 7(c), which shows that the node degree linearly decreases with respect to the node rank (notice that in Figure 7(c), the y-axis is in log-scale).

We also find that node degree mean of G is 3.26 and node degree standard deviation is 38.2. To further examine the structure of the graph G, we calculate the local clustering coefficient (CC) [25] for all nodes in V. As shown in Figure 8, more than 80% of nodes has $CC = 0$, these nodes are all leaf nodes which have only one neighbor (i.e., the experiment phone). Since 80% of nodes have $CC = 0$, the global CC of the graph is 0.157, which is greater than the global CC of a random graph with $|V| = 9015$ and mean node degree 3.26 (which is 3.26/9015 = 0.00036).

Furthermore, we create a social graph $G_1 =< V_1, E_1 >$ of experiment phones and calculate the CC for G_1. Here, V_1 is the set of experiment phones and $|V_1| = 28$. Also, for a pair of nodes $v_1, v_2 \in V_1$, if v_2 appears in one scanned result of v_1, then the edge $(v_1, v_2) \in E_1$. Figure 8 shows the local CC of G_1 in which 60% of phones have the local CC greater than 0.8. Because of this, the global CC of G_1 is 0.814, which indicates that the graph formed by phones is highly clustered.

From our analysis, the graph G is a connected graph with 9015 nodes and graph diameter is 4. The low mean of node degree (e.g., 3.26) results from the ad hoc MACs, which are the leaf nodes in the graph with only edges to the experiment phones. From Figure 7(b) we see that the first 50 nodes have degree greater than 25, these nodes form the hubs of G and reduce the graph diameter. Meanwhile, we have only 28 phones, that means the external ad hoc MACs also are hubs in G. Besides, although the global CC of the graph is 0.157, it is considerably greater than the global CC of a random graph with $|V| = 9015$ and mean node degree 3.26 (which is 3.26/9015 = 0.00036). So, we conclude that G exhibits a small-world network in structure.

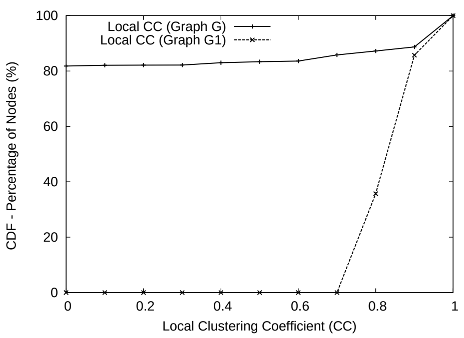


Figure 8: Comparison of Local Clustering Coefficient Distribution

6. HYBRID EPIDEMIC DATA DISSEMINATION

As shown in Figure 2(b), in many days during our experiment period, the number of scanned wifi MACs is more than that of ad hoc MACs. Also, our 28 phones collected 6951 wifi access points during the experiment period. So, we believe a data dissemination protocol, which uses both wifi access points and ad hoc contacts to forward data messages, becomes applicable in the university campus. This motivates us to design a new data dissemination protocol named Hybrid Epidemic Data Dissemination protocol (or Hybrid Epidemic protocol for short), which combines both wifi access points and ad hoc contacts in data dissemination.

6.1 Design of Hybrid Epidemic Protocol

Figure 9 shows the network model of the Hybrid Epidemic protocol with two main components: wifi access points and mobile nodes. We assume that the wifi access points are connected via the WLAN or Internet connection (e.g., AP_1 and AP_2 are connected and can exchange data via the WLAN backbone or Internet connection). Besides, the mobile nodes can communicate in infrastructured-based and ad hoc modes. The ad hoc connectivity can be either Bluetooth or wifi.

Figure 9 also shows how the Hybrid Epidemic protocol works. Particularly, when the sender P_1 sends a message m to the receiver P_5, P_1 uploads m to the wifi access point

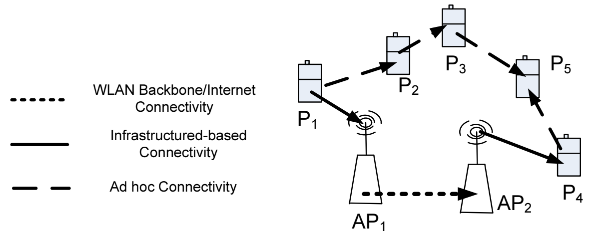


Figure 9: Network Model of Hybrid Epidemic protocol

AP_1[6] whenever P_1 is within the transmission range of AP_1. At the same time P_1 and other nodes in the network perform the epidemic procedure to forward m toward the destination. For example, P_1 sends the message m to P_2 when two mobile nodes are in contact. Again, P_2 forwards m to P_3 when P_2 and P_3 are in contact, and so forth. After P_1 uploads m to the wifi access point AP_1, AP_1 broadcasts m to other wifi access points in the network. Upon receiving m from AP_1, AP_2 advertises m to its surrounding area and thus if P_4 is in AP_2's range, P_4 can download m from AP_2 via the infrastructured connectivity. After that, P_4 can use ad hoc contacts to expedite the forwarding of m toward the receiver P_5 when P_4 and P_5 are in contact. The receiver P_5 can receive m from wifi access points or ad hoc contact.

We use the "forwarding delay" metric to evaluate Hybrid Epidemic protocol. For a pair of sender/receiver (s/r), the forwarding delay is the time period since s starts sending m toward r, until r receives m. We are seeking the answer for the question: how much forwarding delay improvement the Hybrid Epidemic protocol can achieve. To obtain the answer, we compare Hybrid Epidemic protocol to the Epidemic protocol [23], which only uses ad hoc contacts to forward data messages (no wifi access points are used in Epidemic protocol). The Epidemic protocol has been the fundamental data dissemination protocol in DTN research [21, 14]. In Figure 9, if the Epidemic protocol is used to forward data message m from P_1 to P_5, the forwarding path is P_1, P_2, P_3, P_5. Notice that although Epidemic protocol incurs a high network overhead, it does achieve a high delivery ratio and a nearly optimal forwarding delay [19] since Epidemic protocol exploits all possible ad hoc paths from the sender to the receiver.

Since we are only interested in the forwarding delay rather than other metrics (e.g., network overhead), we have left following design issues for our future work. First, we do not limit the number of copies of m in the network (e.g., mobile node P_1 makes a copy of m and forwards to P_2). That means, the message m is "flooded" to the entire network by the ad hoc contact and wifi access points[7]. Second, how long the wifi access points cache the data messages is not the focus of this paper. Figure 6(b) shows that the location popularity follows a heavy-tailed distribution. That means, it is possible that the wifi access points at the more popular locations can cache data message for a longer period so that mobile nodes have a higher probability to obtain the message. Third, figure 6(a) shows that people movement is regular since they visit locations at the same time periods. Our protocol does not exploit this movement regularity in data dissemination yet. The Hybrid Epidemic protocol follows the trend of combining Infostations and ad hoc connectivity to improve data delivery in previous works [15, 18], which were evaluated by mean of simulation. Our main contribution in this paper is to *evaluate and compare the performance of Hybrid Epidemic and Epidemic protocols on the real movement trace obtained by UIM.*

[6] We assume that the wifi access point has the storage to cache data message.

[7] This is the nature of epidemic data dissemination.

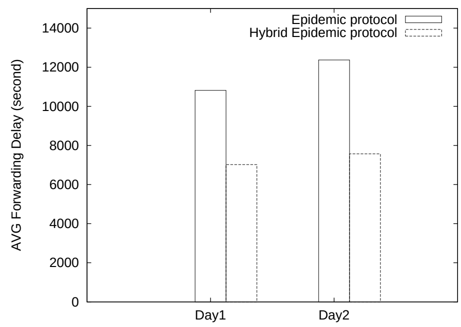


Figure 10: Performance of Hybrid Epidemic protocol

6.2 Evaluation Setting

As presented in a survey of 300 computer science faculty members and students [17], the forwarding delay that people can tolerate is from one to several hours, depending on the delay-tolerant networking applications and services [17]. Therefore, we evaluate the performance of Hybrid Epidemic protocol for a day-long period. Particularly, we compare the performance of Epidemic protocol and Hybrid Epidemic protocol using the ad hoc trace and wifi trace collected by 8 phones carried by grad students in the same research group for two different days. Let D_4 and D_5 denote the collected traces for these two days.

Since the participants come from the same research group, D_4, D_5 provide richer sets of contacts among 8 phones as well as a richer overlapping set of external ad hoc MACs. This is important for the Epidemic protocol in order to improve the forwarding delay of the message since the performance of this protocol depends fully on ad hoc contact. If D_4 and D_5 are traces collected by a random set of participants, the data set may not have a good overlapping set of ad hoc MACs, which makes the data forwarding unreachable or incurs an unacceptable long forwarding delay. Our formation of D_4 and D_5 also represents the realistic scenario since 8 participants from the same research group are from the same "community", thus they may share mutual content interest and share mutual contacts. Notice that D_4 has 186 unique Bluetooth MACs while D_5 has 209 unique Bluetooth MACs.

Using the data sets D_4 and D_5, the Hybrid Epidemic protocol works as follows: at time t_1 the phone P_1 starts sending message m to a receiver P_2. At time $t_2 \geq t_1$, P_1 uploads m to the wifi access points if P_1 sees a wifi access point in the trace at time t_2. After the time t_2, another phone P_3 can download m from P_3's wifi access points. Notice that P_1 and P_3 also use their ad hoc contacts in the ad hoc trace to forward m. In many cases P_3 may receive m from its ad hoc contacts before P_3 encounters a wifi access point since in our wifi trace a phone scans wifi trace every 30 minutes. This is the limitation of our wifi scanner since we do not capture the "continuous" wifi trace. However, it is also the limitation of any wifi scanners due to the battery consumption constraint. More importantly, if we have a more frequently scanned wifi trace (e.g., $\delta_W < 30(minutes)$), the performance of Hybrid Epidemic protocol may improve since P_3 can download m from its wifi access point at a earlier time after P_1 uploads m to the wifi access points. Here, P_2 can receive m from wifi access point or ad hoc contact.

6.3 Performance Evaluation

We select 50 random pairs of (sender, receiver) from D_4, and 50 random pairs of (sender, receiver) from D_5 and apply Epidemic protocol and Hybrid Epidemic protocol on the two data sets to forward the message from the sender to the receiver. Figure 10 shows that Hybrid Epidemic protocol achieves much shorter average forwarding delay than Epidemic protocol (e.g., 3500 (s) and 5500 (s) for day 1 and day 2, respectively). This is because Hybrid Epidemic protocol combines both ad hoc contact and wifi access points to improve the forwarding of the data messages. In our experiment, when Hybrid Epidemic protocol scheme is used to forward messages, the messages always reach the destination. However, for Epidemic protocol, 10% and 17% of messages can not reach the destination, for day 1 and day 2 respectively. Notice that in Figure 10, the forwarding delay for a pair (sender,receiver) is only taken for the average delay calculation if the message is received at the receiver.

7. CONCLUSION

We present a novel framework in collecting the human movement trace. Our system provides a comprehensive data set of both ad hoc and wifi traces obtained by our Bluetooth and wifi scanners. Given the wifi trace, we infer the location trace of the experiment phones.

The combination of ad hoc and location traces provides a new opportunity in analyzing the human movement in university campus. Particularly, our analysis shows that the scanning period and the accepted number of missing scans have crucial impacts on (inter)-contact duration distribution. We also find that people have regular movement patterns in daily movement and the location popularity follows a heavy-tailed distribution. Next, we study the social graph formed by ad hoc trace and find that the graph exhibits a small-world network in structure. Finally, we present the Hybrid Epidemic data dissemination protocol, which uses both wifi access points and ad hoc contact to expedite the data forwarding. We evaluate Hybrid Epidemic protocol with our collected ad hoc and wifi traces and find that in comparison with Epidemic data dissemination protocol, the Hybrid Epidemic protocol improves data forwarding delay considerably. Since the wifi access points are universally available in densely populated areas such as cities, campuses, etc., we believe that the Hybrid Epidemic Data Dissemination protocol is widely applicable.

In the future, we will use the UIM trace currently being collected by 120 participants in University of Illinois campus to model the movement behavior and then exploit the model for more efficient data dissemination schemes.

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