Weighted Waypoint Mobility Model and its Impact on Ad Hoc Networks

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Abstract

To evaluate the performance of routing protocols in ad hoc networks we propose a generic framework called the Weighted Way Point (WWP) mobility model that captures preferences in choosing destinations to characterize pedestrian mobility patterns in a campus environment. We estimate the parameters of this model using mobility survey data for the USC campus scenario and then compare the survey results with information drawn from wireless network traces where applicable. We further compare WWP model with the widely used Random Waypoint model and demonstrate that in the WWP model mobile nodes display uneven (clustering), time-varying spatial distribution and WWP model is less mobile than Random Waypoint model with typical parameter settings. Additionally, the clustering effect can cause higher congestion in WLAN and lower success rate of route discovery in ad hoc networks.

I. Introduction

Mobility modeling is an emerging branch of study in ad hoc networks. In this work we propose a new mobility model, weighted waypoint (WWP) model and investigated the issue of non-uniform weights distribution (preferences) in choosing destinations and location dependent behavior (in terms of pause duration and different sets of weights for selecting the next destination) of mobile nodes (MNs). While WWP model itself is a generic framework, we built one example of WWP model based on a mobility survey carried out on the campus of University of Southern California (USC). Using this example of WWP model as the input to ad hoc network simulation, we show that preferences in destination selection leads to significant discrepancy in ad hoc routing protocol performance.

The rest of this paper is organized as follows: Section 2 introduces some related works and explains the reason we chose to take survey approach in mobility modeling study. Section 3 details the WWP model and the mobility survey results on USC campus, with some related findings from 802.11 wireless network traces. Section 4 shows the impacts of WWP model on both wireless and ad hoc network performance. Section 5 concludes the paper and outlines the future work.

II. Related Work

Most currently available mobility models for ad hoc network are synthetic models based on simple, homogeneous random process [1],[2],[3] rather than based on detailed parameters setting obtained from real mobility traces. While synthetic models are more tractable for mathematical analysis [7] and easy to use for trace-generation, they do not capture important details of pedestrian mobility patterns, such as time/location dependence, non-uniform pause-time/speed distribution, multi-node group formation and split, among others. Hence, although they provide adequate high-level abstraction of mobility processes, synthetic mobility models lack the subtlety so they cannot be tuned to a specific environment. In [1] it is shown that the underlying mobility models used in simulation will significantly influence the result of performance evaluation. Hence, understanding of the underlying environment in which the ad hoc network will be formed and using realistic mobility models to evaluate the performance of protocols are important for drawing valid conclusion from simulation results.

There are several potential approaches to study what might be the "realistic mobility scenario" to use in simulation studies. The earlier research toward this end has been based on intuition and observation about mobility and has suggested various new synthesis mobility models [1],[2],[3] to capture important aspects of mobility process. There also have been some studies that used wireless network user association traces from 802.11 wireless networks to extract mobility-related information. In [5] and [4] the authors used the snmp and syslog traces obtained from 802.11 access points (APs) respectively to get partial information about mobility. While this approach is based on large amount of measurement data from in-operation networks and provides valuable insights on network *usage analysis* and thorough understanding of current operation status of studied wireless networks, it does not provide direct information for *mobility analysis* due to the following reasons. First, the AP-trace collection process is a sampling process based on usage pattern, not mobility pattern. As technology evolves, for example as computing devices become small enough to be used while the user is physically moving, the usage pattern may change significantly. Current wireless network association pattern is mostly a "use-when-stationary, turn-off-before-move" style. AP traces we see today also heavily depend on how and where people use their devices (given that the laptops are still not easily portable today, people do not tend to carry them around all the time). On the other hand, mobility pattern, which is rooted on the daily activity of users, is less likely to change significantly as technologies evolve. Secondly, the current 802.11 devices keep searching for the AP with strongest signal to associate with during its usage. Therefore even if the device itself is stationary, in the association trace it may appear to move back and forth between APs due to wireless channel condition variations, and in this case its difficult to deduce its actual location from the AP traces. One proposal is to record all APs seen by the device instead of the strongest one only [6]. However this approach requires changing the end devices and cannot be taken in large-scale study. Thirdly, the AP-traces mainly capture the relationship between mobile nodes and the infrastructure (APs), while the formation of ad hoc network is only between mobile nodes and is not dependent on the currently deployed infrastructure. The potential ad hoc network connectivity patterns may be richer than what we observe from the infrastructure-based AP association records today.

We can view the whole picture as mobility pattern being the underlying base upon which the other things are derived. For example, the AP traces we see today is a combined result of underlying mobility pattern, the percentage of people who own wireless network capable devices, their pattern of using those devices, and deployment policy of APs. The AP traces approach hence is a function of actual penetration and deployment of current technology. Therefore, we proposed to study the underlying mobility pattern directly, in complimentary to AP trace based study. We argue that the underlying mobility pattern will not change significantly for a given environment (e.g. a university campus), and establishing good mobility models by the direct study of movement patterns is essential for ad hoc network studies.

For direct study of mobility we currently pursue two approaches. One is based on systematic observation and the other is based on mobility survey. Each approach has its strengths and weaknesses. The former approach is investigated in [8], while we investigate the latter approach in this study.

III. Weighted Waypoint Mobility Model

3.1 General framework

The fore-mentioned previous works on mobility modeling did not address an important issue: The destination is not pure randomly chosen for pedestrians on campus. Given the environment setting of a campus, there are usually popular locations where people tend to visit more often than others. We investigate this issue in this work and propose a new model called the Weighted Way Point (WWP) model. The major differences of WWP model and the popular Random Waypoint (RWP) model are: (a) *MN no longer randomly chooses its destination*: In daily life, it is very unlikely that a person chooses a random location as his/her destination. We model such behavior by defining popular locations in the simulation area and assigning different "weights" to them according to the probability of choosing destination from the area. In an instance of WWP model, weights can be assigned by evaluating relative popularity of locations in the environment to be modeled. We refer to such identified areas as *locations* henceforth. (b) *The "weights" of choosing next destination location depends on both current location and time*: We use a Markov model to capture this location-dependent weight assignment. If there are totally M locations in the simulation area, the weights can be represented using an M×M matrix. If time-dependency is also considered, then we have a time-variant matrix. (c) *The pause time distribution at each location is different* and is a property of that location. In WWP model, the simulation area is no longer a homogeneous area without any special point of interest.

3.2 Establishing WWP model example for USC campus

We applied the above general framework to model a small part of the USC campus, covering several major intersections and buildings. The modeled area is shown in Fig. 1. We refer this topology as "virtual campus" henceforth. This virtual campus topology is adopted from a small part of the actual USC campus. In this scenario we define noncontiguous locations: 3 classrooms (CL), 2 libraries (L), and 2 cafeterias (Ca).

In order to find adequate parameters for our WWP model example for USC campus, we conducted a mobility survey targeted at randomly selected students on campus. During the period between March 22nd and April 16th, we collected 268 survey responses on USC campus. The granularity of our mobility survey is at per-building level on campus. In each survey, the student is asked to fill in his/her current location (building), the previous building visited, the next building to visit, and the pause duration at each of these 3 buildings. From the survey we captured statistics about the following parameters: (a) To set up WWP model for a campus environment, we categorize buildings on campus into 3 different location types: *classrooms, libraries, and cafeterias*. The area that does not belong to these 3 types is referred as *other area*. The pause time distributions at these 4 types of locations are obtained from the survey. Although our study focuses on a campus environment, we also model the mobile nodes leaving the campus with certain probabilities and coming back later to include a more general behavior. This is the *off-campus* area in our location definition. As a final result, the whole simulation area is divided into 5 different types of areas (5 different colorings in Fig. 1), and MNs choose its next destination from one of these 5 types according to a Markov model, as shown in Fig. 2. We set up the transition probabilities to different location types according to its "weights" or popularity. (b) The time-varying transition probability matrix of going to each type of location, given the current location type and time section of the day. We found the transition behavior is different in the mornings and the afternoons hence we separated the data set into 2 time sections: morning from 9 am to 1 pm and afternoon from 1 pm to 5 pm. (c) In addition to mobility-related parameters, we also survey for wireless network usage-the probability and duration a respondent uses wireless networks at different types of locations. Unlike previous studies on AP traces, ours is a novel approach to capture *real mobility patterns* with wireless usage data. Although AP traces also provide some information about wireless network usage, the mobility-related parameters (pause time distribution and transition probabilities) cannot be directly obtained from these traces. Also, AP-traces capture the *on-line* users only, not *potential* users; hence it observes only part of the total population, and the relationship between on-line and potential users (captured by probability of using wireless networks) cannot be directly deduced from AP traces.

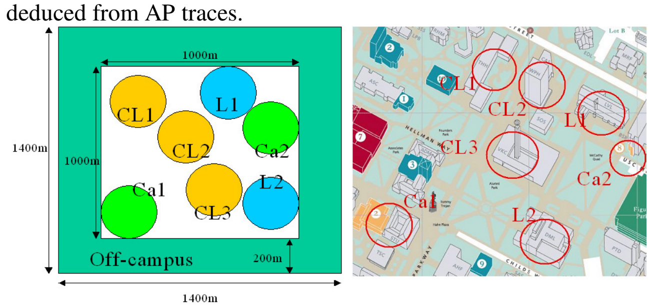

Fig. 1 Virtual Campus

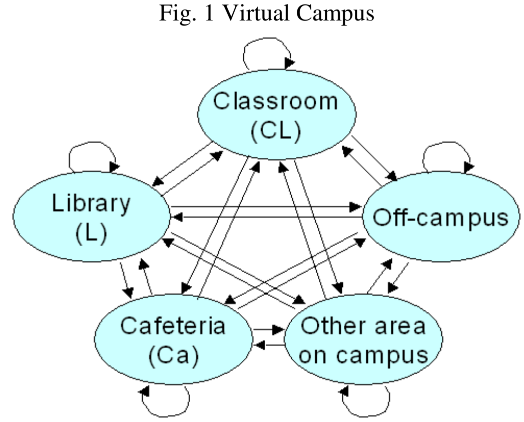

Fig. 2 Markov model of location type transition of MN

We discuss the main findings of our mobility survey study thus far.

Pause Time Duration

The pause time duration is as shown in Fig. 3. a) The distribution of pause time at classroom is like a bell-shaped normal distribution with the peak around the 60-120 minutes interval (USC average class duration is 90 minutes) b) Also we can see that people are more likely to stay in the library for intervals greater than 240 minutes than in any other locations (heavy tailed distribution). For *other* area on campus, the duration tends to be exponentially distributed.

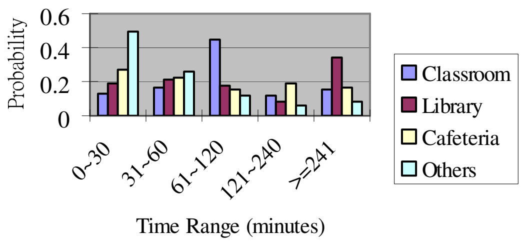

Fig. 3 Pause Time Distribution at the different locations

Transition Probability

The "transition probability matrix" from the survey data is shown in Table 1. a) People tend to go to a cafeteria more in the morning interval (lunchtime) than in the afternoon. Instead of visiting the "other" category, most transitions (more than 50%) are between classrooms and libraries. b) Also most transitions are of the type 'offcampus-class-offcampus' or 'offcampus-library-offcampus' which we believe reflects the general student movement on-campus. Note that usually when people come to campus they first visit classroom or library locations rather than cafeterias or others. This reflects the fact that off-campus students come to campus mainly to attain classes or to use libraries.

Destination / source (and time)		Classroom	Library	Cafe	Others	Off Campus
Classroom	**9~13**	**0.26**	**0.31**	**0.23**	0.14	**0.06**
	13~17	**0.17**	**0.30**	**0.00**	0.19	**0.34**
Library	**9~13**	**0.14**	**0.14**	**0.26**	0.03	**0.43**
	13~17	**0.36**	**0.23**	**0.04**	0.13	**0.24**
Café	**9~13**	0.15	0.44	0.00	0.22	0.19
	13~17	0.20	0.50	0.00	0.30	0.00
Others	**9~13**	0.09	0.12	0.25	0.30	0.24
	13~17	0.20	0.43	0.09	0.14	0.14
Off Campus	**9~13**	**0.69**	**0.21**	0.05	0.05	0.00
	13~17	**0.64**	**0.24**	0.02	0.04	0.06

Table 1. Transition probability matrix

We also try to obtain the transition probability matrix from USC wireless network traces, with building-level granularity. There are 3 initial findings on this: a) Starting from a given building, the transition probabilities toward the others are not equally distributed. There are a few major buildings (main libraries and classrooms) which are accessed from many other buildings. This supports our assumption that some locations are more popular than others in a campus environment. b) From the trace we observe similar trends to the survey- Cafeterias are more popular in the morning interval, and there are a lot transitions between libraries and classrooms. c) From a given building, the transition probabilities toward close-by buildings are higher than far buildings. This may suggest that pedestrian mobility on campus exhibits *locality*. However, although we tried to remove ping-pong effect in the AP traces, this might still be an artifact that some MNs sit in between buildings and alternatively associate with APs in both building. We plan to further conduct extensive analysis of these traces in our future work.

Wireless Network flow duration

The histogram of flow duration distributions at different types of locations is shown in Fig. 4. The flow duration distribution shows a heavier tail for library, probably due to people working in library with their laptop connected to the wireless network. We further check the finding of this part with the distribution of user online time in the Dartmouth AP-traces [4]. From the trace we find that for most buildings the online time distribution is highly skewed toward short durations, regardless of the building type (in [4] buildings on Dartmouth campus are divided into 7 types: academic, library, social, athletic, residential, administration, and others.). The observation based on our surveys and traces are similar except for the libraries. This may be attributed to differences between the USC and Dartmouth campuses and bears further investigation.

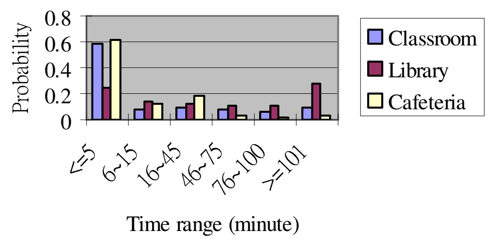

Fig. 4 Flow duration distribution at the different locations

IV. Simulation results

4.1 Properties of WWP model

We use simulations to show the characteristics of WWP model, in comparison to RWP model. First, WWP model shows *uneven spatial distribution* of mobile nodes (MNs). The MNs tend to cluster within the popular locations as shown in Fig. 5 for classroom1 and library1. However the node density is quite low for other area and off campus locations. This is a combined effect of popular locations being chosen as destination with higher probability and pause time at those locations being long with higher probability. Second, although for a given fixed transition probability matrix there should be some theoretical steady state of MN distribution, the transition probability matrix is time-dependent and changes from time to time throughout the day, hence MN distribution in simulation area never reaches a steady state. This suggests *converging to a steady-state distribution is not necessarily a requirement of realistic mobility models*. Third, we use move-stop ratio (total move time divided by total stationary time) as one metric of a mobility model and found that the WWP model based on parameters from mobility survey data has a lower move-stop ratio than the RWP model with common parameter settings, as shown in table 2. This indicates *in a campus scenario people are less mobile then typical scenario generated by RWP model*.

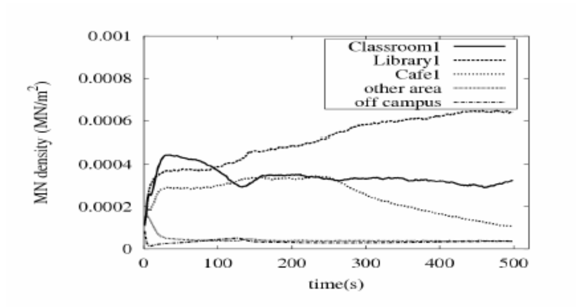

Fig 5. MN Density vs. time

Model and parameters	Move-stop ratio
WWP with both transition matrix	0.12
RWP with pause time=[0,100](s) speed=[2,50](m/s) – typical parameter setting	0.99

Table 2. Move-stop ratio

4.2 Impact of WWP model

We further show the impact of WWP model on network performance. We consider both last-hop wireless networks (802.11 WLANs) and ad hoc networks. Assuming MN only uses wireless networks with some probability when it stops within classrooms, libraries, and cafeterias, we find that as the number of MNs increases in the system, the WWP model has about twice the number of flows as compared to the RWP model. Also the congestion ratio (ratio of flows connected to an AP with 7 or more simultaneously flows) of the WWP model is double that of the RWP model. Another interesting result reveals even when both models have the similar number of flows, the WWP model always has a higher congestion ratio than the RWP model (graphs not shown due to space limitation, please refer to [10]). This is because in the WWP model locations are chosen as MN destinations with non-uniform weights. If a location is more popular than others, it attracts more MNs hence a greater proportion of the flows are initiated at the location. Thus some locations have seen more flows and these flows are likely to be congested. Where as in the RWP model the flows are more evenly distributed among the locations hence the congestion ratio is not as high given the same number of total flows.

For ad hoc networks, we compare the success rate of route discovery using DSR [9] under 2 different MN location relationships, MN pairs in the same locations and MN pairs in different locations. If WWP model is used, we show that a) for MNs within the same location it is relatively easy to discover a route between them (with 88.61% route discovery success rate). b) If the MNs are in different locations the route discovery success reduces to about a third of the value of the first relationship, with only 28.53% success rate. The reason for this is that due to the preference of choosing popular locations as destinations, the number of nodes present between these locations is very small. Hence few nodes are able to serve as the intermediate nodes to establish a route between MNs in different locations. Therefore it is likely that the network is partitioned into small subsets clustered at the popular locations, and it is difficult to find a route between these subsets.

V. Conclusion and Future Work

We suggested studying mobility pattern directly in this paper. Among several potential approaches, we chose the survey-based approach and used it to get parameters for our generic mobility model, WWP model, for USC campus environment. Based on our simulation study, we came to the conclusion that preference in choosing destination in a mobility model has a non-negligible impact on wireless network performance.

We are currently working towards several directions related to this paper. We are analyzing available AP traces, such as Dartmouth traces and USC traces, to get both possible mobility-related information and connectivity graph information. Also we are looking into potential improvement and combination of observation and survey methods to create a more generic and systematic methodology to capture important mobility characteristics for campus environment.

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