Weighted Waypoint Mobility Model and its Impact on Ad Hoc Networks

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To realistically evaluate performance of ad hoc networks we propose a generic framework called the Weighted Way Point (WWP) mobility model. WWP model captures preferences in choosing destinations of pedestrian mobility patterns in a campus environment. We estimate the parameters of this model using mobility survey data for the USC campus. We further compare WWP model with widely used Random Waypoint (RWP) model and demonstrate that in the WWP model mobile nodes display uneven (clustering), time-varying spatial distribution. WWP model is also less mobile than RWP model with typical parameter settings. The clustering effect can cause 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 generic mobility model named weighted waypoint (WWP) model. WWP model captures influences of mobile node preferences in choosing destinations. It also incorporates location-dependent pause duration and weights for choosing next destination. We built one example of WWP model based on a mobility survey carried out on the campus of University of Southern California (USC). We further show that preferences in destination selection lead to significant discrepancy in ad hoc routing protocol performance.

II. Related Work

Most currently available mobility models for ad hoc network are synthetic models based on simple, homogeneous random process [1],[2]. While synthetic models are more tractable for mathematical analysis 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, among others. Hence, although they provide adequate generic high-level abstraction of mobility processes, current synthetic mobility models need to be enriched in order to closely model 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.

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 synthetic mobility models [1], [2] 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 [4] and [3] 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 its current operation status, 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. Users are only observable in the AP traces when they turn on their devices. 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.

Mobility pattern of individual mobile node is an important factor that should be investigated directly if one want to closely model node behavior for a given environment. For example, it is one of the basic factors that influence the AP traces we collect today: The AP traces is a combined result of underlying mobility pattern, the percentage of people owning wireless network capable devices, their pattern of using those devices, and deployment policy of APs. The observed AP traces may change if any of these factors change. On the other hand, mobility pattern for a given environment, which is rooted in the daily activity of users, is less likely to change significantly as technologies evolve. Therefore, we propose to study the underlying mobility pattern directly, in complementary to AP trace based study. We argue that 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 [5], while we investigate the latter approach in this study.

III. Weighted Waypoint Model

III.A. General framework

For mobility modeling, it is important to address the following issue: The destination is *NOT* 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) *mobile nodes (MN) no longer randomly choose their respective destinations*. We model such behavior by identifying popular locations in the enviroment and assigning different weights to them according to the probability of choosing destination from the area. 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 time-variant Markov model to capture this location and time dependent weight assignment. (c) *The pause time distribution at each location is different* and is a property of that location.

III.B. Establishing an example WWP model based on 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. In this scenario we identify 7 noncontiguous locations: 3 classrooms (CL), 2 libraries (L), and 2 cafeterias (Ca).

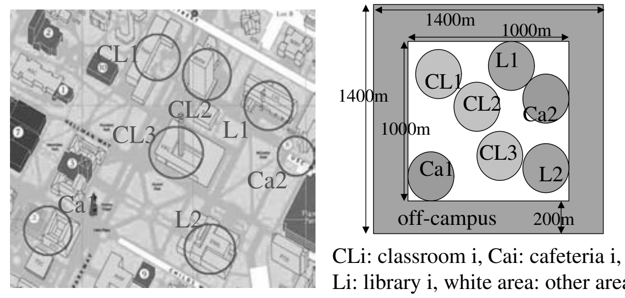

Figure 1: Virtual Campus

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 2004 and April 16th 2004, we collected 268 survey responses on USC campus. The granularity of our mobility survey is per-building. 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. To set up WWP model for a campus environment, we categorize buildings on campus into 3 different location types: *classrooms*, *libraries*, and *cafeterias*. The buildings and area that does not belong to these 3 categories are collectively referred to as *other area*. We also model the mobile nodes moving to *off-campus area* with certain probabilities. MN chooses its next destination from one of these 5 *location* 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. From the survey we captured statistics about the following parameters: (a) The pause time distributions at classrooms, libraries, cafeterias, and other area. (b) The time-varying transition probability given the current location type and time section (*morning*:9AM-1PM or *afternoon*:1PM-5PM) of the day. (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.

We discuss the main findings of our mobility survey study thus far. Due to space constraint, we only shortly outline the results here. Interested readers are refered to [8] for more details.

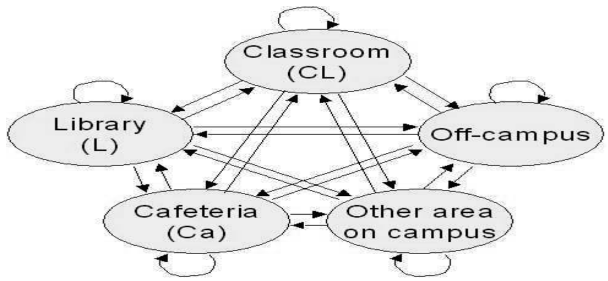

Figure 2: Markov model of location transition of MN

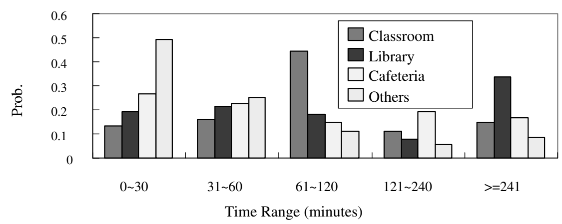

Figure 3: Pause time distribution for locations

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, which is regular class duration. (b) Also we can see that people are more likely to stay in the library for intervals greater than 240 minutes (heavy tailed distribution) than in any other locations. For *other area* on campus, the duration tends to be exponentially distributed.

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 involving off-campus location are of the type "offcampus-class-offcampus" or "offcampus-library-offcampus" which we believe reflects the general student behavior. This implies the fact that off-campus students come to campus mostly to attend classes or to use libraries.

We also try to obtain the transition probability matrix from USC wireless network traces, with building-level granularity. There are 2 initial findings on this: (a) Starting from a given building, the transition probabilities toward the others are not equally distributed. 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. We plan to further conduct extensive analysis of these traces in our future work.

Destination / Current location/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	9-12	**0.14**	**0.14**	**0.26**	0.03	**0.43**
	13-17	**0.36**	**0.23**	**0.04**	0.13	**0.24**
Cafe	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

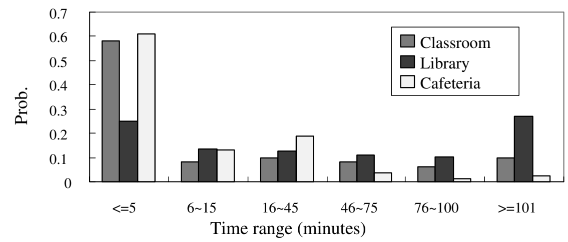

Figure 4: Flow duration distribution for locations

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 [3]. From the trace we find that for most buildings the online time distribution is highly skewed toward short durations, regardless of the building type. The observation based on our surveys and traces are similar except for the libraries.

IV. Simulation results

IV.A. Properties of WWP model

We use simulations to show the characteristics of WWP model, in comparison to RWP model (for details, refer to [7]). First, WWP model shows *uneven spatial distribution* of MNs. The MNs tend to cluster within the popular locations. 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 find that the WWP model based on mobility survey data has a lower move-stop ratio 0.12 as compare to 0.99 from RWP model with common parameter settings. This indicates *in a campus scenario people are less mobile then typical scenario generated by RWP model*.

IV.B. Impact of WWP model on network performance

We further show the impact of WWP model on network performance. We considered last-hop wireless networks (802.11 WLANs) in our previous work [7] and turn our focus to ad hoc networks in this work. For ad hoc networks, we compare the success rate of route discovery using DSR [6] under 2 different MN location relationships, MN pairs in the same location and MN pairs in different locations. If WWP model is used, we show that the route discovery success rates are 88.61% and 28.53% for MNs in the same location and in different locations, respectively. The reason for the low success rate for MNs in different locations is that the number of nodes present between these locations is very small due to the preference of choosing popular locations as destinations. 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 will be 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 suggest to study 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 for mobility study.

VI. Acknowledgement

The authors would like to thank F. Bai and S.C. Wang for their valuable discussion, Dr. Kotz and Dr. Henderson of Dartmouth University for sharing their wireless traces, and Mr. Yamaguchi of USC Information Services Division for providing USC wireless traces.

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