Understanding and Modeling Pedestrian Mobility of Train-station Scenarios

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ABSTRACT

This work presents the observations of pedestrian mobility characteristics based on the traces collected in a train station; provides a mobility model using these observations.

Categories and Subject Descriptors: C.2.1 [Network Architecture and Design]: Wireless Communication

General Terms: Design, Performance.

1. INTRODUCTION

One approach to evaluate communication protocols in wireless networks is to use mobility models. Theoretical mobility models like random waypoint model (RW), area-constrained random models [1] are commonly oversimplified. They do not consider the travel decisions of mobile users, thus poorly reflect the simulation results. Another approach for simulation is to use real traces of movement collected in specific domains. However, these traces do not allow for flexible performance simulation, as they are specific for a given scenario with fixed connectivity properties. As a result, mobility models based on real traces that capture precise user characteristics are needed.

In [2], authors develop a mobility model by observing the actual movement patterns of people on campus. In [3], the authors extracted various mobility parameters from traces of Wi-Fi devices. These parameters were then used in a synthetic mobility model. In [4], the authors use GPS traces to generate a Levy Walk movement model. However, as these traces are collected from conferences and campus environment, they only consider restricted type of wireless users. In practice, recent network services (e.g. emergency management, security, friend finding) attract more attentions in other outdoor environment like a train station, but the corresponding pedestrian mobility patterns are not well studied. In this work, we investigate the statistical patterns of walking people from the real traces collected in a train station. The following findings are observed: 1)The movement directions of pedestrians are not purely random, they have obvious direction preferences; 2)pedestrians have a high probability to visit a few hotspot subregions. From these findings, we build a mobility model that captures the pedestrian mobility patterns of train station scenarios. Using the mobility model, network simulation results show interesting routing performance that are not observed in RW.

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2. DATA COLLECTION

The trace data were collected from a train station in Japan in June 2006. The feet patterns of the pedestrians are tracked by eight laser scanners that can directly measure the trajectories of human feet [6]. The traces include two data sets, one five-minute set with 367 pedestrians from 19:00 (D_1) and one ten-minute set with 2,438 pedestrians from 20:00 (D_2) inclusive. The tracking accuracies of two sets are 93.4% and 88.7% respectively. Each pedestrian has a description of his/her trajectory about 20 seconds, including ID number, frame tag, time tag, and location information.

3. OBSERVATIONS FROM THE TRACES

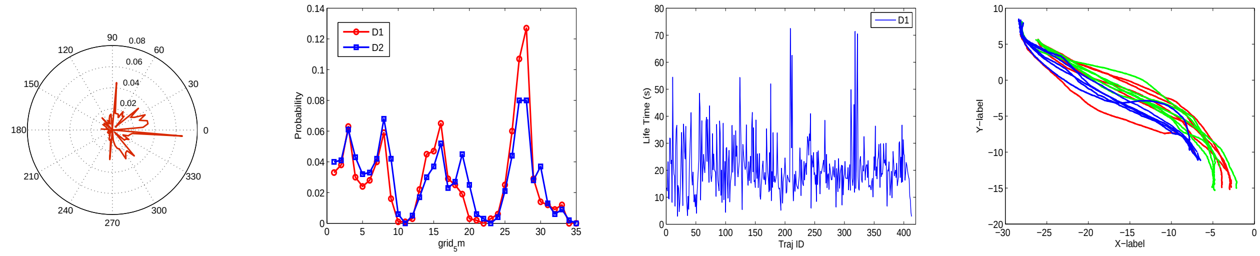
To understand the pedestrians' mobility patterns, we extracted the detailed information from the traces.

The pedestrians' average speed is $1.296m/s$ and $1.321m/s$ in D_1 and D_2, respectively. For the purpose of characterizing mobility, we are interested in grouping a subset of pedestrians. Since the population distributions also show fluctuant curves [5], we base our definition of "busy user" on that an individual's speed is 20% faster than the average speed; and the speed 10% slower than the average are classified as "leisure users". In D_1 we found that 19.07% people belong to the "busy users", while 19.9% in D_2. These results may be because 8:00pm is a peak hour in Japan, people walk faster while they are commuting in weekday.

Figure 1(a) shows the probability density function of movement directions of D_1. It indicates that in contrast with RW, pedestrians' walking directions in a station show a high regularity. Most people follow obvious and explicit orientations. Some directions attract more people; interestingly, the movements to other directions are very few.

Figure 1(b) shows the hotspot and cold subregions of D_1. In real world environment, there are many popular areas where a lot of people visit, and some areas where few people visit. To determine a subregion that corresponds to a hotspot or a cold subregion, we divide the whole area into 35 fixed size grids. If the stay time in one grid is longer or less than a threshold T_{stay}, this grid will be marked. It is interesting that similar results were found in D_1 and D_2: hotspot subregions correspond to the ticket window and the ticket gates are also very popular.

Figure 1(c) indicates the amount of time that the pedestrians spent on their "moving trips" in D_1. To understand their walking preferences, we are also interested in classifying the paths they have taken. One example of "moving trips" is shown in Figure 1(d): 15 pedestrians that have similar origins and destinations are selected. The figure indicates that



(a)PDF of directions (b) Hotspot and cold subregions (c) Time durations (d) Movement trips

Figure 1: Observations from the traces

most people select the shortest path between his/her source and destination, while their source and destination locations correspond to the ticket gates and exits.

4. MODELING PEDESTRIAN MOBILITY

From above observations, we found that on a detailed level, similar human activities appear in the area, resulting in preference-oriented movement. These mobility characteristics allow us to define a mobility model, called train station pedestrian(TSP) mobility model.

In TSP, all nodes move on a train station map; no obstacles are considered. The ticket gates and exits are extracted as small rectangles and plotted as origin and destination areas (OD); ticket windows, convenience stores are marked as hotspot subregions (HS). Each hotspot subregion has limitations of a minimum and a maximum duration of stay. The model consists three submodels: a busy node (BN) submodel; a leisure node (LN) submodel and a random node (RN) submodel. A configurable percentage of nodes in the submodels can be set.

In the BN submodel, a node makes a short pause at the hotspot subregion. At the beginning, a BN selects an arrival time from the arrival time distribution to enter the network. It selects origin and destination areas from ODs randomly. At each step k, a BN selects a speed from the speed distribution of busy users, and a random direction between its origin towards the destination. When it hits the hotspot area, it pauses for a short period chose from the minimum duration of stay of that subregions.

In the LN submodel, a node makes a long pause at one or more hotspot subregions. The time a LN stay inside a hotspot is selected from the maximum duration of stay of that area. Its selections of an arrival time, origin, destination areas and the movement procedures are the same as a BN. The speed of a LN is chosen from the speed distribution of leisure users. The model also allows a LN to choose one or more hotspot subregions as its midway pauses.

In the RN submodel, a node (pedestrian) behaves as a node in the random waypoint model.

5. PERFORMANCE ANALYSIS

TSP model is implemented to generate simulation trace scenarios for ns2 [7]. AODV routing protocol is evaluated in a 100x100m meter area with 30 nodes, transmission range is $30m$. Traffics are CBR. The movement of the nodes separately follows RW and TSP models. In RW, pause time is set as $0s, 2.5s$, and $5s$. In the TSP model, three scenarios are studied, the ratio of busy, leisure and random nodes is 20%, 70% and 10%; 40%, 50% and 10%; and 10%; 80%, 10% and 10% respectively. Two metrics are considered in the simulations: 1)Packet delivery ratio (PDR): the number of packets delivered to destination divided by the number of packets sent by the source; 2)Average end to end delay (AED): the average time interval for the packets to traverse from the sources to the destinations. Simulation results are shown in Table 1. We can see that TSP3 has the lowest PDR and AED because of too many leisure users.

Table 1: Simulation results

	RW1	RW2	RW3	TSP1	TSP2	TSP3
PDR	95.7%	96.9%	96.6%	88.3%	70.5%	54.8%
AED	1.88	1.72	1.71	1.70	2.05	6.92

6. DISCUSSION AND CONCLUSION

In this work, we present a pedestrian mobility model TSP based on the traces collected from a train station, which classifies different type of users and points out their movement preferences. The effectiveness of this model is shown by the evaluation of AODV routing protocol. There are several refinements can be made for TSP: 1)validate TSP to capture the main features obtained from the traces; 2)incorporate multiple path selections for each submodel; 3)other statistical patterns need to be described, such as flows of people, inter-contact times, and sensitivity to geographical constraints, etc.

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