Designing Temporally and Spatially Integrated Social Mobility Models for Wireless Network Researches

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***Abstract*—Modeling the mobility of mobile devices has always been a key issue for researchers as mobility needs to be taken into consideration in a variety of research situations in wireless networks. For many years, researchers have been striving to come up with more accurate mobility models which produce results similar to real mobility data. Although recent focuses on social relationship have improved the performance of mobility models, they still neglect or underestimate the influence of spatial and temporal factors which might greatly affect the movement of people. In this paper, we propose a novel way of modeling human movement on the basis of social, spatial and temporal factors by adopting a unique model structure and by introducing new mobility features such as roads. Simulation demonstrated that these measures produce results similar to real mobility data.**

I. Introduction

A key issue for researchers has long been how to model the mobility of mobile devices. This problem affects many aspects of wireless networks such as transmission protocol, resource reservation and location management. Although a number of experiments have been conducted to collect real movement traces, real movement data has rarely been used for the evaluation and testing of protocols and applications for wireless networks [1] due to its difficulty in implementation and lack of generality. In contrast, synthetic mobility models are highly preferred thanks to their theoretical attributes, which make them relatively easy to implement.

In the research of mobility models, although data transmission is conducted using wireless devices, attention is focused on people because mobile devices are carried by people most of the time, so the mobility problem of wireless devices is actually the mobility problem of people.

In recent years, researchers have found that a person's movements are closely connected to his or her social network, prompting the emergence of social mobility models which concentrate primarily on social relationships. In previous studies of social mobility models, social relationships were assumed to be the driving force of a person's movements. However, social relationships cannot account for all aspects of human movement. For example, the notion of familiar strangers [2] states that some people frequently cross paths although they do not actually know each other. It is estimated that social relationships can explain only about 10% of a person's movements as derived from cell phone data and up to 30% as derived from location-based social networks [3]. In this paper, we propose a novel way of modeling human movement on the basis of social, spatial and temporal factors by adopting a unique model structure and by introducing new mobility characteristics. Simulation demonstrated that these measures compensate for the deficiencies of using social factors alone and produce results similar to real mobility data.

The structure of this paper is as follows: Section 2 gives a brief overview of related work in the research of mobility models. Section 3 describes the system model of our proposed mobility model. Section 4 compares the simulation results of our proposed model with real mobility data. Section 5 concludes with a summary of the key points and a discussion of possible future research directions.

II. Related work

In this section, we discuss several important existing mobility models and their respective characteristics.

The earliest and most widely used mobility model is the random waypoint model [4] in which a person's speed, direction, and destination are assumed to be random. It is widely used in simulation and evaluation because of its simplicity. However, it fails to consider any practical influence on a person's movement, and the results of this model were proved to be largely at variance with real mobility data [5].

Researchers have since identified temporal and spatial factors such as location preferences and difference between workday and weekend that affect a person's movements. Their incorporation has made mobility models more accurate and reality-oriented.

The working day movement model [6] combines several submodels representing home activity, office activity, evening activity and transport and thus can simulate a person's movements during a working day. The time-variant community (TVC) mobility model [7] incorporates skewed location visiting preferences and periodical re-appearance at same locations, which are outcomes of temporal and spatial factors in real life.

Recently, social factors have caught the attention of researchers. The first model to incorporate them, the community-based mobility (CMM) model [1], is based on the assumption that the main factor controlling a person's movements is his or her social relationships. This model simulates communities using social network theory and has people move toward a goal which is calculated from the ratio of relationships. Although this model opened up new horizons in the research of mobility models by bringing into social factors, the results are not in complete accord with real mobility data. Several improved models of CMM have thus been put forward. The home-cell community-based mobility model [8] (HCMM) is based on the assumption that each node has a home cell and the home cell has strong attraction toward the node while other cells only have a relatively low attraction toward the node. The enhanced community-based mobility model [9] (ECMM) further improves the HCMM by introducing important mobility characteristics like pause period and group movement. Another major contribution of ECMM is improvement in the arbitrary social network input ability, i.e., separating the social network model from the conventional CMM, which makes the model more flexible and easier to use.

In addition to these models in the CMM family, the mobility model put forward by S. Yang et al. [10], which focuses on the concept that a person belong to different communities at different time is able to capture some temporal features of a person's movements.

However, all of these models place too much emphasis on the effects of social factors on a person's movements while underestimating or even neglecting the effects of spatial and temporal factors. In the following section, the system model of our mobility model is presented which offers a new way of combining social factors with temporal and spatial factors.

III. Proposed mobility model

In order to make our model easier to use, our model inherited the feature of separating the social network model from the mobility model put forward by Fischer et al. [11]. After having the input information of social network and community affiliation, a number of nodes representing people are generated and their related information is initialized. A goal is given to each node, and during each time slot, each node moves toward its goal. After reaching its goal, a node stays there for a period of time. It leaves for the next goal in accordance with a goal-deciding algorithm, which will be discussed in detail in the following paragraphs.

As mentioned, spatial and temporal factors are overlooked in most previous social mobility models, and even a few social mobility models which did consider spatial and temporal factors do not have a very reasonable mechanism. For example, some previous mobility models simulate temporal factors by exactly duplicating the movement patterns of same time previous day or week which is decided by social factors. This could emphasize the effects of social factors while undermining the effects of temporal factors.

Our model differentiated itself from previous models by taking into account social, spatial and temporal factors as a whole during the process of goal-deciding instead of focusing mainly on social factors as done by previous models.

In our model, people are represented by nodes and the entire map is made up of several grids. The possibility of nodes moving to a certain grid is represented by Grid Attraction Factor(GF) which is calculated from Grid Attraction(GA) while GA is calculated from Social Attraction Factor(SF), Place Attraction Factor(PF) and Distance Attraction Factor(DF). The detailed equation will be explained in the following text.

A. Social Factors

In our research we used the social network generated from the Toivonen algorithm [12] because the social factors were not our main focus. We also used the Newman and Girvan algorithm [13] to discover communities in the social network.

The social attraction between nodes u and v is defined as follows:

$$SC_{u,v} = w_{u,v} \times \delta_{u,v}, \tag{1}$$

where $w_{u,v}$ is the weight between node u and v in the social network, and correction factor $\delta_{u,v}$ strengthens the influence between nodes within the same community while weakening the influence between nodes from different communities. And the social attraction of a grid G_0 toward a certain node u at time t is defined as follows:

$$SA_u^{G_0}(t) = \sum_{v' \in G_0} SC(t)_{u,v'} \tag{2}$$

The social attraction of G_0 toward node u at time t is the sum of the social attraction between u and all nodes v' at G_0 at time t. Then the social attraction factor of a grid G_0 in goal-deciding over node u at time t is:

$$SF_u^{G_0}(t) = \frac{SA_u^{G_0}(t)}{\sum_{G' \in G} SA_u^{G'}(t)} \tag{3}$$

The social attraction factor of G_0 over node u at time t is the proportion of the social attraction of G_0 toward node u at time t to the sum of the social attraction of all grids in the map G toward node u at time t.

B. Spatial Factors

1) Roads: In previous models, the factor of road has always been ignored. People are regarded as being able to travel between two places directly following a straight line, as shown in figure 1. This kind of movement is inconsistent with our real life experience because in reality people generally move along the road. We therefore added the factor of road to our model, and we intend to study whether this factor would have influence on the final result of mobility models and how much influence they have. What's more, nodes will have higher speed in roads representing the movements of cars and public transportation in real life.

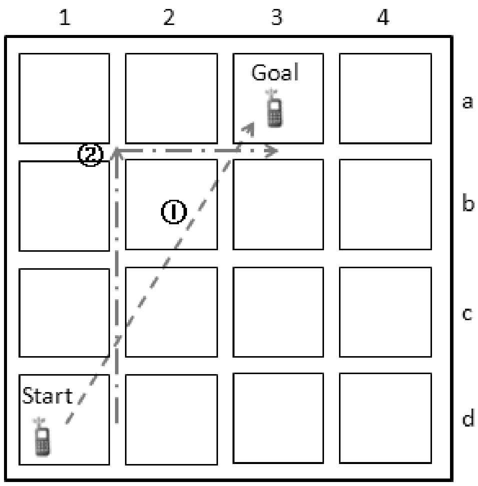


Fig. 1. Direct movement and road movement

2) Pause time: In real life, when people arrive at a place, they usually stay for a period of time before starting to move again. This phenomenon is a fairly important aspect in real mobility, and it is represented by pause time in our model. After a node reaches its current goal, the node will not start another movement immediately. Instead, it stays for a period of time.

In order to get a more accurate mathematical equation of pause time, we made a statistical analysis of the staying time of trips covering from one minute up to one day collected by the NHTS [14]. We found that the distribution of pause time follows a power law distribution with a negative exponent. Therefore, the pause time in our model is predicated on a mathematical equation following power law distribution drawn from data of real trips.

3) Place attraction: Apart from social attraction, in our model, every grid also has a place attraction toward each node. The mechanism of place attraction consists of three aspects.

The first aspect is general place attraction. Every grid in the map has a very weak attraction toward each node, and about one quarter of all grids in the center of the map have a slightly stronger attraction toward each node, and then several grids in the very center of the map have a much stronger attraction toward each node. This is to simulate the situation where places in the center of a city like downtown areas have a profusion of amenities and are often visited by people.

The second aspect is random place attraction. Several grids have a strong attraction over certain nodes, representing people's interests and hobbies.

The third aspect is home/work place attraction. Every node has its a "home place" and "work place", and nodes within the same community tend to have home place and work place close in distance. In real life, most people tend to stay at or near their home during their free time, and equally, they tend to stay at or near their work place during their work time. Therefore, the home place and work place will have very strong attraction toward nodes during different time periods.

The place attraction factor of a grid G_0 in goal-deciding over node u at time t is defined as:

$$PF_u^{G_0}(t) = \frac{PA_u^{G_0}(t)}{\sum_{G' \in G} PA_u^{G'}(t)} \tag{4}$$

The place attraction PA is calculated from the previously stated three aspects. And the place attraction factor of G_0 over node u at time t is the proportion of place attraction of G_0 toward node u at time t to the sum of place attraction of all grids in the map G toward node u at time t.

4) Distance attraction: In real life, people generally prefer to go to closer places than to more distant places [15]. The factor of distance attraction is introduced to simulate this preference.

We found that the mechanism of distance attraction also follows a power law distribution with a negative exponent. The equation is also calculated from statistical analysis of data of the travel distance in NHTS. The value of this negative exponent is -1.1. The value of distance attraction is computed by substituting for the base of the equation the distance between the grid where the node currently is at and the grid where the goal is at. Take figure 1 as an example, if currently the node is at Grid G_{a3}, then the distance attraction for G_{a2}, G_{a4} and G_{b3} is $1^{-1.1}$, and the distance attraction for G_{a1}, G_{b2}, G_{b4} and G_{c3} is $2^{-1.1}$. Then the distance attraction factor of a grid G_0 in goal-deciding over node u at time t is thus defined as:

$$DF_u^{G_0}(t) = \frac{DA_u^{G_0}(t)}{\sum_{G' \in G} DA_u^{G'}(t)} \tag{5}$$

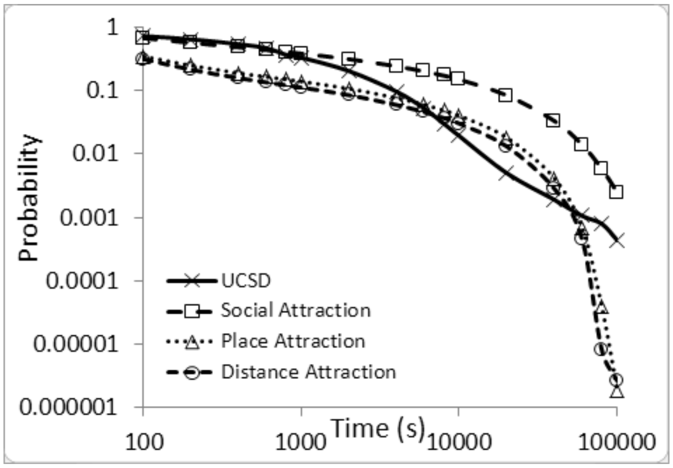
The distance attraction factor of G_0 over node u at time t is the proportion of distance attraction of G_0 toward node u at time t to the sum of distance attraction of all grids in the map G toward node u at time t.

C. Temporal Factors

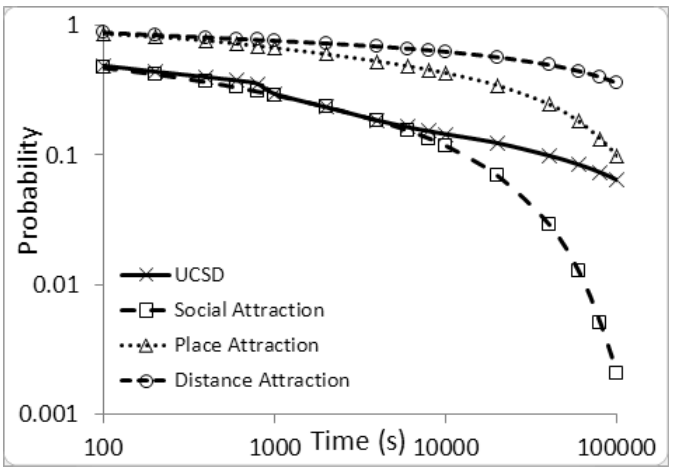
In previous models, temporal difference is marked between workday and weekend. However, we think that a more accurate demarcation of the temporal difference should be drawn between work time and free time. In our model, the period 8 a.m. to 6 p.m. during workday is deemed to be work time, and the rest of the time is deemed to be free time.

During work time, we assume that the work place has a strong attraction toward nodes and that place attraction plays a more important role than social attraction. During free time, we assume that the home place has a strong attraction toward nodes and that social attraction plays a more important role. Therefore, the grid attraction combining social, spatial and temporal factors of grid G_0 toward node u at time t is defined as:

$$GA_u^{G_0}(t) = \alpha(t) SF_u^{G_0}(t) + \beta(t) PF_u^{G_0}(t) + \gamma(t) DF_u^{G_0}(t), \tag{6}$$

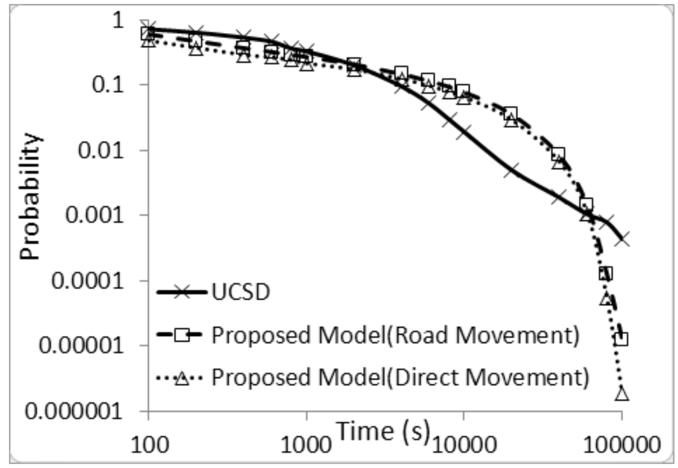


(a) Contact duration

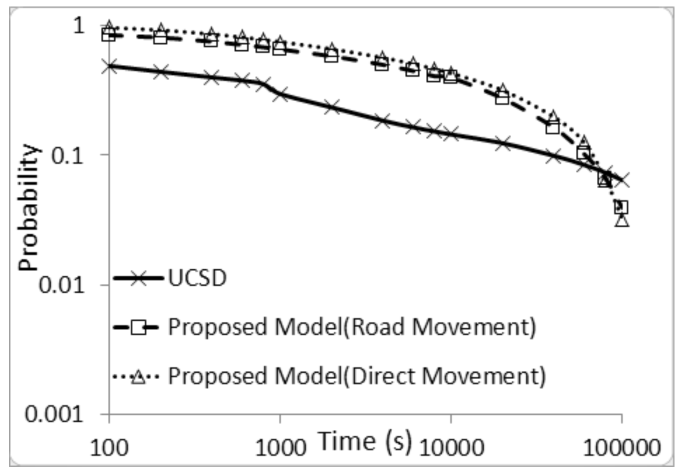


(b) Inter-contact time

Fig. 2. CCDF of each attraction factor compared with UCSD



(a) Contact duration



(b) Inter-contact time

Fig. 3. CCDF of our model under road movement, direct movement compared with UCSD

where the temporal correction functions of α(t), β(t), and γ(t) are determined completely on the basis of the timing of goal-deciding, and the sum of α(t), β(t), and γ(t) should be 1 at any time to ensure the fairness of goal-deciding. Then the final grid attraction factor for node u to go to grid G_0 at time t is defined as:

$$GF_u^{G_0}(t) = \frac{GA_u^{G_0}(t)}{\sum_{G' \in G} GA_u^{G'}(t)} \tag{7}$$

The grid attraction factor of G_0 over node u at time t is the proportion of grid attraction of G_0 toward node u at time t to the sum of grid attraction of all grids in the map G toward node u at time t. After a goal grid is decided, the actual goal position is randomly chosen within that grid.

IV. Evaluation

The simulation of our mobility model introduced in the previous section was carried out in a map of 4km×4km, and the size of each grid was 200m×200m so the total number of grids was 400. The total number of nodes was 100, and the range of transmission for a mobile device was considered to be 200 meters. The speed of the nodes was randomly distributed from 1m/s to 6m/s, and when a node entered a road, the speed range changed from 1m/s to 6m/s to 1m/s to 20m/s. The duration of this simulation was 20 days, and the final outcome was the average value of the simulation from several times of running in order to achieve a balanced result.

In order to measure the performance of our mobility model, we used the metrics of inter-contact time and contact duration. Inter-contact time is the time duration between two consecutive contacts of the same people. Contact duration is the time duration of one contact. Both metrics are of great importance in ad hoc networks, and particularly in opportunistic mobile network [16]. Contact duration indicates the length of a contact, therefore influencing the total amount of information that could be transmitted during a contact. Inter-contact time often indicates the frequency and probability of being in contact, thus affecting the speed of relaying information.

Apart from the results of our mobility model, the result of a real mobility data set called UCSD [17] was also introduced to give a comparison between our results and real movement data. UCSD is a real data set collected from wireless handheld PDAs in a campus wireless network with 275 participants.

Figure 2 shows the complementary cumulative distribution function (CCDF) of contact duration and inter-contact time of social attraction, place attraction, distance attraction respectively against UCSD.

As shown in these figures, none of the three attractions alone could give a similar result to the real mobility data. Although the social attraction bears some resemblance both in short contact duration and short inter-contact time, it fails to capture the characteristics of long contact duration and long inter-contact time which is the strength of place attraction and distance attraction.

Figure 3 shows the CCDF of contact duration and inter-contact time of our proposed model combining social, spatial, temporal factors in situations where node moves along the road and node moves directly to its goal against UCSD.

As shown in figure 3, although both road movement and direct movement produce similar results, road movement produces results closer to real movement as far as UCSD is concerned. While our model produces similar result to real data most of the time, the results still remain to be improved as far as long contact duration and short inter-contact time are concerned. There is apparently a connection between long contact duration and short inter-contact time; i.e., when the contact duration becomes longer the inter-contact time is bound to be shorter. Therefore, we are considering strengthening such social aspects as group movement in order to achieve long contact duration.

It should be noted that the mobility data of UCSD has its limitations as well. It would be inappropriate to represent human movement only by one data set. As a next step, we are considering introducing several mobility data sets to enhance the comparability of our results.

V. Conclusion and future work

In this paper, a mobility model combining social factors with spatial and temporal factors and incorporating several new mobility features was proposed. In order to compare the results of our proposed mobility model with real movement of people, we used a data set with real mobility data. It was shown that the spatial factor of road movement improves, although not greatly, the final result of the mobility model. Generally speaking, our proposed model produces similar movement results to real data. We are thinking about introducing group mobility to further improve the results.

However, real mobility data set has its own limitations, and one data set cannot represent the generality and intricacy of people's movements. Therefore, more results of real data set are needed to better evaluate our mobility model.

Because some spatial and temporal factors used in this model are based on assumptions and preset conditions, it would be better to use more realistic input data. We thus intend to change the input method by adopting a more flexible way of inputting spatial and temporal factors like the social network model, which should make our mobility model easier to use.

In order to further improve the accuracy of our model, we will look into the effect of dynamic changes [18] because the input factors might change over time. For example, people may move their homes or change their jobs, which would change their mobility patterns. Therefore, dynamic changes in the input data are crucial to the accuracy of mobility models, and we will thus consider the addition of dynamic changes.

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