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Next-cell Prediction Based on Cell Sequence History and Intra-cell Trajectory

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***Abstract*—In this work, we study a novel mobility prediction algorithm based on past long-term and short-term trajectories of users. In particular, we perceive the regularity of users' movements by training a Markov Renewal Process (MRP) using the long-term trajectory history. Moreover, short-term trajectory data, recorded within the current residing cell, is utilized to incorporate possible randomness of users' behavior into the algorithm. In fact, each neighboring cell is assigned two distinct probabilities of being chosen as next crossing cell, one given by MRP, while another is obtained from the direction of movements across the current cell. Lastly, assigned probabilities, i.e. the pieces of information extracted from the two aforementioned trajectory data sets, are combined with the aid of Dempster-Shafer theory to reach the best possible decision about the future crossing cell. Simulation results illustrate that the algorithm reliably predicts the next crossing cell with around 70% accuracy.**

***Index Terms*—Mobility prediction, Markov renewal process, Dempster-Shafer Theory, Bayesian Inference, user trajectory**

I. Introduction

Maintaining Quality of Service (QoS) is a challenge in current mobile communication networks, and so will be in the next generation of mobile systems (5G). One of the approaches adopted in literature to meet this challenge is to provide or reserve the amount of required resources before the arrival of the user to the cell [1]. To this end, knowing the future crossing cell of users appears to be essential.

In cellular systems, Mobility Prediction (MP) enables us to predict future crossing cell of users and to allocate required resources to the cell in advance, thereby reducing the number of failed handovers, alleviating unsuccessful call-attempts in the network [2], and increasing the total throughput of the network [3].

The Markov model in [4] is deployed to perceive the users' habitual movements and thereby predicting their future movements. In [5], a Markov Renewal Process (MRP) has been employed to predict the future crossing cell and, correspondingly, to reserve the required resources for the users prior to their arrival. Hidden Markov Model (HMM) is applied in [6], [7] to utilize prior knowledge such as movement history for learning and inference. Machine and Deep Learning techniques investigated in [8]–[12] are other approaches adopted in literature to predict users' next crossing cell. In [13] the locations of the user in the current cell are recorded and exploited to predict the future crossing cell. Moreover, user tracking with the aid of Kalman filtering along with user mobility pattern form hierarchical mobility prediction in [14]. In [15], [16], the application of Dempster-Shafer (DS) theory in tracking and prediction has been discussed and its potential functionality has been indicated. DS theory has been combined with a Markov model in [17] to predict users' destinations and transitions to road segments. All the aforementioned works have made valuable contributions towards MP, however, they either solely rely on long-term history of movements [4]–[12] or short-term data history [13], [15]. In particular, neglecting short-time data (which contains information about randomness of movements) while predicting based only on long-term history of movements (or vice versa) can in principle lead to poor performance of prediction algorithm. Furthermore, whereas the continuous tracking [14] of users may result in better predictions, such a scheme will likely suffer from the large overhead due to constant monitoring.

From the mobility point of view, the users' behavior in their daily life can generally be divided into regular and random behavior. For example, the path between home and office can be regarded as an example of regularity in behavior whereas exploring new areas of the city can be viewed as randomness in users' movements. In particular, it appears that gathering information about regularity and randomness of users' behavior and subsequently combining them with each other is a technically reasonable approach and likely to lead to an accurate next-cell prediction. To the best of our knowledge, such an approach has not been yet adopted in the literature. Given these explanations, the manner of gathering the pieces of information about regularity and randomness of users' movements, and the method of combining them are introduced as the challenges we meet in this paper.

In this work, we draw on the MRP [5] to capture the regularity in the behavior of the users. A MRP is a semi-Markov process wherein the next-state transition probabilities are governed by a Markov process and the sojourn time in any state is dependent on the current and next state. Furthermore, as done in [13], we record the instantaneous position of each user within its current residing cell and suggest a mathematical expression to extract information about randomness of its movements from the recorded raw data. In essence, MRP represents the information about regularity while instantaneous positions contain information about randomness of users' movements. Additionally, to combine the pieces of evidence collected from independent sources of information, among all the existing combiners [18] and classifiers [19]–[21], we choose DS theory [22], which has also been employed in [15] to infer future candidate locations.

The contributions of this paper are summarized as follows:

- We introduce and briefly discuss the DS theory, MRP and their employment in combining the obtained pieces of information and perceiving regularity in users' movements, respectively.
- We propose a novel mathematical expression to capture the randomness in users' behavior based on the direction of movement in the current residing cell.
- We propose an algorithm to predict the future crossing cell of a user by combining MRP and the instantaneous direction of movement and study its performance in terms of prediction accuracy.

The rest of the paper is structured as follows: In Section II, we give an introduction to DS theory and explain the MRP as well as their functionality in this work. In Section III, we discuss the perception of randomness in users' behavior. Section IV summarizes the previous sections by introducing a prediction algorithm. In Section V, simulation results are presented and discussed. Finally, Section VI concludes this work and indicates the future works.

Notation:

We use $\emptyset$ to denote an empty set. $\oplus$ and $\wedge$ represent the combination of evidence pieces in DS Theory and *logical and*, respectively. $[x]^+$ returns 0 when $x < 0$ and returns x if $x \geq 0$.

II. Background

To develop the prediction algorithm based on the idea mentioned in previous section, we firstly provide an overview of DS theory and MRP. The former combines the pieces of information obtained from several sources while the latter serves as a source whose information is employed by the former.

A. Dempster-Shafer Theory

A correct and reliable decision about the next crossing cell demands utilization of all the information collected from two sources of evidence, namely long-term data history and current-cell location history. To this end, among all combination theories, DS theory proposes a rule of combination which recently has aroused enormous interest despite its complexity [23], [24]. DS theory involves gathering a number of pieces of uncertain information, which are presumed to be independent. Each piece of information is represented by a *mass function*. Later, all the mass functions are combined to reach the final decision about the future crossing cell [22]. In special cases, as proved in [16], DS theory can be considered equivalent to Bayesian theory of inference. In the following, we briefly give an overview of DS theory and its application to mobility prediction.

1) Mass Function: DS theory begins with assuming a Universe of Discourse Θ, which is a set of mutually exclusive propositions about a domain. We let 2^Θ be the set of all subsets of Θ.

A *mass function* $m : 2^\Theta \rightarrow [0, 1]$, also known as *basic probability assignment* (*bpa*), is defined with the following conditions:

$$m(\emptyset) = 0, \quad \sum_{A_i \subseteq \Theta} m(A_i) = 1, \tag{1}$$

where A_i is a subset of Θ. It is worth mentioning that a mass function assigns numbers directly to the pieces of evidence (subsets of Θ), while traditional probability theory assigns numbers to the elements of Θ [15]. Let us consider a set of possible future cells $\Theta = \{C_1, C_2, C_3\}$. A mass function would assign numbers to the elements of the set of subsets $2^\Theta = \{\emptyset, \{C_1\}, \{C_2\}, \{C_3\}, \{C_1, C_2\}, \{C_1, C_3\}, \{C_2, C_3\}, \{C_1, C_2, C_3\}\}$, whereas traditional probability theory would assign numbers to individual elements $\{C_1\}, \{C_2\}$ and $\{C_3\}$, i.e. elements of Θ. In the case where we have evidence only about the individual elements of Θ (singletons), the mass function is equivalent to traditional probability theory [25].

2) Evidence Combination: Suppose m_H and m_L are two mass functions of the same set Θ from two distinct and independent sources of evidence, namely H and L. The rule of combination which combines *bpas* is given by [15]

$$m_H \oplus m_L(C) = \frac{\sum\limits_{X \cap Y = C} m_H(X) m_L(Y)}{1 - \sum\limits_{X \cap Y = \emptyset} m_H(X) m_L(Y)}, \forall\ C \neq \emptyset, \tag{2}$$

where X and Y are two subsets of Θ, i.e. elements of set of the subsets 2^Θ, C denotes a potential hypothesis and the denominator is a normalization factor to keep the value of $m_H \oplus m_L(C)$ in $[0, 1]$.

It has been proved in [16] that DS theory is equivalent to Bayesian theory when we assign numbers only to the singletons of set 2^Θ, i.e. the mass functions are *Bayesian*. Consequently the DS rule of combination in (2) turns into a Bayesian rule of inference, given by [16]

$$Pr(C_i | H \wedge L) = \frac{Pr(H \wedge L | C_i) Pr(C_i)}{Pr(H \wedge L)}, \tag{3}$$

where C_i denotes the future possible cell, $i \in \{1, 2, \cdots, 6\}$. Assuming independence of the sources, i.e. knowing that H provides no extra information about L or vice versa,

$$\begin{aligned} Pr(H \wedge L | C_i) &= Pr(H|C_i) Pr(L|C_i) Pr(C_i), \\ Pr(H \wedge L) &= \sum_{i=1}^{N} Pr(H|C_i) Pr(L|C_i) Pr(C_i). \end{aligned} \tag{4}$$

With the help of (4), we can rewrite (3) as

$$Pr(C_i | H \wedge L) = \frac{Pr(H|C_i) Pr(L|C_i) Pr(C_i)}{\sum_{i=1}^{N} Pr(H|C_i) Pr(L|C_i) Pr(C_i)}. \tag{5}$$

After reformulation using Bayes' theorem

$$Pr(C_i | H \wedge L) = \frac{Pr(C_i|H) Pr(C_i|L)}{\sum_{i=1}^{N} Pr(C_i|H) Pr(C_i|L)}. \tag{6}$$

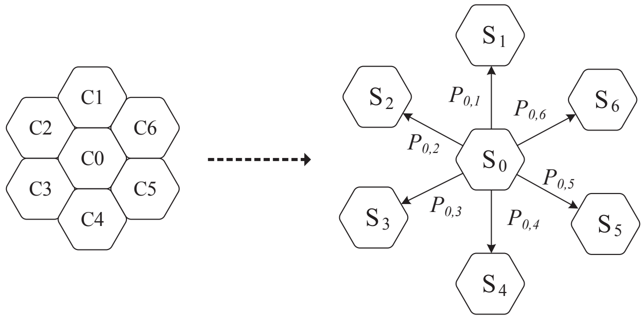

Fig. 1. Markov model for each cell in cellular network.

Thus the problem of predicting the future crossing cell is equivalent to

$$\arg\max_{i} \; Pr(C_i|H \wedge L). \tag{7}$$

In particular, as it is pointed out in upcoming sections, assigning numbers to singletons based on short- and long-term history of users' movements allows us to use (7) to infer the future crossing cell.

B. Markov Renewal Process (MRP)

History-based prediction methods with the aid of Markov models have been addressed in literature [5], [6], [26]. In this work, as done in [5], we employ the MRP to obtain the probability of each neighboring cell being chosen as the next crossing cell from the long-term data history. MRP is a generalization of a renewal process in which the time between renewals are selected according to a Markov chain [27]. As depicted in Figure 1, each cell is modeled as a state in the Markov model and the transition probabilities in the Markov model denote the probability that the user transitions to each neighboring cell. Note that we construct a 7-state Markov chain for each cell (Figure 1) which is then utilized to construct MRP as is explained below.

The semi-Markov kernel for a time-homogeneous process is given by [5]

$$Q_{j,i}(t) = Pr\{S_{n+1} = i, T_{n+1} - T_n \leq t | S_n = j\}, \tag{8}$$

where S_n and S_{n+1} represent the state of the system after the n-th and $(n+1)$-th transitions, respectively, with T_n and T_{n+1} being the times at which the n-th and $(n+1)$-th transitions occur, respectively. $Q_{j,i}(t)$ denotes the probability that, after transitioning into state j, the process transitions into state i within t units of time. We then rewrite (8) as

$$Q_{j,i}(t) = P_{j,i} G_{j,i}(t), \tag{9}$$

where

$$G_{j,i}(t) = Pr\{T_{n+1} - T_n \leq t | S_{n+1} = i, S_n = j\}. \tag{10}$$

$G_{j,i}(t)$ represents the conditional probability that a transition will take place within t amount of time, given that the process has just entered state j and will subsequently make a transition to state i. $P_{j,i}$ denotes the transition probability from state j to state i, and is obtained by training the Markov model of each cell.

An exponential distribution can typically be assumed to represent $G_{j,i}(t)$ [28]. Such distribution is defined with the parameter $\lambda_{j,i}$ considered to be the *rate of transition from j to i*. Hence $G_{j,i}(t)$ is given by [29]

$$G_{j,i}(t) = 1 - exp(-\lambda_{j,i} t). \tag{11}$$

$\lambda_{j,i}$ is chosen such that (11) fits the used data set. By combining (9) and (11), the time variant transition probability for each neighboring cell is obtained as follows:

$$Q_{j,i}(t) = P_{j,i} \cdot \left[1 - exp(-\lambda_{j,i} t)\right], \tag{12}$$

with $t \in [0, T_{n+1} - T_n]$.

III. Current-cell location history

To take the best possible decision about the next crossing cell of a user, one cannot only rely on the long-term history of movements. In particular, although every user exhibits some regularity in its movements, e.g. going everyday to work or university, there is still a degree of randomness in users' movements due to traffic condition, construction barriers, or exploring new areas. Therefore, it is necessary to access other sources of information to be able to incorporate the randomness of movements into the prediction algorithm.

A. Location-aware Next-cell Probability

Users' short-term location history across the current cell contains valuable information about possible randomness in their behavior. Specifically, based on the past trajectory of a user in the current cell, we assign probabilities to each neighboring cell being the next crossing cell. We define the current-cell location history as vector $L_N = [l_1, l_2, \cdots, l_N]$, whose elements are the locations that a user has crossed within the current cell. Clearly, the number of elements, N, depends on frequency of recording the user's location. Furthermore, we assume that this information is provided by network, e.g. using different localization methods such as range-based and angle-based [30], [31].[1] Note that vector L_N denotes the past locations of the user in the current cell, whereas the long-term trajectory history that we utilize to train the MRP are sequences of cells crossed by the user in long periods of time, e.g. weeks or months. Knowing the vector L_N, the following probability can be calculated,

$$Pr(C_i|L_N). \tag{13}$$

Generally, we expect that each user's movements tend to head for its final destination. Therefore, monitoring the users' direction of movement within the current cell enables us to perceive their overall direction. As shown in Figure 2, a change of direction can be perceived by calculating the variation of user's angle to the vertexes of the cell. In particular, with each movement, θ_i will change and, as the user moves towards one

[1] Owing to multiple location-based services [32], it is expected that user localization will play a significant role in 5G networks and be embedded therein [33].

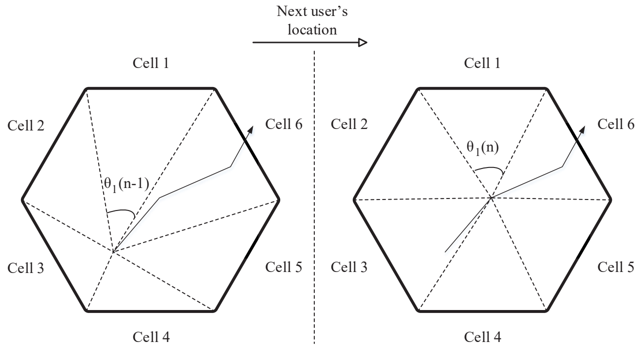

Fig. 2. Capturing direction of user movements by calculating the angle to cell vertex ($i = 1$).

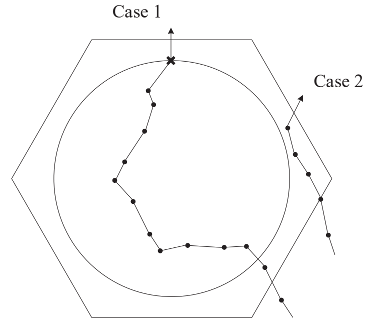

Fig. 3. Graphical example of the movements of a user within a cell.

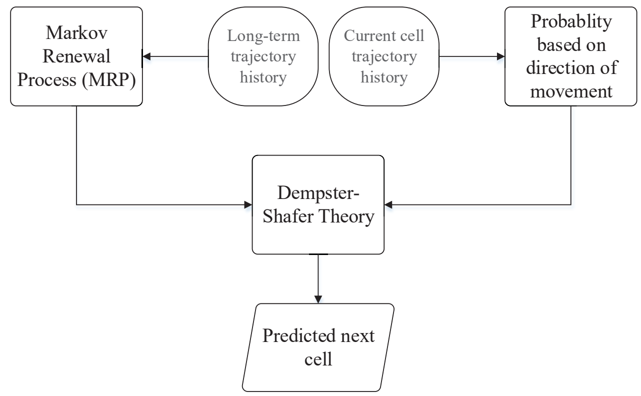

Fig. 4. Block diagram of prediction algorithm.

of the neighboring cells, the corresponding angle θ_i grows. θ_i can be readily calculated at each point of the cell using cell geometry [14].

Knowing the variation of θ_i, the next step is to assign an *instantaneous probability* to each neighboring cell. In particular, with each movement, depending on the change of angle θ_i, we assign a probability to each of the neighboring cell being chosen as next crossing cell. The assigned probability is as follows:

$$Pr_{inst.}^{[i,n]}(C_i|l_n) = \begin{cases} \frac{\beta_i(n)}{\sum_{i=1}^{6}\left[\beta_i(n)\right]^+} & \beta_i(n) > 0, \\ 0 & \beta_i(n) \leq 0. \end{cases} \tag{14}$$

where

$$\beta_i(n) = \theta_i(n) - \theta_i(n-1). \tag{15}$$

In fact, we assign positive probabilities according to (14) to the cells towards which the user is moving and assign zero probabilities to the cells from which the user gets away. In other words, using (14), we assert that the user approaches a cell (or group of cells) and simultaneously retreats from a number of cells.

We further follow the approach introduced in [13] and define a virtual circle wherein the Base Station (BS) records the movements and assigns the instantaneous probability to each movement. Eventually, the prediction is made as the user crosses the border of the virtual circle (*case 1*, Figure 3). Furthermore, the prediction of the next cell in *case 2* where the user enters the cell and leaves it without crossing the virtual circle is only based on MRP. In fact, as soon as the user enters a new cell, we assign a temporary prediction based on MRP and, as he moves across the cell inside the circle, we record the trajectories and make a new prediction based on both MRP and instantaneous probabilities at the border of the circle, where the user is likely to leave the circle (and subsequently the cell). The circle radius can be readily determined based, e.g. on Received Signal Strength (RSS).

B. Exponential Moving Average (EMA)

To determine the probability of each cell being the future crossing cell, we need to consider the movement of the user throughout the current cell. In particular, it is expected that the movements of the user are directed to his intended future cell. Therefore, averaging over instantaneous probabilities would be the first idea to take such overall behavior into account. However, user's intended future cell becomes more evident as the user approaches the border of the current cell. In other words, the final movements appear to play a decisive role in next-cell prediction. Given that, instead of using a simple equal weight moving average, we employ the *Exponential Moving Average (EMA)*, where the probabilities corresponding to recent movements are assigned larger weights [34]. Thus (13) can be written as

$$Pr(C_i|L_N) = \text{EMA}_n(Pr_{inst.}^{[i,n]}(C_i|l_n)), \tag{16}$$

where the operator $\text{EMA}_n(\cdot)$ applies exponential moving average over index n.

IV. Prediction algorithm

Given the previous sections, we now introduce our prediction scheme depicted in Figure 4. Furthermore, we develop Algorithm 1 which begins in step 1 with training the Markov model using the sequences of user crossed cells obtained from long-term history of movements, thereby calculating $P_{j,i}$. Moreover, having the sojourn time of the user at each cell before transitioning into a neighboring cell, we fit them into the exponential distribution for each neighboring cell and obtain $\lambda_{j,i}$, correspondingly $G_{j,i}(t)$. Finally, $Q_{j,i}(t)$ is calculated using (12). In step 2, as mentioned in Section III-A, a temporary prediction based solely on MRP, i.e. $Q_{j,i}(t)$, is assigned to the user as it enters the cell j (first we assume *case* 2, Figure 3). This is conducted as follows:

$$\arg\max_i Q_{j,i}(t=0) \text{ for } j = \text{current-cell index}. \quad (17)$$

Later on, in step 4, if the user enters the circle, i.e. the condition in step 3 is satisfied, the instantaneous probabilities are calculated based on its recorded locations within the virtual circle (step 5) and averaged (step 7). In step 8, the new probabilities assigned to neighboring cells based on MRP are obtained and combined in step 9 with the probabilities from step 7. Finally in step 10 the next crossing cell is predicted.

As an example, we assume user U_0 has entered the virtual circle of cell J_0 and arrives at the border of the circle at time T_0 after being localized N_0 times. Using (6) and (7) the predicted next cell for this user is obtained as follows:

$$C_{Next} = \arg\max_i \frac{Q_{J_0,i}(t=T_0)P(C_i|L_{N_0})}{\sum_{i=1}^{6} Q_{J_0,i}(t=T_0)P(C_i|L_{N_0})}$$

Algorithm 1 Prediction Algorithm

1: Train the MRP using long-term data history.
2: Make primary prediction based on MRP in (9).
3: **if** User crosses the border of the circle **then**
4: Record the locations of user inside the circle.
5: Assign instantaneous probabilities with each record using (14).
6: **if** User is at the border of the circle **then**
7: Obtain the exponential average of probabilities obtained in step 5 using (16).
8: Obtain the probability of each cell being next crossing cell using MRP in (12).
9: Combine the probabilities from step 7 and step 8 using (6).
10: Predict the next crossing cell using (7).
11: **end if**
12: **return** Predicted cell (outcome of step 10)
13: **end if**

V. Results and Discussions

To evaluate the performance of our proposed algorithm in terms of prediction accuracy we use the collected data from [35]. The data set includes the trajectory of 4 users, each of them at a different site. We only use the data from the city of New York (39 days) and the university campus KAIST (92 days) since they show both random and regular behavior. The trajectories of the users have been recorded each 30 seconds in XY Cartesian coordinates. Moreover, we divide the XY-plane into several cell clusters and map the trajectories of the data set onto it to obtain the cell sequences for training the MRP. Furthermore, 60% of the available data is used to train MRP and the rest to evaluate the proposed algorithm. Finally, as a benchmark, we consider the prediction model based solely on Markov model.

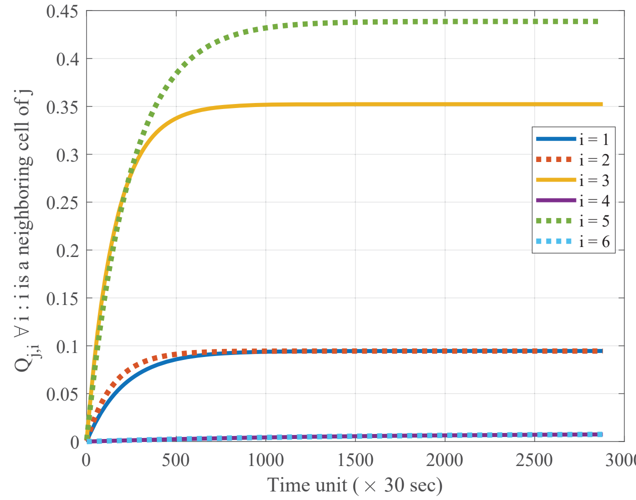

Fig. 5. Probability of transition to neighboring cells, $Q_{j,i}(t)$, for an exemplary cell j.

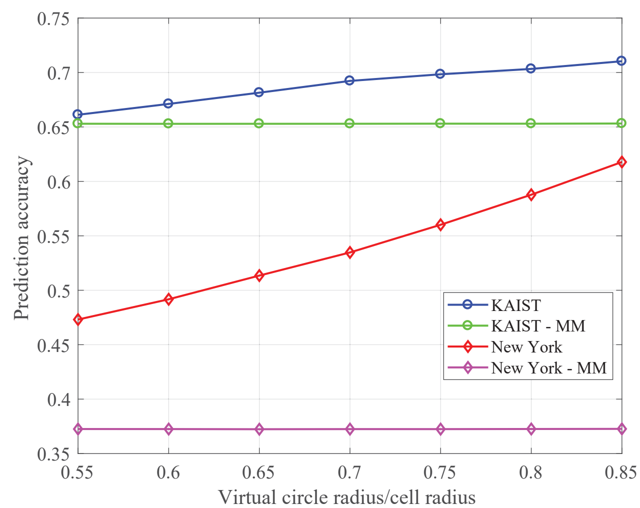

Fig. 6. Prediction accuracy for Algorithm 1 and Markov model in two sites, namely New York city and KAIST university campus.

Figure 5 indicates the convergence of transition probabilities to the neighboring cells. As can be observed, in accordance with (11), $Q_{j,i}(t)$ converges to $P_{j,i}$ as the sojourn time grows. In other words, as we expect,

$$\lim_{t\to\infty} Q_{j,i}(t) = P_{j,i}. \quad (18)$$

Specifically, in the course of prediction, as the user arrives at the border of the virtual circle, $Q_{j,i}(t)$ is calculated based on the sojourn time of the user in the current cell up to the moment of prediction. Later on, it is combined with (13) by the combination rule in (6) to make a prediction about the future crossing cell. In fact, the instant in which the prediction is made, can have significant impact on the outcome of the prediction as $Q_{j,i}(t)$ is time-variant.

Figure 6 shows the prediction accuracy versus the ratio of *virtual circle radius* to *cell radius* for Algorithm 1 and Markov model (MM). The prediction accuracy is averaged over different cell sizes varying from 500 meters to 1200 (with the step size of 10 meters). As can be seen, for Algorithm 1, the prediction accuracy increases as the virtual circle radius grows, whereas the MM indicates constant behavior. Indeed, as the circle's radius grows, the number of recorded locations increases and we can include the last movements of the user into the prediction algorithm. Thus we are able to overcome the random behavior that might happen in the last moments of the user's residence in the current cell. It is worth mentioning that the gap between Algorithm 1 and MM for KAIST campus is less than that of New York city. Particularly, owing to the bigger data set for KAIST campus, namely 92 days of user's trajectory, the Markov model achieves higher prediction accuracy. Note that the size of the data set for New York city is only 39 days.

VI. Conclusion and Future Works

In this work, we proposed a new mobility prediction algorithm employing long- and short-term history of users' movements. In particular, we perceived the regularity in users' movements with the aid of Markov renewal process while the randomness of their behavior was captured by utilizing the recorded locations in their current residing cell. The latter was further incorporated into the algorithm by assigning probabilities to each neighboring cell based on the direction of movement. Furthermore, Dempster-Shafer theory was employed to combine above pieces of evidence, thereby predicting the next crossing cell of the users. Simulation results indicate that the prediction can be made with high accuracy and reliability using the proposed algorithm.

In future works, we will investigate the impact of different combining and inference methods currently employed in reasoning and decision making theory. In addition, we will include more pieces of evidence into the prediction algorithm. In particular, utilizing more pieces of information and deploying sophisticated inference methods, which take more aspects of the collected data into considerations (e.g. dependence between sources of information or reliability of the sources), we expect to enhance the accuracy of the prediction. However, in this case, complexity is going to be the challenge to be overcome. Furthermore, in the course of conducting this work, we observed that there is a range of cell sizes where our proposed algorithm operates significantly better (i.e. more than 85% accuracy), therefore considering the optimal ratio of *location recording frequency* to *cell radius* is another aim to be pursued in future works.

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