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 in 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 from two sources of information 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, Baysian 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].

Markov model in [4] is deployed to perceive the habitual movements and thereby predicting user movement. 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. Hidden Markov Model (HMM) is applied in [6], [7] to utilize prior knowledge such as movement history for learning and inference. Machine and learning, as in [8], [9], [10], [11], [12] are other approaches adopted in literature to predict users next residing cell. In [13], the locations of the user in the current cell is 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.

Generally, the users show both random and regular behavior in their daily life, e.g. 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. Therefore, it appears technically reasonable to consider both regularity and randomness in the prediction algorithm in order to enhance its accuracy. In [5], the MRP is used to capture the regularity in 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 current and next state. Furthermore, in [13], the instantaneous position of each user within its current residing cell is recorded and exploited to take the randomness into account. In brief, MRP represents the information about regularity while instantaneous positions contain information about randomness of users' movements. Additionally, to combine evidences from independent sources of information, among all the existing combiners [18] and classifiers [19], [20], [21], DS theory [22] has received huge attraction in recent years. In particular, in [15], multiple evidences about future candidate locations are combined using DS to predict future location of the user.

The contributions of this paper may be summarized as follows:

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

The rest of this paper is structured as follows: In Section II, we give an introduction to Dempster-Shafer theory and explain the Markov renewal process as well as its functionality in this work. In Section III, we discuss the perception of randomness in user's 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.

Notation:

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

II. Preliminaries

To develop the prediction algorithm, we firstly provide an overview of DS theory and MRP. The former combines the information obtained from several sources while the later acts as a source whose information is employed by the former.

A. Dempster-Shafer Theory

In order to reach a correct and reliable decision about the next crossing cell, we are required to utilize all the collected information 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 mass functions are combined in order 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 following conditions:

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

where A_i is a subset of Θ. It's worth mentioning that a mass function assigns numbers directly to the evidences (subsets of Θ) while traditional probability theory assigns numbers to the elements of Θ [15]. To clarify, we consider a set of possible future cells $\Theta = \{C_1, C_2, C_3\}$. A mass function would assign numbers to element 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 independet 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. an element 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 (1) turns into a Bayesian rule of inference which is 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 a the future possible cell, $i \in \{1, 2, \cdots, 6\}$. Assuming independence of the sources (i.e. knowing H provides no extra information about L or otherwise)

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

We can then rewrite (3) as

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

After reformulation using Bayes' theorem we can rewrite (5) as follows

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

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 singeletons based on short- and long-term history of user 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 [6], [5], [26]. In this work, we employ the MRP from [5] to obtain the probability of each neighboring cell, being chosen as the next crossing cell. 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

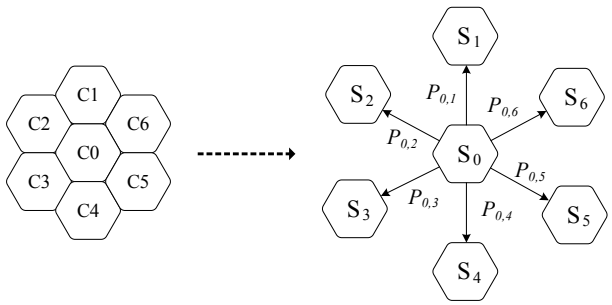

Fig. 1. Markov model for each cell in cellular network.

Markov model denote the probability that the user transitions to each neighboring cell. Note that we construct a 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]

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

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. $Q_{i,j}(t)$ denotes the probability that, after transitioning into state i, the process transitions into state j within t units of time. We then rewrite (8) as

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

where

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

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

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

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

$\lambda_{i,j}$ is chosen such that (11) fits the used data set. By combining (9) and (11), the transition probability for each neighboring cell can be obtained based on MRP. The probability then is written as

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

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, university, etc., there is still a degree of randomness in user's 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

User's location history across the current cell contains valuable information about possible randomness in the behavior of the user. 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. Note that vector L denotes the past locations of the user in the current cell, whereas the long-term data 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,

$$Pr(C_i | L_N). \quad (13)$$

Generally, we expect that each user's movements tend to head for its final destination. Therefore, monitoring the user's direction of movements 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 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

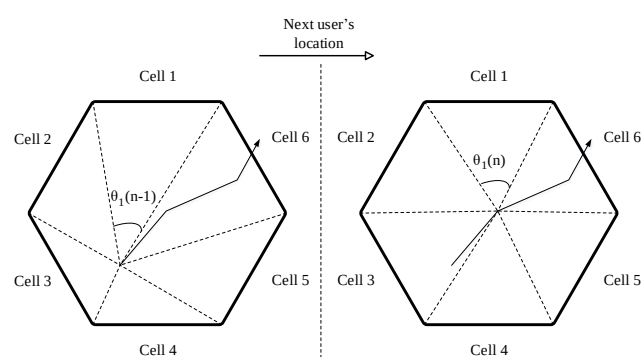

Fig. 2. Capturing direction of user movements by calculating the angle to cell vertex ($i = 1$).

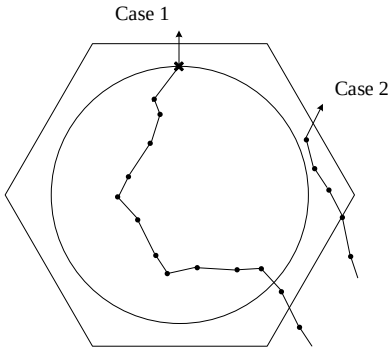

Fig. 3. Graphical example of the movements of a user within a cell.

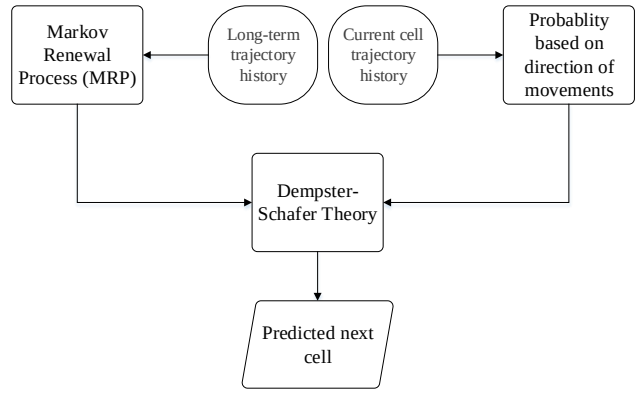

Fig. 4. Block diagram of prediction algorithm.

θ_i, we assign a probability to each of the neighboring cell being chosen as next crossing cell. The assigned probability is as follows

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

where

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

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

We follow the approach introduced in [13] and define a circle wherein the BS records the movements, assigns the instantaneous probabilities and, eventually, makes the prediction on the border of the 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 aforementioned 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 could 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 into account such overall behavior. However, user's intended future cell becomes more evident as the user approaches the border of the current cell. In other words, the final direction of movements appears 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 [30].

IV. Prediction Algorithm

Given the previous sections, we are now ready to introduce our prediction scheme depicted in Figure 4. Furthermore, we develop algorithm 1 which begins in state 1 with training the Markov model using the sequences of user crossed cells obtained from long-term history of movements, thereby calculating $P_{i,j}$. Moreover, having the reside 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 $\lambda_{i,j}$, correspondingly $G_{i,j}$. Finally, $Q_{i,j}$ is calculated using (12). In state 2, as mentioned in Section III-A, a temporary prediction is assigned to the user as it enters the cell (first we assume *case* 2, Figure 3). Later on, in state 4, if the user enters the circle (i.e. the condition in state 3 is satisfied), the instantaneous probabilities are calculated based on its locations within the circle (state 5) and averaged (state 7). In state 8, the new probabilities assigned to neighboring cells based on MRP are obtained and combined with the probabilities from state 7 in state 9. Finally in state 10 the next crossing cell is predicted.

V. Results and Discussions

To evaluate the predicting performance of our proposed algorithm we use the collected data in [31]. The data set includes the trajectory of 4 users, each of them at a different site including two university campuses (NCSU and KAIST), New York City, Disney World (Orlando) and North Carolina state fair. We only use the data from the city of New York (39 days) and the university campus KAIST (92 days) since they show dynamic behavior. The trajectories of users have been recorded each 30 seconds in XY Cartesian coordinates. Moreover, we map the cells manually onto the trajectories of data set to obtain the cell sequences for training the MRP. Furthermore, 60% of the available data is used to train MRP. Finally, as a benchmark we consider the prediction model based solely on Markov model.

Algorithm 1 Prediction Algorithm

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

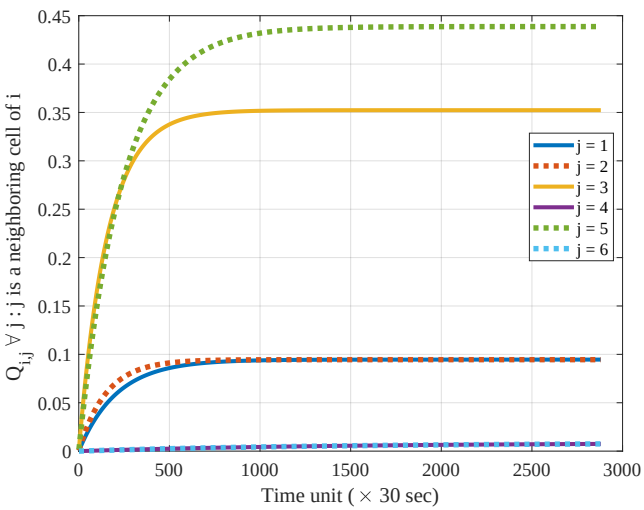

Fig. 5. Probability of transition to neighboring cells, $Q_{i,j}$, for an exemplary cell.

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

$$\lim_{t\to\infty} Q_{i,j}(t) = P_{i,j}. \tag{16}$$

Specifically, in the course of prediction, as the user arrives at the border of the virtual circle, $Q_{i,j}$ is chosen based on the residing time of the user in current cell up to the moment of prediction. Later on, this is used by 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 $Q_{i,j}$ varies with time growth.

Figure 6 shows the prediction accuracy versus the virtual circle radius to cell radius ratio 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 Markov model indicates constant behavior. Indeed, as this ratio 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 Markov model 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 trajectory, the Markov model achieves higher prediction accuracy. Note that size of the data set for New York city is only 39 days of user trajectory.

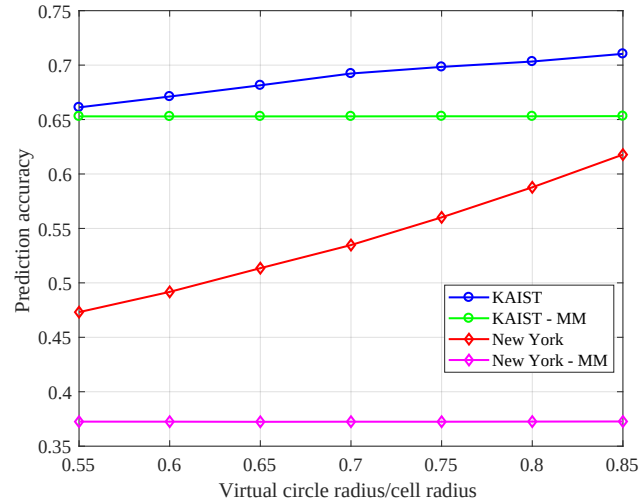

Fig. 6. Prediction accuracy for algorithm 1 and Markov model in two sites, namely New York city and KAIST university campus.

VI. Conclusion

In this work, we designed a new mobility prediction algorithm employing long-term and short-term movement history of users. In particular, we perceived the regularity in users' movement with the aid of MRP whereas the randomness of users' behavior was captured by utilizing the user's recorded locations in the current cell and incorporated into the algorithm by assigning probabilities to each neighboring cell based on the direction of movements. Furthermore, Dempster-Shafer theory was employed to combine above pieces of evidence in order to predict the next crossing cell. Simulation result indicate that the prediction can be made with high accuracy and reliability using the proposed algorithm.

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