On the Estimation of User Mobility Pattern for Location Tracking in Wireless Networks

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Abstract— **This paper presents a new scheme to estimate the user mobility by incorporating the aggregate history of mobile users and system parameters. With this approach, each user's position within the location area is differentiated by zone partition for more accurate prediction. In order to provide the flexibility of tradeoff between quality demand and computation complexity, the estimation is adjusted dynamically according to the constraint of prediction order. Then an adaptive algorithm is developed to predict the future position of mobile terminals in terms of location probabilities, while considering each terminal's movement direction, residence time, and path information. Simulation results demonstrate that the signaling cost for location tracking under delay bound is greatly reduced based on the estimated user mobility pattern.**

Key Words: *Wireless Networks, User Mobility Pattern, Location Tracking, Delay.*

I. Introduction

With the increasing demand for access to Internet and the advance technologies of wireless systems, it is envisioned that mobile users are able to enjoy the same quality that available to fixed users when they move from one position to another. The mobility support, which enables mobile users to communicate with others regardless of their locations, is related to the mobility pattern of the mobile terminals (MTs). The user mobility pattern is very important in wireless networks because it is the fundamental information for location tracking and the enhancement of *Quality of Service* (QoS). For example, the information of user mobility can be used to efficiently allocate the radio channels to each MT,red ucing the hand-off dropping probability caused by the shortage of bandwidth and yielding maximum system throughput [5], [9]. Also many mobility management schemes utilize the user mobility pattern to improve system performance by reducing signaling cost under delay bound [3], [6].

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In order to capture the user mobility pattern, we need to consider the user historic records and path availability in the observation areas. Some of the existing methods are aimed to find the most probable cell or a cluster of cells without considering the historic records, which may overlook some probable cells [4], [10]. Another issue is that most of the previous solutions do not take the path information into account, preventing them from practical application [2], [8]. Also, it is critical to consider the computation scalability for real-time applications in mobile environment.

In this paper, we propose a new method to estimate the user mobility in terms of location probabilities for each MT. The rest of this paper is organized as follows. In Section II, a system model is presented in which new concepts of *zone* and *prediction order* are introduced. In Section III, an algorithm is developed for calculating the number of probable cells and predicting the future cells. It is also used to derive location probabilities for a set of cells instead of choosing the most probable cell. In Section IV, we describe the simulation model and the parameters in our experiments. The effect of the proposed scheme on location tracking is shown in Section IV. Finally, we conclude the paper in Section V.

II. The Concepts of Zone Partition and Prediction Order

A typical wireless network is composed of a wirelined backbone and a number of base stations (BSs). A mobile switching center (MSC) controls a set of BSs, manages the resources as well as the signaling exchanges. If an MT is moving from one cell to a cell which belongs to another MSC, location registration and identity authorization may be involved. In order to predict the future locations of an MT, we should differentiate an MT's current position in a large area. Here, we extend the *shadowing cluster* concept, which was introduced in [9]. For the two-dimensional topology, hexagons are used to denote the cells; thus, each cell has six neighbors and the probability of an MT leaving along one side is assumed to be $\frac{1}{6}$. However, this is unfair for the MTs with an active connection and a specific destination.

Therefore, we propose the *zone partition* concept within the coverage of an MSC to predict the MTs' position in smaller granularity. There may be varying number of zones in real environment, depending on geographic circumstances and network architectures. As an example, the service area of each MSC is divided into n zones ($n = 7$)as shown in Fig. 1. The MT's current position is closely related to its next position because of the continuity of an MT's movement. If an MT is currently in zone 2, it is likely to move into zone 0,1,3 and even to the coverage area of MSC-C in the next moment. In such a way, we incorporate the MT's movement direction and position (zone) in estimating an MT's mobility pattern.

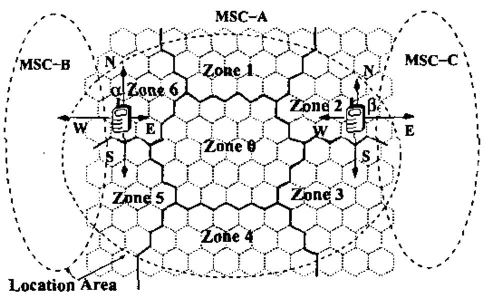
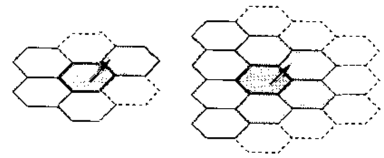


Fig. 1. Zone Partition.

An MT's current resident cell can be determined in several ways. First, when an MT initiates a call, it sends routing request to the serving MSC through the serving BS. As a result, the network knows in which cell the calling MT is residing. Second, when an incoming call arrives at an MT, the network first locates the MSC with which the called MT has registered. Then the MSC pages the BSs in its controlling area so as to find which BS is serving the called MT. Thus, the called MT's current cell is known to the network. Third, the MT's location can also be obtained through location services management provided by wireless systems [1].

Furthermore, we introduce the concept of *prediction order* because it is necessary to know how many cells are covered in the prediction. If the estimated cells cover only the cells of the first ring, which are adjoining to the MT's current cell, then it is called *first order prediction*. Similarly, the *second order prediction* is associated with those cells that are adjacent to the cells in the first ring and those cells covered in the first order prediction as in Fig. 2. Prediction order is a very helpful parameter in balancing the computation complexity and the prediction accuracy. For the first order prediction, only six cells are considered, i.e., the computation is simple. If the second order prediction is required, there are eighteen cells to be considered. Correspondingly, the complexity of computation increases, which is demonstrated in Section III.



(a) The First-order Prediction (b) The Second-order Prediction

Fig. 2. Prediction Order.

III. Estimation Algorithm and Procedure

In this section, we discuss how to identify those cells in which an MT will probably move into and how to determine their location probabilities. Let $\vec{\mathbf{P}}_{x,i}(t)$, be the location probabilities of the cells that an MT will move into. If an MT x is currently in cell i, then

$$\vec{\mathbf{P}}_{x,i}(t) = [P_{x,i,0}(t)\ P_{x,i,1}(t)\ P_{x,i,2}(t)\ \cdots\ P_{x,i,N}(t)], \quad (1)$$

where $P_{x,i,j}(t)$ in (2), is the probability that an MT, x, currently in cell i, will be in cell j and N is the total number of cells for prediction. $\vec{\mathbf{P}}_{x,i}(t)$ depends on the MT's historic records, current position, velocity, and moving direction. Therefore, $P_{x,i,j}(t)$ has the general form

$$P_{x,i,j}(t) = F(v_x(t), \gamma_x(t), l_x(t), \theta_x(t)), \qquad (2)$$

where $v_x(t)$ is the velocity of the MT x, $\gamma_x(t)$ is the probability density function (pdf) of the MT's residence time in a cell. $l_x(t)$ is used to specify the current MT's zone position and the moving direction, $\theta_x(t)$, is defined as the degree from the current direction clockwise or counter-clockwise. Based on these parameters, the computation can be divided into following steps: 1) Determine the MT's current and future zone partitions; 2) Calculate the number of cells for estimation; and 3) Compute the location probabilities.

A. Estimation of Zones

The coordinate system shown in Fig. 3 is defined with its origin at the current location of the MT, i.e., the MT is always in its origin and its previous direction is the positive direction of the X axis. Y axis is obtained by turning 90^o counterclockwise from the X axis.

Assume an MT is moving from point O (Z_0)to ward A; thus, its next position may be in zone 1, Z_1. In general, the future zone, *Case k* ($1 \leq k \leq n-1$) can be determined as

$$Z_k \quad = \begin{cases} \lceil \frac{\theta_x(t)}{\theta_0} \rceil & \text{if } \theta_x(t) \geq 0 \\ n - 1 - \lceil \frac{|\theta_x(t)|}{\theta_0} \rceil & \text{if } \theta_x(t) < 0 \end{cases} \qquad (3)$$
$$\rightsquigarrow \text{Case } 1 \text{ to } n-1 \rightarrow Z_1 \text{ to } Z_{n-1},$$

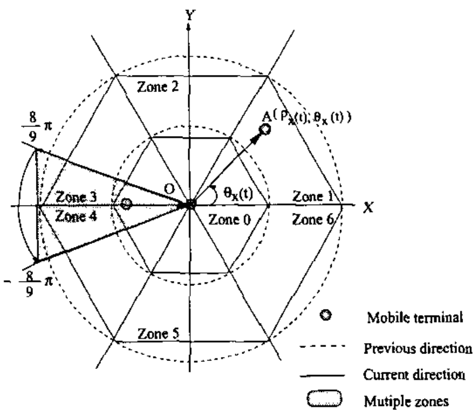


Fig. 3. Coordinate System with Zone Partition.

where n is the total number of zones and θ_0 is the angle of each zone. It is possible that more than one zone will be involved in estimating location probabilities because it is difficult to differentiate an MT's position around the boundary of zones as the dark region shown in Fig. 3. Thus, we extend the possible zones for *Case* k $(n \leq k \leq 2n-1)$ by the following expression:

$$\begin{aligned} &\mid \theta_x(t) \mid \pmod{\pi} \leq \tfrac{1}{3}\cdot\theta_0 \\ &\quad\rightsquigarrow \text{Case } n \to Z_{n-1} \text{ and } Z_1 \\ &\mid \theta_x(t) - \theta_0 \mid \pmod{\pi} \leq \tfrac{1}{3}\cdot\theta_0 \\ &\quad\rightsquigarrow \text{Case } n+1 \to Z_1 \text{ and } Z_2 \\ &\qquad\vdots \\ &\mid \theta_x(t) - (n-2)\cdot\theta_0 \mid \pmod{\pi} \leq \tfrac{1}{3}\cdot\theta_0 \\ &\quad\rightsquigarrow \text{Case } 2n-1 \to Z_{n-2} \text{ and } Z_{n-1} \end{aligned} \tag{4}$$

B. Calculation of Cells Number

We compute the number of cells that an MT may have traveled during the time window ΔT. Let $v_x(0)$ be the average velocity of an MT and consider that the MT traversed a cell with an average time of its residence time. The pdf of an MT's residence time is assumed to be Gamma distribution, which has Laplace transform $Q_{x,T}(s)$ with the mean value $1/\mu$ and the variance V, i.e., $Q_{x,T}(s) = \left(\frac{\mu\gamma}{s+\mu\gamma}\right)^{\gamma}$, where $\gamma = \frac{1}{V\mu^2}$. Given the mean residence time, $E_x[T] = \frac{1}{\mu}$, the *travel order*, $\overline{o_x(t)}$, that an MT may reach along one direction is obtained by

$$\overline{o_x(t)} = \lceil \frac{\Delta T}{E_x[T]} \rceil. \tag{5}$$

To ensure the cell coverage required by the prediction order, $O_x(t)$, we must consider the maximum number of cells needed by both travel order and the prediction order. We denote $N_x(\max\{\overline{o_x(t)}, O_x(t)\} = r : t, k)$, which is rewritten as $N_x(r : t, k)$ in short, as the number of probable cells in the mobility profiles with order r at time t for *Case* k. The most simple scenario is $\overline{o_x(t)} = O_x(t) = 1$, the number of the probable cells for *Case 1* in (3), $N_x(r = 1 : t, 1)$, is then determined by

$$N_x(r = 1 : t, 1) = \lceil 6 \cdot \frac{\mid \theta_x(t) \mid}{2\pi} \rceil. \tag{6}$$

Similarly, we can have a general form for calculating the number of probable cells for other cases, $N_x(r : t, k)$, that is

$$N_x(r : t, k) = \begin{cases} k - 1 + \lceil 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil + \lceil 2 \cdot 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil \\ \quad + \cdots + \lceil k \cdot 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil \\ \qquad \text{if } 1 \leq k \leq n-1 \\ 2 \cdot (k - 1 + \lceil 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil + \lceil 2 \cdot 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil \\ \quad + \cdots + \lceil k \cdot 6 \cdot \frac{|\theta_x(t)|}{2\pi} \rceil) \\ \qquad \text{if } n \leq k \leq 2n-1. \end{cases} \tag{7}$$

C. Prediction of Location Probabilities

Consider a particular cell, the number of paths or travel routes through this cell is finite. Then the path information can be recorded in a *trace records matrix* (TRM) of $L \times M$, where L is the total number of records and M is the total number of cells that an MT has traversed in the period of observation. The element $z_{\alpha\beta}$ $(\alpha = 1, 2, \ldots, L;$ $\beta = 1, 2, \ldots, M)$, of the TRM, denotes whether the MT has traversed a cell, $z_{\alpha\beta} = 1$ or not, $z_{\alpha\beta} = 0$, respectively.

Given this matrix $\mathbf{Z}$, the probability of going through each cell can be estimated by comparing with *path database* (PD), which is a part of the digital map. Moreover, we assume that an aggregate historic path database $\mathcal{D}_x^H$ is available to retrieve in the network administration center. Each record in this database is the previous path that the MT x has traversed. Then $P_{x,i,j}(t)$ in (2), for $j = 1, 2, \cdots, N_x(r : t, k)$, is computed by the following procedures:

- **Step 1:** Select a value $0 < p_0 < 1$ as the initial point for computing the location probabilities.
- **Step 2:** Start from the bottom line of TRM and take the last two non-zero elements of the TRM to make a temporary path $\mathcal{P}$ as shown in Fig. 4(a).
- **Step 3:** Compare the path $\mathcal{P}$ to the equal or close segment in PD as shown in Fig. 4(b). There may be a set of cells that can be the next cell along with path $\mathcal{P}$, which is represented by a set $\mathcal{P}_x^S$. Each element of this set, $X_j \in \mathcal{P}_x^S$ is a probable cell in Fig. 4 (c), and it gives a *possible path*, $\widetilde{\mathcal{P}}(X_j)$.

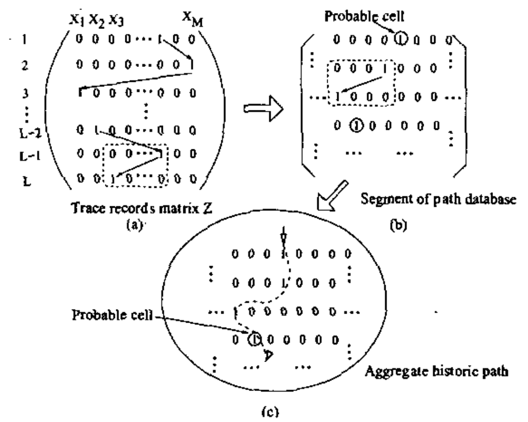


Fig. 4. Prediction of Location Probabilities.

• **Step 4:** Estimate location probabilities, $P_{x,i,j}(t)$, under the process shown in Fig. 5. This algorithm starts from examining each cell in the set of possible cells, $X_j \in \mathcal{P}_x^S$,and the total number of cells in this set is $\mathcal{N}_x(r:t,k)$ from (7). If a probable cell, X_j,is in the first order prediction and the its corresponding path, $\widetilde{\mathcal{P}}(X_j)$, can be found in the historic path database $\mathcal{D}_x^H$, then the cell X_j has the highest location probability. This emphasizes the importance of prediction constraints and the user history. After that, as the probable cells are getting farther away from the MT's current position, and they are not relevant to the historic paths, the location probabilities decrease. This process continues until all cells in the possible set are scrutinized.

As a result, a sequence of location probabilities is obtained in terms of p_0, where p_0 can be solved by applying the following expression:

$$\underbrace{\sum}_{j\in(\mathcal{P}_x^S \bigcup \mathcal{N}_x(r:t,k))} P_{x,i,j}(t) = 1 \qquad (8)$$

IV. Performance Analysis

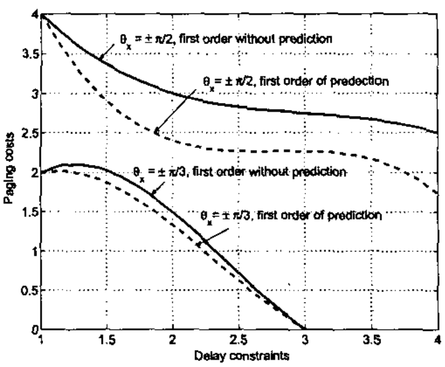
There are many ways to evaluate the effectiveness of the proposed scheme [5], [6], [9]. Here we show the effect of these results on location tracking in wireless networks. In current wireless systems, location tracking is realized through paging process, in which an MSC sends polling message to BSs to determine the serving cell of the called MT. Paging cost is concerned with network resource because the paging message is sent via down-link channels; thus, it should be reduced as much as possible. On the other hand, paging delay affects the latency of service delivery, which is regarded as one of the QoS parameters. Therefore, the paging cost must be reduced under delay bound.

p_0 := initial value of the highest probability
$\mathcal{P}$:= temporary path of TRM
$\mathcal{P}_x^S$:= set of probable cells in PD along path $\mathcal{P}$
$\widetilde{\mathcal{P}}(X_j)$:= possible path of cell $X_j \in \mathcal{P}_x^S$
$\mathcal{N}_x(r:t,k) := \mathcal{N}_x(\max\{\overline{o_x(t)}, O_x(t)\} = r:t,k)$
$P_{x,i,j}(t)$:= location probability at cell j given an MT x
  is currently in cell i
P_0 := threshold of probability computation
while $n \le \mathcal{N}_x(r:t,k)$ **do**
  for all $X_j \in \mathcal{P}_x^S$ **do**
    if $X_j \in \mathcal{N}_x(1:t,k)$ and $\widetilde{\mathcal{P}}(X_j) \in \mathcal{D}_x^H$ **then**
      $P_{x,i,j}(t) := p_0$
    else
      case : $X_j \in \mathcal{N}_x(2:t,k)$ and $\widetilde{\mathcal{P}}(X_j) \in \mathcal{D}_x^H$
        $P_{x,i,j}(t) := \frac{1}{2}p_0$
      case : $X_j \in \mathcal{N}_x(2:t,k)$ and $\widetilde{\mathcal{P}}(X_j) \notin \mathcal{D}_x^H$
        $P_{x,i,j}(t) := \frac{1}{4}p_0$
      case : $X_j \notin (\mathcal{N}_x(1:t,k) \cup \mathcal{N}_x(2:t,k))$ and $\widetilde{\mathcal{P}}(X_j) \in \mathcal{D}_x^H$
        $P_{x,i,j}(t) := \frac{1}{4}p_0$
      others :
      for all $r > 2$ **do**
        while $P_{x,i,j}(t) \le P_0$ **do**
          case : $X_j \in \mathcal{N}_x(r:t,k)$
            $P_{x,i,j}(t) := (\frac{1}{2})^{r-1}p_0$
          case : $X_j \notin \mathcal{N}_x(r:t,k)$
            $P_{x,i,j}(t) := (\frac{1}{2})^{r}p_0$
        end while
      end for
    end if
  end for
end while

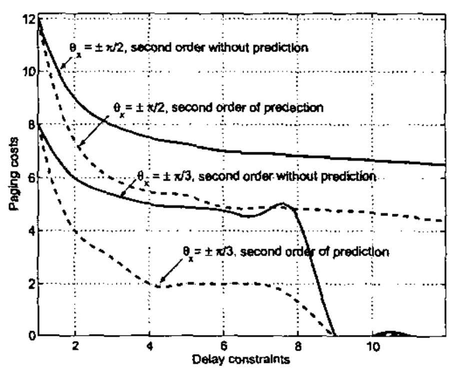
Fig. 5. Estimation of Location Probabilities (Step 4).

We consider that the MTs move with varying speed and directions [7], [11]. The initial velocity of an MT is assumed to be a random variable with Gaussian probability density function truncated in the range of $[0, 112km/h]$ and the velocity increment is taken to be a uniformly distributed random variable in the range of $\pm 40\%$ of the average velocity, $80km/h$. As for the residence time distribution, the values of μ is taken with 1.65 [12].

The most important feature of this simulation is that we use an actual digital map instead of mathematical models. The cell radius is assumed to be $2km$ in our simulation. The full area of the segmentation map is covered by this type of cells. For $\theta_x(t) = \pm\pi/3$, and $\theta_x(t) = \pm\pi/2$, we first determine the probable zones using (3) and (4), limiting the probable cells in a particular region. Then the number of probable cells is computed by using (5) and (7) in Section III.



(a) First order



(b) Second order

Fig. 6. Comparison of Paging Costs

The paging costs resulted from the location probabilities of first and second order prediction are compared to that of uniform distributions without prediction. The numerical results of paging costs are given in Fig. 6, in which paging costs are measured by the number of cells to be searched before finding the MT.W hen the variation of moving direction is high, the improvement of paging costs is more visible as shown in Fig. 6(a). For example, when $\theta_x = \pm\frac{\pi}{3}$, the reduction in paging costs due to the location probabilities is not as large as that of $\theta_x = \pm\frac{\pi}{2}$. This means that it is more important to predict location probabilities if the MTs are moving randomly,i. e., the movement of the MTs is not uniformly distributed in the location area. If the prediction order is higher, the paging costs can be significantly reduced compared to without prediction. Specifically, if the MTs are moving very fast and they may go to other cells in a short time, it is more difficult to locate the MT. Accordingly, the prediction of MTs' location probabilities is more effective and important.

V. Conclusion

In this paper, we presented a predictive scheme for estimating user mobility in wireless networks. We proposed the concept of zone partition which helps to identify the MTs' position inside a location area. Also, the prediction order is introduced to dynamically determine the probable cells with respect to the computation complexity and the QoS requirements. Based on an MT's zone partition and the prediction order,an adaptive algorithm is developed to incorporate the MTs' historic records and the path information. In addition, this method takes the moving direction and MTs' residence time into account for better prediction. The simulation results demonstrated that the signaling cost of location tracking under delay bound can be significantly reduced with the user mobility prediction.

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