Available at www.ComputerScienceWeb.com
POWERED BY SCIENCE @ DIRECT®

ELSEVIER

Computer Communications 26 (2003) 1288–1301

computer communications

www.elsevier.com/locate/comcom

A Stop-or-Move Mobility model for PCS networks and its location-tracking strategies[☆]

Yu-Chee Tseng[a,*], Lien-Wu Chen[b], Ming-Hour Yang[a], Jan-Jan Wu[b]

[a]*Department of Computer Science and Information Engineering, National Chiao-Tung University, Hsin-Chu 30050, Taiwan*
[b]*Institute of Information Science, Academia Sinica, Taipei 11529, Taiwan*

Received 18 June 2002; revised 12 December 2002; accepted 13 February 2003

Abstract

This paper considers the *location-tracking* problem in PCS networks. Solutions to this problem in fact highly depend on the mobility patterns of mobile subscribers [ACM DIAL-M (1999) 72]. In the literature, many works have assumed a simple *random walk* model, where mobile subscribers always stay in a roaming state and can move in any direction with equal probability. In this paper, we propose a new *Stop-or-Move Mobility* (SMM) model, which is characterized by the following features: 'transition between stop and move', 'infrequent transition', 'memory of roaming direction', and 'oblivious in different moves'. Based on this mobility model, a static and an adaptive location-tracking Scheme are developed. The schemes only need to keep very little information for each user. Analyses and simulations are provided, which show that the proposed schemes are quite prospective.

Keywords: Location management; Location update; Mobile computing; Paging; Personal communication service; Wireless communication

1. Introduction

The *Personal Communication Service* (PCS) is one of the fastest growing industries in recent years, and it is expected to remain so in the next decade. Typically, PCS networks have a cellular architecture. One essential issue in PCS networks is the *location management* problem, or known as the *location-tracking* problem. To keep its location up-to-date, a mobile subscriber must update its current location with its home location register (HLR) from time to time. On a call arriving, the system will page the subscriber based on its recent update(s). Since it is a tradeoff between updating and paging, considerable research has been devoted to this direction [1–6,8,10,11, 13,14,18,20].

The current GSM system adopts the *location area* approach [14]. The physical area is statically partitioned into a number of location areas (LAs), each containing some neighboring cells. When a mobile subscriber enters a new LA, it always updates its current LA with its HLR. To assist subscribers, base stations in a LA will broadcast the corresponding LA identity periodically. When a call arrives, the system simply pages all cells in the subscriber's current LA. Since LAs are statically partitioned, the ping-pong effect may take place on the boundary cells of LAs, causing high updating costs. Also, since updates always happen at boundary cells, extra traffic loads may be incurred on them. How to optimally partition LAs is considered in Ref. [19], and the subscribers' moving directions are further discussed in Ref. [9].

Dynamic update scheme developed based on users' activity have also been proposed. Such solutions can be generally divided into three categories [5]:

1. Time-based: a mobile user registers with its HLR whenever a preset timer expires since its previous update [5,13].
2. Movement-based: a mobile user registers whenever it has crossed a preset number of cell boundaries since its previous update [2,5].

☆ A preliminary version of this paper has appeared in the *Int'l Conf. of Distributed Computing Systems*, 2001. This work is co-sponsored by the Lee and MTI Center for Networking Research at the National Chiao Tung University and the MOE Program for Promoting Academic Excellence of Universities under grant numbers A-91-H-FA07-1-4 and 89-E-FA04-1-4. Part of this work was done while Y.-C. Tseng was visiting the Institute of Information Science, Academia Sinica, Taiwan.
* Corresponding author.
E-mail address: yctseng@csie.nctu.edu.tw (Y.-C. Tseng).

0140-3664/03/$ - see front matter © 2003 Elsevier Science B.V. All rights reserved.
doi:10.1016/S0140-3664(03)00112-9

3. Distance-based: a mobile user registers whenever the distance between its current cell and its previously registered cell exceeds a preset threshold [3,5,8,11].

On a call arriving for a subscriber, the system has to determine the cell where the subscriber currently resides. The subscriber's recent updates can provide some clues to confine the paging area. Thus, updating costs and paging costs are tradeoffs. In addition, paging must be completed within some delay constraint. The fastest approach is *single-step paging*, where all potential cells are searched concurrently. An alternative is *selective paging* [2,3,8], where the potential cells are partitioned into a number of sets, which are searched sequentially until the subscriber is found.

How a location-tracking strategy performs in fact highly depends on the *mobility pattern* of subscribers. As observed by Siddiqi and Kunz [16], different mobility models, when being applied to different Scheme, may lead to very different performance conclusions. However, as one may imagine, there is no single conclusive model that can characterize all possible roaming behaviors [21]. For example, a housewife is more likely to be static than mobile, while a taxi driver may be mobile all the time. A salesman is likely to transmit between a stop state (when meeting a customer) and a moving state (when heading for the next customer). Under the moving state, different drivers will have quite different driving speeds and directions (e.g. a white-collar worker may have a fixed moving direction every morning, while a taxi driver's driving directions might be quite random). Further, when being mobile, exceptional situations may always occur (traffic lights, speed limits, traffic jams, etc.).

In the literature, most works assumed a simple, but unrealistic, *random walk* model [2,3,8,17]. It is certainly very difficult to have a general model that can characterize the mobility patterns of all mobile users. The works by Bar-Knoy and Kessler and Birk and Nachman [5,7] have taken directional bias of user movement into consideration. In Ref. [1], the roaming directions of mobile subscribers are considered, and it is assumed that users tend to pick the *shortest paths* leading to their destinations. Observing that works in Refs. [1–3,5,7,8] do not consider the mobility variation of users, Ref. [16] presents an *activity-based model*, which assumes that users may transit from activity to activity, where an *activity* has an associated time of day, duration, and location. In Ref. [6], an efficient way to record a user's roaming history is proposed. While more efficient, the database for Refs. [6,16] could be very large because information is maintained in a per user, per cell/LA basis. The design of location areas for one-dimensional cells (e.g. highway or street) is discussed in Ref. [15], where two types of users, vehicles and pedestrians, are considered. A *profile-based* strategy [12] can potentially capture all kinds of mobility patterns since individual users' previous roaming patterns are registered to predict their future patterns. However, establishing the historical database is very complicated and costly, sometimes even requiring users' involvement.

In this paper, we propose a new, but simple, model called *Stop-or-Move Mobility* (SMM) model. The model is characterized by the following features: (i) *transition between stop and move states*: a user is either in a stop or a move state, (ii) *infrequent transition*: once entering a state, a user has the tendency to remain in the same state for quite a while, (iii) *memory of roaming direction*: once entering the move state, a user will have some preference on some particular direction, and (iv) *oblivious in different moves*: between different moves, their roaming directions have little correlation. The first two features are to capture users' mobility variations. The third is to take roaming directions into consideration, while the last is to limit the amount of roaming histories to be kept by the system. These features will be elaborated further in Section 2. Intuitively, the model is derived based on the observation of human's daily life. Taking a salesman as an example, he/she may head from home to office in the morning, stay in office for some while, and then go for a meeting. After the meeting, he/she may visit a few customers, and then end his/her day by staying in a supermarket for a while and then returning home. Such a stop-or-move behavior is illustrated in Fig. 1.

Based on the SMM model, we then propose a new strategy for location management. The mobility database will be maintained on a per user basis. Only few variables have to be recorded for each user. The basic idea is to predict a user's current state (stop or move) based on some threshold values. Under the stop state, a subscriber can be paged with very low cost, while under the move state he/she will be selectively paged in several steps based on the movement-based approach. We also extend our strategy to an adaptive one by dynamically adjusting the threshold values. Analysis and comparisons are provided, which show that our scheme is very promising.

The rest of this paper is organized as follows. Section 2 discusses the SMM model in more details. A location management strategy based on the SMM model is proposed in Section 3. Section 4 shows how to optimize the paging cost with location prediction and selective paging when there is memory in roaming direction. Section 5 extends our

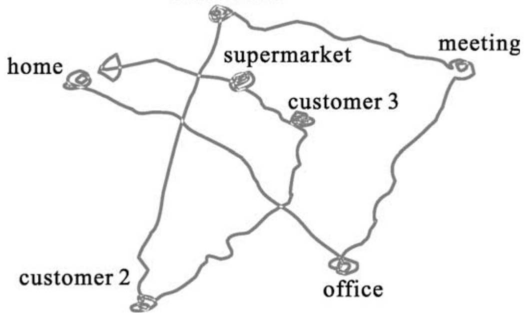


Fig. 1. An example of a salesman's stop-or-move roaming behavior.

strategy to an adaptive one. Performance comparisons and simulation results are in Section 6. Conclusions are drawn in Section 7.

2. The Stop-or-Move Mobility (SMM) model

In this section, we propose a new Stop-or-Move Mobility (SMM) model. This model is actually obtained from observing human's daily activities. The model is characterized by the following features.

- *Transition between Stop and Move*. In the SMM model, we assume that a mobile subscriber will mainly switch between two states: *stop* and *move*. Under the stop state, the subscriber is perhaps working in his/her office, talking to customers, or attending a meeting. From time to time, the subscriber will be mobile and switch to the move state. Under the move state, the subscriber is perhaps on the way to his/her home or office or to the next meeting. Once reaching the next destination, the subscriber will enter the stop state. The subscriber will repeatedly transit between these two states. This can be modeled by a state-transition diagram as in Fig. 2, where the subscriber has probabilities of p and q to remain in the stop and move states, respectively, and probabilities of $1-p$ and $1-q$ to transit to the other state after each time unit. Here a time unit is a predefined, system-wide parameter.
- *Infrequent transition*. A subscriber has the tendency to remain in the same state rather than switching states. That is, if the subscriber is currently in the stop state, it is more likely that the subscriber will remain in the same state in the next moment than switching to the move state. Similarly, once in the move state, the subscriber will remain in the same state until the subscriber arrives at his/her next destination. Reflecting by Fig. 2, we will assume that both probabilities p and q are very close to 1. For instance, one possibility is to set $p = 0.99$ and $q = 0.97$.
- *Memory of roaming direction*. Once in the move state, the subscriber's mobility pattern may be affected by many factors, such as type of vehicles used, traffic jam, and speed limits. These are certainly very difficult to characterize by a mathematical model. However, there should be a destination for this trip. So there will be a tendency in the subscriber's roaming direction. Using a hexagonal cellular system in Fig. 3 as an example, we can use six (different) probabilities to characterize the subscriber's roaming directions into the six neighboring cells. These probabilities should be affected by the subscriber's recent roaming history. Preference will be given to some particular directions. For example, directions 0, 1, and 2 may be favored over 3, 4, and 5.
- *Oblivious in different moves*. When the subscriber newly transits to the move state, the subscriber's current roaming pattern should have little correlation to the subscriber's previous roaming patterns. Intuitively, the subscriber may now have a different destination (and thus roaming direction) from his/her previous trips. That is, there is memory of the roaming direction in the *same* trip, but it is 'memoryless' between different trips. As a result, the memory of roaming pattern should be refreshed when the subscriber newly transits to the move state.

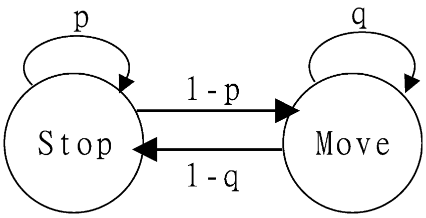


Fig. 2. The state-transition diagram of the SMM mobility model.

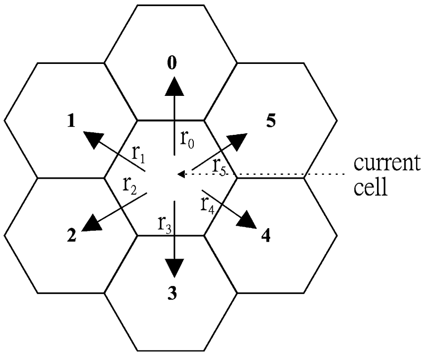


Fig. 3. Roaming directions and their probabilities $(r_0, r_1, \ldots, r_5)$ in a hexagonal system.

3. Update and paging strategies

In this section, we present our update and paging strategy. The strategy is developed with an intention to capture the characteristics of the SMM model, and thus optimize the total update and paging cost. Our update strategy will reflect the 'stop-or-move' and 'infrequent-transition' features. A mobile subscriber will always update, based on its guess, its current state (stop or move) with its HLR. When the subscriber is under the move state, it will use a *movement-based* strategy to update its current location with its HLR. To page the subscriber, we will apply a *selective paging* strategy similar to the work in Ref. [2]. On the contrary, when the subscriber is currently under the stop state, we will simply page the cell where the subscriber registered previously. In this case, we will be able to find the user 'in one shot.'

3.1. The strategy

Since a HLR can only determine whether a mobile subscriber has moved or not at the cellular level, we will interpret the move state in Fig. 2 as a boundary crossing. Similarly, the stop state will also be interpreted as whether the subscriber still stays in the same cell or not. Based on these interpretations, our strategy defines two thresholds:

- D : the boundary-crossing threshold. When a mobile subscriber under the move state makes this number of boundary crossings, it should update with its HLR.
- T : the transit-to-stop threshold. When a mobile subscriber under the move state stays in a cell for this number of time units, we regard that it has transited to the stop state.

In response to these constants, each subscriber should keep two local variables: (i) d, the number of boundary crossings the subscriber has made since its previous update, and (ii) t, the number of time units the subscriber has stayed in the current cell.

When a handset was initially turned on, we can assume that it is either in the move or in the stop state (the initial state does not matter). The subscriber should update with its HLR based on the following rules.

1. Under the stop state, whenever the subscriber crosses a cell boundary, it should change to the move state and update this fact as well as its current cell with its HLR. Also, the subscriber sets its d to 0 and t to 0.
2. Under the move state, whenever the subscriber experiences a boundary crossing, it should increment its d by 1 and reset its t to 0. Whenever d reaches the threshold D, it should update its current location with its HLR again, on which event it should reset its d to 0. This step is basically similar to the movement-based scheme.
3. Under the move state, the subscriber should increment its t by 1 whenever it stays at the same cell over a duration of one time unit. Whenever t reaches the threshold T, the subscriber should change to the stop state and update this fact as well as its current location with its HLR.

When a call arrives, the system will page the subscriber based on the following rules:

1. When the callee is in the stop state, the system will simply page the cell where the subscriber registered previously.
2. When the subscriber is in the move state, we will adopt the *selective paging* strategy as in Ref. [2] to locate the subscriber. Specifically, we will partition the cells that are at the distance of $D-1$ from the cell where the subscriber registered previously, into a number of subsets (how to determine these subsets will be discussed in Section 3.2). Then we will page the subset (of cells) with the highest hit probability first. If this fails, the subset with the second highest hit probability will be paged. This is repeated until the subscriber is located.

Note that in the first rule, the system is able to locate the subscriber 'in one shot' because based on our update rules a subscriber under the stop state will always update with its HLR whenever there is a boundary crossing.

3.2. Cost analysis

This section analyzes the total update and paging cost of our strategy under the SMM model. We will apply a Markov model for our analysis. We first define the possible states of a mobile subscriber based on its local variables.

- S : The subscriber is under the stop state.
- $M_{i,j}, i=0\ldots D-1,\ j=0\ldots T-1$: The subscriber is under the move state, having made i boundary crossings, but having stayed in the current cell for j units of time.

From the above states, we draw a state-transition diagram in Fig. 4. The probability associated with each transition is obtained based on the probabilities in Fig. 2. From this diagram, we need to determine the probability that the subscriber will stay in each state. Let's denote this by Prob(x), where x is any state defined earlier. Since the sum of probabilities over all states must be 1, we have:

$$\mathrm{Prob}(S) + \sum_{i=0\ldots D-1, j=0\ldots T-1} \mathrm{Prob}(M_{i,j}) = 1.$$

Considering state S, from the equilibrium of flows, we have

$$\mathrm{Prob}(S)(1-p) = \sum_{i=0}^{D-1} \mathrm{Prob}(M_{i,T-1})p.$$

Similarly, we can derive from the equilibrium of flows for state $M_{0,0}$,

$$\mathrm{Prob}(M_{0,0}) = \mathrm{Prob}(S)(1-p) + \mathrm{Prob}(M_{D-1,0})q + (1-p)\sum_{j=1}^{T-1} \mathrm{Prob}(M_{D-1,j}),$$

and for states $M_{i,0}$, $i=1\ldots D-1$,

$$\mathrm{Prob}(M_{i,0}) = \mathrm{Prob}(M_{i-1,0})q + (1-p)\sum_{j=1}^{T-1} \mathrm{Prob}(M_{i-1,j}).$$

For the rest of the states, we can derive, for $i=0\ldots D-1$ and $j=2\ldots T-1$, that

$$\mathrm{Prob}(M_{i,1}) = \mathrm{Prob}(M_{i,0})(1-q)$$

$$\mathrm{Prob}(M_{i,j}) = \mathrm{Prob}(M_{i,j-1})p.$$

There are $DT+1$ state probabilities to be determined. From the above equations, we can obtain for $i=0\ldots D-1$ and $j=1\ldots T-1$ that (note that only those state probabilities

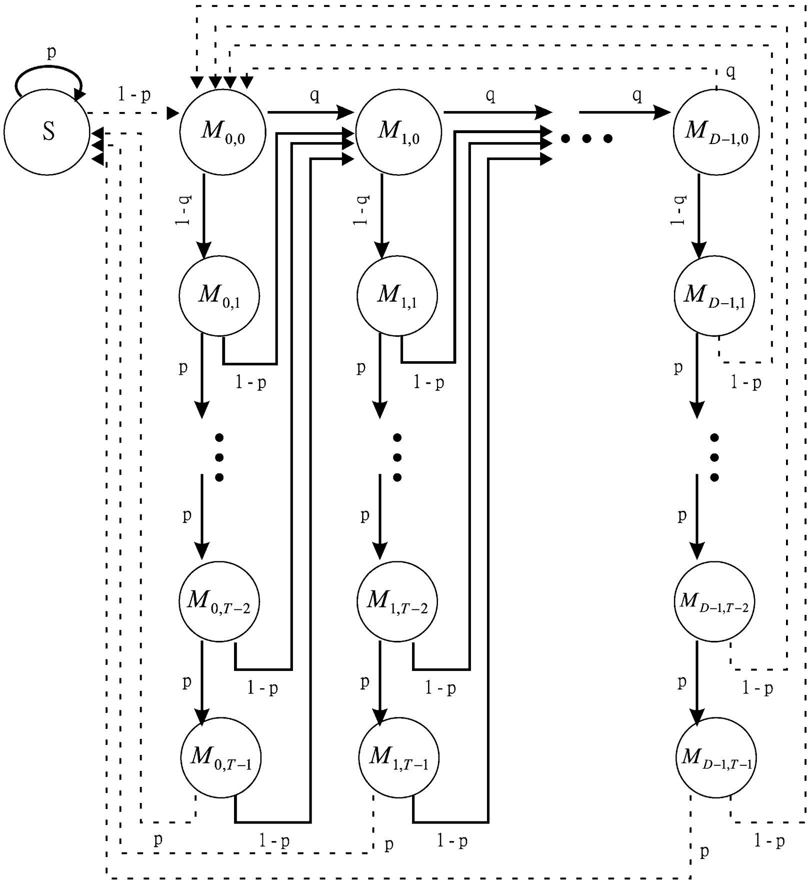


Fig. 4. The state-transition diagram of a mobile subscriber under the SMM model.

that will be used subsequently are shown here)

$$\mathrm{Prob}(S) = (1-q)p^{T-1}/(2-p-q)$$

$$\mathrm{Prob}(M_{i,T-1}) = \frac{[q+(1-q)(1-p^{T-1})]^i(1-p)(1-q)^2p^{2T-3}}{1-[q+(1-q)(1-p^{T-1})]^D(2-p-q)}$$

$$\mathrm{Prob}(M_{D-1,0}) = \frac{[q+(1-q)(1-p^{T-1})]^{D-1}(1-p)(1-q)p^{T-1}}{1-[q+(1-q)(1-p^{T-1})]^D(2-p-q)}$$

$$\mathrm{Prob}(M_{D-1,j}) = \mathrm{Prob}(M_{D-1,0})(1-q)p^{j-1}$$

Recall that in our strategy there are three events which will trigger a mobile subscriber to update its location: (i) the subscriber switches from stop to move, (ii) the subscriber switches from move to stop, and (iii) under the move state, the subscriber crosses D cell boundaries. These events are illustrated in Fig. 4 by dashes. Let C_u be the cost to perform an update. Then the average update cost per time unit is:

$$C_{\mathrm{update}} = C_u\Big(\mathrm{Prob}(S)(1-p) + p\sum_{i=0\ldots D-1}\mathrm{Prob}(M_{i,T-1}) + q\sum_{j=0\ldots T-1}\mathrm{Prob}(M_{D-1,j})\Big) = C_u\frac{(1-p)(1-q)p^{T-1}(2-[q+(1-q)(1-p^{T-1}]^D)}{(2-p-q)(1-[q+(1-q)(1-p^{T-1})^D])}.$$

Next, we calculate the paging cost per call. Let the cost to page a cell be C_p. Consider the time when a call arrives. There are two possibilities. If the subscriber is under the stop state, then the cost is C_p. Multiplying by the probability that the subscriber is under the stop state, the cost is

$$C_{\mathrm{stop}} = \mathrm{Prob}(S)C_p.$$

Otherwise, there is a probability of $1-\mathrm{Prob}(S)$ that the subscriber is under the move state. Consider the time t_1 when the previous call arrived and the time t_2 when the subscriber entered the current move state (refer to Fig. 5). There are two cases.

$t_1 < t_2$: If so, there was an update at time t_2. The paging cost will depend on the number of boundary crossings (say k) that the subscriber has made from t_2 to now. Specifically, from t_2 to now, the subscriber would update every time when it made D boundary crossings. The probability that the subscriber has made exactly k continuous boundary

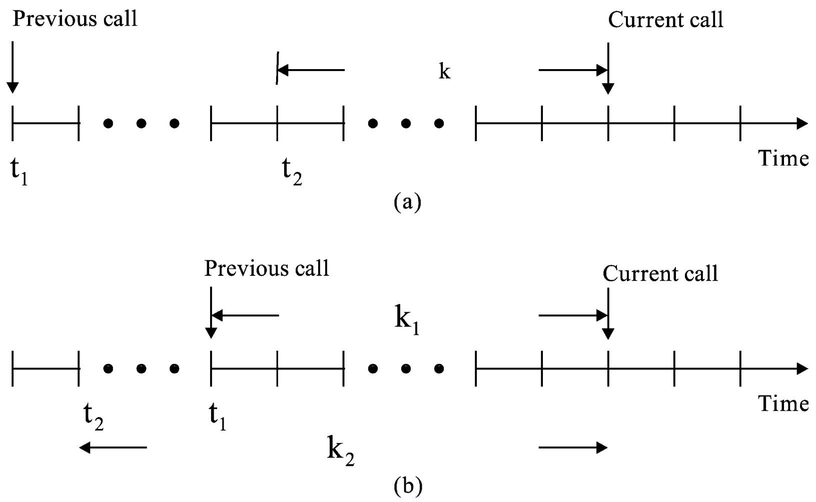


Fig. 5. Relationship of t_1 (time of the previous call) and t_2 (time of the subscriber entering the move state): (a) $t_1 < t_2$ and (b) $t_1 \geq t_2$.

crossings is $(1-q)q^k$ (i.e. k continuous moves preceded by a stop were made). Also, to satisfy $t_1 < t_2$, there must be no calls arriving from t_2 up to now, which has a probability of $e^{-\lambda k}$. As a result, the paging cost under the condition that $t_1 < t_2$ is

$$C_{\text{move1}} = \sum_{k=0\ldots\infty} (1-q)q^k\, e^{-\lambda k}\text{PAGE}(k \bmod D),$$

where PAGE(i) is the cost to page a subscriber which is under the move state and which has made i boundary crossings before its previous update. This value depends on whether selective paging is adopted or not, and will be derived in Section 4.

$t_1 \geq t_2$: If so, there was an update at time t_1. Suppose that there are k_1 time intervals from t_1 up to now, and k_2 time intervals from t_2 up to now. Similar to the earlier case, the paging cost will depend on the value of k_1, the number of boundary crossing from t_1 up to now. The probability that the subscriber has made exactly k_2 continuous boundary crossings is $(1-q)q^{k_2}$. The probability that the call prior to the current one happened at t_1 is

$$e^{-\lambda k_1}(1-e^{-\lambda})$$

Since k_1 must be less than k_2, the paging cost when $t_1 \geq t_2$ is

$$C_{\text{move2}} = \sum_{k_2=0\ldots\infty} \times \left(\sum_{k_1=0\ldots k_2-1} (1-q)q^{k_2}\, e^{-\lambda k_1}(1-e^{-\lambda})\text{PAGE}(k_1 \bmod D) \right)$$

As a result the paging cost per call is

$$C_{\text{page}} = C_{\text{stop}} + (1-\text{Prob}(S))(C_{\text{move1}} + C_{\text{move2}}).$$

Summing all the above together, the total update and paging cost of our strategy in one time unit is

$$C_{\text{total}} = C_{\text{update}} + (\lambda)C_{\text{page}}. \qquad (1)$$

4. Cost optimization with location prediction and selective paging

One unsolved problem in Section 3 is the paging cost PAGE(i), which was defined to be the cost to locate a subscriber which has made i boundary crossings after its previous update (of course, the value of i is unknown to the HLR). If no selective paging is applied, the HLR will search all the cells that are within a distance of $D-1$ from the previous update cell. In this case, PAGE(i) will be independent of i, giving

$$\text{PAGE}(i) = C_p(3(D-1)^2 + 3(D-1) + 1).$$

On the contrary, if a selective paging is applied, the above PAGE(i) will change and it is possible to further optimize the paging cost.

In Section 4.1, we first show how to predict the subscriber's location under the move state. We will conduct the prediction based on the assumption that the subscriber has a 'memory of roaming direction' as discussed in Section 2. Then Section 4.2 shows how to optimize the paging cost by integrating these predictions with PAGE(i).

4.1. Location prediction with directional preference

Suppose a subscriber is under the move state. Consider the six roaming directions 0,1,…,5 in Fig. 3. Based on our memory of roaming direction' assumption, let the probabilities that the subscriber will roam from its current cell toward these directions be $r_0, r_1, \ldots, r_5$, respectively (these probabilities may be obtained from the user's previous roaming pattern under the same move period).

Let x be the cell where the subscriber registered previously. Given any cell y, we will derive the probability that the user will be located in cell y after the user made n boundary crossings, denoted as $P_y(n)$. Apparently, $P_x(0) = 1$, which means that without boundary crossing, the user must be located in the original cell.

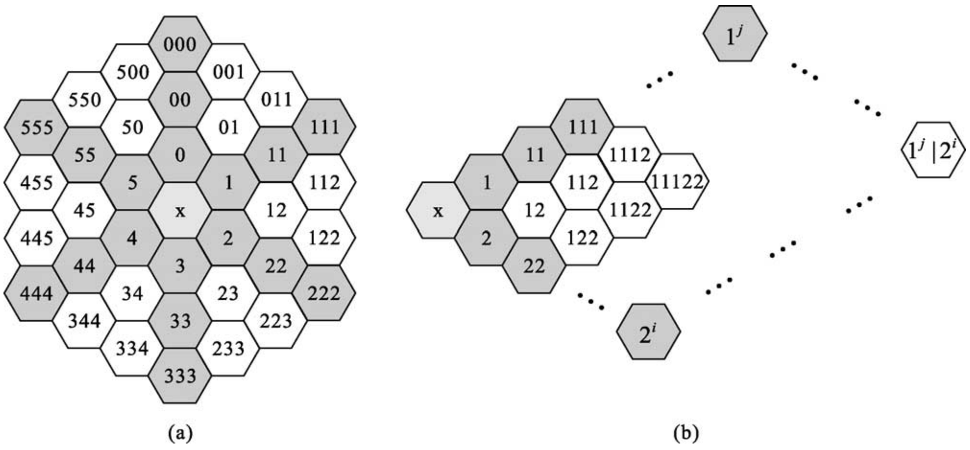


Fig. 6. (a) Numbering of cells with respect to a cell x. (b) Numberings based on a parallelogram coordinate.

To resolve our problem, we need a scheme to number cells. Fig. 6 shows our numbering scheme. The numbering is relative to cell x.

1. Number the cell on the north of x by 0, and that on the same direction at a distance of k by 0^k. Similarly, for the other five neighbors of x, number them by 1,2,…,5, and those on the same directions at a distance of k by 1^k, $2^k,\dots,5^k$. (Refer to the gray cells in Fig. 6(a).)
2. The above numberings (for gray cells) have partitioned the area into six sectors of cells. To number the other cells, let us take the cells in the sector bounded by cells 1^i and 2^i, $i = 1\dots\infty$, as an example. The cell that will form a parallelogram together with cells x, 1^i, and 2^j will be numbered $1^i|2^j$, where '|' means a string concatenation (refer to Fig. 6(b)). The cells in the other sectors are numbered similarly.

Clearly, when $n = 1$, we have

$$P_0(1) = r_0, \quad P_1(1) = r_1, \quad P_2(1) = r_2,$$
$$P_3(1) = r_3, \quad P_4(1) = r_4, \quad P_5(1) = r_5 \tag{2}$$

For $n > 1$, we will take a recursive approach. Consider any cell y. Let $y_0, y_1, \dots, y_5$ be the six neighbor cells of y along directions 0,1,…,5, respectively. The probability that the user will stay at y after n boundary crossings is the sum of the probabilities that the user stays at the six cells $y_0, y_1, \dots, y_5$ after $n-1$ boundary crossings, and the last boundary crossing brought the user to y. This leads to

$$P_y(n) = P_{y_0}(n-1)r_3 + P_{y_1}(n-1)r_4 + P_{y_2}(n-1)r_5 + P_{y_3}(n-1)r_0 + P_{y_4}(n-1)r_1 + P_{y_5}(n-1)r_2 \tag{3}$$

This equation can be expressed more specifically if the numbering for cell y is known. When $y = 0^i$, we can rewrite Eq. (3) as

$$P_y(n) = P_{y|t(y)}(n-1)r_3 + P_{y|1}(n-1)r_4 + P_{r(y)|1}(n-1)r_5 + P_{r(y)}(n-1)r_0 + P_{5|r(y)}(n-1)r_1 + P_{5|y}(n-1)r_2,$$

where $t(y)$ is the last element of y (i.e. tail), $r(y)$ is y after removing $t(y)$ (i.e. prefix). In general, for cells $y = i^k$, $i = 0\dots5$, we have

$$\begin{aligned} P_y(n) = {} & P_{y|t(y)}(n-1)P_{[t(y)+3]\bmod 6}(1) \\ & + P_{y|[t(y)+1]\bmod 6}(n-1)P_{[t(y)+4]\bmod 6}(1) \\ & + P_{r(y)|[t(y)+1]\bmod 6}(n-1)P_{[t(y)+5]\bmod 6}(1) \\ & + P_{r(y)}(n-1)P_{t(y)}(1) \\ & + P_{[t(y)+5]|r(y)\bmod 6}(n-1)P_{[t(y)+1]\bmod 6}(1) \\ & + P_{[t(y)+5]|y\bmod 6}(n-1)P_{[t(y)+2]\bmod 6}(1). \end{aligned} \tag{4}$$

When y is a mixture of different symbols, we need a different approach. Let cell y be in the sector bounded by the cells 0^i and 1^i, $i = 1\dots\infty$, we can derive that

$$\begin{aligned} P_y(n) = {} & P_{r(y)}(n-1)r_1 + P_{y|t(y)}(n-1)r_4 \\ & + P_{h(y)|y}(n-1)r_3 + P_{h(y)|r(y)}(n-1)r_2 \\ & + P_{s(y)}(n-1)r_0 + P_{s(y)|t(y)}(n-1)r_5, \end{aligned}$$

where $h(y)$ is the first element of y (i.e. head), $s(y)$ is y after removing $h(y)$ (i.e. suffix). In general, we have

$$\begin{aligned} P_y(n) = {} & P_{r(y)}(n-1)P_{t(y)}(1) + P_{y|t(y)}(n-1)P_{[t(y)+3]\bmod 6}(1) \\ & + P_{h(y)|y}(n-1)P_{[t(y)+2]\bmod 6}(1) + P_{h(y)|r(y)}(n-1) \\ & \times P_{[t(y)+1]\bmod 6}(1) + P_{s(y)}(n-1)P_{[t(y)+5]\bmod 6}(1) \\ & + P_{s(y)|t(y)}(n-1)P_{[t(y)+4]\bmod 6}(1). \end{aligned} \tag{5}$$

4.2. Cost optimization

With the above derivation, we can formulate PAGE(i), which is defined to be the paging cost when the mobile subscriber is known to make i boundary crossings after its previous update. We will adopt a selective paging strategy similar to Ref. [2]. Suppose that the previous cell where the subscriber registered is x. Let c be the allowed paging delay in the selective paging scheme. The cells that are at a distance of $D-1$ from x should be divided into c subsets of cells, denoted $S_1, S_2, \ldots, S_c$, to be paged sequentially. Then the first subset S_1 of cells are paged first. If this succeeds, the paging is completed and the cost will be $|S_1|C_p$. Otherwise, the second subset S_2 of cells need to be paged, and the expected cost will be

$$\left(1 - \sum_{y \in S_1} P_y(i)\right)|S_2|C_p,$$

where the leading probability is that for the subscriber not in S_1. If this succeeds, the paging is completed; otherwise, S_3 will be paged, which will cost

$$\left(1 - \sum_{y \in S_1 \cup S_2} P_y(i)\right)|S_3|C_p.$$

This will be repeated until last subset S_c is searched. The total cost will be

$$\mathrm{PAGE}(i) = |S_1|C_p + \left(1 - \sum_{y \in S_1} P_y(i)\right)|S_2|C_p + \left(1 - \sum_{y \in S_1 \cup S_2} P_y(i)\right)|S_3|C_p + \cdots + \left(1 - \sum_{y \in S_1 \cup S_2 \cup \cdots \cup S_{c-1}} P_y(i)\right)|S_c|C_p$$

Next, we integrate the above cost into the C_{total} in Eq. (1). This will give the exact cost of our update and paging strategy. It remains to determine the way the partition the cells within a distance of $D-1$ from x into subsets $S_1, S_2, \ldots, S_c$. When D and c are small, one straight-forward is to exhaustively test all possible partitions, and pick the one which gives the smallest C_{total}. We believe that in reality these two values will not be too large.

5. Extension to adaptive update and paging strategies

The above derivation is based on the assumption that the two thresholds, D and T, are constant. One would wonder what values of D and T should be used. Indeed, in our yet-to-be-presented experimental results (Section 6), different D and T do perform differently under different situations. To resolve this problem, we propose to extend our result to an adaptive approach. Specifically, we can pre-compute the best values of D and T under different environmental parameters for each subscriber (such as call arrival rate λ, state-transition probabilities p and q, directional preference r_i, $i = 0\ldots5$, and selective paging delay c). The system can estimate the current values of these parameters for each subscriber, and then adaptively apply the appropriate thresholds to the location-tracking strategy. Performance of the adaptive approach will be evaluated in Section 6.

6. Performance comparisons and simulation results

6.1. Analytical comparisons

In this section, we compare the performances of the movement-based scheme and the proposed scheme based on the above analysis. The movement-based scheme also has a boundary-crossing threshold D. A subscriber has to update whenever it makes D boundary crossings. Selective paging is not adopted for this scheme, so directional preference has no effect in its cost. Under the SMM model, the movement-based scheme will have a total cost of:

$$C'_{\mathrm{total}} = \frac{1-p}{(2-q-p)} \frac{1}{D} C_u + (3(D-1)^2 + 3(D-1) + 1)C_p\lambda.$$

(The first term is the probability that a subscriber makes a boundary crossing in one time unit times the probability that this is the Dth boundary crossing times the update cost. The second term is the paging cost.) The parameters used in the comparison are in Table 1. In our experiment, since c is quite small (≤ 3), an exhausted search is used to find the best partitioning of $S_1, S_2, \ldots, S_c$.

(A) *Effects of the boundary crossing threshold D*. Fig. 7 shows the costs at various D under different call arrival rates λ. As can be seen, at low λ (0.005 and 0.01), the movement-based scheme is better when D is small, but will degrade faster than ours as D gradually increases. When $\lambda \geq 0.1$, our scheme is better in almost all range of D. This is because our scheme pays more update cost to capture the state (move or stop) of the subscribers, hoping in reward of lower paging cost. Thus, at low λ, the benefit will be overwhelmed by the higher update cost. With calls arriving more frequently, the benefit will be more significant. Thus, our scheme is more useful in busy environment.

Table 1
The parameters used for comparison

Boundary crossing threshold (D)	1–7
Transit-to-stop threshold (T)	1–7
Allowed paging delay (c)	1–3
Call arrival rate (λ)	0.005, 0.01, 0.1, 1
Update-to-paging-cist ratio (C_u/C_p)	1, 10
Transition probabilities (p, q)	0.7–0.99
Roaming direction probabilities ($r_0, r_1, \ldots r_5$)	(0.6, 0.15, 0.04, 0.02, 0.04, 0.15)

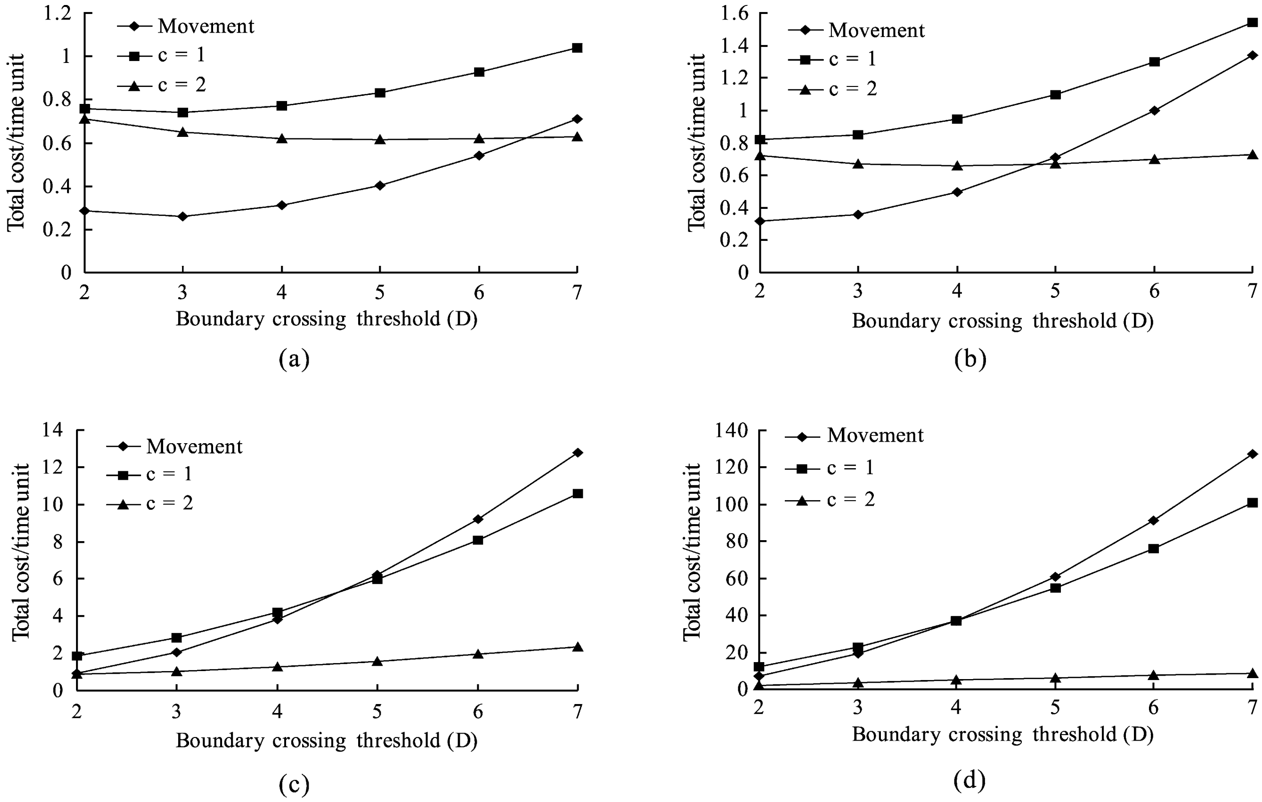


Fig. 7. Costs at various boundary crossing threshold D when (a) $\lambda = 0.005$, (b) $\lambda = 0.01$, (c) $\lambda = 0.1$, and (d) $\lambda = 1$ ($T = 3$, $C_u : C_p = 1 : 1$, $p = q = 0.9$).

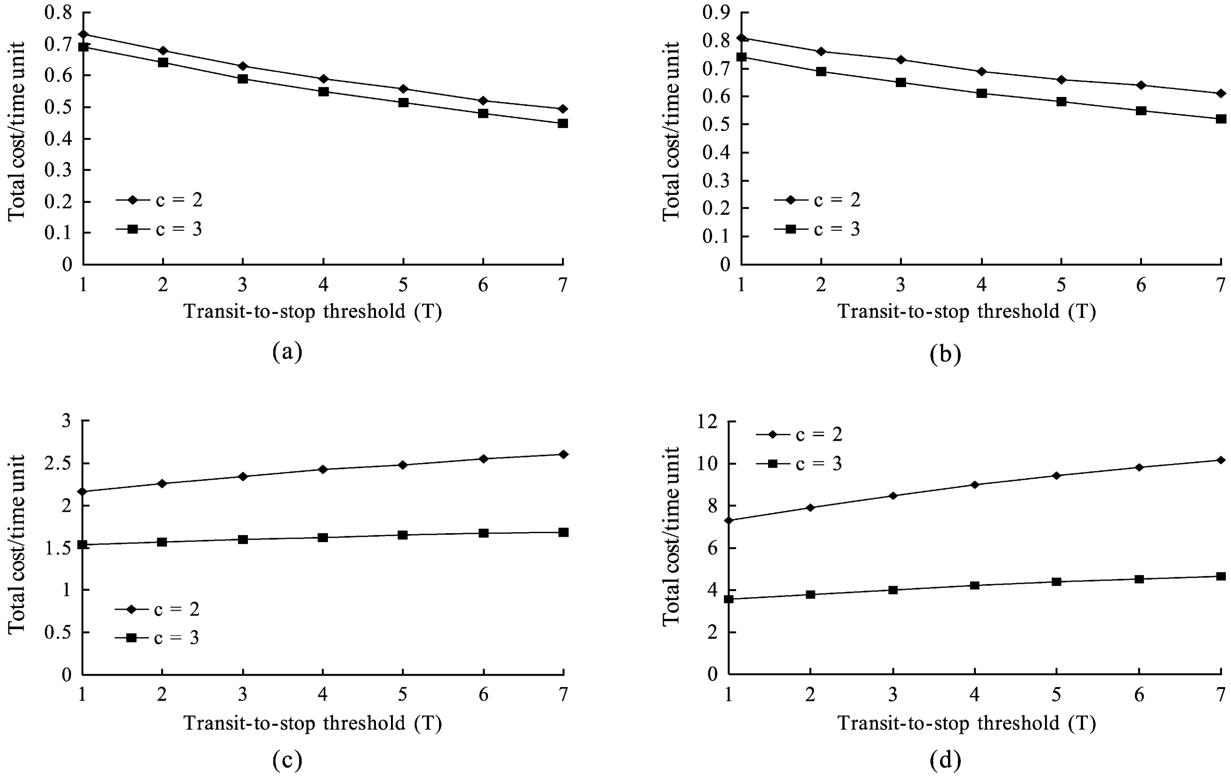


Fig. 8. Costs at various transit-to-stop threshold T when (a) $\lambda = 0.005$, (b) $\lambda = 0.01$, (c) $\lambda = 0.1$, and (d) $\lambda = 1$ ($D = 7$, $C_u : C_p = 1 : 1$, $p = q = 0.9$).

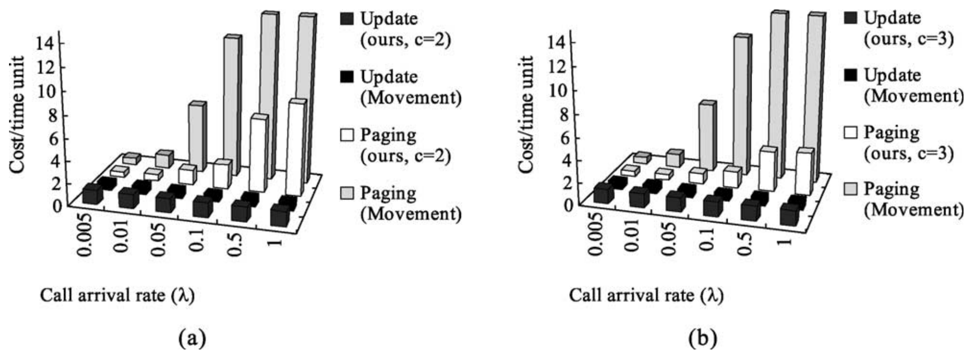


Fig. 9. Costs at various call arrival rates λ when (a)$c = 2$, and (b) $c = 3$ ($D = 7$, $T = 3$, $p = q = 0.9$, $C_u : C_p = 10 : 1$).

(B) *Effects of transit-to-stop threshold T*. In the previous comparison, we used a fixed $T = 3$. Fig. 8 shows the costs at various T under different λ. At lower λ, increasing T will reduce the total cost. On the contrary, at larger λ, increasing T will slightly increase the total cost. This shows an interesting behavior that a larger T will decrease the accuracy in predicting subscribers' states (move or stop). Thus, this may result in a higher paging cost. However, at the same time a less number of update messages will be sent. Since the call arrival rate λ will affect the paging cost, this explains why we see different trends for different λ.

(C) *Effects of call arrival rate λ*. Both of the above experiments show that the call arrival rate has some effect on our scheme. To understand this issue, we show Fig. 9 by varying λ. The figure is drawn by separating the update cost and paging cost. As can be seen, the paging cost will increase sharply as λ increases, while the update cost is quite insensitive to the change of λ. Also, note that we have used $C_u : C_p = 10 : 1$ in this experiment to signify the update cost. Thus, it is worthwhile to use our scheme, especially when calls arrive more frequently.

(D) *Effects of transition probabilities p and q*. Recall that p (resp., q) is the probability for a host currently in the stop state (resp., move state) to remain in the same state in the next moment. To understand how these probabilities affect our scheme, we show Fig. 10. The result in Fig. 10(a) shows that a larger p and a smaller q will favor our scheme. The intuition is as follows: (i) a larger p implies a higher probability that a mobile host remaining in the stop state, and thus a larger saving in paging (we may find the host in 'one shot'), and (ii) a larger q implies a higher probability that a mobile host remaining in the move state, and thus higher inaccuracy in determining its location when calls arrive. Fig. 10(b) shows the amount of improvement by our scheme as compared to the movement scheme. The range of improvement is about six times to 12 times.

(E) *Effects of movement direction bias*. The roaming direction probabilities $r_0, r_1, \ldots, r_5$ (refer to Fig. 3) may also affect the accuracy in predicting a user's location. In this experiment, we vary probability r_0 between 0.3 and 0.8. Then we let probabilities $r_2 = r_4 = 0.04$, $r_3 = 0.02$, and $r_1 = r_5 = 0.9 - r_0/2$. Apparently, a larger r_0 means a stronger preference in the directions in which the user roamed previously. Fig. 11 shows the total cost per time unit at various r_0. As can be seen, a strong tendency in certain roaming directions will lead to a lower cost. Also, the effect is

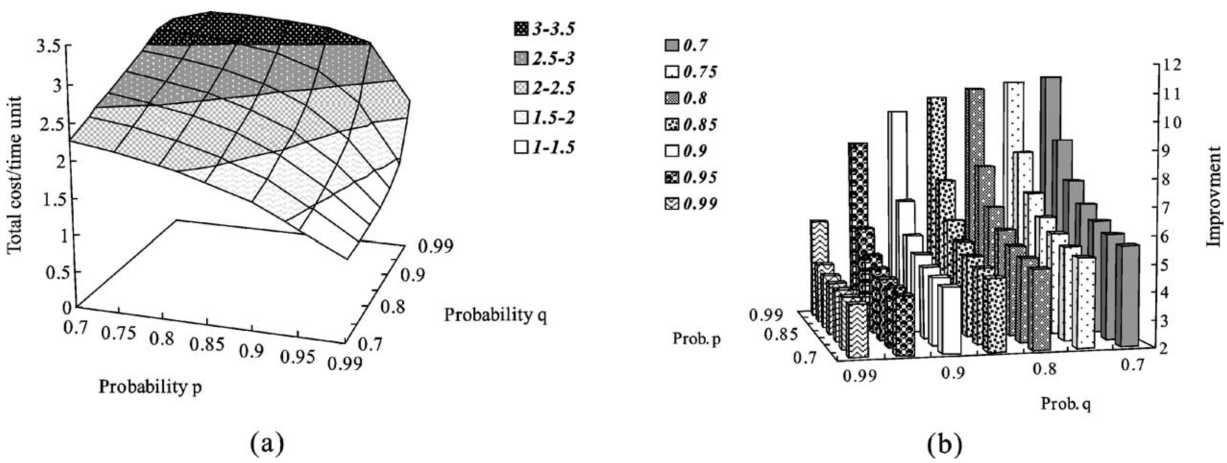


Fig. 10. (a) Costs at various values of p and q, and (b) the improvement by our scheme compared to the movement scheme ($D = 7$, $T = 3$, $C_u : C_p = 1 : 1$, $\lambda = 0.1$, $c = 2$).

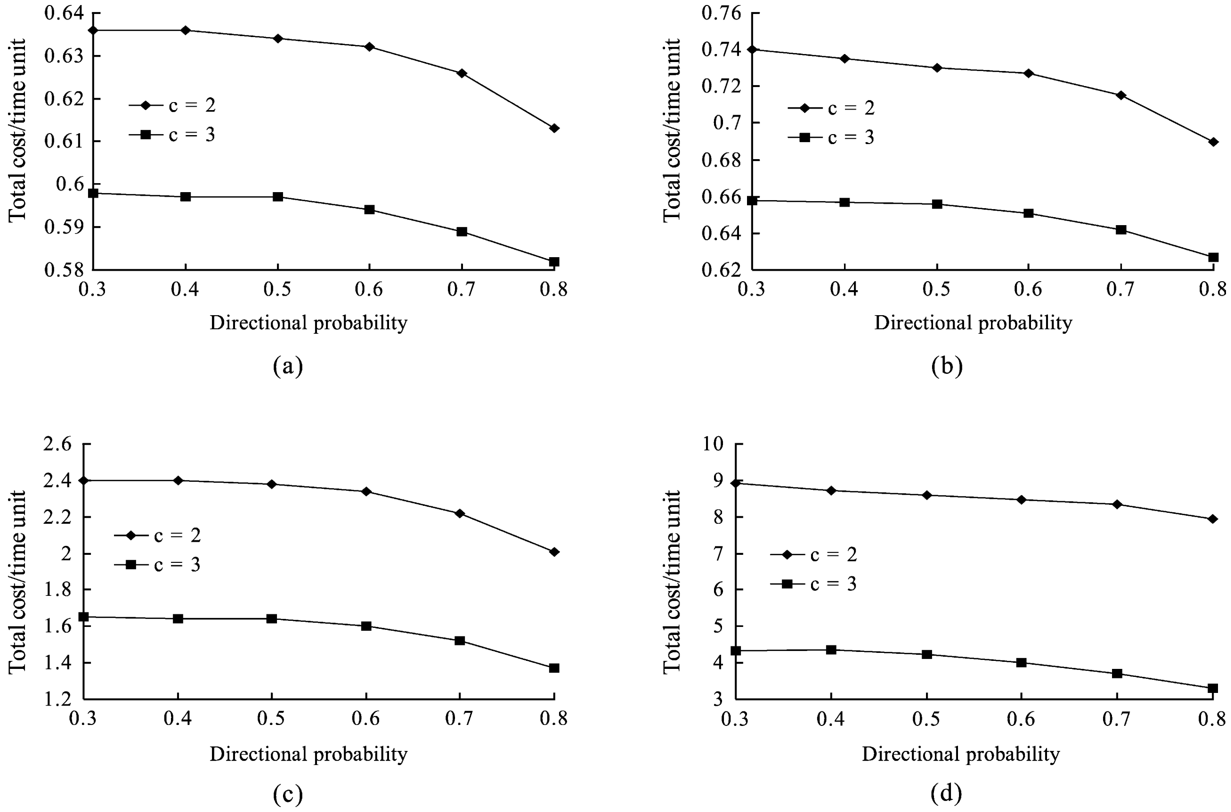


Fig. 11. Costs at various roaming direction probability r_0 :: (a) $\lambda = 0.005$, (b) $\lambda = 0.01$, (c) $\lambda = 0.1$, and (d) $\lambda = 1$ ($D = 7$, $T = 3$, $C_u : C_p = 1 : 1$, $p = q = 0.9$).

more observable for smaller λ. This is perhaps because when calls arrive less frequently, we need to more precisely determine the possible locations to find the users as calls arrive.

6.2. Simulation comparisons based on static thresholds

To verify our analysis, we have developed a simulator. An area of size 127 cells was simulated, on which a number of mobile subscribers were generated randomly. Each mobile subscriber roamed around in the environment based on the SMM model. The same parameters in Table 1 were used in the simulation. The two thresholds, D and T, were fixed throughout each simulation run. Since the SMM model does not specify the roaming speed and direction of a mobile subscriber, we assumed that under the move state a mobile subscriber roamed as follows. Each time unit was divided into eight small slots. In each slot, the subscriber could move by 1/8 diameter of a cell. One of the six directions (30°, 90°, 150°, 210°, 270°, and 330°) was randomly picked as its preferred roaming direction. A higher probability was assigned to this preferred direction, and lower probabilities to the other five directions (refer to the assignment in part E in Section 6.1). This preferred direction was used throughout the same trip until the subscriber entered the stop state. Note that all the remaining parameters (i.e. d and t) were still counted in a per time unit basis. We also include simulation results for the distance-based Scheme, by using the same distance threshold as ours.

Fig. 12 shows the costs at various threshold D under different call arrival rates λ. The trend is very close to our earlier analysis (Fig. 7). As expected, the distance-based schemes are slightly better than the movement-based schemes. By further looking at the absolute values in each point, we see that at high call arrival rates ($\lambda = 0.1$ and 1.0), our analysis is quite accurate, but at low call arrival rates ($\lambda = 0.005$ and 0.01) our analysis is somewhat over-pessimistic. The gaps between the movement-based schemes and ours actually reduce at lower arrival rates. By separating the paging and updating costs (not shown in the figure), we found that this is because of a higher hit rate at the first paging in the simulation (about 10% higher than the analysis). And this will have a chaining effect on the subsequent paging, giving a reduction of about 30% on the overall paging cost in the simulation. However, as calls arrive more frequently, the gap will be less significant because the gap between the first hit rates of the simulation and analysis will reduce.

The reason for the above error at lower arrival rates could be as follows. We have used a hexagonal cellular structure in the analysis, while a real geometrical space was used in our simulation. This makes the prediction of mobile subscribers' positions less accurate. With a cellular structure, a mobile host could roam away from its current

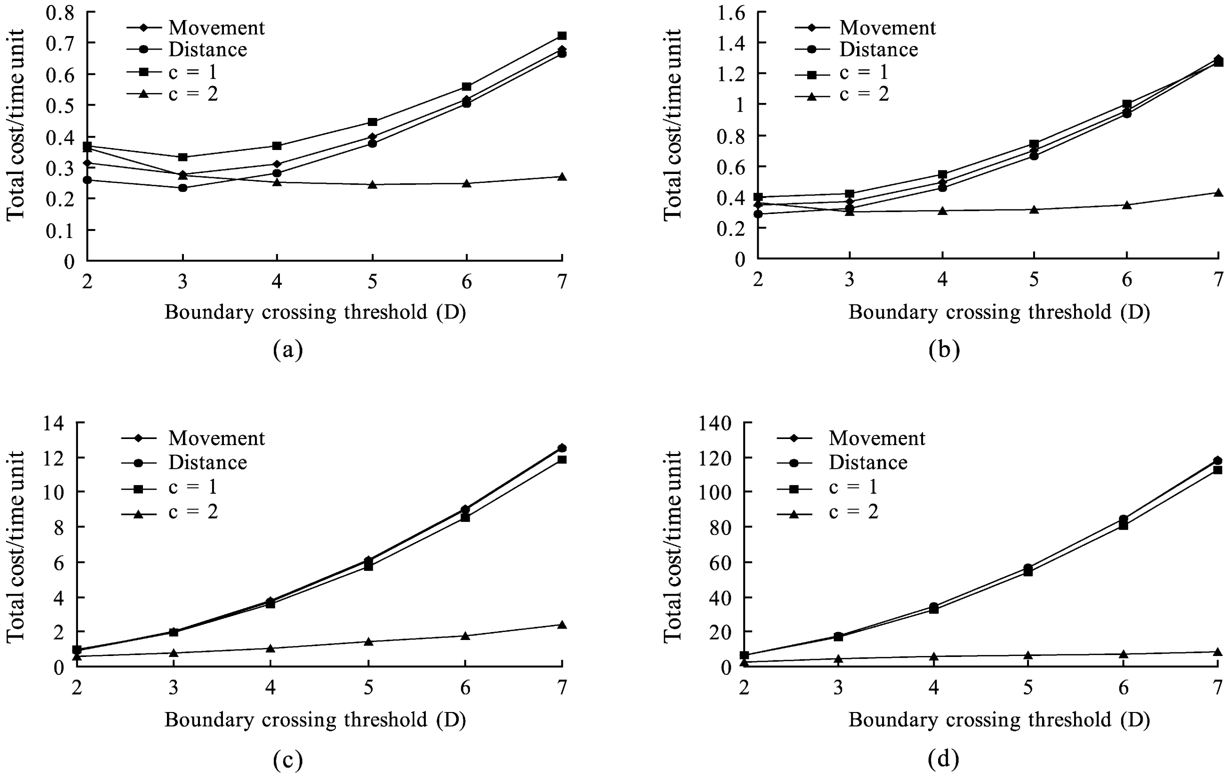


Fig. 12. Simulated costs at various boundary crossing threshold D when (a) $\lambda = 0.005$, (b) $\lambda = 0.01$, (c) $\lambda = 0.1$, and (d) $\lambda = 1$ ($T = 3$, $C_u : C_p = 1 : 1$, $p = q = 0.9$).

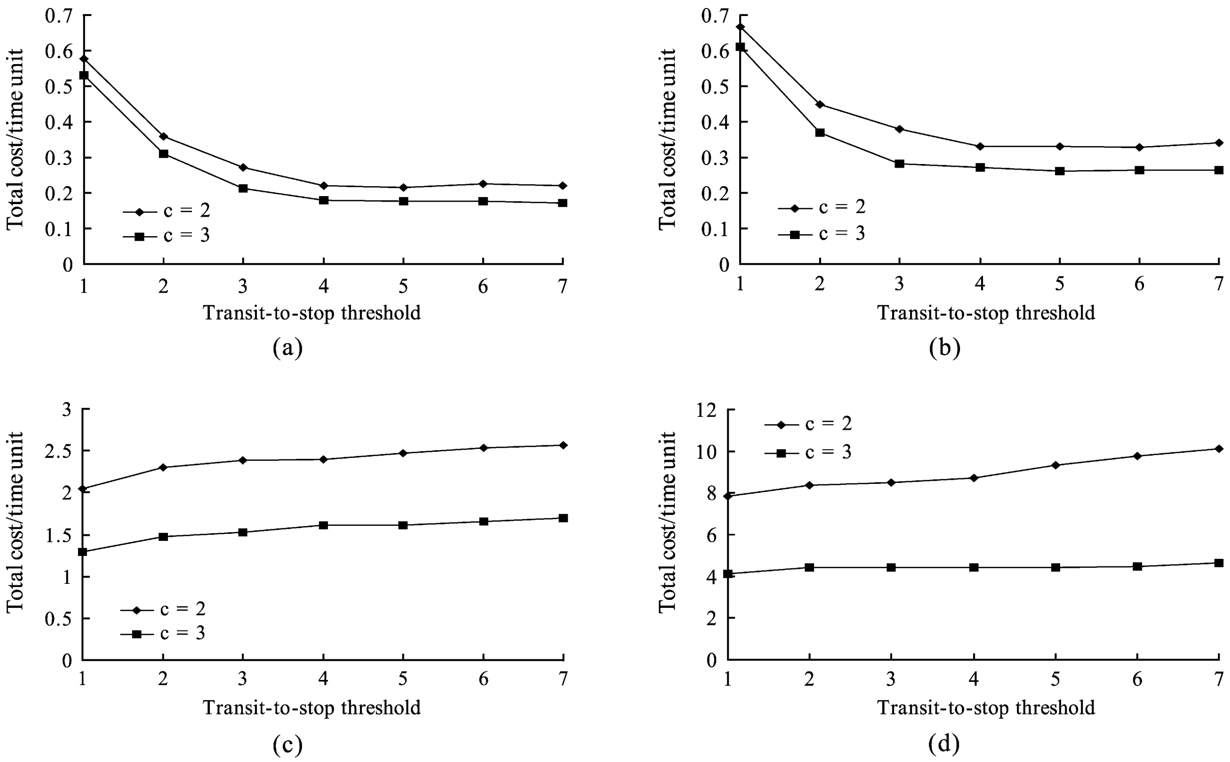
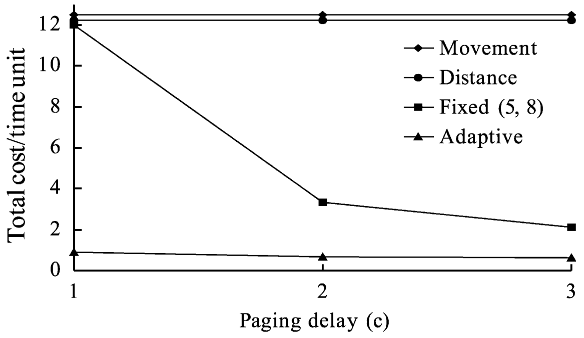


Fig. 13. Simulated costs at various transit-to-stop threshold T when (a) $\lambda = 0.005$, (b) $\lambda = 0.01$, (c) $\lambda = 0.1$, and (d) $\lambda = 1$ ($D = 7$, $C_u : C_p = 1 : 1$, $p = q = 0.9$).

λ \ c	1	2	3
0.005	(3, 8)	(6, 12)	(6, 8)
0.007	(3, 8)	(5, 9)	(5, 7)
0.009	(2, 8)	(5, 8)	(5, 12)
0.01	(2, 8)	(5, 8)	(5, 8)
0.03	(1, 8)	(3, 8)	(4, 10)
0.05	(1, 7)	(2, 8)	(3, 9)
0.07	(1, 8)	(2, 8)	(2, 8)
0.09	(1, 8)	(2, 8)	(2, 7)
0.1	(1, 7)	(2, 7)	(2, 7)
0.3	(1, 4)	(1, 4)	(1, 4)
0.5	(1, 10)	(1, 10)	(1, 10)
0.7	(1, 2)	(1, 2)	(1, 2)
0.9	(1, 6)	(1, 6)	(1, 6)

(a)



(b)

Fig. 14. Performance of the adaptive scheme under different paging delay: (a) lookup table and (b) cost ($r_0 = 0.6$,, $p = q = 0.9$).

cell more quickly than that in our simulation. As we used a roaming speed of 1/8 diameter of a cell in our simulation, mobile subscribers will have a tendency to stay closer to where they updated their locations previously than that in our analysis. This makes the hit rate of the first paging higher. As stated earlier, our scheme pays more update cost to capture the state (move or stop) of the subscribers, in hope of saving in paging cost. Therefore, at lower λ, the benefit will be less significant and will be overwhelmed by the higher update cost. As calls arrive more frequently, the error will be less significant because the search space will reduce.

In the previous comparison, we have used a fixed threshold $T = 3$. Fig. 13 shows the costs at various T under different λ. Again, we see that the simulation result matches pretty well with our analysis at higher λ, but will be lower than our analysis at lower λ (compared to Fig. 8). The reason is the same as the earlier scenario: we have an over-pessimistic paging cost at low λ in our analysis. And this will be signified as T increases (which will reduce the accuracy in predicting subscribers' states and positions).

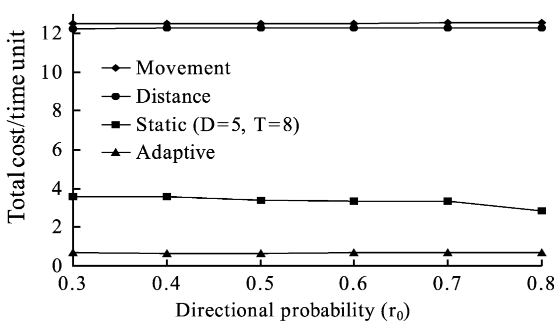
6.3. Simulation comparisons based on dynamic thresholds

From the above simulation results, we see that different values of D and T give different performances under different situations. In the adaptive approach, we built a table of which each entry indicates the best (D, T) pair under different situations. A table lookup mechanism is used to pick the best pair for use. In the simulation, a mobile subscriber's call arrival rate is no longer a constant, but switches uniformly among $\lambda = 0.01$, 0.05, and 0.5. A mobile subscriber is not aware of its current call arrival rate, but takes the average of its previous 10 calls to predict its current rate. The adaptive scheme is compared with the movement- and distance-based schemes (with threshold $D = 5$) and our static scheme (with thresholds $D = 5$ and $T = 8$).

(A) *Effects of selective paging delay c*. For fixed c and λ, we conducted simulations to determine the best (D, T) pair to be used. The result is shown in Fig. 14(a). Then we used this table to choose thresholds for the adaptive scheme when the call arrival rate is unknown. As Fig. 14(b) shows, the cost can be reduced significantly as opposed to the static-threshold scheme.
(B) *Effects of directional preference r_0*. For fixed r_0 and λ, we conducted simulations to determine the best (D, T) pair to be used, as shown in Fig. 15(a). This table is then used by the adaptive scheme to compare to the other Scheme, as shown in Fig. 15(b).
(C) *Effects of transition probabilities p and q*. For fixed p, q, and λ, we conduct simulations to determine the best (D, T) pair to be used. Here we always let $p = q$. The result is in Fig. 16. For all schemes, the costs slightly

λ \ r_0	0.3	0.4	0.5	0.6	0.7	0.8
0.005	(5, 8)	(5, 12)	(6, 9)	(6, 12)	(5, 11)	(5, 8)
0.007	(5, 7)	(5, 8)	(5, 12)	(5, 9)	(5, 9)	(5, 12)
0.009	(4, 12)	(4, 9)	(5, 8)	(5, 8)	(4, 8)	(4, 8)
0.01	(4, 12)	(4, 11)	(5, 8)	(5, 8)	(4, 8)	(4, 8)
0.03	(2, 7)	(2, 8)	(2, 7)	(3, 8)	(3, 8)	(3, 8)
0.05	(2, 6)	(2, 8)	(2, 8)	(2, 8)	(3, 10)	(3, 10)
0.07	(2, 8)	(2, 8)	(2, 8)	(2, 8)	(2, 8)	(2, 8)
0.09	(2, 6)	(2, 7)	(2, 8)	(2, 8)	(2, 7)	(2, 7)
0.1	(2, 7)	(2, 9)	(2, 10)	(2, 7)	(2, 11)	(2, 8)
0.3	(1, 5)	(1, 7)	(1, 12)	(1, 4)	(1, 5)	(1, 4)
0.5	(1, 8)	(1, 5)	(1, 4)	(1, 10)	(1, 7)	(1, 12)
0.7	(1, 3)	(1, 8)	(1, 3)	(1, 2)	(1, 5)	(1, 5)
0.9	(1, 10)	(1, 10)	(1, 6)	(1, 6)	(1, 6)	(1, 3)

(a)

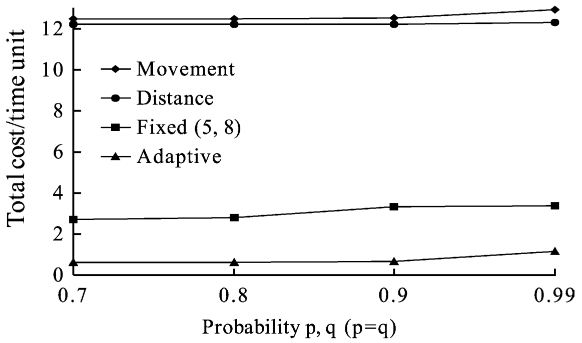


(b)

Fig. 15. Performance of the adaptive scheme under different directional preference: (a) lookup table and (b) cost ($c = 2$, $p = q = 0.9$).

λ \ p=q	0.7	0.8	0.9	0.99
0.005	(6, 8)	(6, 10)	(6, 12)	(7, 8)
0.007	(6, 8)	(5, 7)	(5, 9)	(6, 12)
0.009	(6, 12)	(5, 7)	(5, 8)	(6, 9)
0.01	(6, 11)	(5, 9)	(5, 8)	(6, 8)
0.03	(3, 11)	(3, 11)	(3, 8)	(3, 9)
0.05	(2, 9)	(2, 4)	(2, 8)	(3, 10)
0.07	(2, 12)	(2, 4)	(2, 8)	(3, 8)
0.09	(2, 10)	(2, 12)	(2, 8)	(2, 3)
0.1	(2, 9)	(2, 3)	(2, 7)	(2, 7)
0.3	(1, 9)	(1, 12)	(1, 4)	(1, 8)
0.5	(1, 8)	(1, 5)	(1, 10)	(1, 3)
0.7	(1, 8)	(1, 10)	(1, 2)	(1, 5)
0.9	(1, 10)	(1, 8)	(1, 6)	(1, 4)

(a)



(b)

Fig. 16. Performance of the adaptive scheme under different transition probabilities: (a) lookup table and (b) cost ($c = 2$, $r_0 = 0.6$).

go up as p and q increase. The reason is that each mobile subscriber, once entering a state, tends to stay in the same state (stop or move) for longer time. The negative effect is that when a subscriber keeps on moving, more update cost has to be paid, no matter which scheme is used.

7. Conclusions

We have proposed a new Stop-or-Move Mobility (SMM) model to characterize mobile subscribers' roaming pattern. Most existing works assumed a random walk roaming pattern, which is unrealistic. Based on the SMM model, we then propose location-management strategies that are based on static thresholds and adaptive thresholds. Analysis and experimental results for these strategies are presented, which show significant improvement over the traditional movement-based strategy. In this work, a mobile subscriber is considered as in the stop state if it stays in one cell over a pre-defined time duration. One possible extension is to relax the definition by allowing it to make a few number of boundary crossings within a pre-defined time duration. This can eliminate the problem of ping-pong effect at cell boundaries. Another possible direction is to extend our 2-state SMM model to a multi-state model (for example, the move state can be separated into high-mobility and low-mobility states). Different boundary crossing thresholds may be used for these states according to the subscriber's velocity.

References

[1] A. Abutaleb, V.O.K. Li, Location update optimization in personal communication systems, ACM/Baltzer Wireless Networks 3 (3) (1997) 205–217.

[2] I. Akyildiz, J. Ho, Y. Lin, Movement-based location update and selective paging for PCS networks, IEEE/ACM Transactions on Networking 4 (4) (1996) 629–638.

[3] I.F. Akyildiz, J.S.M. Ho, Dynamic mobile user location update for wireless PCS networks, ACM/Baltzer Wireless Networks 1 (2) (1995) 187–196.

[4] D.O. Awduche, A. Ganz, A. Gaylord, An optimal search strategy for mobile stations in wireless networks, ICUPC'96, Sept, 1996, pp.946–950.

[5] A. Bar-Noy, H. Kessler, Mobile users: to update or not to update?, ACM/Baltzer Wireless Networks 1 (2) (1995) 175–186.

[6] A. Bhattacharya, S.K. Das, Lezi-update: an information-theoretic approach to track mobile users in PCS networks, MobiCom'99, August, 1999, pp. 1–12.

[7] Y. Birk, Y. Nachman, Using direction and elapsed-time information to reduce the wireless cost of locating mobile units in cellular networks, ACM/Baltzer Wireless Networks 1 (4) (1995) 403–412.

[8] J.S.M. Ho, I.F. Akyildiz, Mobile user location update and paging under delay constraints, ACM/Baltzer Wireless Networks 1 (4) (1995) 413–426.

[9] S.J. Kim, C.Y. Lee, Modeling and analysis of the dynamic location registration and paging in microcellular systems, IEEE Transactions on Vehicular Technology 45 (1) (1996) 82–90.

[10] S. Madhavapeddy, K. Basu, A. Roberts, Adaptive paging algorithms for cellular systems, WINLAB, April, 1995, pp. 976–980.

[11] U. Madhow, M.L. Honiga, K. Steiglitz, Optimization of wireless resources for personal communications mobility tracking, IEEE/ACM Transactions on Networking 3 (6) (1995) 698–707.

[12] G.P. Pollini, C.-L. I, A profile-based location strategy and its performance, IEEE Journal on Selected Areas in Communications 15 (8) (1997) 1415–1424.

[13] C. Rose, Minimizing the average cost of paging and registration: A timer-based method, ACM/Baltzer Wireless Networks 2 (2) (1996) 107–116.

[14] C. Rose, R. Yates, Minimizing the average cost of paging under delay constraints, ACM/Baltzer Wireless Networks 1 (2) (1995) 211–219.

[15] C.U. Saraydar, O.E. Kelly, C. Rose, One-dimensional location area design, IEEE Transactions on Vehicular Technology 49 (5) (2000) 1626–1632.

[16] A.A. Siddiqi, T. Kunz, The peril of evaluating location management proposals through simulations, ACM DIAL-M, 1999, pp. 72–77.

[17] Y.-C. Tseng, W.-N. Hung, An improved cell type classification for random walk modeling in cellular networks, IEEE Communications Letters 5 (8) (2001) 337–339.

[18] M. Verkama, Optimal paging—a search theory approach, ICUPC'96 Sept (1996) 956–960.

[19] H. Xie, Dynamic location area management and performance analysis, IEEE Vehicular Technology Conference, May, 1993, pp. 536–539.

[20] A. Yener, D. Rose, Highly mobile users and paging: optimal polling strategies, IEEE Transactions on Vehicular Technology 47 (4) (1998) 1251–1257.

[21] M.M. Zonoozi, D. Dassanayake, User mobility modeling and characterization of mobility patterns, IEEE Journals on Selected Areas in Communication 15 (7) (1997) 1239–1252.