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Computer Networks 38 (2002) 603–612

COMPUTER NETWORKS

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Modeling variable user mobility with stochastic correlation concept

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Received 17 September 2001; accepted 12 October 2001

Responsible Editor: I.F. Akyildiz

Abstract

Analyzing stochastic behavior of user mobility is a basic study for traffic performance analysis in land–mobile cellular communications. Due to the heavy burden in simulation considering significant mobility parameters, many analytical models have been proposed as alternatives. However, analytical approach to figure out the stochastic behavior is so difficult that realistic features can hardly be reflected without simplification. As expected, the effect of variable user mobility (VUM) on traffic performance may not be reasonably analyzed with such simplified models, especially in a case of micro-cellular systems where traffic performance, such as handover rate, is more sensitively affected by user mobility. Thus we are motivated to investigate an improved alternative. This paper has focused on developing a VUM model. Considering VUM in mobility modeling, we figure out its effect on probability distributions of cell dwell time which is basic for traffic performance analysis in land–mobile cellular communications. A new concept on variable characteristics of user mobility called *stochastic correlation* is introduced for the analysis. Probability distribution of path length during a call is also studied using our model of VUM. We believe that our model with stochastic correlation could be applied to many performance modeling problems in land–mobile cellular systems with mobility sensitive traffic performance.

Keywords: Random walk; User mobility; Stochastic correlation; Cell dwell time; Channel holding time

1. Introduction

Recent advances toward the third/fourth generation cellular communication networks will provide ubiquitous subscribers with high-quality multimedia services. Emerging problems from increasing demand of individual access to land–mobile cellular networks have so far been intensively studied for quality-of-service (QoS) guarantee [1–5]

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1389-1286/01/$ - see front matter
PII: S1389-1286(01)00274-2

as well as for efficient mobility and resource management [6–16]. It has been considered that traffic performance in cellular networks is affected by user mobility [4–6,9–21]. Especially, the effect of user mobility on traffic performance is studied [17–23], and the need for consideration of user mobility effect in traffic performance analysis is addressed [24–29]. This is because reasonable mobility models capable of providing sufficient accuracy for traffic performance analysis and traffic estimation are required in future cellular communication systems due basically to both increasing bandwidth requirement and limited available resource.

In order to obtain valid results, simulation approaches to analyze variable user mobility (VUM) require considering many factors that actually affect traffic performance. As a result, heavy computing burden will follow. As an alternative, analytical modeling has been challenged. Until now, a number of mobility models have been proposed for the purpose of mathematical analysis on traffic performance. Hereafter, we focus on analytical modeling of VUM in this paper. The authors in Refs. [2,4,5,24] have provided user mobility models with randomly chosen fixed direction and studied cell dwell time and channel holding time distributions. The authors in Ref. [9] have proposed a similar mobility model for traffic analysis in their hypothetical cell shapes. Urban area cells could be modeled by their cell models, but actual features of VUM might be much simplified. In Refs. [10,26], VUM is modeled by a discrete time Markov chain for handover performance analysis, but the VUM stochastic of individual users is not considered. So-called *random walk* model [31–33] is applied to user mobility modeling in Refs. [27,28]. However, stochastic auto-correlation of user mobility is not considered. Generalized two-dimensional random walk models considering variable speed and direction are proposed in Refs. [11,12,29]. Another random walk model is proposed with computational complexity reduction from $O(n^2)$ to $O(n)$ in a hexagonal cell configuration where n is the number of *layers* (a set of cells defined for analysis purpose) [30]. Gambler's ruin model [32] is applied to location management in a mesh cell configuration [13]. The model in Ref. [14] provides a formula for handover rate estimation using site-environmental parameters such as cell area, cell boundary length, and the average speed of users.

One of the simplified user mobility models has a common assumption of constant speed and fixed direction while users are moving. In such models, the direction is randomly chosen, but the direction is fixed during a call if it has been chosen. Performance analysis using such a model is valid in highway cellular environments with relatively large size cells or in urban on-street environments with deterministic patterns of user mobility. An advance in mobility modeling from such a deterministic concept is achievable by relaxing such simplifying assumptions and taking randomness of user mobility into account. It is a desirable advance because users actually change their moving directions and speeds with randomness, due to street layout, traffic flow condition, and so on. In this case, the user mobility could be modeled by random walk, or by Gambler's ruin problem [32] which is an application of a random walk model [31,32].

The effect of user mobility on traffic performance in a cellular system has been considered as an important and fundamental issue [17–21]. However, it has been considered very difficult to figure out the effect of VUM stochastic on dwell time, and "variable" characteristic (i.e., one of the most important characteristics of geographical user mobility) is much simplified as shown in the literature [2,4,5,9,24,27,28,30] and the references therein. As a result, such a model is not valid for providing sufficient accuracy in micro-/pico-cellular systems with mobility sensitive traffic performance. Thus, we are motivated to develop an improved analytical model reflecting VUM and figure out the effect of VUM characteristics on a basic performance measure (i.e., cell dwell time) introducing a new concept called *stochastic correlation*. Since cell dwell time distribution is an essential and fundamental measure for deriving several important performance measures such as channel holding time, handover rate, and location update rate [6,8,12,15,25,29], we primarily focus on the VUM effect on cell dwell time with the stochastic correlation concept of stochastic correlation factor (SCF) newly defined in this paper. A number of numerical examples show that the average dwell time is shorter as SCF is greater and the variance of dwell time is smaller as SCF is greater. With our VUM model, we also study the probability distribution of user path length during a call. Since stochastic variation of user mobility is considered in our improved probability model, we believe that our mobility model could provide more sufficient accuracy and resulting information of VUM.

The remainder of this paper is organized as follows. Section 2 presents our user mobility model and our definition of SCF. The effect of VUM on cell dwell time is studied in Section 3. Path length distribution is studied in Section 4. Finally, we conclude our work in Section 5.

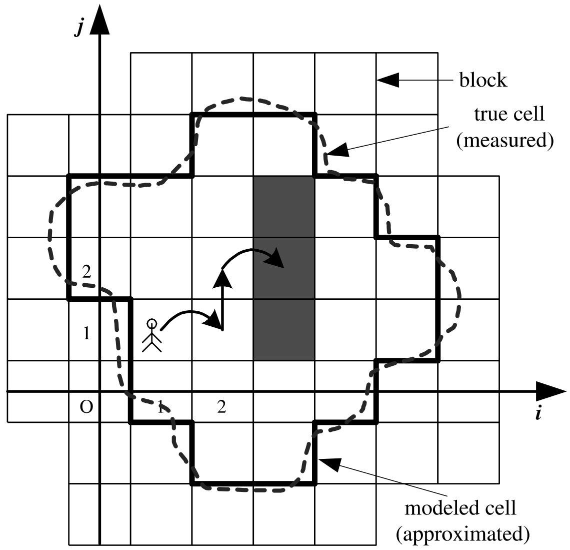

Fig. 1. Transition model in a mesh-type partitioning (grayed blocks: dense area).

2. User mobility model

In general cellular communication networks, there are several mobility classes of users such as vehicles, walking users, and immobile users. In our user mobility model, however, we consider a class out of several mobility classes because our formulation is the same with respect to every mobility class and each mobility class could be characterized by a different set of mobility parameters (mentioned later in Section 2.1).

2.1. Block-to-block transition

In order to mathematically formulate VUM, we partition each hypothetical cell area into a number of sub-areas called a *block* each. And VUM is represented as a sequence of stochastic transitions among adjacent blocks. Fig. 1 shows an example of cell partitioning and our transition model. In the figure the measured/estimated cell area is partitioned into 24 rectangular blocks and the cell boundary is approximated.

To obtain a mathematical formulation on our block-to-block (BTB) transition process, we propose a discrete time Markov chain model: *mesh transition model*. In our BTB model, the transitions of speed state and direction state occur at every step. The speed states of a user are divided into two states: state 1 is the transition state where a user moves to one of the four neighboring blocks, whereas state 0 is the state without transition where a user stays at the current block. The state transition probability matrix of moving speed is given by

$$S = \begin{pmatrix} s_{00} & s_{01} \\ s_{10} & s_{11} \end{pmatrix}, \tag{1}$$

where s_{ij} denotes the probability that next state is j given that the current state is i. Different mobility classes (e.g., vehicles, walking users, etc.) are able to be characterized in our model by giving different values of s_{ij}. For example, higher probabilities about BTB transition (s_{01} and s_{11}) could be given to vehicles (high mobility users, HMU) than to walking users.

In a real situation, it is very complex to define moving direction states to approximate true mobility with. Instead of using the concept of 'moving direction of users', we define BTB transition direction states. The direction states of our mesh transition model is visualized in Fig. 2. As shown in the figure, we have four direction states in the mesh model. The state transition probability matrix of moving direction is given by

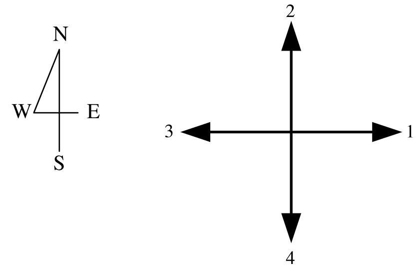

Fig. 2. Direction states: mesh transition model.

$$R_4 = \begin{pmatrix} r_0 & r_1 & r_2 & r_1 \\ r_1 & r_0 & r_1 & r_2 \\ r_2 & r_1 & r_0 & r_1 \\ r_1 & r_2 & r_1 & r_0 \end{pmatrix}. \quad (2)$$

In matrix R_4, the (i,j)th entry denotes the transition probability from direction state i to j. It means that, for a given BTB transition direction, the probability that a user keeps its current direction at next step is represented by r_0, changes its current direction at next step is by r_i where $i = 1, 2$. The transition probabilities about direction states are visualized in Fig. 3. That is, the transition probability from state i to j is denoted by $r_{|i-j|}$.

2.2. Stochastic correlation factor

As discussed above, there are a number of analytical models on user mobility in cellular systems. The major purpose of our model building consists in analyzing the effect of variable characteristics of user mobility on traffic performance (we mainly focus on cell dwell time in this paper because it is a basic measure for deriving other measures). Our approach is based on a distrete-time stochastic process with a stochastic correlation concept, and it is new and original. In order to make a quantified result, SCF is defined in this section. Suppose that r_0 is unity for a reference user A. Then user A moves linearly and it is called that user A has perfect stochastic correlation between direction states of two concatenate steps. Suppose that r_0 is 0.8 for another reference user B. Then it is called that user B does not have perfect stochastic correlation. From the same starting point, user A goes away more faster than user B. As the value of r_0 gets small (from unity), the motion of the reference user is becoming nonlinear and the correlation gets small. As a measure of stochastic correlation, we define r_0 as SCF in this paper. In the following sections, SCF is used in mathematical formulations for cell dwell time and we present several numerical examples with different values of SCF.

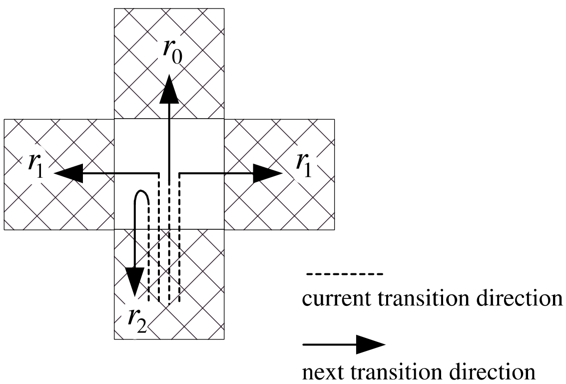

Fig. 3. State transition probabilities of BTB transition direction depicting a current block (at the center) and four candidate blocks given that next speed state is 1.

3. Cell dwell time

3.1. Probability distribution of cell dwell time

In this section, we formulate cell dwell time distribution based on mesh transition model suggested in Section 2. Cell dwell time analysis is one of the most fundamental studies in traffic performance analysis. Traffic performance such as channel holding time (service time of a server in a queuing system), handover rate, the number of handover requests could be analytically studied based on cell dwell time distribution. This is because most performance measures have functional relations with cell dwell time distribution in land–mobile cellular systems and they could be analytically derived from this. The following performance measures could be formulated using cell dwell time distribution:

- cell boundary crossing rate,
- channel holding time distribution in a given cell,

- probability distribution of the number of handover requests,
- forced termination probability.

For mathematical formulations of dwell time distribution, we have notations as follows:

- $H^d_{ij}(n) = \Pr($a user currently residing in block (i,j) leaves its current cell at next nth step, given that its direction state is d and speed state is 1).
- $L^d_{ij}(n) = \Pr($a user currently residing in block (i,j) leaves its current cell at next nth step, given that its direction state is d and speed state is 0).
- **B** is the set of all blocks in a given cell.
- $\mathbf{A}(\mathbf{B})$ denotes the set of *adjacent* blocks of **B**. For example, block (i,j) has four adjacent blocks: $(i-1,j)$, $(i+1,j)$, $(i,j-1)$, $(i,j+1)$. Thus, if $\mathbf{B} = \{(i,j)\}$, then $\mathbf{A}(\mathbf{B}) = \{(i-1,j), (i+1,j), (i,j-1), (i,j+1)\}$.
- w_{ij} is the normalized density of user (or ongoing call) distribution in block (i,j) such that $\sum_{(i,j)\in\mathbf{B}} w_{ij} = 1$.

In Fig. 1, dense and sparse areas (with respect to user density) are shown. Owing to the parameters $\{w_{ij}\}$, such non-uniform traffic (or user) distributions could be formulated in our model. For easy understanding of important notations, two simple examples are shown below.

Example 1. In Fig. 1, $\mathbf{B} = (2,-1),(3,-1),(1,0),(2,0),(3,0),(4,0),(1,1),\ldots,(2,3),(2,4)\}$ and $|\mathbf{B}| = 24$.

Example 2. In Fig. 1, let us find the probability that a user in block $(1,0)$ leaves its current cell at next step given that the direction state is 3 (West) and the speed state is 0 (i.e., low speed). To leave the cell in one step, speed state transition from the current low-speed to high-speed state, i.e., "$0 \to 1$" is required, and direction state transition either to state 3 or to state 4 is required. Thus it is represented as

$$\begin{aligned} &L^3_{10}(1) \\ &= \Pr(\text{speed: } 0 \to 1) \cdot \Pr(\text{direction: } 3 \to 3 \text{ or } 4) \\ &= s_{01}(r_0 + r_1). \end{aligned}$$

3.2. Dwell time in a generalized-mesh cell configuration

A general form of our dwell time distribution in a given region denoted by **B** based on a generalized-mesh transition model could be obtained by the following recursive relations for $n \geqslant 1$:

$$\begin{pmatrix} H^1_{i,j}(n) \\ H^2_{i,j}(n) \\ H^3_{i,j}(n) \\ H^4_{i,j}(n) \end{pmatrix} = s_{11}R_4 \begin{pmatrix} H^1_{i+1,j}(n-1) \\ H^2_{i,j+1}(n-1) \\ H^3_{i-1,j}(n-1) \\ H^4_{i,j-1}(n-1) \end{pmatrix} + s_{10}R_4 \begin{pmatrix} L^1_{i,j}(n-1) \\ L^2_{i,j}(n-1) \\ L^3_{i,j}(n-1) \\ L^4_{i,j}(n-1) \end{pmatrix}, \tag{3}$$

and

$$\begin{pmatrix} L^1_{i,j}(n) \\ L^2_{i,j}(n) \\ L^3_{i,j}(n) \\ L^4_{i,j}(n) \end{pmatrix} = s_{01}R_4 \begin{pmatrix} H^1_{i+1,j}(n-1) \\ H^2_{i,j+1}(n-1) \\ H^3_{i-1,j}(n-1) \\ H^4_{i,j-1}(n-1) \end{pmatrix} + s_{00}R_4 \begin{pmatrix} L^1_{i,j}(n-1) \\ L^2_{i,j}(n-1) \\ L^3_{i,j}(n-1) \\ L^4_{i,j}(n-1) \end{pmatrix}, \tag{4}$$

with boundary conditions:

$$H^d_{i,j}(0) = \begin{cases} 1, & \text{if } d=1, (i,j) \notin \mathbf{B}, (i-1,j) \in \mathbf{B}, \\ 1, & \text{if } d=2, (i,j) \notin \mathbf{B}, (i,j-1) \in \mathbf{B}, \\ 1, & \text{if } d=3, (i,j) \notin \mathbf{B}, (i+1,j) \in \mathbf{B}, \\ 1, & \text{if } d=4, (i,j) \notin \mathbf{B}, (i,j+1) \in \mathbf{B}, \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

$$L^d_{i,j}(0) = 0 \quad \text{for all } i,j,d, \tag{6}$$

$$H^d_{i,j}(n) = 0, \quad \text{if } n > 0 \text{ and } (i,j) \notin \mathbf{B}, \tag{7}$$

$$L^d_{i,j}(n) = 0, \quad \text{if } n > 0 \text{ and } (i,j) \notin \mathbf{B}. \tag{8}$$

From the recurrence relations, our dwell time distribution of new calls is written as

$$\Pr(T_{\mathrm{DN}} = n) = \sum_{(i,j)\in\mathbf{B}} \left(w_{ij} \sum_{d=1}^{4} \frac{\phi_1 H_{ij}^d(n) + \phi_0 L_{ij}^d(n)}{4} \right) \tag{9}$$

given that new call users are distributed with user density w_{ij} of block (i,j). Using the user density factors w_{ij} for $(i,j) \in \mathbf{B}$, our dwell time distribution of handover calls (i.e., the probability distribution of unencumbered dwell time) could be expressed as

$$\Pr(T_{\mathrm{DH}} = n) = \left(\sum_{\substack{(i,j)\in\mathbf{B} \\ d\in D(i,j;\mathbf{B})}} w_{ij} \right)^{-1} \sum_{\substack{(i,j)\in\mathbf{B} \\ d\in D(i,j;\mathbf{B})}} w_{ij} H_{ij}^d(n), \tag{10}$$

where $D(i,j;\mathbf{B})$ is the set of all directions along which a user in block $(i,j) \in \mathbf{B}$ enters one of blocks belong to $\mathbf{A}(\mathbf{B})$ in one step.

3.3. Numerical examples

A number of numerical examples are presented to show the effect of SCF on cell dwell time in this section. In the first example, we use the cell shown in Fig. 1 where the cell is partitioned into 24 rectangular blocks and the irregular cell shape is approximated with those blocks. Fig. 4 shows several cell dwell time distributions of new calls obtained by our generalized-mesh model. It is observed that the average dwell time gets shorter as SCF becomes greater. Two results from geometric and gamma distribution functions shown in previous work are used to show how much *goodness-of-fit* is obtained in case that cell dwell time is modeled by the distribution functions (i.e., exponential and gamma distributions). As shown in the figure, previous simple models do not provide good agreements in both cases: `type-a` (SCF = 0.75) and `type-b` (SCF = 1.00). Fig. 5 shows several dwell time distributions of handover calls using the same model and the same values used in Fig. 4. In Fig. 5, it is observed that the average dwell time of handover calls gets larger as the motion of the mobility gets linear. According to the above two examples, we can safely conclude that the variance of each dwell time distribution (of handover calls or not) is small if the r_0 is great (within the range of $0.75 \leqslant \mathrm{SCF} \leqslant 1.00$). This is because the motion of users converges to linear motion as SCF → 1, which leads to reducing long dwell time. Table 1 shows the variance for each

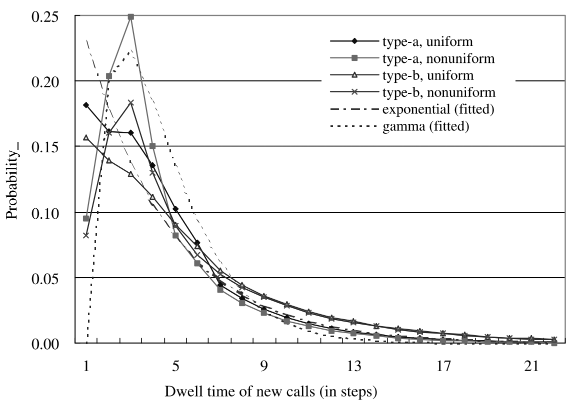

Fig. 4. Probability distribution of cell dwell time of new calls in an irregularly shaped cell using a generalized-mesh transition model. Uniform and non-uniform block user distributions. `type-a` (SCF = 0.75): $(r_0, r_1, r_2) = (0.75, 0.10, 0.05)$; `type-b` (SCF = 1.00): $(r_0, r_1, r_2) = (1.00, 0.00, 0.00)$.

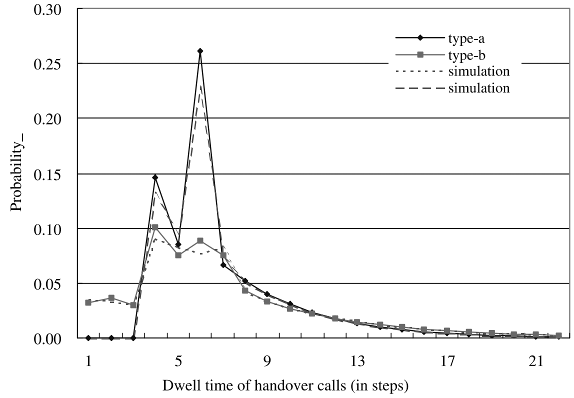

Fig. 5. Probability distribution of cell dwell time of handover calls in an irregularly shaped cell using a generalized-mesh transition model. Non-uniform block user distributions. `type-a` (SCF = 0.75): $(r_0, r_1, r_2) = (0.75, 0.10, 0.05)$; `type-b` (SCF = 1.00): $(r_0, r_1, r_2) = (1.00, 0.00, 0.00)$.

Table 1
Variances of dwell time distributions: `type-a` and `type-b`

	`type-a`	`type-b`	Difference
New call	1.376	0.747	45.712 (%)
Handover call	1.301	1.166	10.377 (%)

distribution. type-a is the case of $(r_0, r_1, r_2) = (0.75, 0.10, 0.05)$ and type-b $(r_0, r_1, r_2) = (1.00, 0.00, 0.00)$.

In next examples, we test the effect of SCF on dwell time in 10 randomly generated cells with 30 blocks, respectively. In addition to the effect of SCF, the effect of the fraction of HMU on dwell time distribution is also considered. In this paper HMU have a different matrix S from the matrix S that low mobility users have. The classification of HMU out of the total users is not important in these examples, but the effect of the fraction of HMU on the average dwell time should be focused on. Figs. 6 and 7 show dwell time distributions of new calls and handover calls with respect to SCF and the fraction of HMU, respectively. As shown in the previous examples, it is observed that a great value of SCF makes the variance small. Also, it is observed that the variance is smaller as the fraction of HMU is greater. Comparing the two figures, we can safely conclude that the average dwell time of handover calls is relatively longer than that of new calls *cetris paribus*. This is because the dwell time of a new call is the residual lifetime (encumbered dwell time) while the dwell time of a handover call is the whole lifetime (unencumbered dwell time) where lifetime is defined as the dwell time in a given cell whether a user is engaging a call or not. As shown in Figs. 6 and 7, the average dwell time is small if s_{11} is great and s_{00} is small (this could be regarded as a case of HMU). Note that s_{11} of HMU is greater than that of low mobility users and s_{00} of low mobility users is greater than that of HMU.

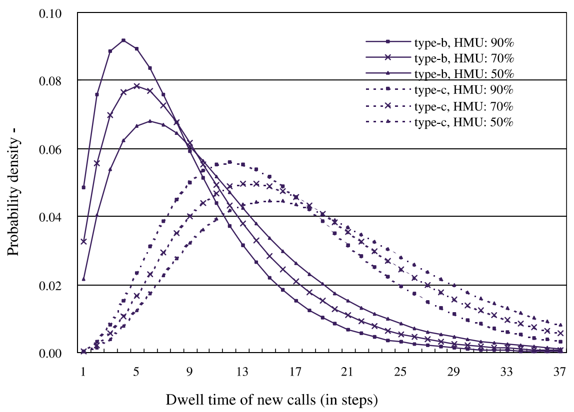

Fig. 6. Probability distribution of cell dwell time of new calls using a hexagonal transition model with randomly generated cell ($|\mathbf{B}| = 30$) shapes. type-b (SCF = 1.00): $(r_0, r_1, r_2) = (1.00, 0.00, 0.00)$; type-c (SCF = 0.85): $(r_0, r_1, r_2) = (0.85, 0.05, 0.05)$.

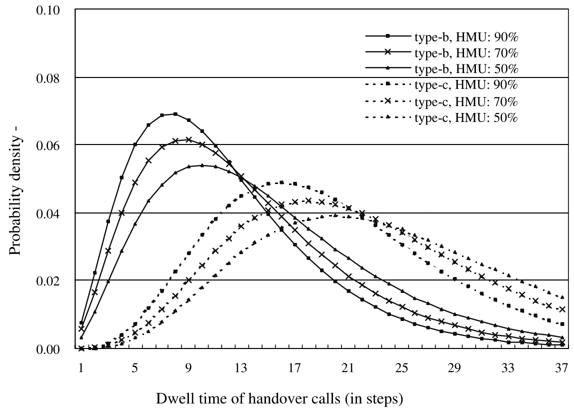

Fig. 7. Probability distribution of cell dwell time of handover calls using a hexagonal transition model with randomly generated cell ($|\mathbf{B}| = 30$) shapes. type-b (SCF = 1.00): $(r_0, r_1, r_2) = (1.00, 0.00, 0.00)$; type-c (SCF = 0.85): $(r_0, r_1, r_2) = (0.85, 0.05, 0.05)$.

4. Path length distribution

Path length (during a call) is defined as the path length of calling user between the call setup time and the call completion time. A specified form of path length distribution is able to be formulated by some methods, for example, as shown in Ref. [6]. However, no specified mobility pattern is modeled for characterizing path length distribution in Ref. [6]. We focus on characterizing path length distribution considering a specified mobility characteristic as shown in our model. In classical teletraffic theory, the probability distribution of call holding time (call duration) is usually assumed to be negative exponential (note that the effect of forced termination is reflected in call holding time). Under the condition that users move with randomly chosen fixed speed and exponential call holding time, the distribution of path length during a call is also negative exponential regardless of moving direction stochastic. However, under a realistic condition that users move with variable speed, it is different from an exponential distribution. In this section we figure out the effect of VUM on user path length with a major focus on stochastically variable speed of users.

Probability distribution functions of user path length in a given geographic environment during a call could be utilized in traffic estimation such as handover rate estimation and location-area update rate estimation which are very significant and useful in cellular system design for efficient resource and mobility management.

4.1. Formulation

We formulate our path length distribution based on BTB mobility model. To utilize the discrete time approach in the model, we approximate the true path of a user with the set of successive links connecting the centers of blocks visited by the user. Let $l_{m,n}$ denote the probability that the path length is m (the unit size of a link g is omitted for the sake of convenience) given that the call holding time is n and the previous speed state is 0, and $h_{m,n}$ denote the probability that the path length is m given that the call holding time is n and the previous speed state is 1. Then we obtain the following recurrence relation:

$$\begin{pmatrix} l_{m,n} \\ h_{m,n} \end{pmatrix} = \begin{pmatrix} s_{00} & s_{01} \\ s_{10} & s_{11} \end{pmatrix} \begin{pmatrix} l_{m,n-1} \\ h_{m-1,n-1} \end{pmatrix} \tag{11}$$

and boundary conditions

$$l_{m,n} = \begin{cases} s_{01}s_{11}^{m-1}, & m = n > 0, \\ s_{00}^{n}, & m = 0, n > 0, \\ 0, & m > n > 0, \end{cases} \tag{12}$$

$$h_{m,n} = \begin{cases} s_{11}^{m}, & m = n > 0, \\ s_{10}s_{00}^{n-1}, & m = 0, n > 0, \\ 0, & m > n > 0. \end{cases} \tag{13}$$

Then the distribution of path length during a call can be written as

$$\Pr(L = m) = \sum_{n=m}^{\infty} (\phi_0 l_{m,n} + \phi_1 h_{m,n}) \ \Pr(X = n), \tag{14}$$

where random variable X denotes call holding time (in steps).

4.2. Numerical examples

We have two cases of test examples: one is a case that call holding time is geometrically distributed, i.e., $\Pr(X = x) = p(1-p)^{x-1}$ for $x = 1, 2, \ldots$; the other is a case that call holding time follows a negative binomial distribution, i.e., $\Pr(X = x) = \binom{x+r-2}{r-1} p^r (1-p)^{x-1}$ for $x = 1, 2, \ldots$ Fig. 8 shows four examples of our probability distribution function of path length (two with geometric distributions with parameters $p = 0.040$ (case A1) and $p = 0.080$ (case A2), respectively; the other two with negative binomial distributions with parameter sets $(r, p) = (2, 0.100)$ (case B1) and $(r, p) = (2, 0.150)$ (case B2), respectively). Also four approximated curves (two with geometric distributions with parameters $p = 0.069$ and $p = 0.106$, respectively; the other two with negative binomial distributions with parameter sets $(r, p) = (2, 0.141)$ and $(r, p) = (2, 0.207)$, respectively) are also provided in order to show the *goodness-of-fit*. As shown, good agreements between the path length distributions and the approximating probability distributions are observed in cases A1 and A2 (i.e., geometric call holding time). In cases B1 and B2, however, path length distribution is not accurately approximated by any negative binomial distribution with parameter $r \geqslant 2$. This is because: when $r = 2$, it is asserted by our best approximation; when $r = 3, 4, \ldots$, it can be asserted by

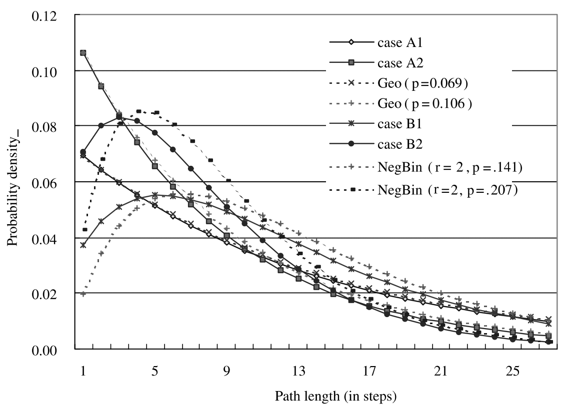

Fig. 8. Path length distribution. case A: geometric call holding time (A1: $p = 0.04$; A2: $p = 0.08$); case B: negative binomial-2 call holding time (B1: $p = 0.1$; B2: $p = 0.15$).

probability theory, i.e., as $r \to \infty$, more peakedness of a negative binomial distribution is shown. According to our numerical examples, it is expected that the path length distribution is not approximated by a negative binomial distribution (the discrete version of a gamma distribution) with sufficient accuracy in case that call holding time also follows a negative binomial distribution.

5. Conclusions

Since simulation approach to user mobility analysis requires high cost for valid results, many analytical models have been developed. However, such models are very weak for reflecting variable feature of user mobility and, therefore, they are not valid for traffic analysis in micro-/pico-cellular systems with mobility-sensitive traffic performance. As an improved alternative, this paper has focused on developing an analytical model for variable user mobility (VUM) with stochastic correlation. A new concept of *stochastic correlation* in mobility modeling is introduced in order to figure out the effect of VUM on cell dwell time. With SCF suggested in this paper, we formulate our cell dwell time distribution and study the effect of VUM on shaping the cell dwell time distribution. Also, path length distribution is studied in consideration of stochastic variation of moving speed. A number of numerical examples show that the average dwell time is shorter as SCF is greater. We believe that our improved model of VUM with stochastic correlation could be utilized for more valid traffic analysis and estimation in micro-/picocellular systems where traffic performance is much affected by user mobility characteristics.

Acknowledgements

The authors are very grateful to the anonymous reviewers and H.Y. Kim for their valuable comments. This work was prepared during the authors' work at KAIST and supported in part by the Brain Korea 21 (BK21) Project from Ministry of Education. It was completed at Radio & Broadcasting Laboratory, ETRI. It is a pleasure to acknowledge their kind hospitality.

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