User mobility profile prediction: An adaptive fuzzy inference approach

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Predicting the probabilities that a mobile user will be active in other cells at future moments poses a significant technical challenge to network resource management in multimedia wireless communications. The probability information can be used to assist base stations to maintain a balance between guaranteeing quality of service (QoS) to mobile users and achieving maximum resource utilization. This paper proposes a novel adaptive fuzzy logic inference system to estimate and predict the probability information for direct sequence code division multiple access (DS/CDMA) wireless communications networks. The estimation is based on measured pilot signal strengths at the mobile user from a number of nearby base stations, and the prediction is obtained using the recursive least square (RLS) algorithm. Numerical results are presented to demonstrate the performance of the proposed technique under various path loss and channel shadowing conditions.

1. Introduction

An interworked wireless/wireline network is a suitable platform for providing multimedia services to mobile users anywhere at anytime. However, widespread user mobility, limited radio frequency spectrum, radio channel impairments etc. in the wireless segment pose significant challenges in the management of resources in the integrated network. Resource management, including flow control, resource allocation, congestion control, and call admission control, is critical to quality of service (QoS) provisioning. Resource management functions should capture the effect of user mobility in order to balance the tradeoff between the satisfaction of QoS and the maximization of resource utilization. Several techniques have been proposed to attain the tradeoff. The shadow cluster [8] and virtual connection tree (VCT) [1,19] approaches make use of statistical multiplexing of data traffic to and from mobile users so that a higher resource utilization can be obtained without increasing the call dropping probability. However, statistical multiplexing requires a knowledge of the user movement patterns and trends.

User mobility information can be used to assist user mobility management (traffic routing) [1], to manage network resources (resource allocation, call admission control, congestion and flow control) [12], and to analyze handoff algorithms in integrated wired/wireless networks [20]. Previous research efforts on mobility information have focused on statistics such as mobility model [3,6], user location tracking and trajectory prediction [9], channel holding time [4], cell boundary crossing rate [11,15,18], mean handover rate [6,13], and cell residence time [6,23]. Different from the previous work, in this paper we are interested in the probabilities that a mobile user will be active in a particular cell at future moments. The mobility information is directly related to statistical multiplexing and plays an important role in efficient resource management of wireless cellular systems.

In general, if a mobile user is closer to a base station (BS), then the propagation path attenuation from the BS to the mobile user is smaller, and vice versa. Hence, if the BS transmits a pilot signal with constant transmitted power, then the received power of the signal at the mobile user carries the information of the distance between the mobile user and the BS. Since the probability that the mobile user will be active in a particular cell at a future moment is a function of the current distances between the mobile user and its nearby BSs, the probability can be estimated based on real-time measurements of the received pilot signal power at the mobile user from the BSs. Furthermore, the probability depends on the mobile user movement pattern (such as movement trajectory). Although the movement patterns of mobile users are random in nature to the wireless system, the movement of each mobile user has a relatively smooth trajectory most of the time. That is, the location of a mobile user at a future moment depends on its locations at the current moment and previous moments. As a result, it is possible to predict the mobility information based on the current and previous measurement data. If the predictions of future mobility information can be obtained with reasonable accuracy, then the network resource management will become substantially efficient in terms of user QoS and resource utilization [8,9].

The challenges in estimating and predicting the mobility information based on the pilot signal power measurements come from the following facts:

(a) Normally there is no one-to-one relation between the distance and the probability. Even when such a relation exists for some special environments, it is very difficult (if not impossible) to describe the relation accurately, e.g., using mathematical expressions.

(b) There exists a relatively slow fluctuation of the received signal level due to physical structure blocking the transmission path between the BS and the mobile user. The shadowing process randomizes the relation between the received pilot signal power and the distance from the mobile user to the BS. On the average, the larger the power, the smaller the distance. However, the relation may not hold for each measurement.

(c) The received signals are contaminated by the multiple access interference (MAI) due to other users in the system and unavoidable background noise. That is, the measured data are not accurate.

As a result, it is impossible to accurately derive the probability information based on the measurements. To tackle the difficulty, an adaptive fuzzy inference system is presented in this paper. The system deals with

(a) the uncertainty inherent in the relation between the distance and the probability and

(b) the random shadowing effect by using training data from real measurement or from statistical models of practical propagation environments.

To handle the measurement error, the system incorporates the degree of certainty (or accuracy) of the measurements by giving a larger degree of importance to the data with higher measurement accuracy.

A fuzzy inference system was proposed in [16] to estimate the current mobility information based on the real-time measurements. The main concern of this paper is to predict the mobility information of future moments with an adaptive fuzzy inference approach. The remainder of the paper is organized as follows. Section 2 describes the system model which uses direct sequence code division multiple access (DS/CDMA). By using the pilot signals in the forward channel (down link), no extra signaling is needed for obtaining user mobility information. Section 3 is devoted to the design of the adaptive fuzzy inference system which combines fuzzy inference logic with a recursive least square (RLS) predictor. Numerical results and discussions on the performance and applications of the proposed technique are presented in section 4. Section 5 gives some concluding remarks of this work.

2. Mobility information model

We consider a wireless communication network operating in a frequency division duplex (FDD) mode. Mobile users in each cell share the radio frequency spectrum through the DS/CDMA protocol. The same total frequency bandwidth is reused in every cell to increase the radio spectral efficiency and to eliminate the need for frequency coordination. Due to the universal frequency reuse and the use of Rake receivers, soft handoff becomes possible. A mobile can transmit to and receive from more than one BS at any time. During transition from one cell to a neighboring cell, the mobile user establishes a communications link with the new BS while, at the same time, keeping its communications link with the original BS. The original communications link is terminated only after the mobile user has firmly established itself in the new cell. In the forward link, each base station transmits a distinct pilot signal for pseudorandom noise (PN) code and carrier synchronization at the receiver of the mobile user. Prior to any transmission, the mobile user monitors the received pilot signal power levels from nearby base stations. It chooses its home BS according to the maximum pilot signal power received. The network uses mobile user assisted soft handoff as in the CDMA2000 proposal [17]. While tracking the signal from the home BS, the user searches for all the possible pilots and maintains a list of all pilots whose levels are above a prescribed threshold. This list is transmitted to a mobile switching center (MSC) periodically through the home BS. The MSC uses the information to make decision on when the soft handoff should start. In addition, the MSC uses the information to estimate and predict the probabilities that the mobile will locate in a particular cell at the future moments.

Consider a uniform grid of hexagonal cells, as shown in figure 1, where the mobile user under consideration is located in the sub-region O_1 of cell_0. For each mobile user, we will focus on the mobility information related only to its home BS (denoted by BS_0) and to the six first-tier neighboring BSs (denoted by BS_1, BS_2, ..., BS_6). The index i will be used throughout this paper to denote variables related to the home BS ($i = 0$) and to the neighboring BSs ($i = 1, 2, \ldots, 6$). The time t will be discretized and represented as t_n ($= n\Delta t$), $n = 1, 2, \ldots,$ where Δt is the

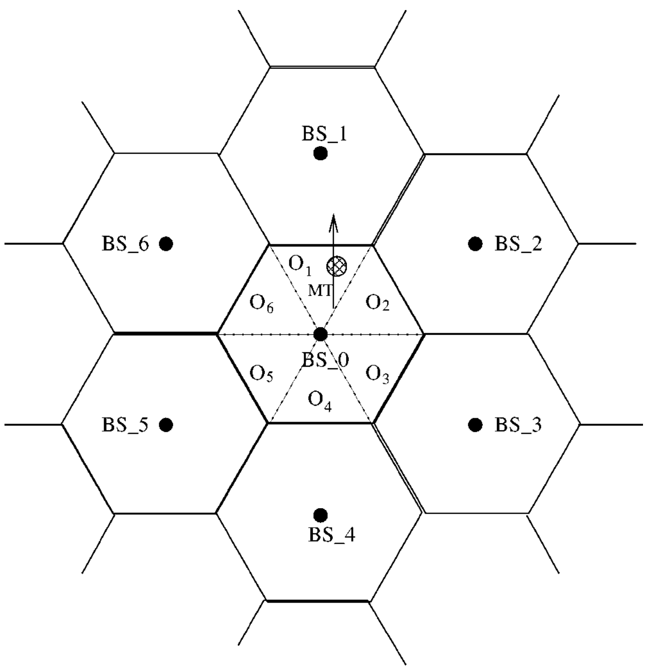

Figure 1. The hexagonal cell layout.

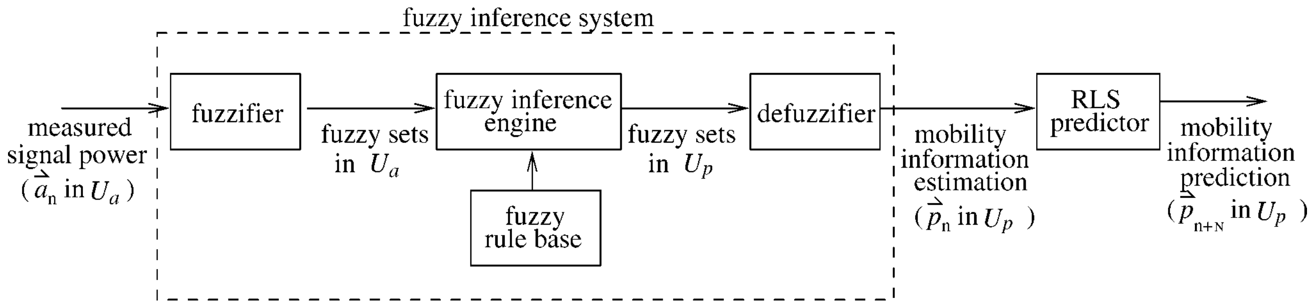

Figure 2. The adaptive fuzzy inference system.

time interval over which the received pilot signals are measured once and then the estimation and prediction of the probabilities are updated. Let $d_i(t_n)$ denote the distance at time t between the mobile user and BS_i. Given the coverage areas of the BSs, the probabilities that the mobile user will be in cell_i at the next moment t_{n+1} mainly depends on the distances $d_i(t_n)$, the velocity and moving direction of the user. The larger the distance $d_i(t_n)$, the smaller the probability that the user will be in cell_i. By measuring the power of the pilot signal from BS_i received at the mobile user, the distance $d_i(t_n)$ can be estimated. At t_n, the local mean of the pilot signal amplitudes received at each mobile user can be modeled by [14]

$$a_{n,i} = \gamma_i \left[\frac{d_i(t_n)}{D_0}\right]^{-\kappa} 10^{\xi_i(t_n)/10}, \quad i = 0, 1, \dots, 6, \tag{1}$$

where γ_i is a constant proportional to the amplitude of the transmitted pilot signal, κ is the path loss exponent, D_0 is the close-in reference distance which is determined from measurements close to the transmitter, and $\xi_i(t_n)$ is to characterize the effect of shadowing and can be modeled by a normal random variable (for any t_n) with zero mean and variance σ^2. For $i \neq j$, $\xi_i(t_n)$ and $\xi_j(t_n)$ are independent. If the transmitted pilot signals have the same power, then $\gamma_i = \gamma$ for $i = 0, 1, \dots, 6$.

Here we use the relation between the distance $d_i(t_n)$ and the probability, under the assumption that the wireless propagation condition is homogeneous over the service area of the system. This is to compensate the effect of the shadowing (experienced by the pilot signals) on the probability estimation. If the assumption does not hold, other criteria may be used to estimate the probability, such as directly using the received pilot signal powers.

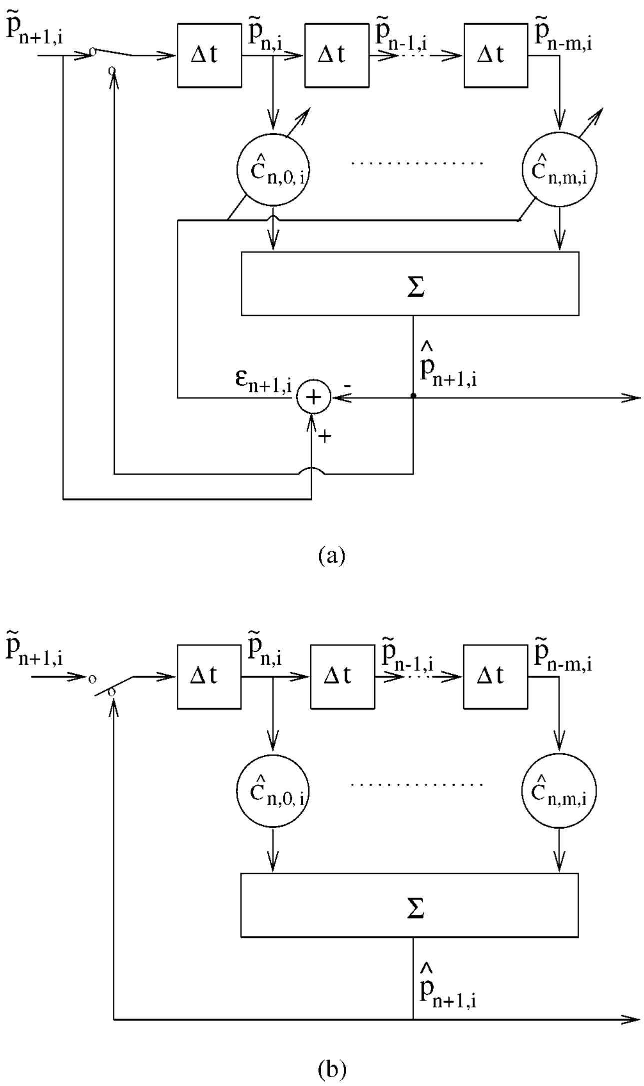

Figure 3. The structure of the RLS predictor for one component of the probability vector: (a) training, (b) prediction.

3. Adaptive fuzzy inference system design

Figure 2 shows the block diagram of an adaptive fuzzy inference prediction system. It consists of two subsystems: a fuzzy inference system, and an RLS predictor. The fuzzy inference system estimates the probability that a mobile user will be active in cell i at time t_n based on the measured pilot signal strengths at time t_n. Before measurements at t_{n+1} are available, the RLS predictor predicts the probability that the mobile user will be active in cell i at time t_{n+N} for $N = 1, 2, \dots$ based on the estimates from the fuzzy inference system up to time t_n, as depicted in figure 3(b). The predicted probability information can be used in resource management to handle user mobility in advance of the mobile user's next move. The design of the subsystems is given in sections 3.1 and 3.2.

3.1. The fuzzy inference system

This subsystem is a special expert system. It employs a knowledge base, expressed in terms of fuzzy inference rules, and an appropriate inference engine to estimate the probability of a mobile user being active in cell_i at t_n based on the measurement data $a_{n,i}$. The knowledge base can be designed to take into account

(a) the wireless propagation environment such as the one described by equation (1),

(b) intuitive understanding of the general relation between the distance and the probability, and

(c) measurement errors.

The system is capable of utilizing knowledge elicited from human operators. The knowledge is expressed by using natural language, a cardinal element of which is linguistic variables [7,21]. Let the linguistic variable $a_{n,i}$ be the received signal level from BS_i at time t_n, then the corresponding universe of discourse is the set of all possible received signal levels. We choose the term set of $a_{n,i}$, denoted by $U_{a_{n,i}}$, to contain the following elements: extremely small (ES), very small (VS), small (S), small-to-medium (SM), medium-to-large (ML), large (L), very large (VL), extremely large (EL). Let the linguistic variable $p_{n,i}$ be the probability that the mobile user will be active in cell_i at epoch t_n, with the universe of discourse being the interval [0, 1]. We choose the term set of $p_{n,i}$, denoted by $U_{p_{n,i}}$, to be the set containing the following elements: zero (ZE), extremely small (ES), very small (VS), small (S), small-to-medium (SM), medium-to-large (ML), large (L), very large (VL), extremely large (EL), and one (OE). The number of terms in $U_{a_{n,i}}$ and $U_{p_{n,i}}$, respectively, is selected so as to achieve a compromise between the complexity and the fuzzy inference system performance. The membership functions of the input (the received signal levels) and the output (the probabilities) depend on the BS coverage areas, transmitted pilot signal power, the path loss exponent κ and channel shadowing statistics.

The fuzzifier translates the measured data into linguistic values of the fuzzy set in the input universe of discourse. Each specific value of the measured signal level $a_{n,i}$ is mapped to the fuzzy set $U^1_{a_{n,i}}$ with degree $\mu^1_{x_i}(a_{n,i})$ and to the fuzzy set $U^2_{a_{n,i}}$ with degree $\mu^2_{x_i}(a_{n,i})$, and so on, where $U^J_{a_{n,i}}$ is the name of the Jth term or fuzzy set value in $U_{a_{n,i}}$.

The fuzzy rule base is the control policy knowledge base, characterized by a set of linguistic statements in the form of IF–THEN rules that describe the fuzzy logic relationship between the measured data and the mobility information. The kth rule has the following form:

$$
\begin{aligned}
R_k\colon\ & \text{if } a_{n,0} \text{ is } A_{0k} \text{ and } a_{n,1} \text{ is } A_{1k} \text{ and } \ldots \\
& \quad \text{and } a_{n,6} \text{ is } A_{6k}, \\
& \text{then } p_{n,0} \text{ is } P_{0k} \text{ and } p_{n,1} \text{ is } P_{1k} \text{ and } \ldots \\
& \quad \text{and } p_{n,6} \text{ is } P_{6k},
\end{aligned}
$$

where $k = 1, 2, \ldots, K$, K is the total number of the fuzzy rules, $(a_{n,0}, a_{n,1}, \ldots, a_{n,6}) \in U_{a_{n,0}} \times U_{a_{n,1}} \times \cdots \times U_{a_{n,6}} \triangleq U_a$ and $(p_{n,0}, p_{n,1}, \ldots, p_{n,6}) \in U_{p_{n,0}} \times U_{p_{n,1}} \times \cdots \times U_{p_{n,6}} \triangleq U_p$ are linguistic variables, A_{ik} and P_{ik} are fuzzy sets in $U_{a_{n,i}}$ and $U_{p_{n,i}}$, respectively.

In the fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF–THEN rules in the fuzzy rule base into a mapping from fuzzy sets in U_a to fuzzy sets in U_p:

Given Fact:

$$a_{n,0} \text{ is } \widetilde{A}_0 \text{ and } a_{n,1} \text{ is } \widetilde{A}_1 \text{ and } \ldots \text{ and } a_{n,6} \text{ is } \widetilde{A}_6,$$

Consequence:

$$p_{n,0} \text{ is } \widetilde{P}_0 \text{ and } p_{n,1} \text{ is } \widetilde{P}_1 \text{ and } \ldots \text{ and } p_{n,6} \text{ is } \widetilde{P}_6,$$

where $\widetilde{A}_i$ and $\widetilde{P}_i$ $(i = 0, 1, \ldots, 6)$ are linguistic terms for $a_{n,i}$ and $p_{n,i}$, respectively. The fuzzy rule base can be created from training data sequence (e.g., measured input–output pairs). To avoid tedious field trials, the training data can be generated in computer simulation based on propagation model and cell structure. Given a set of desired input–output data pairs, a set of fuzzy IF–THEN rules can be generated. In addition, a degree which reflects the expert's belief of the importance of the rule can be assigned to each rule. For example, the importance of a rule increases if the corresponding input data has a higher measurement accuracy. The measurement accuracy increases as the received signal-to-interference-and-noise ratio (SINR) increases. With the same interference-and-noise component for all received pilot signals, the differences among the SINR values are proportional to the differences among the received power values of the pilot signals. If the mobile is closer to BS_i than to BS_j, the average received signal power from BS_i is larger than that from BS_j. Hence, the measured data for BS_i should be weighted more (i.e., have a larger degree) than that for BS_j. The degree assigned to rule k is calculated by using product operations

$$Q_k = \mu_k \prod_{i=0}^{6} \mu_{I_{ik}}(a_{n,i}) \prod_{i=0}^{6} \mu_{O_{ik}}(p_{n,i}), \tag{2}$$

where I_{ik} denotes the input region of rule k for $a_{n,i}$, O_{ik} the output region for $p_{n,i}$, $\mu_{I_{ik}}(a_{n,i})$ is the degree of $a_{n,i}$ in I_{ik} obtained from the membership functions, $\mu_{O_{ik}}(p_{n,i})$ the degree of $p_{n,i}$ in O_{ik}, and μ_k is the degree of the data vector $(a_{n,0}, a_{n,1}, \ldots, a_{n,6})$ assigned by human operators. When there is more than one rule in one box of the fuzzy rule base, the rule that has the largest degree is chosen.

The defuzzifier performs a mapping from fuzzy sets $(p_{n,0}, p_{n,1}, \ldots, p_{n,6}) \in U_p$ (the output of the inference engine) to a crisp point $(p_{n,0}, p_{n,1}, \ldots, p_{n,6}) \in U_p$. Among the commonly used defuzzification strategies, the center average defuzzification method yields a superior result [2]. Let $\tilde{p}_{n,i}$ denote the estimate (generated by the fuzzy inference system at time t_n) of the true probability $p_{n,i}$. The formula for the estimate at the defuzzifier output is

$$\widetilde{p}_{n,i} = \frac{\sum_{k=1}^{K} \overline{Q}_k \prod_{j=0}^{6} \mu_{I_{jk}}(a_j)\bar{p}_{ik}}{\sum_{k=1}^{K} \overline{Q}_k \prod_{j=0}^{6} \mu_{I_{jk}}(a_j)}, \tag{3}$$

where $\bar{p}_{ik}$ is the center value of the output region of rule k, and $\overline{Q}_k$ is the degree (normalized to 1) of rule k.

3.2. The RLS predictor

For each mobile user, there is a strong correlation among its locations at adjacent time moments if the product of the mobile user velocity and the time interval Δt is small. As a result, there may exist a strong correlation among the $(p_{n,0}, p_{n,1}, \ldots, p_{n,6})$ values for some consecutive discrete time moments. This makes it possible to predict the future probability value based on its current and previous values. The RLS algorithm is used for the prediction here because

(a) it is easily implemented using a tapped-delay line and

(b) a forgetting factor can be introduced to take into account the fact that the correlation between two locations fades as the time interval separating the corresponding time moments increases.

The RLS predictor takes the probability estimates up to time t_n from the fuzzy inference system and processes the data to predict the probability that a mobile user will be active in neighboring cells at a future moment t_{n+N}, where $N = 1, 2, 3, \ldots$. Figure 3(a) shows the structure of the RLS predictor for $N = 1$, which is basically a tapped-delay-line filter with $(m+1)$ taps. The tap coefficients are obtained using the RLS algorithm [5,10]. In figure 3(a), the values $\widetilde{p}_{n,i}, \widetilde{p}_{n-1,i}, \ldots, \widetilde{p}_{n-m,i}$ are available from the fuzzy inference system. We use these and future values, shown by $\widetilde{p}_{n+1,i}$, to train the linear least square filter. After the tap coefficients have been trained, the system can be used as an RLS predictor to perform the prediction. When $\widehat{p}_{n+1,i}$ becomes available, $\widehat{p}_{n+1,i}, \widetilde{p}_{n,i}, \ldots, \widetilde{p}_{n-m+1,i}$ are used to refresh the contents of the tapped-delay line and perform the next set of prediction steps.

At time t_n, the input vector of the predictor is

$$V_n = \left(\vec{p}_n, \vec{p}_{n-1}, \ldots, \vec{p}_{n-m}\right)^{\mathrm{T}},$$

where the superscript $^{\mathrm{T}}$ denotes transposition, and $\vec{p}_{n-l} = (\widetilde{p}_{n-l,0}, \widetilde{p}_{n-l,1}, \ldots, \widetilde{p}_{n-l,6})$, $l = 0, 1, \ldots, m$, is the fuzzy inference system output at t_{n-l}. All the elements are set to zero for the initial moments $n \leqslant l$. The corresponding tap coefficient vector is

$$C_n = \left(\vec{c}_{n,0}, \vec{c}_{n,1}, \ldots, \vec{c}_{n,m}\right)^{\mathrm{T}},$$

where $\vec{c}_{n,l} = (c_{n,l,0}, c_{n,l,1}, \ldots, c_{n,l,6})$, corresponding to $\vec{p}_{n-l}$. C_n should be chosen (optimized) to minimize the mobility information estimation error. Over a short time duration, the RLS predictor can be described by the following system model equations:

$$C_{n+1} = C_n, \tag{4}$$

$$\vec{p}_{n+1} = V_n^{\mathrm{T}} C_n + w_n, \tag{5}$$

where C_n is the optimal tap-coefficient vector under the constraint of a finite tap number, $\vec{p}_{n+1}$ is the output of the fuzzy inference system at time t_{n+1} and is used as the desired output of the predictor, w_n is the measurement error with zero mean and finite variance to capture the effects due to the stochastic nature of wireless propagation environments, random movement of the mobile user, etc. Equation (4) is adequate over a short duration of time (a small number of Δt intervals) if Δt is relatively small compared with the average channel shadowing duration. However, the model is inadequate over a long time interval, which is to be compensated for by introducing an exponential forgetting factor to the filtering algorithm. In figure 3(a), the ith component $(i = 0, 1, \ldots, 6)$ of the predictor output is given by

$$\widehat{p}_{n+1,i} = \sum_{l=0}^{m} \widehat{c}_{n,l,i} \widetilde{p}_{n-l,i} = V_{n,i}^{\mathrm{T}} \widehat{C}_{n,i}, \tag{6}$$

where

$$V_{n,i} = \left(\widetilde{p}_{n,i}, \widetilde{p}_{n-1,i}, \ldots, \widetilde{p}_{n-m,i}\right)^{\mathrm{T}}$$

is the ith element of V_n and

$$\widehat{C}_{n,i} = \left(\widehat{c}_{n,0,i}, \widehat{c}_{n,1,i}, \ldots, \widehat{c}_{n,m,i}\right)^{\mathrm{T}}$$

is an estimate of the ith tap-coefficient vector $C_{n,i}$ at t_n, under the assumption that $C_{n,i}$ is time-invariant over a small number of Δt intervals. The estimate $\widehat{C}_{n,i}$ is computed based on the fuzzy inference system output up to t_n. The ith estimation error component at t_{n+1} is defined as

$$\varepsilon_{n+1,i} \triangleq \widetilde{p}_{n+1,i} - \widehat{p}_{n+1,i} = \widetilde{p}_{n+1,i} - V_{n,i}^{\mathrm{T}} \widehat{C}_{n,i}, \tag{7}$$

where $\widetilde{p}_{n+1,i}$ is the estimated probability from the fuzzy inference system at time t_{n+1}, and $\widehat{p}_{n+1,i}$ is a least square estimate of $\widetilde{p}_{n+1,i}$ obtained based on $\widetilde{p}_{n-l,i}$, $l = 0, 1, \ldots, m$.

In the RLS algorithm, the estimation error vector sequence $\{\vec{\varepsilon}_n\} = \{(\varepsilon_{n,0}, \varepsilon_{n,1}, \ldots, \varepsilon_{n,6})\}$ is considered to be a deterministic process. The algorithm starts with an initial estimate $\widehat{C}_{0,i}$ and uses the information contained in new data samples to update the old estimates. Therefore, the length of observable data is variable. The design criterion is to adaptively estimate the tap-coefficient vector $\widehat{C}_{n,i}$ such that the weighted squared error (cost function) at t_{n+1}, defined as

$$\begin{aligned} J_{n+1,i} &= \sum_{j=0}^{n+1} \lambda^{n+1-j} |\varepsilon_{n+1-j,i}|^2 \\ &= \sum_{j=0}^{n+1} \lambda^{n+1-j} \left|\widetilde{p}_{n+1-j,i} - V_{n-j,i}^{\mathrm{T}} \widehat{C}_{n-j,i}\right|^2, \end{aligned} \tag{8}$$

is minimized. In equation (8), λ^{n+1-j} is an exponential forgetting factor taking into account that the correlation between V_n and V_{n+N} decreases as N increases. If $\lambda = 1$, then all the estimates $V_{n-j},\ j = 0, 1, \ldots, n$, are to be treated equally; if $\lambda < 1$, then the estimate obtained at earlier times (with larger j values) are to have a smaller influence than more recent estimates (with smaller j values). The RLS algorithm with a constant λ for updating the estimate of the tap-coefficient, $\widehat{C}_{n+1,i}$, can be summarized as

$$\widehat{C}_{n+1,i} = \widehat{C}_{n,i} + G_{n+1,i}\bigl(H_{n+1,i} - V_{n,i}^{\mathrm{T}}\widehat{C}_{n,i}\bigr), \tag{9}$$

$$G_{n+1,i} = H'_{n,i}V_{n,i}\bigl(1 + V_{n,i}^{\mathrm{T}}H'_{n,i}V_{n,i}\bigr)^{-1}, \tag{10}$$

$$H_{n+1,i} = \frac{H_{n,i} - G_{n+1,i}V_{n,i}^{\mathrm{T}}H_{n,i}}{\lambda}, \tag{11}$$

where the $(m+1)$-by-$(m+1)$ matrix $H_{n+1,i}$ is defined as $H_{n+1,i} \triangleq [\sum_{l=1}^{n} \lambda^{n-l}V_{n,i}V_{n,i}^{\mathrm{T}}]^{-1}$ and $H'_{n,i} = H_{n,i}/\lambda$. The initial values of $\widehat{C}_{n,i}$ and $H_{n,i}$ can be chosen as

$$\widehat{C}_{0,i} = \vec{0}, \qquad H_{0,i} = \delta I$$

for a soft-constrained initialization, where $\delta \gg 1$ is a large positive constant, and I is the identity matrix of $(m+1)$ dimension.

The above discussion shows how to predict the probability information for the time moment t_{n+1} based on the measurement data up to time t_n. If it is desirable to further predict the probability information for t_{n+2} based on the measurement data up to time t_n, one way is to update the input vector of the RLS predictor to

$$\widehat{V}_{n+1} = \bigl(\widehat{\vec{p}}_{n+1}, \vec{p}_n, \ldots, \vec{p}_{n+1-m}\bigr)^{\mathrm{T}},$$

where the first component is the previous output of the RLS predictor and all other components are the previous outputs of the fuzzy inference system. The ith element of the probability vector $\widehat{\vec{p}}_{n+2}$, $\widehat{p}_{n+2,i}$, can then be obtained from equation (6) using the same tap coefficient $\widehat{\vec{C}}_{n,i}$. The structure of the RLS predictor for one component of the probability vector, $\widehat{p}_{n+2,i}$, is shown in figure 3(b). The probability vector at t_{n+N} for $N > 3$ can be predicted in a similar way. However, it is expected that the prediction error will increase as the value of N increases, due to the fact that the prediction is based on previous estimates up to time t_n.

3.3. Discussions

Several issues regarding the adaptive fuzzy inference system and its applications need to be discussed.

1. The complexity of the multiple-input $(a_{n,i})$ multiple-output $(p_{n,i})$ fuzzy inference system (for $i = 0, 1, \ldots, 6$) may be a concern. However, in practice, the complexity can be significantly reduced if (a) we make use of the relation $\sum_i p_{n,i} = 1$ and (b) the number of BSs to which the mobile user has a potential to handoff at t_{n+1} is limited to less than 6 by neglecting the BSs which have weak pilot signal power at the mobile user. For example, for the mobile user shown in figure 1, it is reasonable to limit the future BSs that the mobile user will communicate with (at t_{n+1}) to BS_1, BS_2, and BS_6, since the mobile user locates in sub-region O_1 of cell_0 at time t_n.

2. The implementation cost for the fuzzy inference system is low in the sense that (a) it is a one-pass build-up procedure that does not require time-consuming on-line training; (b) it makes use of the available pilot signal power measurement and transmission of the measured data to the MSC in the wireless system; no extra signaling and measurement are necessary; (c) the required real-time measurement and computation are a linear function of the number of mobile users. As a result, the proposed system is practical even when the number of mobile users is large.

3. Based on the propagation model, equation (1), the probabilities are estimated and predicted using the received pilot signal powers. There are other (handoff initiating) criteria, such as carrier-to-interference ratio, which can affect the estimation and prediction. The fuzzy inference system proposed here can be directly extended to situations using other handoff initiating criteria. By defining the relation between the mobility information and the criterion under consideration, the same training procedure can be used to establish the fuzzy rule base according to the criterion employed.

4. In the proposed adaptive fuzzy inference system as shown in figure 2, the fuzzy inference system and the RLS predictor are connected in tandem. The proposed structure offers the advantage of implementation simplicity. Another possible approach is to integrate the fuzzy inference system with the RLS predictor, i.e. to put the RLS predictor inside the fuzzy inference system, as suggested in [21]. By combining the RLS algorithm with each fuzzy inference rule, the prediction accuracy may be increased. However, this is achieved at an increased implementation complexity, which may not be practical for real-time prediction especially when the number of the neighboring BSs taken into consideration is large.

5. With the RLS predictor, the adaptive fuzzy inference system can predict the probability vectors a few steps in the near future. The mobility information is particularly useful in prediction-based wireless network resource management such as call admission control and rate-based flow control. Due to user mobility, QoS provisioning in wireless/wired network environments is technically very challenging. The approach of shadow cluster and VCT [1,8,19] has been proposed as an effective way to manage network resources. In the approach, base stations reserve resources in advance for handoff calls according to predicted mobility information, which

reduces the chance of handoff dropped calls and ensures the QoS provisioning for mobile users. In other words, if the resource reserved for a mobile user in a neighboring cell is weighted by the probability of the user handing off to the cell, a large statistical multiplexing gain can then be achieved in the resource management when the network operates in the neighborhood of its full capacity, taking into account a large number of mobile users. This, on the other hand, will allow the network to accept more new call requests without breaking the QoS commitments made to the mobile users already admitted to the network. The prediction of the probability will also allow the network to allocate its resources dynamically to mobile users with different QoS requirements. For instance, if it is predicted that a mobile user with real-time traffic has a high chance to handoff to a neighboring cell, then the future home BS can reserve enough resources for the mobile user by allocating less resources to non-real-time traffic sources in the cell through rate-based flow control.

4. Numerical results

This section first gives the details of how the simulation environment is set up, then presents the performance of the fuzzy inference subsystem, and finally evaluates the adaptive fuzzy inference system for predicting the mobility information.

4.1. The simulation system

The microcellular network under consideration has a hexagonal cell structure as shown in figure 4. The BS is located at the center of each cell. The probability $p_{n,i}$ that a mobile user will be active in cell_i at t_n depends on its location ($x_{\mathrm{MT}}, y_{\mathrm{MT}}$) at t_n. In order to reduce the complexity of the estimation, the following assumptions are made:

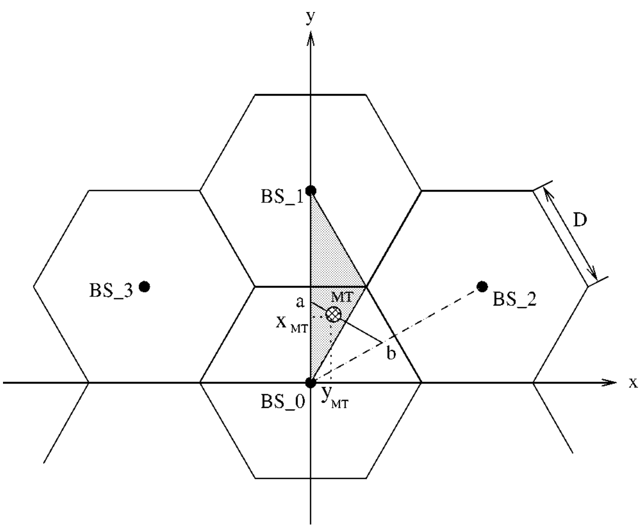

Figure 4. A mobile user located at ($x_{\mathrm{MT}}, y_{\mathrm{MT}}$) in the cellular system.

1. Limit the number of BSs for handoff to 3. For the mobile user shown in figure 4, since $y_{\mathrm{MT}} > 0$, let $p_{n,4} = p_{n,5} = p_{n,6} = 0$.
2. Further reduce the number of BSs for handoff to 2. For the mobile user shown in figure 4, since $x_{\mathrm{MT}} > 0$ (i.e. the mobile user is located on the right side of cell_0), let $p_{n,3} = 0$.
3. The probability that the mobile user will remain in cell_0 depends on y_{MT}
$$p_{n,0} = 1 - \frac{y_{\mathrm{MT}}}{\sqrt{3}D}. \qquad (12)$$
4. $p_{n,1}$ and $p_{n,2}$ can be solved by
$$p_{n,1} + p_{n,2} = 1 - p_{n,0}, \qquad (13)$$
$$\frac{p_{n,1}}{p_{n,2}} = \frac{d_2}{d_1}, \qquad (14)$$
where the distances d_1 (from point a to the mobile user) and d_2 (from the mobile user to point b) depend on x_{MT} and y_{MT}. It can be derived that
$$d_1 = \frac{x_{\mathrm{MT}}(y_{\mathrm{MT}}/\sqrt{3} - x_{\mathrm{MT}})}{\sqrt{x_{\mathrm{MT}}^2 + y_{\mathrm{MT}}^2}\sin(\alpha)}, \qquad (15)$$
$$d_2 = d_1 + 2\sqrt{x_{\mathrm{MT}}^2 + y_{\mathrm{MT}}^2}\sin(\alpha), \qquad (16)$$
where $\alpha = \pi/6 - \arctan(x_{\mathrm{MT}}/y_{\mathrm{MT}})$.

For simplicity, the assumptions specify that the probabilities $p_{n,i}$ are functions only of the locations of the mobile user and the BSs. In practice, the probabilities also depend on other factors such as path attenuations, interference and noise powers at the BSs. The simulation model can be easily generalized if the relation between the probabilities and each of the related factor is known. Based on the assumptions, given the location of each mobile user ($x_{\mathrm{MT}}, y_{\mathrm{MT}}$) at time t_n, the true value of the probability $p_{n,i}$ ($i = 0, 1, \ldots, 6$) can be obtained from equations (12)–(16). The true value is needed to generate the fuzzy IF–THEN rules and to evaluate the performance of the fuzzy system. For presentation clarity, in the following, we consider only the one-dimensional case where the number of BSs that each mobile user has potential to handoff is one. However, the simulation and analysis can be easily extended to a typical two-dimensional case where the number of BSs that each mobile user has potential to handoff is larger than one.

If the fuzzy inference system can identify the potential BS (e.g., BS_1) for the mobile user to handoff, then we need to estimate only $p_{n,0}$ and $p_{n,1}$. The side information may be obtained from the previous locations of the mobile user. As a result, the objective is to estimate $p_{n,0}$ and $p_{n,1}$ based on $a_{n,0}$ and $a_{n,1}$. To obtain the membership functions of $a_{n,i}$ ($i = 0$ and 1), we divide the shadow area shown in figure 4 vertically into 8 subregions corresponding to $p_{n,0}$ in $[0, 0.15]$, $[0.15, 0.25]$, $[0.25, 0.35]$, $[0.35, 0.5]$, $[0.5, 0.65]$, $[0.65, 0.75]$, $[0.75, 0.85]$, $[0.85, 1.0]$, respectively. Due to the symmetry of the area, $p_{n,0}$ can be calculated according to equation (12), and $p_{n,1} = 1 - p_{n,0}$. The membership function of $a_{n,i}$ is determined based on the mean and variance of $a_{n,i}$ for each subregion. The membership function of $p_{n,0}$ is determined based on the probability values for each subregion. In simulations, we consider 50,000 mobile users uniformly distributed in the shadow area shown in figure 4. The simulation parameters are: $D_0 = 100$ m, $D = 1,500$ m, $\kappa = 2, 4, 6$, $\gamma_{n,i} = 1$ (normalized), and $\sigma = 1, 2, \ldots, 6$ dB, respectively. Figures 5 and 6 show the membership functions of $a_{n,0}$ (for $\sigma = 2$ dB) and $p_{n,0}$, respectively. Graphs of these functions have triangular shapes. The overlapping of the triangular shapes possess a natural capability to express and deal with observation and measurement uncertainties (crisp points do not have this capability). Table 1 gives the degree $\mu(a_{n,0}, a_{n,1})$ of expert's belief on each input data pair $(a_{n,0}, a_{n,1})$. If a mobile user is closer to BS_i (i = 0 or 1), then $a_{n,i}$ is large and the effect of shadowing, MAI, and background noise is relatively small. That is, we have a high confidence level about the measurement accuracy of $a_{n,i}$. Therefore, we assign a large value to $\mu(a_{n,0}, a_{n,1})$ corresponding to a data pair $(a_{n,0}, a_{n,1})$ which has one large component. When the mobile user is close to the cell boundary, the shadowing, MAI, and noise have a relatively large effect on both $a_{n,0}$ and $a_{n,1}$; therefore, we assign a small value to $\mu(a_{n,0}, a_{n,1})$ corresponding to a data pair which has a small value for $|a_{n,0} - a_{n,1}|$. The degree $\mu(a_{n,0}, a_{n,1})$ increases linearly as the difference between $a_{n,0}$ and $a_{n,1}$ increases. The overall degree of expert's belief on each training data set $\{a_{n,0}, a_{n,1}, p_{n,0}\}$ to rule k is determined by

$$\mu_k = \frac{\mu(a_{n,0}, a_{n,1})}{(\sigma_{A_{0k}}\sigma_{A_{1k}})}, \tag{17}$$

where $\sigma_{A_{0k}}$ and $\sigma_{A_{1k}}$ are the standard deviations of $a_{n,0}$ and $a_{n,1}$, respectively, for the input region of rule k. The standard deviation characterizes the degree of uncertainty in each measured $a_{n,i}$ value and depends on the value of σ and the cell structure. From equation (2), the degree Q_k assigned to rule k is then

$$Q_k = \mu(a_{n,0}, a_{n,1})\left[\frac{\mu_{I_k}(a_{n,0})}{\sigma_{A_{0k}}}\right]\left[\frac{\mu_{I_k}(a_{n,1})}{\sigma_{A_{1k}}}\right] \times \mu_{O_k}(p_{n,0})\mu_{O_k}(p_{n,1}). \tag{18}$$

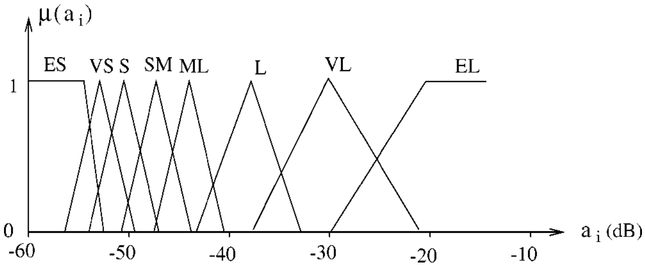

Figure 5. Membership function of $a_{n,i}$ ($i = 0$ and 1) for $\sigma = 2$ dB.

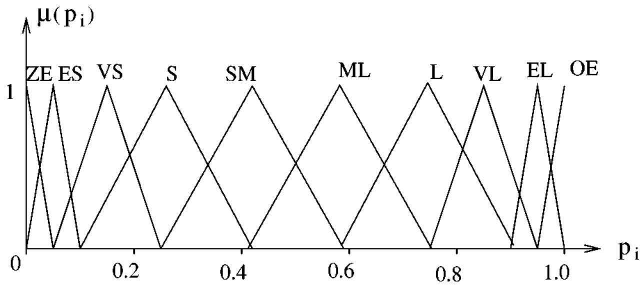

Figure 6. Membership function of $p_{n,i}$ ($i = 0$ and 1).

Table 1
The degree $\mu(a_{n,0}, a_{n,1})$ assigned to input data $(a_{n,0}, a_{n,1})$ which represents the usefulness of the data.

$a_{n,1} \backslash a_{n,0}$	ES	VS	S	SM	ML	L	VL	EL
ES	0.1	0.2	0.3	0.4	0.5	0.8	0.9	1.0
VS	0.2	0.1	0.2	0.3	0.4	0.6	0.8	0.9
S	0.3	0.2	0.1	0.2	0.3	0.4	0.6	0.8
SM	0.4	0.3	0.2	0.1	0.2	0.3	0.4	0.6
ML	0.5	0.4	0.3	0.2	0.1	0.2	0.3	0.4
L	0.8	0.6	0.4	0.3	0.2	0.1	0.2	0.3
VL	0.9	0.8	0.6	0.4	0.3	0.2	0.1	0.2
EL	1.0	0.9	0.8	0.5	0.4	0.3	0.2	0.1

4.2. Performance of the fuzzy inference subsystem

The fuzzy rule base generated based on the 50,000 pairs of training data for $\kappa = 4$ and $\sigma = 2$ dB is shown in table 2 and the degree $\overline{Q}_k$ (normalized to 1) associated with rule R_k is shown in table 3. In table 2, there is no rule for input data pair $(a_{n,0}, a_{n,1})$ where both $a_{n,0}$ and $a_{n,1}$ are small or large, due to the fact that no training data pair falls in the domain. The corresponding degree in table 3 has value equal to zero. In table 3, it can be seen that, in general, a

Table 2
The fuzzy rule base for $p_{n,0}$ ($\sigma = 2$ dB).

$a_{n,1} \backslash a_{n,0}$	ES	VS	S	SM	ML	L	VL	EL
ES					SM	S	VS	ZE
VS				SM	SM	S	VS	ZE
S			SM	SM	SM	S	VS	ES
SM		ML	SM	ML	SM	S	S	VS
ML	ML	ML	ML	SM	SM			
L	L	L	L	ML				
VL	VL	VL	VL					
EL	OE	OE	OE	OE				

Table 3
The degree associated with each rule for $p_{n,0}$ ($\sigma = 2$ dB).

$a_{n,1} \backslash a_{n,0}$	ES	VS	S	SM	ML	L	VL	EL
ES	0.00	0.00	0.00	0.00	0.58	0.91	1.00	0.68
VS	0.00	0.00	0.00	0.25	0.57	0.75	0.88	0.63
S	0.00	0.00	0.10	0.29	0.34	0.47	0.64	0.38
SM	0.00	0.44	0.28	0.11	0.21	0.30	0.38	0.19
ML	0.71	0.46	0.34	0.22	0.08	0.20	0.00	0.00
L	1.00	0.74	0.48	0.33	0.17	0.00	0.00	0.00
VL	0.92	0.85	0.63	0.36	0.00	0.00	0.00	0.00
EL	0.70	0.60	0.52	0.27	0.00	0.00	0.00	0.00

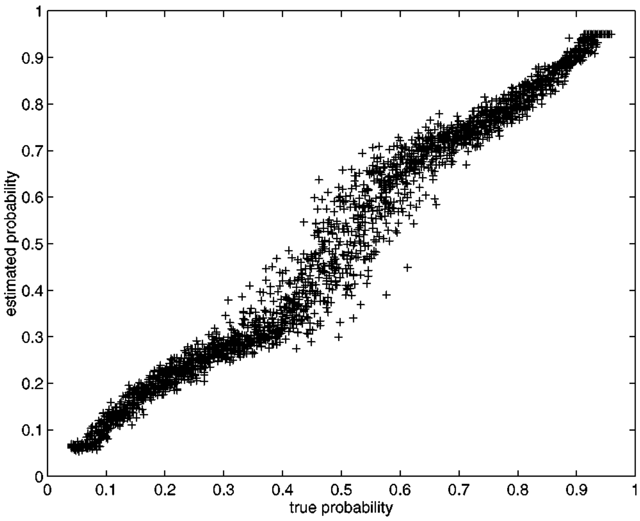

Figure 7. The estimated probability $\widetilde{p}_{n,0}$ versus true probability $p_{n,0}$ with $\kappa = 4$ and $\sigma = 2$ dB.

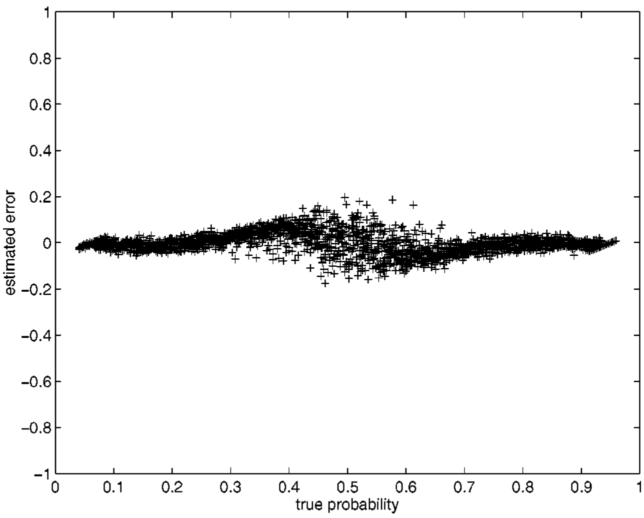

Figure 8. The estimation error $(p_{n,0} - \widetilde{p}_{n,0})$ versus true probability $(p_{n,0})$ with $\kappa = 4$ and $\sigma = 2$ dB.

large difference between the $a_{n,0}$ and $a_{n,1}$ values results in a large value of the degree. However, the relation between the degree and $|a_{n,0} - a_{n,1}|$ is nonlinear and is different from that shown in table 1 because the degree of each rule depends on the membership functions of $a_{n,i}$ and $p_{n,0}$, the standard deviations of $a_{n,0}$ and $a_{n,1}$, etc., in addition to the degree $\mu(a_{n,0}, a_{n,1})$.

Figure 7 shows the comparison between the true probability $p_{n,0}$ and the fuzzy inference system output $\widetilde{p}_{n,0}$ for $\kappa = 4$, $\sigma = 2$ dB, whereas figure 8 shows the corresponding estimation error $p_{n,0} - \widetilde{p}_{n,0}$ versus $p_{n,0}$. Table 4 gives the mean and standard deviation of the estimation error $(p_{n,0} - \widetilde{p}_{n,0})$ for various σ values, where the true probability $p_{n,0}$ is obtained based on the mobile user location $(x_{\mathrm{MT}}, y_{\mathrm{MT}})$ and the estimated probability $\widetilde{p}_{n,0}$ is obtained by the fuzzy inference system according to the measurement data $a_{n,0}$ and $a_{n,1}$. Due to the geometrical symmetry, estimation of $p_{n,1}$ and the estimation accuracy are the same as those of $p_{n,0}$. From the simulation results given in figures 7 and 8 and in table 4, it is observed that:

Table 4
The mean and standard deviation of the estimation error $(p_{n,0} - \widetilde{p}_{n,0})$ of the fuzzy inference system given $\kappa = 4$.

σ (dB)	Mean	Standard deviation
1	−3.55e−4	3.14e−2
2	4.10e−4	4.08e−2
3	−3.39e−3	4.80e−2
4	1.13e−3	6.25e−2
5	−1.75e−3	7.32e−2
6	−5.29e−3	8.32e−2

Table 5
The mean and standard deviation of the estimation error $(p_{n,0} - \widetilde{p}_{n,0})$ of the fuzzy inference system given $\sigma = 2$ dB.

κ	Mean	Standard deviation
2	8.20e−4	6.94e−2
4	4.10e−4	4.08e−2
6	3.00e−4	3.92e−2

(a) The estimator is unbiased since the mean of the estimation error is very small and can take on positive or negative values.

(b) As the value of σ increases, there is an increase in the degree of shadowing effect of the propagation channel, resulting in an increased estimation error.

(c) Given a certain σ value (such as $\sigma = 2$ dB in figures 7 and 8), the estimation error is relatively small when the mobile user is close to one BS (i.e. $p_{n,0}$ is very small or very large), where the shadowing has less effect on degrading the performance of the fuzzy inference system.

In other words, the effect of the shadowing on the estimation accuracy increases as the mobile user moves to the cell boundary, even though the area close to the cell boundary is very important for making handoff decisions. The reduced accuracy is due to the reduced confidence level on the measured data, which is a direct result of the near–far problem inherent in CDMA systems.

Table 5 illustrates how the first and second order statistics of the estimation change as the path loss exponent, κ, changes, where $\sigma = 2$ dB is used for the different κ values. It is observed that, as the value of κ increases, both the mean and the standard deviation decreases. This is because a larger κ value means a faster attenuation of the received signal level as the distance between the mobile user and the BS increases. Correspondingly, the degree of the randomness in the received signal level due to different x_{MT} values in each subregion is reduced, resulting in a better estimation. On the other hand, variations in the value of κ do not significantly change the accuracy of the estimation as long as σ is fixed. From tables 4 and 5, the parameter σ plays a more important role in the estimation accuracy than the parameter κ, because the shadowing characterized by σ is the main source which introduces randomness to the received signal levels.

4.3. Evaluation of the adaptive fuzzy inference system

In order to evaluate the overall system performance, 500 mobile users are simulated with movement patterns characterized by the following:

1. The initial location of each mobile user is uniformly distributed in the sub-region O_1 of cell_0 and O_4 of cell_1 as shown in figure 1.
2. Each mobile user has a constant velocity uniformly distributed in $[10, 30]$ m/s.
3. The initial direction of movement is uniformly distributed in $[0, 2\pi]$ and the movement direction is then changed several times each being uniformly distributed in $[0, 2\pi]$ and independent of previous direction(s).
4. The time interval Δt for updating the mobility information is 1 s.

The parameters κ and σ of the propagation environment are 4 and 2 dB, respectively, and the parameter m of the RLS algorithm is 7. To evaluate the performance of the RLS predictor, table 6 gives the mean and standard deviation of the estimation error for one-step prediction, two-step prediction, and three-step prediction, respectively, where the estimation error is defined as the difference between the fuzzy inference system output $\widetilde{p}_{n+N,0}$ and the corresponding predicted probability $\widehat{p}_{n+N,0}$ at the RLS predictor output for $N = 1, 2, 3$. For the overall performance of the adaptive fuzzy inference system, table 7 shows the mean and standard deviation of the prediction error defined as the difference between the true probability $p_{n+N,0}$ and the corresponding predicted probability $\widehat{p}_{n+N,0}$ at the RLS predictor output for $N = 1, 2, 3$. From tables 6 and 7, it is observed that:

(a) The standard deviation of both estimation error and prediction error increases as the number of the prediction step increases, due to the lack of the most recent measurement data.

(b) The standard deviation of the prediction error is similar to the corresponding value of the estimation error in table 7, but is larger than the corresponding value in table 4. This is because the prediction error includes the estimation error of the RLS predictor and the error of the fuzzy inference system.

(c) Although the mean of both estimation error and prediction error increases as the number of the prediction step increases, from a detailed analysis of the simulation results, it is concluded that both the estimation and prediction are unbiased and the mean of the errors should decrease if the number of mobile users simulated increases.

Table 6
The mean and standard deviation of the estimation error ($\widetilde{p}_{n+N,0} - \widehat{p}_{n+N,0}$, $N = 1, 2, 3$) of the RLS predictor given $\kappa = 4$ and $\sigma = 2$ dB.

Prediction	Mean	Standard deviation
One-step	2.10e−4	9.53e−2
Two-step	1.24e−3	9.56e−2
Three-step	2.56e−3	9.67e−2

Table 7
The mean and standard deviation of the prediction error ($p_{n+N,0} - \widehat{p}_{n+N,0}$, $N = 1, 2, 3$) of the adaptive fuzzy inference system given $\kappa = 4$ and $\sigma = 2$ dB.

Prediction	Mean	Standard deviation
One-step	9.76e−3	9.90e−2
Two-step	1.08e−2	9.94e−2
Three-step	1.21e−2	1.01e−1

As an example, figure 9 shows the movement trajectory of a particular mobile user simulated. The velocity of the mobile user movement is 24 m/s. Figure 10 shows a comparison of the true probability $p_{n+1,0}$ and the corresponding

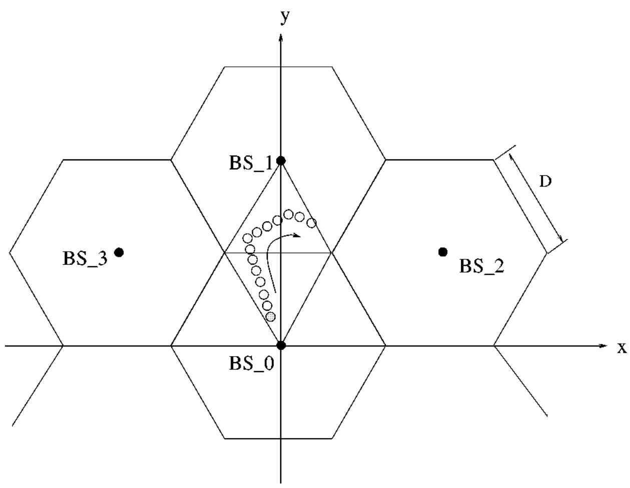

Figure 9. The movement trajectory of a mobile user simulated.

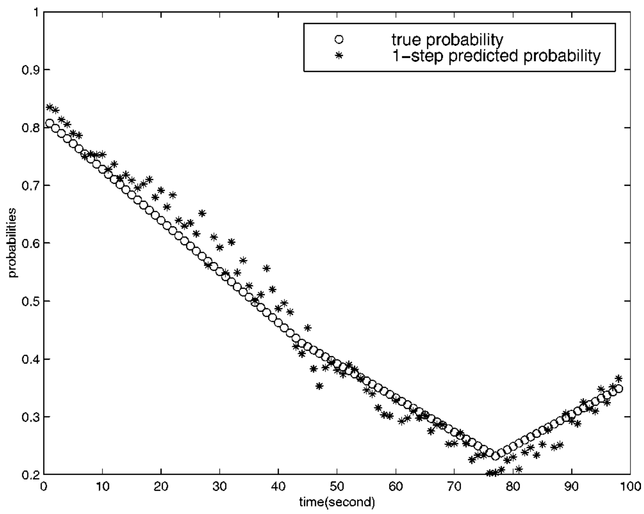

Figure 10. The comparison of the true probability and the corresponding one-step predicted probability for the mobile user.

one-step predicted probability $\widehat{p}_{n+1,0}$ at the adaptive fuzzy inference system output. From figures 9 and 10, it is observed that:

(a) The predicted mobility information at the output of the adaptive fuzzy inference system can track quite well the variation of the true probability as the mobile user moves.

(b) The prediction error is smaller than 0.1 and can be positive or negative. Taking into account statistic multiplexing, the effect of the prediction errors on the resource management of the wireless network will be reduced, because the errors are unbiased. For example, in reserving resources for potential handoff calls, the positive errors will cancel the negative errors to a certain degree in the overall resource reservation.

5. Conclusions

An adaptive fuzzy inference system is developed to predict the probabilities that a mobile user will be active in the nearby cells at future moments using the real-time measurement data of the pilot signal powers received at the mobile user from the BSs. The advantages of the adaptive fuzzy inference system lie in

(a) its simplicity – it is a one-pass build-up procedure that does not require time-consuming on-line training,

(b) its usefulness – the probabilities are critical for balancing efficient utilization of the network resources and satisfying the QoS requirements of mobile users, and

(c) its low cost – the predicted probabilities are obtained based on the existing signaling in CDMA networks for handoff, without requiring extra signaling over wireless channels.

Computer simulation results demonstrate that the performance of the adaptive fuzzy inference system depends on the degree of channel shadowing (characterized by the parameter σ), the construction of the membership, and on the availability of information which limits the number of potential base stations. Taking into account that the overall estimation accuracy can be significantly increased with statistic multiplexing, the fuzzy inference system provides a good solution to obtaining mobility information.

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