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Mobility information for resource management in wireless ATM networks

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Abstract

User mobility poses a significant technical challenge to network resource management in wireless ATM (Asynchronous Transfer Mode) networks. In order to guarantee quality of service (QoS) to mobile users and to achieve a high efficiency in network resource management, the information of mobile users' handoff at a future moment is essential for statistical multiplexing. This paper develops a novel fuzzy logic inference system to estimate the user mobility information for a wireless ATM network which uses a direct sequence code division multiple access (DS/CDMA) protocol. The estimation is based on measured pilot signal strengths from a number of the nearest base stations by the mobile user. Numerical results are presented to demonstrate the performance of the proposed technique under various path losses and channel shadowing conditions. The proposed technique can achieve simplicity, accuracy and low cost.

Keywords: User mobility; Resource management; Wireless networks; Fuzzy logic

1. Introduction

Future wireless ATM networks are expected to interwork with wired broadband networks to provide multimedia services for mobile users anywhere at anytime. The integration of wired and wireless ATM networks poses significant challenges in resource management because of user mobility, limited radio frequency spectrum, radio channel impairments, etc., in the wireless segment. Resource management is critical to quality of service (QoS) provisioning, including flow control, resource allocation, congestion control, and call admission control. Resource management functions should capture the effect of user mobility in order to provide satisfactory QoS. Unless a suitable handoff mechanism is in place to maintain service continuity, user mobility can disrupt an ongoing connection.

Handoff is the process in which a mobile user switches its connection from one base station to another base station (BS) to maintain service continuity. Handoff is often initiated either by cell boundary crossing or poor link quality in the current connection. One way to deal with user mobility is to treat each handoff call as a new call in call admis-

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sion control. This approach tends to increase the number of new calls and, hence, computational intensity in call admission. Another way is to reserve resource in all the cells for a mobile once the mobile is admitted to the network. This approach achieves a low probability of call dropping at the expense of standby capacity, which reduces system efficiency. Because of the limited radio spectrum, it is critical that wireless networks make efficient use of the radio frequency bandwidth. Several techniques have been proposed to make a compromise between system resource utilization and QoS. The shadow cluster [1] and virtual (connection) tree [2,3] approaches make use of statistical multiplexing of data traffic to and from mobile users so that a higher resource utilization can be attained without increasing the call dropping probability. However, statistical multiplexing requires a knowledge of the user movement patterns and trends. To our knowledge, in all the work reported in the literature, the probability that a mobile user will reside in a particular cell is assumed known.

Mobility information plays an important role in the design of cellular systems. Previous research efforts on mobility information have focused on statistics such as mobility model [4–6], channel holding time [6], cell boundary crossing rate [7–9], mean handover rate [4,10], and cell residence time [4,11]. In this paper we are concerned with the determination of mobility information that a mobile user is to handoff to a particular BS at a future moment. The mobility information can be used to assist user mobility management (such as traffic routing) [2], to manage network resources (such as resource allocation, call admission control, congestion and flow control) [12], and to analyze handoff algorithms in integrated wired/wireless ATM networks [14]. In general, if a mobile user is closer to a 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 handoff to a BS at a future moment depends on the current distance between the mobile user and the BS, the probability can be estimated based on the real-time measurement of the received pilot signal power at the mobile user from nearby BSs. As a result, in the proposed scheme to be described, the user mobility information is estimated based on the real-time measurements.

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. After giving the motivation of applying the fuzzy inference approach for mobility information acquisition, Section 3 is devoted to the design of the fuzzy inference system. Numerical results and discussions on the performance 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 ATM 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 the same signal from more than one BS at any time. During transition from one cell to its 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 a mobile terminal. Prior to any transmission, a mobile terminal monitors the received pilot signal power levels from nearby base stations. The terminal chooses its home base station according to the maximum pilot signal power received. The network uses mobile terminal assisted soft handoff as in the IS-95 standard [13]. While tracking the signal from the home base station, the mobile searches for all the possible pilots and maintains a list of all pilots whose signals are above a prescribed threshold. This list is transmitted to a mobile switching center (MSC) periodically through the home base station. The MSC uses the information to make decision on when the soft handoff should start. In addition, the MSC uses the information to determine the probability that the mobile will locate in a particular cell in the next period.

Consider a uniform grid of hexagonal cells, as shown in Fig. 1, where the mobile user under consideration is located in the sub-region R_1 of cell_0. Let $d_i(t)$ denote the distance between the mobile user and the first-tier BS_i at time t, $i=0,1,\dots,6$. The local mean of the received pilot signal amplitudes can be modeled by [15]

$$a_i(t)=\gamma_i\left[d_i(t)/D_0\right]^{-n}10^{\xi_i(t)/10},\ \ i=0,1,\dots,6 \tag{1}$$

where γ_i is a constant proportional to the amplitude of the pilot signal, n is the path loss exponent, D_0 is the close-in reference distance which is determined from measurements close to the transmitter, $\xi_i(t)$ is a normal random variable at any t with zero mean and

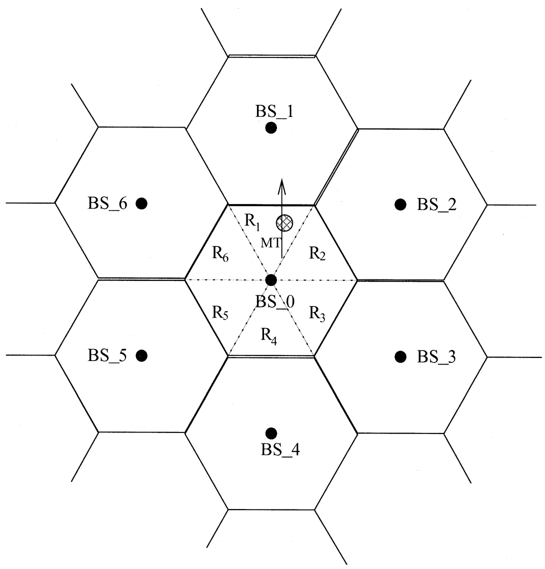

Fig. 1. The hexagonal cell layout.

variance σ^2, $\xi_i(t)$ and $\xi_j(t)$ are independent for $i\neq j$. If the transmitted pilot signals have the same power, then $\gamma_i=\gamma$ for $i=0,1,\dots,6$. For simplicity, assume that the mobile user will communicate with either BS_0 or BS_1 at $t+\Delta t$. Under this assumption, we are interested in the relation between $d_0(t)$ and $d_1(t)$. The probability that $d_1(t)$ is larger than $d_0(t)$ can be derived as

$$p\left[d_1(t)>d_0(t)\right]=\Phi\left(\frac{10\log_{10}\left[a_0(t)/a_1(t)\right]}{\sqrt{2}\sigma}\right) \tag{2}$$

where $\Phi(u)=\int_{-\infty}^{u}\exp(-x^2/2)\mathrm{d}x/\sqrt{2\pi}$. The approach for computing the probability has some drawbacks: (a) the calculation is limited for comparing the distances of the mobile user to two BSs; however, for the probability of handoffs, we need to know the relation among the distances from the mobile user to more than two BSs. It is very difficult (if not impossible) to extend the calculation to a situation involving multiple (more than two) distances; (b) some algorithm needs to be used to predict the probability $p[d_1 t+\Delta t>d_0(t+\Delta t)]$ based on measured data $a_0(t)$ and $a_1(t)$, and the prediction may not be accurate; (c) the calculation does not take into account the errors in measuring $a_0(t)$ and $a_1(t)$. The received signals are contaminated by the multiple access interference (MAI) due to other users in the system and unavoidable background noise. As a result, the measured data are not accurate. To overcome the drawbacks, a fuzzy inference approach can be used which can incorporate the degree of certainty (or accuracy) of the measured data in the process of obtaining the mobility information. The development of such a fuzzy inference system for the mobility information is presented in the following, which is to be implemented at the MSC.

3. Fuzzy inference system design

The configuration of the fuzzy inference system to be designed is shown in Fig. 2, which is a special expert system. It employs a knowledge base, ex-

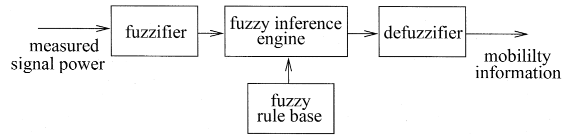

Fig. 2. The fuzzy inference system.

pressed in terms of fuzzy inference rules, and an appropriate inference engine to estimate the probability of handoff at a future moment. The system is capable of utilizing knowledge elicited from human operators. The knowledge is expressed by using natural language, a cardinal elements of which are linguistic variables [16,17]. A fuzzy set X in a universe of discourse U is characterized by a membership function $\mu_X : U \rightarrow [0,1]$, with $\mu_X(u)$ representing the grade of membership of $u \in U$ in the fuzzy set X. Thus, a fuzzy set X in U may be represented as a set of ordered pairs. Each pair consists of a generic element u and its grade of membership function, i.e., $X = \{(u, \ \mu_X(u) | u \in U\}$. A linguistic variable is characterized by a quintuple $(y, T(y), U, G, \tilde{M})$ in which y is the name of the variable; $T(y)$ is the term set of y, i.e., the set of names of linguistic values of y with each value being a fuzzy set defined on U; G is a syntactic rule for generating the names of values of y; and $\tilde{M}$ is a semantic rule for associating each value with its meaning [18]. In other words, if a variable can take words in natural languages as its values, this variable is defined as a linguistic variable. These words are usually labels of fuzzy sets. A linguistic variable can take either words or numbers as its values. For example, if y indicates the linguistic variable for the received signal level, then the universe of discourse is the set of all possible received signal levels and we can choose $T(y)$ to be the set containing 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). If y indicates the linguistic variable for the probability of handoff, then the universe of discourse is the interval [0, 1] and we can choose $T(y)$ 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). In general, a set should be determined at an appropriate level of granularity to describe the values of linguistic variables, and the number of terms in a set should be selected as a compromise between the complexity and the fuzzy inference system performance. The membership functions of the input (the received signal level) and the output (the probability of handoff) depend on service area, transmitted pilot signal power, the path loss parameter n and channel long-term fading statistics. In the following, the four basic components in the fuzzy inference system shown in Fig. 2 are briefly described, which are fuzzifier, fuzzy rule base, fuzzy inference engine, and defuzzifier.

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 $a_i(t)$ $(i = 1, 2, \ldots, 6)$ from BS_i at time instant t (represented by a_i for simplicity) is mapped to the fuzzy set $T^1_{y_i}$ with degree $\mu^1_{y_i}(a_i)$ and to the fuzzy set $T^2_{y_i}$ with degree $\mu^2_{y_i}(a_i)$, and so on, where $T^l_{y_i}$ is the name of the lth term or fuzzy set value belonging to the term $T(y_i)$.

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.

R_k:
If a_0 is A_{0k} and a_1 is A_{1k} and $\ldots$ and a_6 is A_{6k},
then p_0 is P_{0k} and p_1 is P_{1k} and $\ldots$ and p_6 is P_{6k}
$k = 1,2,\ldots,K$

where A_{ik} and P_{ik} are fuzzy sets in U_{a_i} and U_p respectively, and $\vec{a} \triangleq (a_0, a_1, \ldots, a_6)^T \in U_{a_0} \times U_{a_1} \times \ldots \times U_{a_6} \triangleq U_a$ and $\vec{p} \triangleq (p_0, p_1, \ldots, p_6)^T \in U_{p0} \times U_{p_1} \times \ldots \times U_{p_6} \triangleq U_p$ are linguistic variables, with U_{a_i} and U_{p_i} being the universe of discourse of a_i and p_i respectively. Note that the $\vec{a}$ and $\vec{p}$ are the input and output respectively of the fuzzy inference engine.

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_0 is $\tilde{A}_0$ and a_1 is $\tilde{A}_1$ and ... and a_6 is $\tilde{A}_6$

Consequence:

p_0 is $\tilde{P}_0$ and p_1 is $\tilde{P}_1$ and ... and p_6 is $\tilde{P}_6$

where $\tilde{A}_i$ and tilde $\tilde{P}_i$ ($i = 0,1,\ldots,6$ are linguistic terms for a_i and p_i respectively. The fuzzy rule base can be created from training data sequence (measured input–output pairs). To avoid tedious field trials, the training data can be generated in computer simulation based on propagation model, cell structure, and mobile user movement patterns. Given a set of desired input–output data pairs

$$\left(a_0^{(1)},a_1^{(1)},\ldots,a_6^{(1)};p_0^{(1)},p_1^{(1)},\ldots,p_6^{(1)}\right),$$
$$\left(a_0^{(2)},a_1^{(2)},\ldots,a_6^{(2)};p_0^{(2)},p_1^{(2)},\ldots,p_6^{(2)}\right),$$

... ...

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. In general, 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 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

$$Q_k = \mu_k \prod_{i=0}^{6} \mu_{I_{ik}}(a_i) \prod_{i=0}^{6} \mu_{O_{ik}}(p_i) \tag{3}$$

where the subscript k denotes rule k, I_{ik} denotes the input region of rule k for a_i, O_{ik} the output region for p_i, $\mu_{I_{ik}}(a_i)$ is the degree of a_i in I_{ik} obtained from the membership functions, $\mu_{O_{ik}}(p_i)$ the degree of p_i in O_{ik}, and μ_k is the degree of the data vector $(a_0,a_1,\ldots,a_6)$ assigned by human operators. There will be some conflicting rules, i.e., rules which have the same IF part but a different THEN part. 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 $\vec{p}$ in U_p (the output of the inference engine) to a crisp point $\vec{p} \in U_p$ which is the probability that the mobile will be in cell i at $t + \Delta t$. Among the commonly used defuzzification strategies, the center average defuzzification method yields a superior result [19]. The formula for the output of the defuzzifier is

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

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

Two issues regarding the fuzzy inference system need to be discussed:

(i) The complexity of the multiple-input multiple-output fuzzy inference system may be a concern. However, in practice, the complexity can be significantly reduced if (a) we make use of the relation $\sum_i p_i = 1$ and (b) we limit the number of BSs to which the mobile user has a potential to handoff at $t + \Delta t$ 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 Fig. 1, it is reasonable to limit the future BSs that the mobile user will communicate with (at $t + \Delta t$) to BS_1, BS_2, and BS_6, since the mobile user locates in subregion R_1 of cell_0 at time t.

(ii) Based on the propagation model (1), the handoff initiating criterion considered here is the distances between the mobile user and neighboring BSs. In other words, we assume that the mobile user always communicates with the nearest BS(s). However, due to the particular environment surrounding the mobile user at certain time moments, it is very possible that the nearest BS provides poorer link quality than other BSs which are farther away. As a result, accurate handoff decisions depend both on the geometric description and on the specific propagation model. In addition, there are other handoff initiating criteria such as received signal strength or carrier-to-interference ratio. It should be mentioned that the fuzzy inference system developed 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 statistical model of the criterion employed.

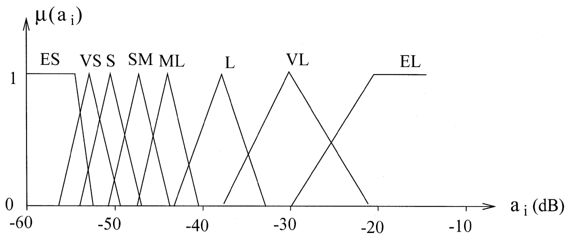

Fig. 4. Membership function of a_i ($i = 0$ and 1) for $\sigma = 2$ dB.

4. Numerical results and discussion

We consider a microcellular system with a hexagonal cell structure as shown in Fig. 1. The BS is located at the center of each cell. The probability p_i ($i = 1,2,\ldots,6$) that a mobile user will handoff to BS_i at $t + \Delta t$ for mobility information update depends on its location (x_{MT}, y_{MT}) at t. As an example, for the mobile user shown in Fig. 3, we make the following assumptions:

(i) Limit the number of BSs for handoff to 3. Since $y_{MT} > 0$, let $p_4 = p_5 = p_6 = 0$;

(ii) Further reduce the number of BSs for handoff to 2. Since $x_{MT} > 0$ (i.e., the mobile user is located on the right side of cell_0), let $p_3 = 0$;

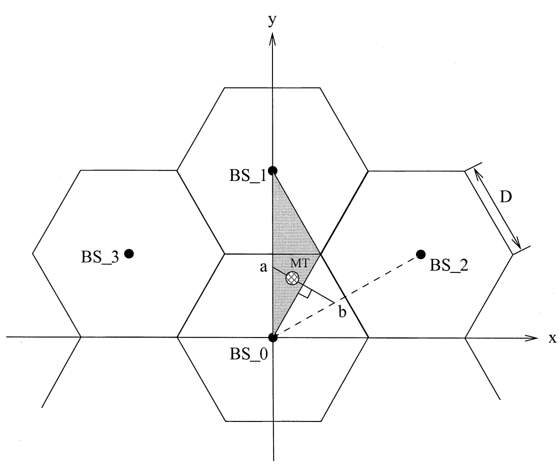

Fig. 3. The mobile user location (x_{MT}, y_{MT}) and mobility information p_i.

(iii) The probability that the mobile user will remain in cell_0 depends on y_{MT}

$$p_0 = 1 - y_{MT}/\sqrt{3}\,D; \tag{5}$$

(iv) p_1 and p_2 can be solved by

$$p_1 + p_2 = 1 - p_0, \tag{6}$$

$$p_1/p_2 = d_2/d_1 \tag{7}$$

where the distances d_1 (from point a to mobile user) and d_2 (from mobile user to point b) depend on x_{MT} and y_{MT}. It can be derived that

$$d_1 = \frac{x_{MT}\left(y_{MT}/\sqrt{3} - x_{MT}\right)}{\sqrt{x_{MT}^2 + y_{MT}^2}\,\sin(\alpha)},$$

$$d_2 = d_1 + 2\sqrt{x_{MT}^2 + y_{MT}^2}\,\sin(\alpha)$$

where $\alpha = \pi/6$-arctan (x_{MT}/y_{MT}).

Based on these assumptions, if the location of a mobile user is known, then the mobility information p_i ($i = 0,1,\ldots,6$) can be obtained. The mobile user location can be estimated based on the local means of the pilot signal power from the BSs. As a result, we can estimate p_i based on the measured power of the three strongest pilot signals (including the one

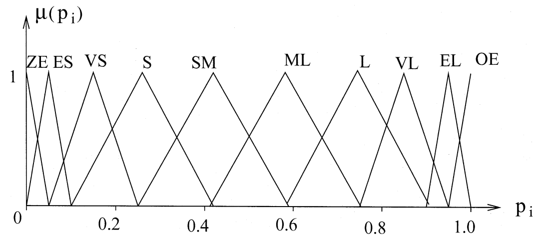

Fig. 5. Membership function of p_i ($i = 0$ and 1).

Table 1
The degree $\mu(a_0,a_1)$ assigned to input data (a_0,a_1) which represents the usefulness of the data

a_0/a_1	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

Table 3
The degree associated with each rule for p_0 ($\sigma=2$ dB)

a_0/a_1	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

coming from the current home BS, i.e., BS_0). To design the fuzzy inference system, we simulate 50,000 mobile users uniformly distributed in the shadow area shown in Fig. 3. The simulation parameters are: $D_0 = 100$ meters, $D = 1{,}500$ meters, $n = 2$, 4, 8, $\gamma_i = 1$ (normalized), and $\sigma = 1, 2, \ldots, 6$ dB, respectively. Based on the location of each mobile user, p_i and a_i can be obtained given the standard deviation σ in (1). From the training data set p_i and a_i obtained from the mobile users, the fuzzy inference system can be developed as described in Section 3. In the following, we consider two cases: (a) one-dimensional space where the number of BSs that each mobile user has potential to handoff is one, and (b) two-dimensional space where the number of BSs is two.

4.1. One-dimensional space

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_0 and p_1. The side information may be obtained from the previous locations of the mobile user. As a result, the objective is to estimate p_0 and p_1 based on a_0 and a_1. To obtain the membership functions of a_i ($i = 0$ and 1), we divide the shadow area vertically into 8 subregions corresponding to p_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_0 can be calculated according to Eq. (5), and $p_1 = 1 - p_0$. The membership function of a_i is determined based on the mean and variance of a_i for each subregion. The membership function of p_0 is determined based on the probability values for the subregions. Figs. 4 and 5 show the membership functions of a_0 (for $\sigma = 2$ dB) and p_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

Table 2
The fuzzy rule base for p_0 ($\sigma=2$ dB)

a_0/a_1	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 4
The mean and standard deviation of the estimation error $p_0 - \hat{p}_0$ given $n = 4$

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

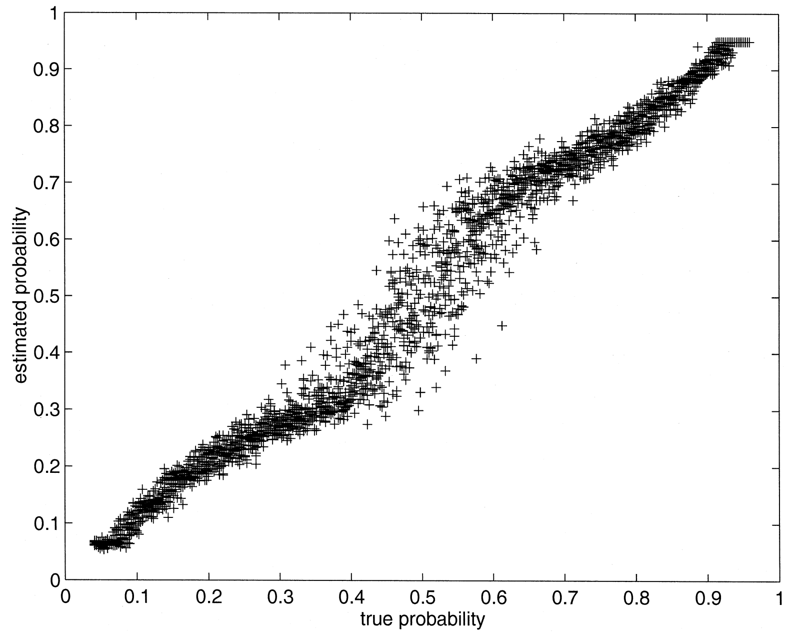

Fig. 6. Relation between estimated probability ($\hat{p}_0$) and true probability (p_0).

degree $\mu(a_0, a_1)$ of expert's belief on each input data pair (a_0, a_1). If a mobile user is closer to BS_i ($i = 0$ or 1), then a_i is large and the effect of shadowing is relatively small. That is, we have a high confidence

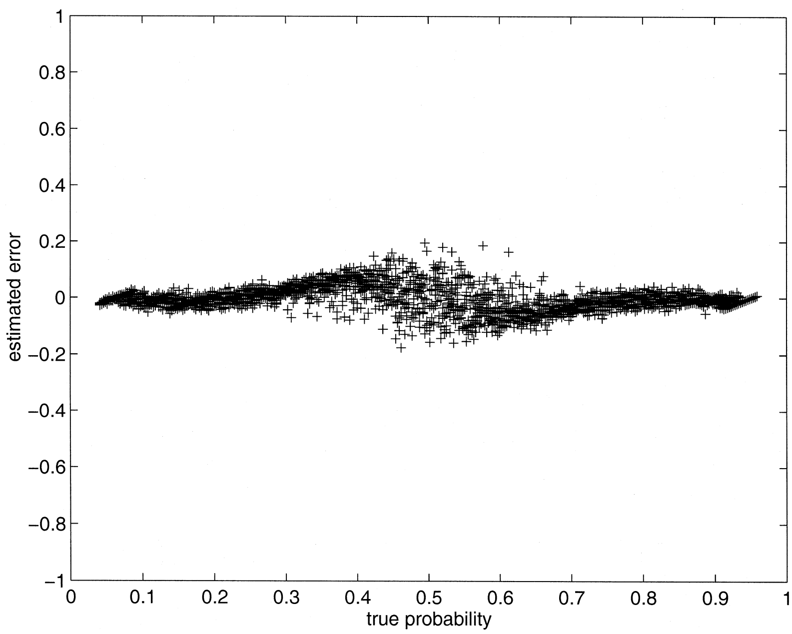

Fig. 7. The estimation error ($p_0 - \hat{p}_0$) versus true probability (p_0) with $\sigma = 2$ dB.

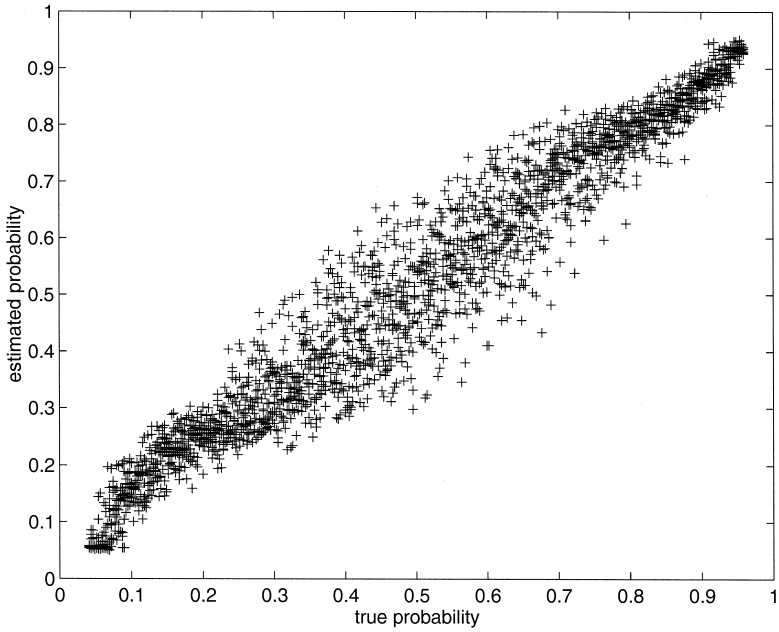

Fig. 8. Relation between p_0 and $\hat{p}_0$ with $\sigma = 4$ dB.

level about the measurement accuracy of a_i. Therefore, we assign a large value to $\mu(a_0, a_1)$ corresponding to a data pair (a_0, a_1) which has one large component. When the mobile user is close to the cell

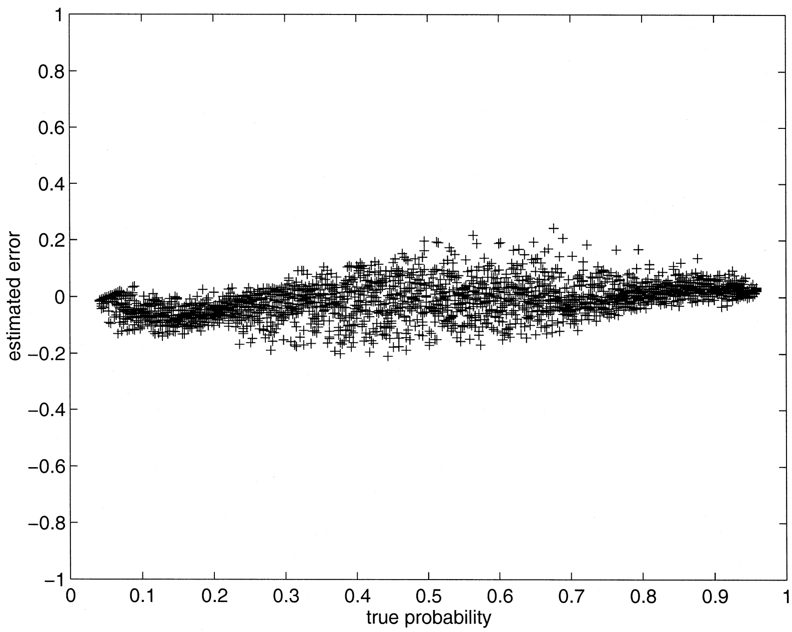

Fig. 9. The estimation error ($p_0 - \hat{p}_0$) versus true probability (p_0) with $\sigma = 4$ dB.

boundary, the shadowing has a relatively large effect on both a_0 and a_1; therefore, we assign a small value to $\mu(a_0,a_1)$ corresponding to a data pair which has a small value for $|a_0 - a_1|$. The degree $\mu(a_0,a_1)$ increases linearly as the difference between a_0 and a_1 increases. The overall degree of expert's belief on each training data set $\{a_0,a_1,p_0\}$ to rule k is determined by

$$\mu_k = \mu(a_0,a_1)/(\sigma_{A_{0k}} \sigma_{A_{1k}}) \tag{8}$$

where $\sigma_{A_{0k}}$ and $\sigma_{A_{1k}}$ are the standard deviations of a_0 and a_1, respectively, for the input region of rule k. The standard deviation characterizes the degree of uncertainty in each measured a_i value and depends on the value of σ and the cell structure. From Eq. (3), the degree Q_k assigned to rule k is then

$$Q_k = \mu(a_0,a_1)\left[\mu_{I_k}(a_0)/\sigma_{A_{0k}}\right] \cdot \left[\mu_{I_k}(a_1)/\sigma_{A_{1k}}\right]\mu_{O_k}(p_0)\,\mu_{O_k}(p_1). \tag{9}$$

As an example, the fuzzy rule base generated by the 50,000 pair of training data for $n = 4$ and $\sigma = 2$ dB is shown in Table 2 and the $\overline{Q}_k$ (normalized to 1) associated with rule k is shown in Table 3. In Table 2, there is no rule for input data pair (a_0,a_1) where both $(a_0$ and $a_1)$ 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 large difference between the a_0 and a_1 values results in a large value of the degree. However, the relation between the degree and $|a_0 - a_1|$ is nonlinear and is different from that shown in Table 1 because the degree of each rule depends on the membership functions of a_i and p_0, the standard deviations of a_0 and a_1, etc., in addition to the degree $\mu(a_0,a_1)$.

Table 5
The mean and standard deviation of the estimation error $p_0 - \hat{p}_0$ given $\sigma = 2$ dB

n	Mean	Standard deviation
2	8.20e-4	6.94e-2
4	4.10e-4	4.08e-2
6	3.00e-4	3.92e-2

Table 6
The fuzzy rule base for p_0 ($\sigma = 2$ dB)

a_0 / a_1	ES	VS	S	SM	ML	L	VL	EL
ES				VS	S	VS	VS	ZE
VS			S	S	VS	VS	S	ZE
S			ML	SM	SM	VS	VS	ES
ML	ML	ML	S	S	VS	VS	S	
ML	ML	ML	S	ML	SM	VS	VS	
L	L	L	L	L	ML	ML		
VL	VL	VL	VL	VL				
EL	OE	OE	OE	EL				

Table 4 shows the mean and standard deviation of the estimation error $p_0 - \hat{p}_0$, where p_0 is obtained based on the mobile user location (x_{MT}, y_{MT}) and $\hat{p}_0$ is obtained by the fuzzy inference system according to the measurement data a_0 and a_1.

Figs. 6 and 8 show the relation between p_0 and $\hat{p}_0$ for $n = 4$, $\sigma = 2$ dB and 4 dB respectively, whereas Figs. 7 and 9 show the corresponding estimation error $p_0 - \hat{p}_0$ versus p_0. Table 4 gives the mean and standard deviation of the estimation error for various σ values. Due to the geometrical symmetry, estimation of p_1 and the estimation accuracy are the same as those of p_0. From the simulation results given in Figs. 6–9 and in Table 4, it is observed that: (a) the estimator is unbiased since the mean of the estimation error is very small and can take on positive or negative values; (b) for a certain σ value, the estimation error is relatively small when the mobile user is close to one BS (i.e., p_0 is very small or very large), where the shadowing has less effect on degrading the performance of the fuzzy

Table 7
The degree associated with each rule for p_0 ($\sigma = 2$ dB)

a_0 / a_1	ES	VS	S	SM	ML	L	VL	EL
ES	0.00	0.00	0.00	0.59	0.84	0.73	0.58	0.52
VS	0.00	0.00	0.39	0.36	0.55	0.50	0.47	0.39
S	0.00	0.00	0.17	0.30	0.44	0.36	0.39	0.31
SM	0.86	0.57	0.33	0.14	0.30	0.29	0.29	0.00
ML	0.75	0.45	0.41	0.22	0.11	0.15	0.15	0.00
L	1.00	0.79	0.54	0.33	0.23	0.05	0.00	0.00
VL	1.00	0.87	0.64	0.38	0.00	0.00	0.00	0.00
EL	0.69	0.61	0.49	0.25	0.00	0.00	0.00	0.00

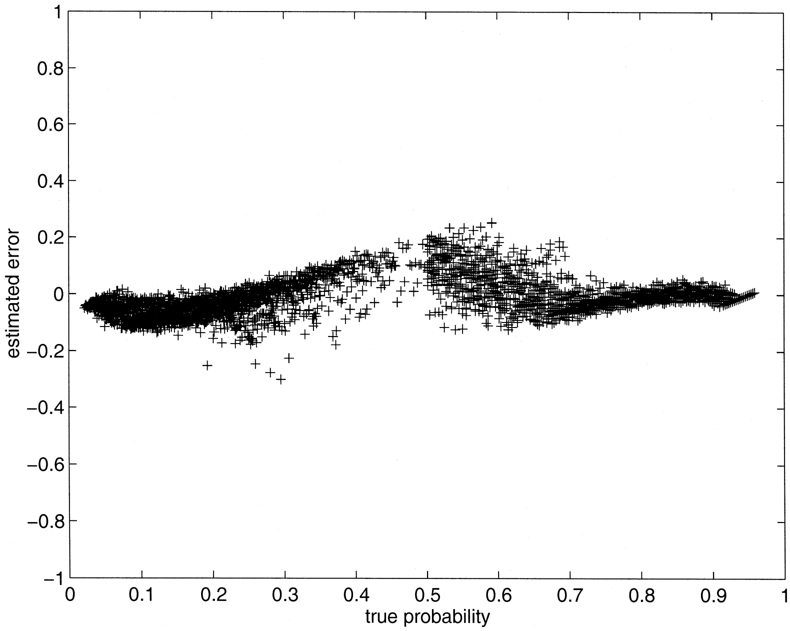

Fig. 10. The estimation error ($p_0 - \hat{p}_0$) versus true probability (p_0) with $\sigma = 2$ dB.

inference system; (c) the effect of the shadowing on the estimation accuracy increases as the mobile user moves to the cell boundary, due to the reduced confidence level on the measured data; (d) as the

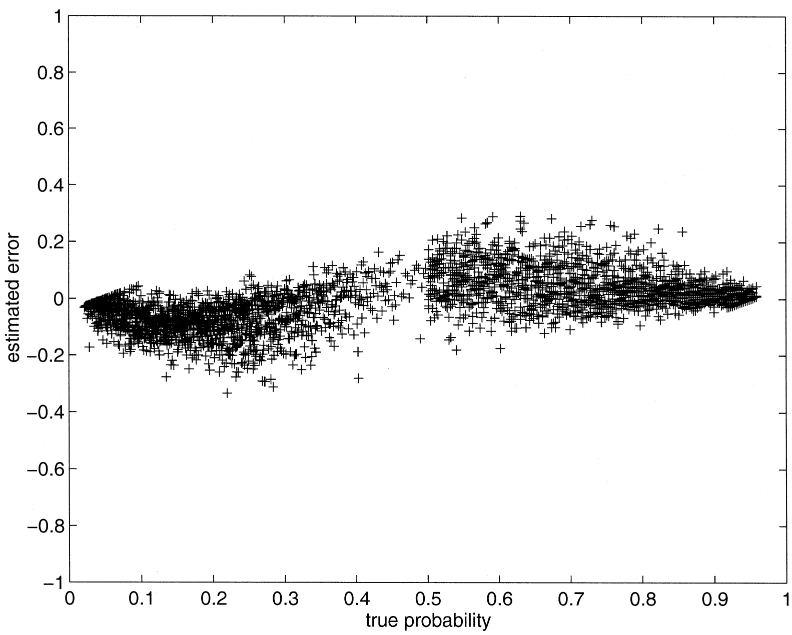

Fig. 11. The estimation error ($p_0 - \hat{p}_0$) versus true probability (p_0) with $\sigma = 4$ dB.

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

Table 5 illustrates how the first and second order statistics of the estimation change as the path loss exponent, n, changes, where $\sigma = 2$ dB is used for the different n values. It is observed that, as the value of n increases, both the mean and the standard deviation decreases. This is because a larger n value means a faster attenuation of the received signal level as the distance between the mobile user and the base station 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 n 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 n, because the shadowing characterized by σ is the main source which introduces randomness to the received signal levels.

4.2. Two-dimensional space

In this case, the estimation of p_0, p_1 and p_2 is based on the three strongest pilot signals. Due to the symmetry of the area, p_0, p_1 and p_2 can be obtained by Eqs. (5)–(7). During the simulations, it is observed that the changes of a_2 are relatively small compared with those of a_0 and a_1 when the mobile user moves from one subregion to another, mainly due to small distance changes from BS_3 to each subregion defined according to p_0. As a result, the estimation of p_0 relies only on a_0 and a_1 for the simplicity of the fuzzy inference system. The estimation procedure is similar to that of estimating p_0 in the one-dimensional case except that p_2 can take on nonzero value. Based on training data from 50,000 mobile users uniformly distributed in the shadow area of Fig. 3, Table 6 gives the decision rules for $\sigma = 2$ dB, and Table 7 gives the corresponding degree assigned to each rule. Figs. 10 and 11 show the estimation error $p_0 - \hat{p}_0$ versus p_0 for σ equals to 2 dB and 4 dB respectively. Table 8 gives the mean and standard deviation of the estimation error for various σ values. Due to the geometrical symmetry, estimation of p_1 and the estimation accuracy are the same as those of p_0. We have some observations similar to those in the one-dimensional case: (a) the estimator is unbiased; (b) for a certain σ value, the estimation error is relatively small when the mobile user is close to one BS; (c) the effect of the shadowing on the estimation accuracy increases as the mobile user moves to the cell boundary; (d) a larger value of σ results in a larger estimation error. Comparing Tables 2 and 6, we see that p_0 in the two dimensional case is the same as, or very close to, the corresponding value in the one-dimensional case when p_0 is relatively large (say, larger than 0.5), where p_2 is equal to or close to zero; on the other hand, when p_0 is relatively small (say, less than 0.5), the value of p_0 in the two-dimensional case is slightly smaller than that in the one-dimensional case due to the fact that p_2 is larger in the former situation. Comparing the estimation accuracy in the two-dimensional case Figs. 10 and 11 and Table 8) with that in the one-dimensional case (Figs. 7 and 9 and Table 4), we see that the side information that the mobile user will communicate with either BS_0 or BS_1 (but not BS_2) improves the performance of the fuzzy inference system.

Table 8
The mean and standard deviation of the estimation error $p_0 - \hat{p}_0$

σ (dB)	Mean	Standard deviation
1	3.35e-3	5.95e-2
2	1.39e-3	6.36e-2
3	-1.92e-3	7.66e-2
4	1.99e-3	9.04e-2
5	-4.76e-3	1.29e-1
6	2.51e-3	1.44e-1

5. Conclusions

We have developed a fuzzy inference system to estimate the probabilities that a mobile user will communicate with different base stations at a future moment based on the real-time measurement data of the received pilot signals' power from the base stations. The advantages of the fuzzy inference system lie in (a) its simplicity — it is a one-pass build-up procedure that does not require time-consuming online training, (b) its usefulness — the probability information is critical in statistical multiplexing for an efficient utilization of the network resources while satisfying the QoS requirements of mobile users, and (c) its low cost — the probability information is obtained based on the signaling in CDMA networks for handoff, without requiring extra signaling over wireless channels. Computer simulation results demonstrate that the performance of the 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, with statistical multiplexing, the overall estimation accuracy can be significantly increased, the fuzzy inference system provides a good solution to obtaining mobility information. Further work on the topic may also incorporate the information of previous pilot signal power (in addition to the current one) to the estimation of the mobility information, which is expected to improve the estimation accuracy at the cost of the fuzzy inference system complexity.

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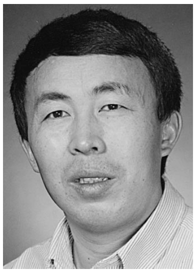

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