Wireless Personal Communications **22:** 57–70, 2002.

Mobile Location Estimation in CDMA Cellular Networks by Using Fuzzy Logic

XUEMIN SHEN, JON W. MARK and JUN YE
Centre for Wireless Communications, Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario, Canada 2NL 3G1
E-mail: {xshen}{jwmark}{jye}@bbcr.uwaterloo.ca

Abstract. An adaptive fuzzy logic estimator for locating mobiles in a direct sequence code division multiple access (DS/CDMA) cellular system is proposed. The location estimation is based on the measured pilot signal strengths by the mobile station (MS) from a number of nearby base stations (BSs). A smoother, which uses past and current output data from the fuzzy estimator to produce a more accurate estimate, is used to improve the accuracy of the location estimation. Numerical performance results under various path loss and channel shadowing conditions are presented to demonstrate the viability of the proposed fuzzy estimator.

Keywords: mobile location estimation, fuzzy logic, wireless communications.

1. Introduction

Mobile location estimation is to determine the position of a mobile station (MS) operating in a geographical area covered by a cellular network. A recent Report and Order issued by the U.S. Federal Communications Commission (FCC) requires that all cellular networks be able to provide the location information of mobile stations (MSs) for the use of Emergency 911 (E-911) public safety agency by 2001 [1, 2]. In specific, the cellular networks must provide latitude and longitude estimates of the MS's position within an accuracy of 125 meters root mean square (RMS) at 67% of the time. In addition to the E-911 safety services, the MS location information can be used for other applications: (a) location-sensitive billing which provides a wireless carrier the ability to offer different rates depending on whether the wireless terminal is used at home, in the office, or on the road; (b) fraud detection in order to battle against cellular phone fraud; (c) intelligent transport system which can enable services such as providing information to travelers, more effective dispatch of vehicle in fleets, and detecting traffic incident and congestion; (d) enhanced network performance for achieving efficient and effective resource management.

An MS's position can be determined by measuring parameters of radio signals that travel between the MS and a number of fixed transceivers. The most important measurements are received signal strength, propagation time of arrival (TOA) [3], time difference of arrival (TDOA) [4, 5], angle of arrival (AOA) [6–8], and carrier phase. Each measurement defines a locus on which the MS (i.e., the object being positioned) must lie. The point at which the loci from multiple measurements intersects defines the position of the MS. Previous research efforts using received signal strength to estimate an MS location were based on a mathematical model describing the path loss attenuation with distance [9, 10]. In general, if an MS is closer to a base station (BS), then the propagation path attenuation from the BS to the MS is smaller, and vice versa. Hence, if the BS transmits a pilot signal with constant transmitted power, then the received signal power at the MS carries the information of the distance between the MS and the BS. Since the location of the MS is a function of the distances between the MS and its nearby BSs, this location can be estimated based on real-time measurements of the received pilot signal power at the MS from the BSs. However the challenges in estimating MS location based on the pilot signal power measurements come from the following facts: (a) There exists a relatively slow fluctuation of the received signal level due to scattering in the propagation medium between the BS and the MS. The shadowing process randomizes the relation between the received pilot signal power and the distance from the MS to the BS; (b) 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, it is impossible to accurately obtain the MS location based on the measurements. To tackle this difficulty, fuzzy inference method can be used as a powerful tool to solve the problems related to uncertainty and imprecision. The fuzzy inference approach represents qualitatively expressed control rules quite naturally with linguistic description [11]. Many applications of fuzzy logic are found in communication networks, such as in call admission control, policing, rate control, traffic control, etc. A fuzzy inference system with a smoothign device based on [12] is presented in this paper for MS location estimation. The system can deal with the random shadowing effect by using training data from real measurements 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. Furthermore, both the current and previous measurement data are used to improve the estimation accuracy since the MS location depends on its movement pattern (such as movement trajectory).

2. Mobility Model

We consider a wireless communication network operating in a frequency division duplex (FDD) mode. MSs 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. An MS can transmit to and receive signals from more than one BS at any time. A CDMA system employs soft handoff, which makes before break. During transition from one cell to a neighboring cell, the MS 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 MS has firmly established itself in the new cell. In the forward link, each BS transmits a distinct pilot signal for pseudorandom noise (PN) code and carrier synchronization. The code and waveform of the pilot signals from all BSs are the same, they are distinguished from one another by the phase or timing offsets of the pilot signals. The relative time-offsets of pilot signals for neighboring cells are either known beforehand or broadcast to all MSs. The MS can detect the pilot signal from any BS when the strength of the signal is above a certain level which is determined by the transmission power of pilot signals. Prior to any transmission, the MS monitors the received pilot signal power levels from nearby BSs. It chooses its home BS according to the maximum pilot signal power received. The network uses MS assisted soft handoff as in the IS-95 proposal [13]. While tracking the signals from the home BS, the MS searches for all the possible pilots and maintains a list of all pilots whose signals are above a

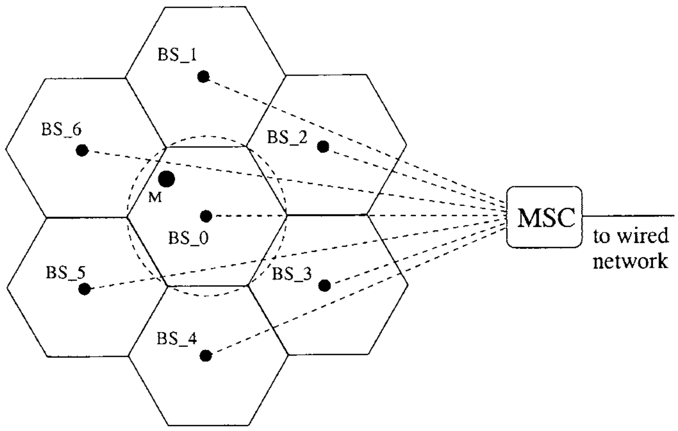

Figure 1. Network structure with hexagonal layout.

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 [14]. In addition, the MSC uses the information to estimate the location of the MS. Figure 1 shows the structure of the network with hexagonal cell layout, where the MS under consideration is located at the point M. The index i will be used throughout this section to denote variables related to the home BS ($i = 0$) and to the neighboring BSs ($i = 1, 2, \ldots, 6$). Let $d_i(t)$ denote the distance between the MS and the first-tier BS_i at the time t. The time t will be discretized and represented as t_n $(= n\Delta t)$, $n = 1, 2, \ldots$, where Δt is the time interval over which the received pilot signals are measured. At t_n, the local mean of the pilot signal amplitudes received at each MS can be modeled by [6]

$$a_{n,i} = \gamma_i \cdot [d_i(t_n)/D_0]^{-\kappa} \cdot 10^{\xi_i(t_n)/10} + v_{n,i} \quad i = 0, 1, \ldots, 6, \tag{1}$$

where γ_i is a constant proportional to the amplitude of the pilot signal. The second term on the right hand side (RHS) of (1) is the path loss with path loss exponent κ, and reference distance D_0 from the transmitter. Both κ and D_0 can be determined from measurements. The third term is lognormal shadowing which characterizes long-term fading. The parameters $\xi_i(t_n)$ 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 $i = 0, 1, \ldots, 6$. $v_{n,i}$ is due to MAI (the information-bearing signals in the forward link to all the mobile stations) and background noise. When there are a large number of users in the system, MAI can be modeled as a Gaussian random process. With the measured strength of the pilot signal from BS_i received at the MS, the three largest signal strengths are chosen for the estimation of the location of the MS.

3. Fuzzy Inference System with Smoother

Figure 2 shows the block diagram of the proposed fuzzy inference smoothing system. It consists of two subsystems: a fuzzy inference system and a smoothing filter. The fuzzy inference system estimates the location of an MS at time t_n based on the measured pilot signal strengths at time t_n. The smoother outputs the improved mobile location estimation based on

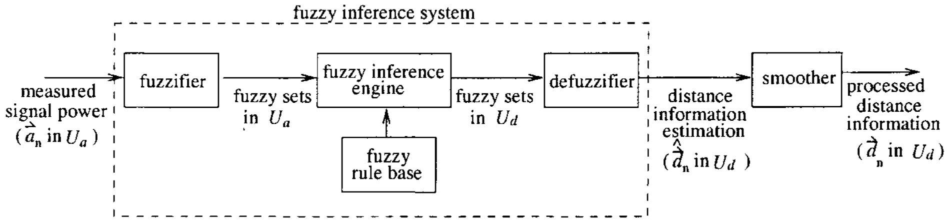

Figure 2. The fuzzy inference system with smoother.

the estimates from the fuzzy inference system up to time t_n. The design of the two subsystems are given in subsections 3.1 and 3.2.

3.1. Fuzzy Inference System

The fuzzy inference system 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 location of an MS 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), and (b) 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 [15]. 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 (M), medium to large (ML), large (L), very large (VL), extremely large (EL). Let the linguistic variable $d_{n,i}$ be the distance between the MS and the cell_i at epoch t_n, with the universe of discourse being the interval $[0, \sqrt{3D}]$ (D is the radius of the circle in Figure 1). We choose the term set of $d_{n,i}$, denoted by $U_{d_{n,i}}$, to be the set containing the following elements: extremely small (ES), very small (VS), small (S), small to medium (SM), medium (M), medium to large (ML), large (L), very large (VL), and extremely large (EL). The number of terms in $U_{a_{n,i}}$ and $U_{d_{n,i}}$, 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 distance) depend on the BS coverage areas, transmitted pilot signal power, the path loss exponent κ and channel shadowing statistics σ.

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 relatinship between the measured data $a_{n,i}$ and the distance $d_{n,i}$. The kth rule has the following form.

R_k:
If $a_{n,j1}$ is A_{1k} and $a_{n,j2}$ is A_{2k} and $a_{n,j3}$ is A_{3k},
then $d_{n,j1}$ is D_{1k} and $d_{n,j2}$ is D_{2k} and $d_{n,j3}$ is D_{3k} ,

where $k = 1, 2, \ldots, K$, and K is the total number of the fuzzy rules, $j1$, $j2$ and $j3$ are indexes of three BSs from which the MS can receive the strongest pilot signals. $(a_{n,j1}, a_{n,j2}, a_{n,j3}) \in$

$U_{a_{n,j1}} \times U_{a_{n,j2}} \times U_{a_{n,j3}} \triangleq U_a$ and $(d_{n,j1}, d_{n,j2}, d_{n,j3}) \in U_{d_{n,j1}} \times U_{d_{n,j2}} \times U_{d_{n,j3}} \triangleq U_d$ are linguistic variables, A_{Jk} and D_{Jk} are fuzzy sets in $U_{a_{n,jJ}}$ and $U_{d_{n,jJ}}$, 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_d.

Given fact:
$a_{n,j1}$ is $\tilde{A}_1$ and $a_{n,j2}$ is $\tilde{A}_2$ and $a_{n,j3}$ is $\tilde{A}_3$
Consequence:
$d_{n,j1}$ is $\tilde{D}_1$ and $d_{n,j2}$ is $\tilde{D}_2$ and $d_{n,j3}$ is $\tilde{D}_3$,

where $\tilde{A}_J$ and $\tilde{D}_J$ $(J = 1, 2, 3)$ are linguistic terms for $a_{n,jJ}$ and $d_{n,jJ}$, 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 also 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, 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

$$Q_k = \mu_k \prod_{J=1}^{3} \mu_{I_{Jk}}(a_{n,jJ}) \prod_{J=1}^{3} \mu_{O_{Jk}}(d_{n,jJ}) , \tag{2}$$

where I_{Jk} denotes the input region of rule k for $a_{n,jJ}$, O_{Jk} denotes the output region for $d_{n,jJ}$, $\mu_{I_{Jk}}(a_{n,jJ})$ is the degree of $a_{n,jJ}$ in I_{Jk} obtained from the membership functions, $\mu_{O_{Jk}}(d_{n,jJ})$ is the degree of $d_{n,jJ}$ in O_{Jk}, and μ_k is the degree of the data vector $(a_{n,j1}, a_{n,j2}, a_{n,j3})$ 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 $(d_{n,j1}, d_{n,j2}, d_{n,j3}) \in U_d$ (the output of the inference engine) to a crisp point $(\tilde{d}_{n,j1}, \tilde{d}_{n,j2}, \tilde{d}_{n,j3})$. $\tilde{d}_{n,jJ}$ denote the estimate (generated by the fuzzy inference system at time t_n) of the true location $d_{n,jJ}$. Among the commonly used defuzzification strategies, the center average defuzzification method yields a superior result [15]. The formula for the estimate at the defuzzifier output is

$$\tilde{d}_{n,jJ} = \frac{\sum_{k=1}^{K} \bar{Q}_k \prod_{J'=1}^{3} \mu_{I_{J'k}}(a_{n,jJ'})\bar{d}_{J'k}}{\sum_{k=1}^{K} \bar{Q}_k \prod_{J'=1}^{3} \mu_{I_{J'k}}(a_{n,jJ'})} , \tag{3}$$

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

The output of the defuzzifier is the estimated distances between the MS and the three individual BSs. These distances can be used to obtain the location of the MS. As shown in Figure 3, the MS is located at point M, and the corresponding BSs are located at points

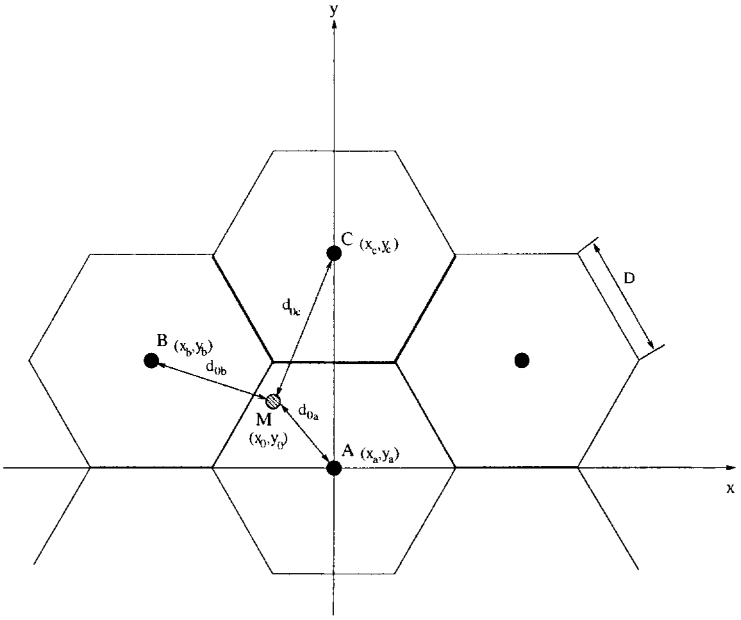

Figure 3. The coordinates of the MS and BSs.

A, B and C. The coordinates for points M, A, B and C are (x_0, y_0), (x_a, y_a), (x_b, y_b) and (x_c, y_c), respectively. The estimated distances from M to the three BSs are d_{0a}, d_{0b} and d_{0c}, respectively. The following three equations give the relation between the location (x_0, y_0) and d_{0a}, d_{0b}, and d_{0c}.

$$(x_0 - x_a)^2 + (y_0 - y_a)^2 = d_{0a}^2 \tag{4}$$

$$(x_0 - x_b)^2 + (y_0 - y_b)^2 = d_{0b}^2 \tag{5}$$

$$(x_0 - x_c)^2 + (y_0 - y_c)^2 = d_{0c}^2 . \tag{6}$$

Each of the above equations represents a circle, with the point (x_0, y_0) located at the circumference of each circle. Equations (4)–(6) can be combined pairwise to yield the following set of three first order equations for determining the point (x_0, y_0).

$$(x_b - x_a)^2 x_0 + (y_b - y_a)^2 y_0 = \frac{d_{0a}^2 - d_{0b}^2 + x_b^2 - x_a^2 + y_b^2 - y_a^2}{2} \tag{7}$$

$$(x_c - x_a)^2 x_0 + (y_c - y_a)^2 y_0 = \frac{d_{0a}^2 - d_{0b}^2 + x_c^2 - x_a^2 + y_c^2 - y_a^2}{2} \tag{8}$$

and

$$(x_c - x_b)^2 x_0 + (y_c - y_b)^2 y_0 = \frac{d_{0b}^2 - d_{0c}^2 + x_c^2 - x_b^2 + y_c^2 - y_b^2}{2} . \tag{9}$$

Each of the above first order equations represents a straight line that is perpendicular to the line connecting the centers of the pair of equations from (4) to (6) used to generate the equation of the straight line. The three individual intersection points which come from a combination of any two straight lines can represent the three possible locations of the MS, i.e., (x_0^1, y_0^1), (x_0^2, y_0^2) and (x_0^3, y_0^3), respectively. By taking the average of these three outcomes, the coordinates of the MS location, (x_0, y_0), can be obtained from the following equation.

$$x_0 = \frac{x_0^1 + x_0^2 + x_0^3}{3}, \; y_0 = \frac{y_0^1 + y_0^2 + y_0^3}{3}\,. \tag{10}$$

In case the three straight lines from (7), (8) and (9) are in parallel, i.e., the three BSs are on the same straight line, the following equation

$$\frac{x_b - x_a}{x_c - x_a} = \frac{y_b - y_a}{y_c - y_a} = \frac{d_{0a}^2 - d_{0b}^2 + x_b^2 - x_a^2 + y_b^2 - y_a^2}{d_{0a}^2 - d_{0c}^2 + x_c^2 - x_a^2 + y_c^2 - y_a^2} \tag{11}$$

can be used to generate another line with the two points (x_a, y_a) and (x_b, y_b). By using (11), (4) and (5), the position (x_0, y_0) can then be obtained.

3.2. The Smoother

For each MS, there is a strong correlation among its locations at adjacent time moments if the product of the MS velocity and the time interval Δt is small. This makes it possible to improve the MS location accuracy based on its current and previous estimation values. Let the current user location estimation from the fuzzy inference system be (x_0, y_0), and the previous $L - 1$ estimates be $(x_{-1}, y_{-1}), (x_{-2}, y_{-2}), \ldots, (x_{-(L-1)}, y_{-(L-1)})$. The following equations constitute a smoothing algorithm that yields the smoothed estimate, $(\bar{x}_0', \bar{y}_0')$, of the current user location.

$$x_{med} = \sum_{j=-(L-1)}^{0} x_j/L \tag{12}$$

$$y_{med} = \sum_{j=-(L-1)}^{0} y_j/L \tag{13}$$

$$\bar{x}_0' = x_{med} + (x_0 - x_{-(L-1)})/2 \tag{14}$$

$$\bar{y}_0' = y_{med} + (y_0 - y_{-(L-1)})/2\,. \tag{15}$$

The smoothing algorithm also reduces the effect of MAI and background noise by averaging the Gaussian random variables. The smoothing algorithm is adequate over a short duration of time. The value of L depends on the variations of the MS's velocity and direction. L should be small if the variations increase, and large if the variations decrease.

4. Simulation Results

This section first explains the simulation set up and training procedure, and then evaluates the performance of simulated fuzzy inference system for MS location estimation.

4.1. The Simulated Fuzzy System

The microcellular network under consideration has a hexagonal cell structure as shown in Figure 1. The BS is located at the center of each cell, and an MS within the dash circle can receive pilot signals from its neighboring BSs. The three largest signal strengths are chosen for the estimation of the MS location.

To choose the type of membership functions, it is necessary to take into account both the computational efficiency and adaptation easiness of the fuzzy inference system. Gaussian, triangular and trapezoidal functions are the most commonly used membership functions. The Gaussian function is chosen as the format of membership function in the simulation because it is a better reflection of the mobility model, since shadowing assumes a lognormal distribution. With the Gaussian function, the degree $\mu_{I_{J'k}}(a_{n,jJ'})$ in Equation (2) can be expressed as following:

$$\mu_{I_{J'k}}(a_{n,jJ'}) = \exp\left(-\left(\frac{a_{n,jJ'} - \bar{a}_{jk}}{\sigma_{jk}}\right)^2\right), \tag{16}$$

where $\bar{a}_{jk}$ and σ_{jk} are adjustable parameters for each Gaussian function.

Substituting Equation (16) into Equation (3), the estimate at the defuzzifier output is

$$\tilde{d}_{n,jJ} = \frac{\sum_{k=1}^{K} \bar{Q}_k \prod_{J'=1}^{3} \exp\left(-\left(\frac{a_{n,jJ'}-\bar{a}_{jk}}{\sigma_{jk}}\right)^2\right) \bar{d}_{J'k}}{\sum_{k=1}^{K} \bar{Q}_k \prod_{J'=1}^{3} \exp\left(-\left(\frac{a_{n,jJ'}-\bar{a}_{jk}}{\sigma_{jk}}\right)^2\right)}. \tag{17}$$

In order to determine parameters $\bar{a}_{jk}$, σ_{jk} and $\bar{d}_{J'k'}$, and to generate fuzzy inference rules, all possible distances $d_{n,i}$ (distance between the MS and each BS) are divided into 9 ranges equally and the center value of each range, denoted by $\bar{d}_{J'k}(0)$, is chosen as the initial center value of the range. The initial values of $\bar{a}_{jk}$ and σ_{jk} are determined based on the mean and variance of $a_{n,i}$ for each distance range, denoted respectively as $\bar{a}_{jk}(0)$ and $\sigma_{jk}(0)$. To obtain the initial fuzzy inference rules, 10,000 MSs uniformly distributed in the dash circle of Figure 1 are simulated, and one pair of training data $(a_{n,jJ'}, d_{n,J'})$ are generated for each MS, where $a_{n,jJ'}$ are the three largest signal strengths received at the MS, and $d_{n,J'}$ are the distances between simulated MS and the corresponding BSs, $J' = 1, 2, 3$. After the initial fuzzy inference rules have been generated, the total number of fuzzy rules K is known. In order to determine the optimal fuzzy inference rules, the back propagation training method, which is an iterative gradient algorithm, is employed to train the fuzzy system, i.e., given a set of training input-output sequences $(a_{n,jJ'}, d_{n,J'})$, $J' = 1, 2, 3$, the parameters in Equation (17) are adjusted such that the error

$$\mathrm{err}(n, J') = \frac{1}{2}(\tilde{d}_{n,J'} - d_{n,J'})^2, \quad J' = 1, 2, 3 \tag{18}$$

is minimized. Since $\tilde{d}_{n,J'}$ is the function of $\bar{a}_{jk}$, σ_{jk} and $\bar{d}_{J'k}$, the optimization problem becomes one of training the parameters $\bar{a}_{jk}$, σ_{jk} and $\bar{d}_{J'k}$ to minimize $\mathrm{err}(n, J')$. At each step, the gradient of the $\mathrm{err}(n, J')$ with respect to the adjusted parameter is calculated by differentiating the $\mathrm{err}(n, J')$ with respect to the parameter, then the parameter is adjusted based on the value of the gradient.

Table 1. Fuzzy inference rule examples.

$a_{n,j1}$	$a_{n,j2}$	$a_{n,j3}$	$d_{n,j1}$	$d_{n,j2}$	$d_{n,j3}$	Q_k
VS	S	MS	VL	ML	MS	1.0
S	S	MS	L	ML	M	0.904
VS	S	M	VL	L	S	0.565
VS	VS	L	VL	VL	VL	0.424
VS	VS	M	VL	L	S	0.383

Let $z_k = \prod_{J'=1}^{3} \exp\left(-\left(\frac{a_{n,jJ'}-\bar{a}_{jk}}{\sigma_{jk}}\right)^2\right)$, $b = \sum_{k=1}^{K} z_k$, $c = \sum_{k=1}^{K}(\bar{d}_{J'k} z_k)$, then $\tilde{d}_{n,jJ} = c/b$. To adjust $\bar{d}_{J'k}$, we use,

$$\bar{d}_{J'k}(n) = \bar{d}_{J'k}(n-1) - \alpha \frac{\partial \mathrm{err}}{\partial \bar{d}_{J'k}}\,, \tag{19}$$

where $J' = 1, 2, 3$ and $n = 1, 2, \ldots, \alpha$ is a positive real-valued constant stepsize.

Using the chain rule, we have

$$\frac{\partial \mathrm{err}}{\partial d_{J'k'}} = (\tilde{d}_{n,jJ} - d_{n,J'}) \frac{\partial \tilde{d}_{n,jJ}}{\partial c} \frac{\partial c}{\partial \bar{d}_{J'k}} = (\tilde{d}_{n,jJ} - d_{n,J'}) \frac{1}{b} z_k\,. \tag{20}$$

Hence, the algorithm to adjust $\bar{d}_{J'k}$ is

$$\bar{d}_{J'k}(n) = \bar{d}_{J'k}(n-1) - \alpha(\tilde{d}_{n,jJ} - d_{n,J'}) \frac{1}{b} z_k\,, \tag{21}$$

where $n = 1, 2, \ldots, k = 1, 2, \ldots, K$ and $J' = 1, 2, 3$.

Similarly, the algorithms to adjust a_{jk} and σ_{jk} can be obtained as following:

$$\bar{a}_{jk}(n) = \bar{a}_{jk}(n-1) - \alpha \frac{\tilde{d}_{n,jJ} - d_{n,J'}}{b} (\bar{d}_{J'k} - \tilde{d}_{n,jJ}) z_k \frac{2(a_{n,jJ'} - \bar{a}_{jk}(n-1))}{\sigma_{jk}^2(n-1)} \tag{22}$$

$$\sigma_{jk}(n) = \sigma_{jk}(n-1) - \alpha \frac{\tilde{d}_{n,jJ} - d_{n,J'}}{b} (\bar{d}_{J'k} - \tilde{d}_{n,jJ}) z_k \frac{2(a_{n,jJ'} - \bar{a}_{jk}(n-1))^2}{\sigma_{jk}^3(n-1)}\,, \tag{23}$$

where $n = 1, 2, \ldots, j = 1, 2, 3, k = 1, 2, \ldots, K$ and $J' = 1, 2, 3$.

After the parameters of a_{jk}, σ_{jk} and $\bar{d}_{J'k}$ have been adjusted using the above algorithms, the fuzzy inference rules can be tuned further according to these adjusted values of parameters and the same training data which are used in generating the initial fuzzy inference rules.

Figures 4 and 5 show the membership functions of $a_{n,i}$ and $d_{n,i}$, respectively, with the parameters $\kappa = 4$ and $\sigma = 2$ dB. The overlapping of the Gaussian functions possesses a natural capability to express and deal with measurement uncertainties (crisp points do not have this capability). Table 1 gives an example of some fuzzy inference rules obtained after the training.

4.2. Performance Evaluation

In order to evaluate the overall system performance, 200 MSs are simulated with movement patterns characterized by the following:

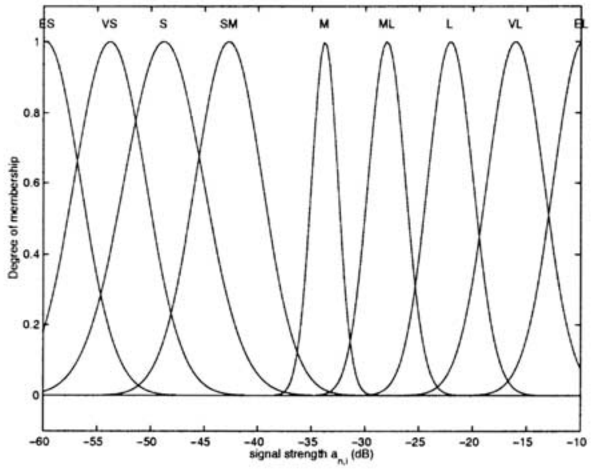

Figure 4. Membership function of the received signal strength ($\kappa = 4$, $\sigma = 2$ dB).

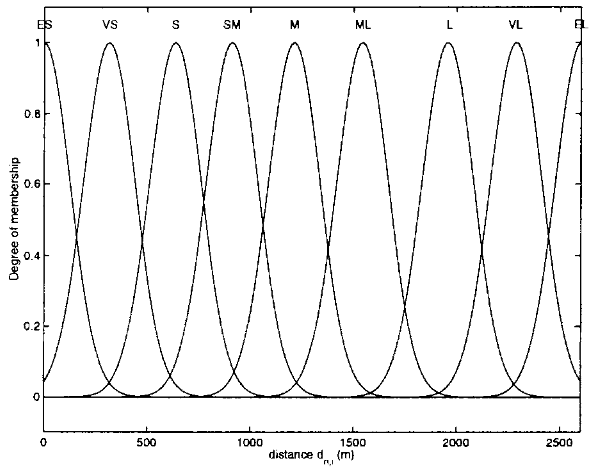

Figure 5. Membership function of the distance between the MS and BS ($\kappa = 4$, $\sigma = 2$ dB).

1. The initial location of each MS is uniformly distributed within the dash circle of Figure 1.
2. The initial velocity of each MS is a constant uniformly distributed in [10, 30] meters per second. When an MS changes its moving direction, its velocity may become a new constant uniformly distributed in [10, 30] meters per second and independent of the previous velocity.
3. The initial direction of movement of each MS's is uniformly distributed in $[0, 2\pi]$, and the direction can be changed any time each being uniformly distributed in $[0, 2\pi]$ and independent of previous direction(s).
4. The time interval Δt for updating the location information is 1 second.

Different propagation environments (i.e., different values of κ and σ) and L of the smoothing algorithm are used to evaluate the system performance.

Table 2 gives the root mean square (RMS) estimation errors for various values of σ with $\kappa = 4$ and $L = 11$. It is observed that the parameter σ plays an important role in estimation accuracy of the fuzzy inference system. As the value of σ increases, there is an increase in

Table 2. Root mean square (RMS) estimation error *Err* in meters given $\kappa = 4$ and $L = 11$.

σ (dB)	RMS estimation error
1	75.516
2	104.474
3	140.504
4	185.780
5	249.476
6	314.024

Table 3. Root mean square (RMS) estimation error *Err* in meters given $\sigma = 2$ dB and $L = 11$.

κ	RMS estimation error
2	190.525
4	104.474
6	71.443

the degree of shadowing effect of the propagation channel, resulting in an increase of the uncertainty in the measurements of the received signal strength and of estimation errors. Table 3 gives the root mean square (RMS) estimation errors for different values of κ with $\sigma = 2$ dB and $L = 11$. It can be seen that, as the value of κ increases, the estimation errors decrease. This is because a larger κ value means a faster attenuation of the received signal level as the distance between the MS and the BS increases. Correspondingly, the degree of randomness in the received signal level will decrease, resulting in a better estimation. Table 4 shows the percentage of RMS estimation errors for various values of tap length L with $\sigma = 2$ dB and $\kappa = 4$. It is observed that the estimation RMS errors decrease when L increases, and over 70% of estimated RMS errors are within 125 meters for $L \geq 11$.

Table 4. Percentage of RMS estimation errors within different range *Ran* given $\kappa = 4$ and $\sigma = 2$ dB with different L.

Ran(m)/L	0	3	5	7	9	11	13
0–125	19.56%	43.39%	55.43%	63.45%	68.58%	72.00%	73.91%
125–200	22.47%	30.51%	30.05%	26.59%	23.14%	20.17%	18.36%
200–300	26.24%	19.38%	12.04%	7.94%	6.02%	5.28%	4.76%
300–400	16.20%	5.38%	1.92%	1.31%	1.36%	1.43%	1.69%
400 up	15.53%	1.35%	0.56%	0.72%	0.90%	1.11%	1.27%

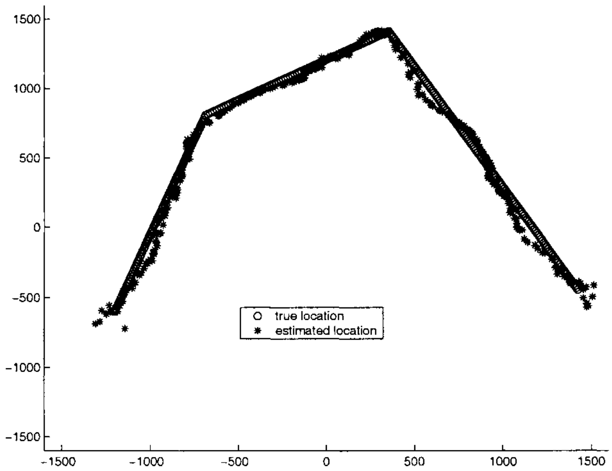

Figure 6. Example of an MS's simulated and estimated movement trajectory.

As an example, Figure 6 shows the comparison of a simulated MS's movement (trajectory) and the estimated trajectory with the values of parameters κ and σ of the propagation environment being 4 and 2 dB, respectively. The initial velocity of the MS is 19 meters per second, and becomes 15 meters per second and 16 meters per second after changing its direction of movement. From the figure, it can be seen that the estimation of the MS's location can closely track the actual location trajectory.

5. Conclusions

A fuzzy inference system with an associated smoothing device is developed to estimate user location based on real-time measurement of the pilot signal powers received at the MS. Computer simulation results have demonstrated the performance of the fuzzy system with different propagation environments. The advantages of the fuzzy system lie in (i) its usefulness since it provides reasonable MS location information, (ii) its simplicity in implementation, since it is a one-pass build up procedure which does not require on-line training, and (iii) low cost, since the location estimation is obtained based on the existing signaling in CDMA networks.

Acknowledgement

This work has been supported by a grant from the Canadian Institute for Telecommunications Research (CITR) under the NCE program of the Government of Canada.

References

1. J.H. Reed, K.J. Krizman, B.D. Woerner and T.S. Rappaport, "An Overview of the Challenges and Progress in Meeting the E-911 Requirement for Location Service", *IEEE Communications Magazine*, Vol. 36, No. 4, pp. 30–37, 1998.
2. J.J. Caffery, Jr and G.L. Stüber, "Overview of Radiolocation in CDMA Cellular Systems", *IEEE Communications Magazine*, Vol. 36, No. 4, pp. 38–45, 1998.
3. J.J. Caffery, Jr. and G.L. Stüber, "Subscriber Location in CDMA Cellular Networks", *IEEE Transactions on Vehicular Technology*, Vol. 47, No. 2, pp. 406–416, 1998.

4. Y.T. Chan and K.C. Ho, “A Simple and Efficient Estimator for Hyperbolic Location”, *IEEE Transactions on Signal Processing*, Vol. 42, No. 8, pp. 1905–1915, 1994.
5. K.C. Ho and Y.T. Chan, “Geolocation of a Known Altitude Object from TDOA and FDOA Measurements”, *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 33, No. 3, pp. 770–783, 1997.
6. T.S. Rappaport, *Wireless Communications: Principles and Practice*, Prentice Hall, 1996.
7. K.T. Wong, “Adaptive Geolocation and Blind Beamforming for Wideband Fast Frequency-Hop Signals of Unknown Hop Sequences and Unknown Arrival Angles Using an Electromagnetic Vector Sensor”, *IEEE International Conference on Communications*, pp. 758–762, 1998.
8. R. Klukas and M. Fattouche, “Line-of-Sight Angle of Arrival Estimation in the Outdoor Multipath Environment”, *IEEE Transactions on Vehicular Technology*, Vol. 47, No. 1, pp. 342–351, 1998.
9. M. Hata and T. Nagatsu, “Mobile Location Using Signal Strength Measurements in a Cellular System”, *IEEE Transactions on Vehicular Technology*, Vol. 29, pp. 245–252, 1980.
10. M. Hellebrandt, R. Mathar and M. Scheibenbogen, “Estimating Position and Velocity of Mobiles in a Cellular Radio Network”, *IEEE Transactions on Vehicular Technology*, Vol. 46, No. 1, pp. 65–71, 1997.
11. T. Munakata and Y. Jani, “Fuzzy System: An Overview”, *Communications of the ACM*, Vol. 37, No. 3, pp. 69–76, 1994.
12. X. Shen, J.W. Mark and J. Ye, “Mobile Location Estimation in Cellular Networks Using Fuzzy Logic”, in *IEEE VTC2000*, Boston, September 2000, pp. 2108–2114.
13. An overview of the application of code division multiple access (CDMA) to digital cellular systems and personal cellular networks, QUALCOMM Inc., 1992.
14. X. Shen, J.W. Mark and J. Ye, “User Mobility Profile Prediction: An Adaptive Fuzzy Inference Approach”, *Wireless Networks*, Vol. 6, No. 5, pp. 363–374, 2000.
15. L.X. Wang, *Adaptive Fuzzy Systems and Control: Design and Stability Analysis*, Prentice-Hall, 1994.

Xuemin Shen received the B.Sc. (1982) degree from Dalian Marine University (China) and the M.Sc. (1987) and Ph.D. degrees (1990) from Rutgers University, New Jersey, U.S.A., all in electrical engineering. From September 1990 to September 1993, he was first with Howard University, Washington D.C., U.S.A., and then University of Alberta, Edmonton, Canada. Since October 1993, he has been with the Department of Electrical and Computer Engineering, University of Waterloo, where he was a visiting research scientist and is an associate professor. Dr. Shen’s research focuses on control algorithm development for mobility and resource management in interconnected wireless/wireline networks (traffic flow control, connection admission and access control, handoff, end-to-end performance modeling and evaluation); large scale system modeling, simulation and performance analysis; stochastic process and H_∞ filtering. He is the coauthor of the books *Singular Perturbed and Weakly Coupled Linear Systems – A Recursive Approach*, Springer-Verlag, 1990, and *Parallel Algorithms for Optimal Control of Large Scale Linear Systems*, Springer-Verlag, 1993.

Jon W. Mark received the B.A.Sc. degree from the University of Toronto, Toronto, Ontario, Canada in 1962, and the M.Eng. and Ph.D. degrees from McMaster University, Hamilton, Ontario, Canada in 1968 and 1970, respectively, all in electrical engineering. From 1962 to 1970, he was with Canadian Westinghouse Co. Ltd. in Hamilton, Ontario, Canada, where he was an engineer and then a senior engineer. Since 1970 he has been with the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario, Canada where he is currently a professor. He was the department chairman during the period July 1984 to June 1990. In 1996 he established the Centre for Wireless Communications at the University of Waterloo where he is currently serving as its founding director. He had previously worked in the areas of adaptive equalization, image coding and spread spectrum communications. His current research interests are in broadband communications, wireless communications and wireless/wireline interworking. Dr. Mark is an IEEE fellow. He was a former editor of the IEEE Transactions on Communications. He is currently a member of the Inter-Society Steering Committee of the IEEE/ACM Transactions on Networking, an editor of Wireless Networks, and an associate editor of Telecommunication Systems.

Jun Ye received the B.Eng. degree in electronic techniques and information systems from Tsinghua University, P.R. China, in 1991 and the M.Eng. degree in communications and electrical systems from South China University of Technology, P.R. China, in 1994. He is currently pursuing the Ph.D. degree in the Department of Electrical and Computer Engineering, University of Waterloo, Canada. His research interests include fuzzy logic, neural networks and their applications in communications networks.