A Noble Fuzzy-based Mobile Tracking Scheme

Soo-Chang Kim
ETRI, Converged Access Network Research Team, Daejeon, Korea
sckim@etri.re.kr

Jong-Chan Lee and Yeon-Seung Shin
Kunsan National Univ., Dept. of Computer Information Science, Korea
chan2000@kunsan.ac.kr
ETRI, Converged Access Network Research Team, Daejeon, Korea
shinys@etri.re.kr

***Abstract*—In this study, we propose a novel mobile tracking method based on Multi-Criteria Decision Making (MCDM), in which uncertain parameters such as Pilot Signal Strength (PSS), the distance between the mobile and the base station, the moving direction, and the previous location are used in the decision process using the aggregation function in fuzzy set theory. In the microcell- or picocell-based system the frequent movements of the mobile bring about excessive traffics into the networks. A mobile location estimation mechanism can facilitate both efficient resource allocation and better Quality of Service (QoS) provisioning through handoff optimization. Through numerical results, we show that our proposed mobile tracking method provides a better performance than the conventional method using the received signal strength.**

***Index Terms*—tracking, location management**

I. INTRODUCTION

There will be a strong need for the mobile terminal tracking in the next generation mobile communication systems [1-5]. The location of a Mobile Terminal must be found out, e.g., in wireless emergency calls already in the near future. It is of great importance to the efficiency of next generation mobile communication systems to know the exact position of the moving mobile user in order to reduce the number of paging messages and cell handover messages. Handover efficiency will be an important aspect in next generation mobile communication systems because it affects directly to the switching road and QoS, particularly in combined microcell of picocell networks. The frequent movements of a mobile terminal or host bring about excessive traffics into the network and may degrade the QoS severely. If its location can be estimated, network resources may be more effectively allocated and better QoS can be provisioned with the combination of handoff optimization.

It will have viable roles in the communication networks of next generation. Global Positioning System (GPS) was initially developed for military purposes but it is also utilized for civil applications such as local traffic information services and geo-location based applications. However incorporating GPS receivers into handsets raises questions of cost, size and power consumption [6].

Other methods for location estimation are based on radio signal propagation such as signposts, dead reckoning, circular or hyperbolic trilateration systems, etc. Many methods and systems have been proposed based on radio signal strength measurement of a mobile object's transmitter by a set of base stations [7-9]. Recently, adaptive schemes based on the use of cellular systems and on fuzzy logic [10], hidden Markov models [11-12] and pattern recognition methods [13] have been used to estimate the position of mobiles. The system studied in [7] estimates mobile location using information on contours but it does not provide a realistic search procedure. In Ref. [8] the estimation is based on the signal strength received at a multi-beam antenna of a base station in the multi-path environment, and the angle of its arrival (AOA). AOA is measured under the assumption that the signal is in line of sight (LOS), but LOS signal may not be received in the microcell where reflections and diffractions occur due to dense building environment. In this situation AOA of the strongest reflected signal is utilized for estimation, and therefore the location estimated differs greatly from real one. Time of arrival (TOA) of a signal from a mobile to neighboring base stations are used in [14], but this scheme has two problems. First, an accurate synchronization is essential between all sending endpoints and all receiving ones in the system. An error of 1 μs in synchronization results to 300 m error in location. Secondly this scheme is not suitable for the microcellular environment because it also assumes LOS environment. Time difference of arrival (TDOA) of signals from two base stations is considered in [15]. TOA scheme and TDOA scheme have been studied for IS-95B where PN code of CDMA system can be used for the location estimation. Enhanced Observed Time Difference (E-OTD) is a TDOA positioning method based on OTD feature already existing in GSM. The mobile measures arrival time of signals from three or more cell sites in a network. In this method the position of mobile is determined by trilateration [16]. E-OTD, which relies upon the visibility of at least three cell sites to calculate it, is not a good solution for rural areas where cell-site separation is large.

The above-mentioned schemes such as AOA, TOA and TDOA have problems as follows.

- These schemes assume that the cellular system consists of LOS areas. They get good results only under this assumption.
- The microcellular system such as IMT-2000 has NLOS areas which are affected by specific reflections and diffractions. In this situation these schemes have great errors in estimation.
- In the microcellular environment the points of the same average signal strength form not a circular contour but a distorted one. These schemes ignore the fact that the propagation rule is affected by many parameters.
- They rely only on the information related to radio signal such as signal strength. Their accuracies are affected by short-term fading, shadowing or diffraction.

In this study, to enhance estimation accuracy, we propose a scheme based on Multi-Criteria Decision Making (MCDM) which considers multiple parameters: the signal strength, the distance between the base station and mobile, the moving direction, and the previous location. This process is based on three step location estimations which can determine the mobile position by gradually reducing the area of the mobile position [17]. Using MCDM, the estimator first estimates the locating sector in the sector estimation step, then estimates the locating zone in the zone estimation step, and then finally estimates the locating block in the block estimate step.

This paper is organized as follows. Section II describes location definition for our system. Using the concepts described in Section II, our estimation scheme is considered in Section III. Simulation environment and results are shown in Section IV in order to compare our schemes with other schemes. Finally concluding remarks are given in Section V.

II. LOCATION MODEL

The location model for our study is shown in Fig. 1. The location of a MT within a cell can be defined by dividing each cell into sectors, zones and blocks and relating these to the signal level received by it at that point. It is done automatically in three phases of sector definition, zone definition and block definition. Then the location definition block is constructed with these results. They are performed at the system initialization before executing the location estimation. The sector definition phase divides a cell into sectors, and assigns a sector number to blocks belonging to each sector. The zone definition phase divides each sector into zones, and assigns a zone number to blocks belonging to each zone. The block definition phase assigns a block number to each block. In order to indicate the location of each block within a cell, 2-dimensional vector (distance d, angle a) is assigned to each block. After the completion of this phase each block has a set of block information. The location estimator presents the position of the Mobile Terminal (MT) using a block number. In our paper we need the direction information to identify the relative location of a block from the BS so we use the polar coordinates converted from the rectangular coordinates.

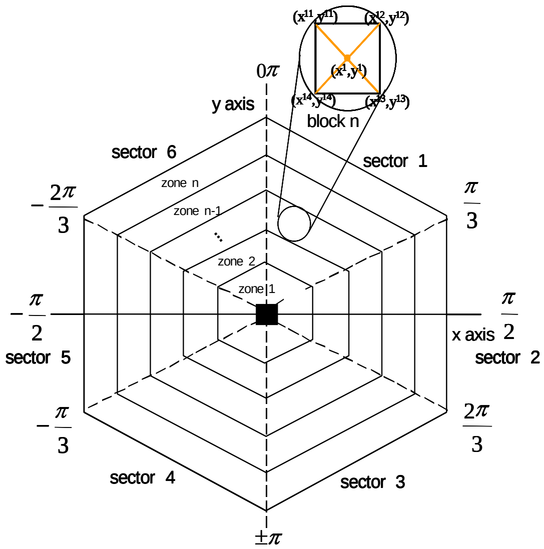


Figure 1. Sectors, Zones and Blocks.

That is, in order to indicate the location of each block within a cell, we use the vector data which is obtained by converting the rectangular coordinate of the block to the polar coordinate with the origin of the BS.

Based on the above location definition method, each block is given his location information which consists of one center point (x^i, y^i) and four of area point (x^{ij}, y^{ij}) as shown in Fig. 1. By comparing the location information of each block and the position information of the MT, the position of the MT within a cell is estimated.

Using MCDM and the block object which is constructed as described above, the proposed scheme estimates the optimal block at which the MT is located. This scheme is implemented as an estimator at the BS. The estimator is started with a timer, and the estimation is performed sequentially in three steps: sector estimation, zone estimation, and finally block estimation.

A. Sector Definition

The sector definition phase divides a cell into six sectors and assigns a sector number to blocks belonging to each respective sector as shown in Fig. 1. All blocks belonging to the same sector have the same sector number. In order to identify which blocks belong to which sector, we utilize the direction information of a vector which shows the direction of a block from the origin of the base station. The sector definition procedure is summarized as follows. Divide a cell into six sectors of a size. Assign an angle for each sector at the interval of $\pi/3$ respectively. Compare the direction information of a block with the angle of each sector, and then determine which sector it belongs to. Assign the corresponding sector number to each block.

B. Zone Definition

The zone definition phase divides each sector into zones, and assigns a zone number to blocks belonging to each respective zone as shown in Fig. 1. This definition phase can be described with two different algorithms depending on LOS model and NLOS model. Each cell is divided into n zones, with each zone classified by PSS threshold as shown in Fig. 2.

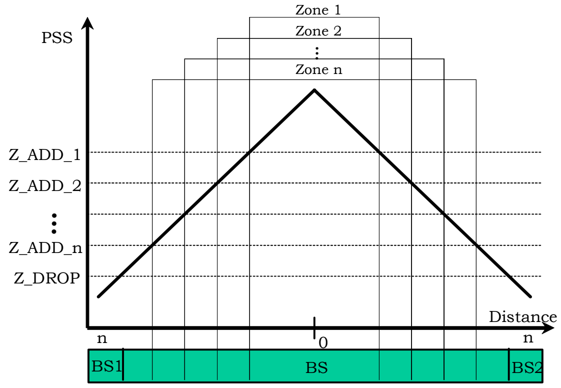


Figure 2. Zone definition with PSS.

The following algorithm summarizes the zone definition procedure for LOS model;

- Select each threshold by considering PSS.
- In order to map the signal strength onto the direction information, determine the distance function for each threshold with (1).

$$p_A(d) = k_1 - k_2 \times \log(d) + u(d)$$
$$p_B(d) = k_1 - k_2 \times \log(D-d) + \upsilon(d) \qquad (1)$$

In (1) D indicates the distance between two base stations, and d the distance between the base station A and the mobile. The k_1 is proportional to the transmission power of station and k_2 has an offset value depending on the radio propagation environment. Two random signals $u(d)$, $\upsilon(d)$ represent power distributions of signals received at a distance d from station A and from station B respectively. They have i.i.d (identical independent distribution) with Gaussian distribution of $N(\mu(d),\sigma)$. In our study the signal attenuation in NLOS environment is estimated based on the distance in LOS model, and this result is reflected in the block object information. Changes in LOS and NLOS environment are depicted by k_2.

a. Classify zones using the distance function.
b. Assign a same zone number and a PSS threshold to all blocks that belong to a same zone.

But above algorithm for LOS is not sufficient in the environment where blocks have a building or a hill. The boundary line for identifying each zone of the same signal strength is severely distorted due to shadowing and diffraction. Further refinement with NLOS data is required as shown below.

a. Identify zones by above LOS algorithm.
b. From blocks belonging to the same zone, select blocks which need NLOS offset. As shown in Fig. 1, each cell is divided into blocks and a position is defined for each block. During this cell planning the blocks needing NLOS offset are selected. This information is stored in the data base.
c. Assign NLOS offset, k_2 , of (1) to the blocks selected.
d. Find the difference between k_2 and PSS threshold which is determined by LOS model.
e. According to (1), a new zone is defined to which the corresponding block will belong. Here, the "difference" represents the difference between the position of the zone determined according to LOS model and that of when k_2 is assigned to the corresponding block.

C. Block Definition

In the block definition phase a block number is assigned to each block as shown in Fig. 3.

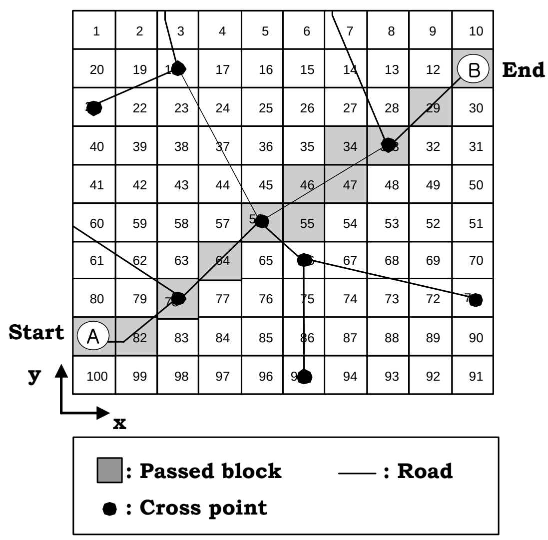


Figure 3. Identifying a block using a vector.

In order to indicate the location of each block within a cell, we use the vector data obtained by converting the rectangular coordinate of a block to the polar coordinate with the origin of the base station. Each vector has the information on a distance and an angle. If the mobile moves along the path (from A to B), it indicates the location of the block that the mobile passes through within the cell. In order to represent the location of a block relative to the base station, we assign a 2-dimensional vector (d, a) to each block.

The set of block information is called the block object. The block object contains the following information: the sector number, the zone number, the block number, the vector data (d, a), the maximum and the minimum values of the average PSS for the LOS block, the compensated value for the NLOS block, and a bit for indicating "node" or "edge".

III. MOBILE TRACKING BASED ON FMCDM

A. Fuzzy multi-criteria decision parameters

In our paper, the received signal strength, the distance between the MTs and the BS, the previous location, and the moving direction are considered as decision parameters. The received signal strength from the present base station and its neighboring base stations has been used in many schemes, but it has very irregular profiles due to the effects of radio environments. The distance, which is measured based on signal received from the present base station, is considered because it can explain the block allocation plan; however, it may also be inaccurate due to the effect of multi-path fading, etc. It is not sufficient by itself. We consider the previous location. It is normally expected that the estimated location should be near the previous one. Therefore, if the estimated location is too far from the previous one, the estimation may be regarded as inaccurate. We also consider the moving direction. Usually the MT is most likely to move forward, less likely to move rightward or leftward, and least likely to move backward more than one block. The low-speed MT (i.e., a pedestrian) has a smaller moving radius, that is, the distance that a MT is expected to move from his current location is short and a more complex moving pattern, while the high-speed MT (i.e., a motor vehicle) has a larger radius and a simpler pattern.

In mobile tracking using MCDM, the Decision function D is defined by combining the degree of satisfaction for multiple evaluation parameters, and the decision is made on the basis of his function. The evaluation parameter can be seen as a proposition. A compound proposition is formed from multiple evaluation parameters with a connective operator, and the total evaluation is performed by totaling the values for the multiple parameters with connective operators. In this method errors in the evaluation parameters impose milder changes on the total evaluation value than in binary logics. This method can also consider multiple inaccurate and insufficient evaluation parameters simultaneously and can compensate for them. This results in the optimal decision. In our study the measure of the ratio was used for indicating the evaluation parameter and a weight was imposed according to the degree of importance of each evaluation parameter.

B. Membership function

The membership function with a trapezoidal shape is used for determining the membership degree of the MT because it provides a more versatile degree between the upper and the lower limits than the membership function with a step-like shape. Let us define the membership functions for the PSSs from neighboring BSs. The membership function of PSS_i, $\mu_R(PSS_i)$, is given by (2). PSS_i is the signal strength received from the BS i, s_1 is the lower limit, and s_2 is the upper limit. 2 PSS values are used for forming the membership function with a trapezoidal shape and for determining the membership degree of estimated signal strength.

$$\mu_R(PSS_i) = \begin{bmatrix} 0, & PSS_i < s_1 \\ 1 - \dfrac{PSS_i - s_1}{|s_2 - s_1|}, & s_1 \le PSS_i \le s_2 \\ 1, & PSS_i > s_2 \end{bmatrix} \quad (2)$$

Now we define the membership function of the distance. The membership function of the distance $\mu_R(D_i)$ is given by (3), where D_i is the distance between the BS i and the MT [18-19]. d_1 is the upper limit, and d_2 is the lower limit.

$$\mu_R(D_i) = \begin{bmatrix} 1, & D_i < d_1 \\ 1 - \dfrac{|D_i - d_2|}{|d_1 - d_2|}, & d_1 \le D_i \le d_2 \\ 0, & D_i > d_2 \end{bmatrix} \quad (3)$$

The membership function of the previous location of the MT $\mu_R(L_i)$ is given by (4), where L_i is a scalar value defined by the estimated current location, $E_1, \cdots, E_4$ is also a scalar value respectively and a trapezoidal fuzzy number for the previous location (a vector value) of a mobile [18-19]. $E_1, \cdots, E_4$ is used for determining the membership degree of estimated current location. In other words, if a current location estimated is too far away from a previous location (that is, if the membership degree is too small), it is likely that we have incorrect location estimated.

$$\mu_R(L_i) = \begin{bmatrix} 0; & L_i < E_1 \\ 1 - \dfrac{L_i - E_1}{E_2 - E_1}, & E_1 \le L_i \le E_2 \\ 1, & E_2 \le L_i \le E_3 \\ 1 - \dfrac{L_i - E_3}{E_4 - E_3}, & E_3 \le L_i \le E_4 \\ 0, & L_i > E_4 \end{bmatrix} \quad (4)$$

The membership function of the moving direction $\mu_R(C_i)$ is given by (5). C_i is a scalar value defined by the moving direction of the MT, $H_1, \cdots, H_4$ means the previous directions and used for determining the membership degree of estimated moving direction. The moving direction (C_i) is defined by comparing the vector information of previous block and that of the estimated block.

$$\mu_R(C_i) = \begin{bmatrix} 0, & C_i < H_1 \\ 1 - \dfrac{C_i - H_1}{H_2 - H_1}, & H_1 \le C_i \le H_2 \\ 1, & H_2 \le C_i \le H_3 \\ 1 - \dfrac{C_i - H_3}{H_4 - H_3}, & H_3 \le C_i \le H_4 \\ 0, & C_i > H_4 \end{bmatrix} \quad (5)$$

C. Location estimation

Most of the MCDM approaches face the decision problem in two consecutive steps: aggregating all the judgments with respect to all the criteria and per decision alternative and ranking the alternatives according to the aggregated criterion. Also our approach uses this two-steps decomposition [20-23].

Each decision problem involves n alternatives and m linguistic attributes corresponding to m criteria. Thus, decision data can be organized in a $m \times n$ matrix. The decision matrix for alternatives is given by (6):

$$\mu = \begin{bmatrix} \mu_R(PSS_{11}) & \mu_R(D_{12}) & \mu_R(L_{13}) & \mu_R(C_{14}) \\ \mu_R(PSS_{21}) & \mu_R(D_{12}) & \mu_R(L_{13}) & \mu_R(C_{14}) \\ \mu_R(PSS_{31}) & \mu_R(D_{12}) & \mu_R(L_{13}) & \mu_R(C_{14}) \\ \cdots & \cdots & \cdots & \cdots \\ \mu_R(PSS_{n1}) & \mu_R(D_{n2}) & \mu_R(L_{n3}) & \mu_R(C_{nm}) \end{bmatrix} \quad (6)$$

The weighting vector for evaluation criteria can be given by using linguistic terminology with fuzzy set theory [23]. It is a finite set of ordered symbols to represent the weights of the criteria using the following linear ordering: very high ≥ high ≥ medium ≥ low ≥ very low. Weighting vector W is represented as (7).

$$W = (w_i^{PSS}, w_i^D, w_i^L, w_i^C) \quad (7)$$

The fuzzification procedure leads to a performance matrix $\mu \in [0,1]^{n \times m}$ where each element μ_{nm} expresses how much the n-th alternative satisfies the m-th criterion. Therefore, each low of the performance matrix is a fuzzy set μ_m expressing the satisfaction of the m-th criterion in the universe of the available alternatives [22-23]. By multiplying the weighting vector by the decision matrix, the performance matrix is given by (8):

$$\mu = \begin{bmatrix} \mu_R(PSS_{11}) \times w_1^{PSS} & \mu_R(D_{12}) \times w_1^D & \mu_R(L_{13}) \times w_1^L & \mu_R(C_{14}) \times w_1^C \\ \mu_R(PSS_{21}) \times w_2^{PSS} & \mu_R(D_{12}) \times w_2^D & \mu_R(L_{13}) \times w_2^L & \mu_R(C_{14}) \times w_2^C \\ \mu_R(PSS_{31}) \times w_3^{PSS} & \mu_R(D_{12}) \times w_3^D & \mu_R(L_{13}) \times w_3^L & \mu_R(C_{14}) \times w_3^C \\ \cdots & \cdots & \cdots & \cdots \\ \mu_R(PSS_{n1}) \times w_i^{PSS} & \mu_R(D_{n2}) \times w_i^D & \mu_R(L_{n3}) \times w_i^L & \mu_R(C_{nm}) \times w_i^C \end{bmatrix} \quad (8)$$

Given the decision matrix and the weighting vector, the decisionmaking objective for the general fuzzy MCDM problem is to rank all alternatives by giving each of them an overall preference rating with respect to all criteria [22-23]. GMV (Generalized Mean Value) is used for ranking the alternatives according to the aggregated criterion. The GMV for alternatives is represented as (9).

$$m(\mu_n) = \frac{(C_i + D_i)^2 - (A_i + B_i)^2 + A_i \cdot B_i - C_i \cdot D_i}{3 \cdot [(C_i + D_i) - (A_i + B_i)]} \quad (9)$$

where $A_i = \mu_R(PSS_{n1}) \times w_i^{PSS}$, $B_i = \mu_R(D_{n2}) \times w_i^D$, and $C_i = \mu_R(L_{n3}) \times w_i^L$, $D_i = \mu_R(C_{nm}) \times w_i^C$, respectively.

1) Sector estimation based on multi–criteria parameters

The decision parameters considered in the Sector Estimation step are the signal strength, the distance and the previous location. The MT is estimated to be located at the sector neighboring to the BS whose total membership degree is the largest. The sector estimation is performed as follows.

Procedure 1: Membership degrees are obtained using the membership function for the signal strength, the distance and the previous location.

Procedure 2: Membership degrees obtained in Procedure 1 for the BS neighboring to the present station are totalized using the fuzzy connective operator as shown in (10).

$$\mu_i = \mu_R(PSS_i) \cdot \mu_R(D_i) \cdot \mu_R(L_i) \quad (10)$$

We obtain (11) by imposing the weight on μ_i. The reason for weighting is that the parameters used may differ in their importance.

$$\omega\mu_i = \mu_R(PSS_i) \cdot W_{PSS} + \mu_R(D_i) \cdot W_D + \mu_R(L_i) \cdot W_L \quad (11)$$

where W_{PSS} is the weight for the received signal strength, W_D for the distance, and W_L for the location. Also $W_{PSS} + W_D + W_L$ is 1, W_{PSS} is 0.5, and W_D and W_L are 0.3, 0.2, respectively.

Procedure 3: Blocks with the sector number estimated are selected from all the blocks within the cell for the next step of the estimation. Selection is done by examining sector number in the block object information.

2) Zone estimation based on multi–criteria parameters

The decision parameters considered in the Zone Estimation step are the signal strength, the distance and the moving direction. From the blocks selected in the sector estimation step, this step estimates the zone of blocks at one of which the MT locates using the following algorithm.

Procedure 1: Membership degrees are obtained using the membership function for the signal strength, the distance and the moving direction.

Procedure 2: Membership degrees obtained in Procedure 1is totalized using the fuzzy connective operator as shown in (12).

$$\mu_i = \mu_R(PSS_i) \cdot \mu_R(D_i) \cdot \mu_R(C_i) \quad (12)$$

We obtain (13) by imposing the weight on μ_i.

$$\omega\mu_i = \mu_R(PSS_i) \cdot W_{PSS} + \mu_R(D_i) \cdot W_D + \mu_R(C_i) \cdot W_C \quad (13)$$

where W_{PSS}, W_D, and W_C are assumed to be 0.6, 0.2, 0.2, respectively.

Procedure 3: Blocks which belong to the zone estimated above are selected for the next step. It is done by examining the zone number of the blocks selected in the sector estimation.

3) Block estimation based on multi–criteria parameters

The decision parameters to be considered in the Block Estimation step are the signal strength, the distance and the moving direction. From the blocks selected in the zone estimation step, this step uses the following algorithm to estimate the block in which the MT may be located.

Procedure 1: Membership degrees are obtained using the membership function for the signal strength, the distance and the moving direction.

Procedure 2: Membership degrees obtained in Procedure 1 are totalized using the fuzzy connective operator as shown in (14).

$$\mu_i = \mu_R(PSS_i)\cdot\mu_R(D_i)\cdot\mu_R(C_i) \qquad (14)$$

We obtain (15) by imposing the weight on μ_i.

$$\omega\mu_i = \mu_R(PSS_i)\cdot W_{PSS} + \mu_R(D_i)\cdot W_D + \mu_R(C_i)\cdot W_C \quad (15)$$

where W_{PSS}, W_D, and W_C are assumed to be 0.6, 0.1, 0.3, respectively.

Procedure 3: The selection is done by examining the block number of the blocks selected in the zone estimation.

IV. Performance Analysis

A. Simulation Model

The moving pattern is described by the changes in moving direction and velocity. In our study we assume that low speed mobiles, pedestrians, occupy 60% of the total population in the cell and high-speed mobiles, vehicles, 40%. One half of the pedestrians are assumed to be still and another half moving. Also the private owned cars occupy 60% of the total vehicle, the taxi 10% and the public transportation 30%. Vehicles move forward, leftward/rightward and turn-back. The moving velocity is assumed to have a uniform distribution. The walking speed of pedestrians is 0~5km/h, the speed of private cars and taxis 30~100km/hr, and buses 10~70km/h. The speed is assumed to be constant during walking or driving. Figure 4 shows the road used in our simulation to consider traffic environments. The black circle indicates the branch of the road, and the shaded areas are blocks that the road passes through. Each block is a square and its side is assumed to have the length of 30m. The time needed for a high speed mobile to pass through a block is calculated from $BT = r/\upsilon$ where r is the length of the road segment crossing at each block and v the mobile speed. As shown in Figure 4, BT is dependent on r. We can consider four different values - r, $n\sqrt{2}\ m$ (crossing diagonally), $\frac{3n}{4}\sqrt{2}\ m$ (3/4 crossing), $\frac{n}{2}\sqrt{2}\ m$ (2/4 crossing) and $\frac{n}{4}\sqrt{2}\ m$ (1/4 crossing) - according to which portion of a block each road segment crosses through. In order to reflect more realistic information into our simulation, it is assumed that the signal strength is sampled every 0.5sec, 0.2sec, 0.1sec, 0.1sec and 0.05sec for the speed of ≤10km/h, ≤ 20km/h, ≤50km/h, ≤70km/h and ≤ 100km/h, respectively. If BT is too small, we cannot obtain enough samples to calculate the average signal strength. We consider the following simulation parameters regarding the received signal strength. The value of k_2, which indicates the changes in LOS/NLOS environments, is in the range of 20 through 50. The mean signal attenuation by the path-loss is proportional to 3.5 times the propagation distance, and the shadowing has a log-normal distribution with a standard deviation of σ = 6dB. A value of received signal strength less than –16 dB is regarded as an error, which is therefore excluded from the calculation.

B. Simulation Results

The effect of the block size on the estimation performance of MCDM and the existing schemes is shown in Fig. 4. As the block size becomes smaller, the accuracies of the three schemes decrease. The accuracies of AOA and TOA decrease rapidly. On the other hand, the performance of MCDM is least affected by block size because it additionally utilizes the previous location and distance between the mobile and the base station for estimation.

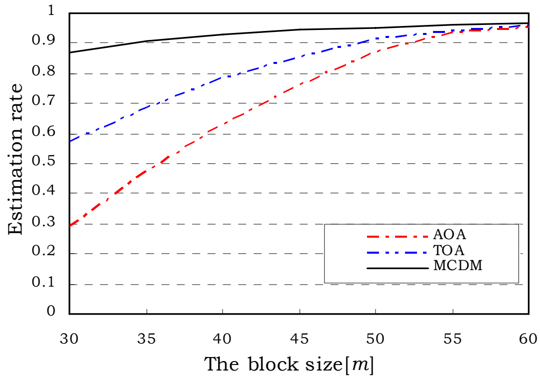


Figure 4. The estimation rate and the block size.

The estimation rate or accuracy of our proposed scheme depending on the mobile speed is shown in Fig. 5. The accuracy of AOA and TOA becomes lower rapidly since the signal measurement error would be large as the mobile speed increases. The performance of MCDM is least affected by the mobile speed because the information such as moving direction and previous location are considered in MCDM and, therefore, errors during the signal evaluation step decrease.

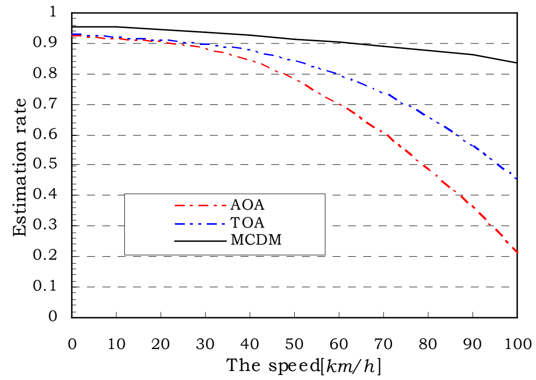
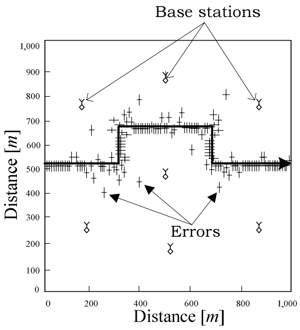
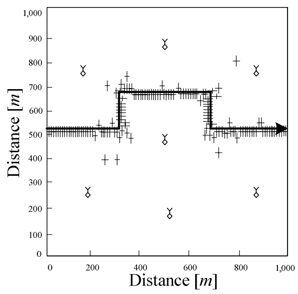


Figure 5. The estimation rate and the mobile terminal's speed.

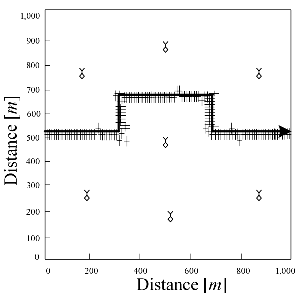
The estimation results of three schemes for the situation where the high speed mobile moves along a straight or curved sector boundary area is shown in Fig. 6. In this figure the horizontal and vertical axes represent the relative location of the area observed and the path generated in this simulation. Results are shown for Area Partitioning (AP), Virtual Area (VA) [5, 17] and MCDM from left to right in this figure respectively. As can be seen AP sometimes selects faulty locations far away from the generated path. That is because inaccurate results in sector estimation stage are escalated into zone and block estimation. VA has better accuracies for curved path. In our understanding it may be attributed to the fact that the average value of pilot signal strengths sampled by high speed mobile passing through two sectors falls into the range of PSS values of the sector boundary area. The performance of MCDM is less affected during a left turn or right turn. A left or right turn causes abrupt signal distortion, but their effects on estimation can be compensated for by using information on previous location and distance to base station. Especially, it can reduce the possibility of selecting a faulty location far away from present location by using information on previous location.



(a) Area Partitioning Scheme.



(b) Virtual Area Scheme.



(c) MCDM scheme.

Figure 6. The estimation results on the move.

We compare our scheme, MCDM with VA [17], E-OTD and TDOA in Fig. 7 [24]. In this figure the mobile maintains its y position at 1,000m and traverse x axis from x = 0m to x = 2,000m. The y axis means how the drms varies with x position of mobile. Distance Root Mean Square (Drms) stands for the root-mean-square value of the distances from the true location point of the position fixes in a collection of measurements. In order to get the estimated values for comparison we take an average of 20 values for each mobile position. We assume NLOS environment and the signal level of mobile may change abruptly due to shadowing. It shows that the performance of MCDM is least affected by abrupt change of signal level. MCDM has the most accurate result. This may well be attributed to the fact that it imposes less weight on the received signal strength in NLOS area and, instead, greater weights on other parameters such as the distance between mobile and base station, previous location, and moving direction are considered as decision parameters.

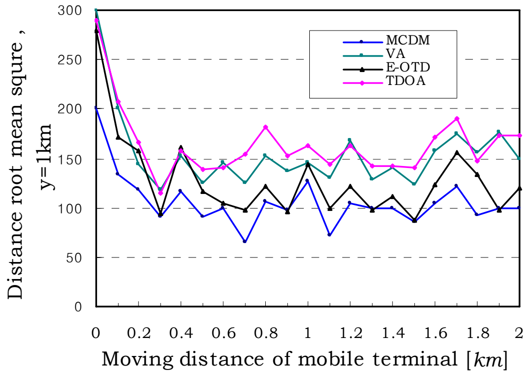


Figure 7. Comparison of the estimation accuracy.

V. Conclusions

In this study, we proposed a MCDM-based mobile tracking method for estimating more accurately the mobile location by considering multiple parameters, such as the signal strength, the distance between the base station and mobile, the moving direction, and previous location. We have demonstrated that our scheme increases the estimation accuracy when the mobile moves along a boundary area. The effect of weight factor variations on the estimation performance of our scheme and the determination of the optimal weight should be the subject of a future study. Also further researches are required on their implementation and applications to the handoff and channel allocation strategies.

References

[1] B. Z. Theodore, G. V. Konstantinos, P. T. Christos, A. Z. Nikolaos and A. N. Nikos, "Global Roaming in Next-Generation Networks," *IEEE Communications Magazine*, pp. 145-151, February 2002.

[2] C. Giovanni, F. Roberto, C. Piergiorgio, D. Salvatore, E. Marcello, P. R. Simon and D. Ada, "End-User Services in

Premium IP Networks," *IEEE Comm. Magazine*, pp. 54-60, January 2003.

[3] M. Victor, L. A. Rui, G. Carlos, I. M. Jose, B. Christophe, M. Eric and L. Marco, "An IP-Based QoS Architecture for 4G Operator Scenarios," *IEEE Wireless Comm.*, pp. 54-62, June 2003.

[4] S. Y. Hui and K. H. Yeung, "Challenges in the Migration to 4G Mobile Systems," *IEEE Comm. Magazine*, pp. 54-59, December 2003.

[5] J. C. Lee, B. Y. Ryu and J. H. Ahn, "Estimating the Position of Mobiles by Multi-Criteria Decision Making," *ETRI Journal*, Vol. 24, Num. 4, pp. 323-327, Aug. 2002.

[6] G. M. Djuknic and R. E. Richton, "Geolocation and Assisted GPS," *IEEE Computer*, Vol. 34, No. 2, pp.123-125, Feb. 2001.

[7] W. G. Figel, N. H. Shepherd and W. F. Trammell, "Vehicle location by a signal attenuation method," *IEEE Trans. Veh. Technol.*, vol. VT-18, pp. 104-109, Nov. 1969.

[8] G. D. Ott, "Vehicle location in cellular mobile radio systems," *IEEE Trans. Veh. Tech.*, Vol. VT-26, pp. 43-46, Feb. 1977.

[9] M. Hatta and T. Nagatsu, "Mobile Location Using Signal Strength Measurements in a Cellular System," *IEEE Transactions on Vehicular Technology*, vol. VT29, pp245 - 252, May 1980.

[10] H. L. Song, "Automatic Vehicle Location in Cellular Communication Systems," *IEEE Transactions on Vehicular Technology*, vol.43, pp902-908, Nov. 1994.

[11] O. Kennemann, "Pattern Recognition by Hidden Markov Models for Supporting Handover Decisions in the GSM system," *Proc. 6th Nordic Seminar Dig. Mobile Radio Comm.*, Stockholm,Sweden, pp.195-202, 1994.

[12] T. Nypan and O. Hallingstad, "Cellular Positioning by Database Comparison and Hidden Markov Models.," *PWC2002*, pp. 277-284, Oct. 2002

[13] O. Kennemann, "Continuous Location of Moving GSM Mobile Stations by Pattern Recognition Techniques," in Proc. *5th Int. Symp. Personal, Indoor, Mobile, Radio Comm.*, denHaag, Holland, pp.630-634, 1994.

[14] H. Staras and S. N. Honikman, "The accuracy of vehicle location by trilateration in a dense urban environment," *IEEE Trans. Veh. Tech.*, vol VT-26, pp. 38-43, Feb. 1972.

[15] T. S. Rappaport, J. H. Reed and B. D. Woerner, "Position Location Using Wireless Communications on Highways of the Future," *IEEE Communications Magazine*, pp. 33-41, Oct. 2002.

[16] Y. A. Spirito, "On the Accuracy of Cellular Mobile Station Location Estimation," *IEEE Trans. Veh. Technol.*, vol. 50, no. 3, pp. 674-685, 2001.

[17] J. C. Lee and Y. S. Mun, "Mobile Location Estimation Scheme," *SK telecommunications Review*, Vol. 9, No. 6, pp. 968-983, Dec. 1999.

[18] M. D. Austine, "Direction biased handoff algorithms for urban microcells," *VTC1994*, Vol. 1, pp. 101-105, 1996.

[19] C. H. Yeh and H. Deng, "An algorithm for fuzzy multi-criteria decision making," *IEEE ICIPS '97*, Vol. 2, pp. 1564 –1568, 1997.

[20] L. J., J. Y. Kuo, and H. W. T., "Fuzzy decision making through relationships analysis between criteria," *Fuzzy Systems Symposium, Soft Computing in Intelligent Systems and Information Processing*, pp. 296 –301, 1996.

[21] Z. H. J. and S. H. J., "Application of fuzzy logic to engineering design and configuration problems-a survey," *IEEE International Conference on Fuzzy Systems*, Vol. 2, pp. 1120-1125, 1996.

[22] C. Naso and B. Turchiano, "A Fuzzy Multi-Criteria Algorithm for Dynamic Routing in FMS," *IEEE ICSMC'1998*, Vol. 1, pp. 457-462, Oct. 1998.

[23] C. H. Yeh and H. Deng, "An Algorithm for Fuzzy Multi-Criteria Decision Making," *IEEE ICIPS'1997*, pp. 1564-1568, 1997.

[24] S. C. Kim, J. C. Lee, Y. S. Shin and K. R. Cho, "Mobile Tracking using Fuzzy Multi-Criteria Decision Making," *International Conference on Mobile Ad-hoc and Sensor Networks 2005 (MSN'05)*, Lecture Notes in Computer Science (LNCS), vol. 3794/2005, pp. 1051–1058, Dec. 2005.

Soo-Chang Kim was born on February 26, 1963 in Samcheok, Korea. He received his Ph.D. in computer and communication engineering from Chungbuk National University, Chungju, Korea in 2006. Before that, he received a M.S. in computer science from Chungnam National University, Daejeon, Korea and a B.S. in computer science from Hongik University, Seoul, Korea, in 1995 and 1986, respectively. He is a principal engineer in Mobile Access Research Group at Electronics and Telecommunications Research Institute (ETRI), Korea. His current research interests are in the areas of radio resource management, mobile access networks of next generation mobile communication system and All-IP. He is active in Next Generation Mobile Communication (NGMC) Forum of Korea.

Jong-Chan Lee was born on September 5, 1967 in Taean, Korea. He has received an M.S. and Ph.D. in computer science and engineering from Soongsil University, Seoul, Korea, in 1996 and 2000, respectively. He is a professor at the Dept. of Information Science, Kunsan National University. He was a senior member of the engineering staff in the Flexible Access Networks Lab. of the Electronics and Telecommunications Research Institute (ETRI). He has published more than 10 papers in International journals, and he has 15 patents. His current research interests are in the area of resource management and handover for the next generation mobile multimedia networks.

Yeon-Seung Shin received his M.S in statistics from Korea University, Seoul, Korea in 1987. Before that, he received a B.S. in statistics from Kangwon National University, Chuncheon, Korea, in 1984. He is a team leader in Mobile Access Research Group at Electronics and Telecommunications Research Institute (ETRI), Korea. His current research interests are in the areas of mobile access systems and SDR.