Discrete Mobile Terminal Location Estimation Using Support Vector Machine

Hady Ghafoor[1, 2] , Hossien Zamiri-Jafarian[1] and Mir Mojtaba Mirsalehi[1]
1 Electrical Engineering Department, Ferdowsi University
Mashhad, Iran
2 Communications and Computer Research Center, Ferdowsi University
Mashhad, Iran
Email: ha_gh85@stu-um.ac.ir, zamiri@um.ac.ir, mirsalehi@um.ac.ir

Abstract- *Mobile terminal location estimation has attracted much interest for its applications in emergency calls, intelligent traffic control, intelligent transportation systems and resource allocation. In this paper, a new implementation of data fusion technique for discrete mobile terminal location which is based on Support Vector Machine (SVM) is introduced. The raw information, i.e., time of arrival (TOA), angle of arrival (AOA) and received signal strength (RSS) obtained from the survey points in a real dense urban environment, is post processed to create feature space. The feature space, which contains the information on the locations of the mobile users, is classified by a previously trained SVM network. The simulation results demonstrate that the location estimation error is less than 100m in almost 72% of the calls.*

Keyword: Mobile location, Data fusion, Pattern recognition, SVM

1. INTRODUCTION

Location estimation of a mobile station in a wireless system has received considerable attention over the past decade. The U.S. Federal Communication Commission (FCC) has announced new regulations regarding mobile user positioning of emergency (E-911) calls. According to these regulations, all mobile service providers are required to enhance the positioning accuracy during emergency (E-911) calls to 100m in 67% of the calls and to 300m in 95% of the calls for network-based solution [1], [2]. By developing this service, other related services could be available on the mobile networks. One can categorize the goals of mobile location estimation technology as short terms (emergency calls, fraud detection and location based bills), intermediate terms (location sensitive browsing, fleet management and intelligent transportation systems (ITS)) and long terms (resource allocation and management) [3], [4].

The idea of combining data (data fusion) for mobile location estimation was proposed in the beginning of this century. Reza fused the time of arrival (TOA) and time difference of arrival (TDOA) in a simple environment via Bayesian rules [5]. At the same time, Mérigeault *et al*. used a multilayer perceptron neural network (MLP-NN) which combined TDOA, TOA and direction of arrival (DOA) to obtain the user's location. By ignoring edge diffraction, they considered an uncomplicated non line of sight (NLOS) wireless channel [6]. McGuire *et al.* mixed TOA and received signal strength (RSS) using a data fusion technique that was based on a non-parametric estimation method [7]. They estimated the position of mobile user in a Manhattan area with a specific mobile station configuration. A hierarchical MLP-NN structure is proposed in [8] based on fusing the signals of the base transceiver station (BTS) antenna array in term of autocorrelation. The mobile location estimation method proposed in [8] used a real environment with two base stations.

In this paper, the feature vectors are obtained by fusing user's signal information and then an effective post processing is employed to estimate mobile locations. Note that each location is presented by a unique feature vector. We consider a real environment that is modeled by a ray tracing software and an actual BTS configuration of the Toronto University campus. Using this model, all details of a wireless channel can be taken into account.

2. PROPOSED ALGORITHM

Several data extraction methods have been used for data fusion procedure. In [6], a multipath mobile channel was modeled based on time information (TOA and TDOA) that is extracted by signal shifting and filtering. In [7], the data were estimated from the proposed channel model. These models result in large error, due to the complex characteristics of mobile channels especially in dense urban areas.. Also important details of mobile channel are ignored. In [9], a complex numerical algorithm (Least Square) was used after statistical mobile channel modeling. Although

radio signal propagation simulation software was used in [8], actual BTS configuration and intelligent combination and recognition of information have never been considered in a real dense urban. All of these methods can estimate the user's position continuously.

In our approach, a combination of all post-processed estimated information, *i.e.*, TOA, AOA and RSS achieved from the radio link between mobile user and BTS by a multi-resolution algorithm i.e., Matrix Pencil (MP), makes an exclusive feature vector for each location. Then by an intelligent pattern recognition method, the location of user is estimated in a real dense urban.

First, the propagation information (location profile) of survey points for the three base stations is obtained by Urban Signal Propagation Simulator (USPS) software, developed in the Electrical Engineering Department of Ferdowsi University of Mashad [8]. This software analyzes the radio signal propagation through a wireless channel and the survey points are randomly distributed over the city. These base stations are made of triangular array antennas which consist of three arrays with M elements in each array. All multi-path information of channel is collected in the location profiles. The received signal to a BTS is simulated by the information in the location profiles and then, MP algorithm is used to estimate the AOA data in each array of a BTS. Using AOA algorithm, the received signal strength in each sector is calculated. The TOA data is estimated by applying the MP algorithm on channel impulse response in the frequency domain.

According to the multi-path nature of wireless channels, this raw estimated information of time, direction and power of received signals is totally useless for pattern recognition algorithms. In the next phase, the raw information is processed for discarding useless information, normalization, feature selection and creating feature vectors in an equal and optimum size for all survey points. The pairs of the feature vectors (data pattern) and their joint locations, called plans, are used for training the SVM network as the pattern recognizer tool. This network can be used as a mobile terminal location estimator. Each SVM can accept or reject the association of an input feature to one class with a confidence coefficient. Therefore, the number of SVM nets is exactly equal to the number of locations (classes).

3. MOBILE LOCATION ESTIMATION PROCEDURE

Having a triangular array antenna in each BTS can reduce the call traffic problem by changing the sub-cells (via main lobe shifting) in rush hours and also it is compatible with 2G and 3G of mobile communication networks [10]. To avoid the complexity, the number of elements in each array and the distance between elements are kept equal. Also, it is assumed that the received signal in each array does not have any effect on its next array's reception.

3.1. TOA AND AOA DATA ESTIMATION USING MP ALGORITHM

Suppose that a linear array of M elements has a normalized element's distance *d*. A set of N plane wave single-frequency signals with $\alpha_1, \alpha_2, \cdots, \alpha_N$ strengths and $\theta_1, \theta_2, \cdots, \theta_N$ directions are arrived to the antenna array. The signal received by the k-th element is:

$$y_k = \sum_{i=1}^{N} \alpha_i \exp\left(j2\pi(k-1)d\cos(\theta_i)\right) = \sum_{i=1}^{N} \alpha_i z_i^{k-1} \quad (1)$$

k=1, 2, . . . , M

The MP method starts by choosing an optional parameter, L, known as the pencil parameter, which not only determines the length of the moving window but also it is an important factor for noise discarding. A window with a length of L+1 on these spatial signals is considered. It can be proved that if L satisfies $N \le L \le M - N$ then in the $X_1 - \lambda X_2$ matrix pencil for $\lambda_i = z_i$, each z_i would be a rank reduction [11]. The matrixes X_1 and X_2 are defined as

$$X_1 = X(:, 1:L)$$
$$X_2 = X(:, 2:L+1) \quad (2)$$

where

$$X = \begin{bmatrix} y_1 & y_2 & \cdots & y_{L+1} \\ y_2 & y_3 & \cdots & y_{L+2} \\ \vdots & \vdots & & \vdots \\ y_{M-L} & y_{M-L-1} & \cdots & y_M \end{bmatrix} \quad (3)$$

In other words, the MP algorithm can estimate the poles of the transfer function. For this reason, it is suitable for TOA estimation. Also, the MP algorithm uses the data from a single snapshot even through using more snapshots (if they are available) improves the estimation. The poles are achieved by

$$\lambda I = X_1^+ X_2 \quad (4)$$

where X_1^+ is the pseudo-inverse of X_1. The AOA data is computed from the λ_is. For noise discarding purposes, an adaptive singular value decomposition (SVD) algorithm is used. A wireless

multipath channel consisting of N-path components can be modeled by:

$$h(t) = \sum_{i=1}^{N} \alpha_i \delta(t - \tau_i) \tag{5}$$

where τ_i and α_i stand for propagation delay and attenuation factor of the i-th path, respectively [12]. The Fourier transfer of $h(t)$ is:

$$H(f) = \sum_{i=1}^{N} \alpha_i Z_i \tag{6}$$

in which $Z_i = \exp(-j2\pi f \tau_i)$. By comparing (6) with (1), it is concluded that the MP algorithm could be used for TOA estimation. To apply the MP method in the frequency domain, M frequencies with equal distance, Δf, are chosen around the channel carrier frequency, f_0, in order to obtain an M-element array in frequency domain. One can rewrite (6) on the chosen M points as:

$$\begin{aligned} H(k\Delta f) &= \sum_{i=1}^{N} \alpha_i \exp(-j2\pi(f_0 + k\Delta f)\tau_i) \\ &= \sum_{i=1}^{N} \alpha_i \exp(-j2\pi f_0 \tau_i) \exp(-j2\pi k \Delta f \tau_i) \\ \mathrm{k} &= 0, 1, 2, \ldots, \mathrm{M}\text{-}1 \end{aligned} \tag{7}$$

the $\exp(-j2\pi f_0 \tau_i)$ has the same phase shift on each point and can be ignored. Then (7) is reduced to:

$$H_k = \sum_{i=1}^{N} \alpha_i \exp(-j2\pi k \Delta f \tau_i) \tag{8}$$

By a proper choice of *L*, the poles of transfer function can be estimated and the propagationdelays, τ_is, can be calculated. If the BTSs work in the synchronized mode, the estimated data will provide the TOA information of the user.

The main problem in estimating TOA by the MP algorithm is lack of channel frequency response. In [12], a Total Least Square (TLS) method is applied on the training bits to estimate the channel. In [11], an optimum number of training bits are used to achieve the Rayleigh channel response. In our procedure, a propagation simulator, USPS, uses a 2D map of the environment to compute the propagation profile of the wireless channel. The profile's information is gathered by ray tracing technique that considers the reflection as well as diffraction of the signal by launching the signal in all directions from the transmitting antenna.

The profile consists of a number of paths between the user and BTS, angle of arrival for each path in the location of BTS, the signal strength and the path propagation delay, all in a single frequency. In channel modeling with this profile, fast fading is ignored. Therefore, the signal attenuation factor is time-invariant.

3.2. RECEIVED SIGNAL STRENGTH ESTIMATION

Consider a linear array antenna which contains M elements. The array output is calculated by [14]

$$y = \sum_{k=0}^{M-1} x_k w_k = WX^T \tag{9}$$

where T stands for transpose operation and the vectors *W* and *X* represent the weighting vector and received signal vector, respectively. It can be shown that *W* is a main parameter for beam forming applications and it determines the antenna main lobe direction. The weighting vector, *W*, sets the array antenna reception in a special direction. If *W* is selected as a steering vector at θ, the array reception direction will be changed to θ. A steering vector for an *M* elements array at θ is defined as:

$$a_\theta = \left[1, e^{j2\pi \frac{d}{\lambda}\cos\theta}, e^{j2\pi \frac{2d}{\lambda}\cos\theta}, \ldots, e^{j2\pi \frac{(M-1)d}{\lambda}\cos\theta}\right]^T \tag{10}$$

where *d* is the normalized distance between the elements. The results show that the estimations of AOA, TOA and RSS are robust to the noisy conditions.

4. SUPPORT VECTOR MACHINE (SVM) NETWORKS

Support Vector Machine (SVM) has been used in pattern recognition problems as a powerful tool. This algorithm uses the Structural Risk Minimization (SRM) technique to increase the distance between classes in feature space via a fixed risk factor [14]. The SVM algorithm defines a hyper-plane in the feature space while data is linearly separable, and the hyper-plane parameters are optimized by SRM technique. But for nonlinear data, such as location data in our problem, a kernel function maps the nonlinear feature space to a linear one. SVM does not stop at a local minimum and always has a unique solution in its global minimum. The two main parameters of the SVM design are the confidence distance and the kind of kernel function. In this paper, because of the nonlinearity of feature space, radial basis function (RBF) or Gaussian kernel is used as K(X, Y) in (11).

$$K(X, Y) = \exp\left(\frac{(X - Y)^2}{\Sigma}\right) \tag{11}$$

where X is the input vector, Y is the network target vector and (X-Y) shows the distance vector. Σ is the kernel parameter chosen from a predefined range. By defining a set of validation data and varying Σ in this range, the best SVM network will be obtained. This process is the same as training phase in neural networks.

5. POST-PROCESSING, FUSION AND FEATURE VECTOR

The raw information is categorized per sector of the receiver antenna. The number of sectors in post-processing is chosen 3, 4, 6 and 8, based on the implementation considerations. In post-processing, the row information of user location (class), *i.e.*, a vector of AOA per each BTS (length varying from one user to another and dependent on the number of sectors), RSS vector per each BTS (reliant on the number of sectors) and TOA vector per each BTS (user's position dependent), are transferred to a determined dimension space and they are mixed together.

The classification procedure categorizes the feature vectors according to the mobile terminal locations, which is known as pattern recognition technique. The feature selection is very important in this technique. Features of the same class must have a small difference and features of two classes should have a significant difference.

To achieve the best result, three kinds of features are chosen from a set of 10. To increase the accuracy, each feature is post-processed by 3, 4, 6 and 8 sectors,

- **Feature Vector 1 (Z1)**: An array with eight elements per BTS; half for RSS data of four sectors and half for statistical TOA data.
- **Feature Vector 2 (Z2)**: An array with eight elements per BTS; half for presenting RSS level (very high, high, normal, weak, very weak and not received) of the sectors and half for statistical TOA data.
- **Feature Vector 3 (Z3)**: An array with six elements per BTS; two elements for two top RSS data and the rest for statistical TOA data.

The statistical data of TOA method is minimum, maximum, variance and mean of time arrival of received signal. The ultimate feature vector is made by mixing these arrays which are obtained from each BTS.

6. SIMULATION

For simulation, a part of the University of Toronto campus in the size of 800 m by 800 m is selected (Fig. 1). Positions of base stations are set to (660,540), (300,265) and (105, 465) according to the mobile net provider's map. The environment is separated to 16 non-overlapping square areas by the side of 200m. More than 2300 randomly survey points are simulated by USPS over the environment, where the user in these points is connected at least to one of the three base stations. The simulation parameters are presented in Table I.

TABLE I. SIMULATION PARAMETER

parameter	Description	Value
M	Number of Array Elements	15
M_f	Number of Frequency Ref. Points	40
L	Pencil Parameter	8
f_o	Carrier Frequency	900 MHz
Δf	Frequency Step	35% of max path delay
Σ	RBF Kernel Parameter	$0.01 < \Sigma < 2$

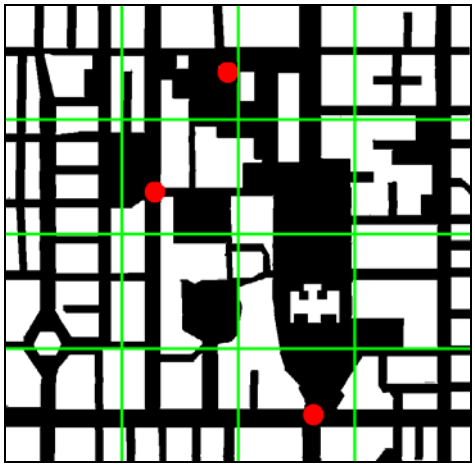

Figure 1. The simulated environment. The base stations are shown by circles.

Eighty percent of data is used for the SVM training phase and the rest is used for the testing phase. The simulation is run by MATLAB® for Z1, Z2 and Z3 feature vectors in 3 sectors (120°), 4 sectors (90°), 6 sectors (60°) and 8 sectors (45°).

Table II shows the classification results as well as the size of features. The misclassification is varying from 23% (as in Z1-3) to 34% (Z1-3). The true classification has an average of 71.5% in a square location of 200 m side. The neighbor misclassification rate as shown in Table II is a little more than 25% and non-neighbor misclassification is about 3%. This result shows that the SVM classification system can locate the mobile user in a square area by a side of 200m (with an in-circle by a radius of 100m). In other words, the

misclassification errors are mostly around the true cell.

The average value of error, defined as the distance of user from cell border, is computed. Table III illustrates this kind of error in squared area around the estimated cell. The results are presented as in-circle's radii. In other words, the first column is the true classification rate, and the last one is the average value of the correctly estimating location in a square area by half side of 400m.

TABLE II. SVM CLASSIFICATION RESULT

Pattern - Sector	size	Correctly Classified	Confused by Neighbor classes	Confused by Non-neighbor classes
Z1 - 3	21	66.0	29.3	4.7
Z1 - 4	24	72.7	24.7	2.6
Z1 - 6	30	77.0	21.5	1.5
Z1 - 8	36	76.4	21.7	1.9
Z2 - 3	21	73.0	24.4	2.6
Z2 - 4	24	73.4	24.2	2.4
Z2 - 6	30	68.4	29.0	2.6
Z2 - 8	36	68.9	27.7	3.4
Z3 - 3	18	75.7	21.7	2.6
Z3 - 4	18	68.2	25.6	6.2
Z3 - 6	18	68.2	28.4	3.4
Z3 - 8	18	70.8	26.6	2.6
Average		71.56	25.40	3.04

TABLE III. SVM LOCATION ERROR PER DISTANCE OF THE CELL CENTER IN SQUARE AREA ACORDING TO THE INCIRCLE RADIUSE

Pattern-Sector	100m	175m	200m	250m	300m	400m
Z1-3	66.0	75.9	79.8	89.5	94.6	95.7
Z1-4	72.7	82.6	86.0	91.2	97.2	98.5
Z1-6	77.0	84.7	88.2	92.7	98.1	98.3
Z1-8	76.4	84.3	88.6	94.7	97.6	98.1
Z2-3	73.0	82.9	86.9	91.4	97.2	97.9
Z2-4	73.4	81.3	84.5	91.4	97.8	98.5
Z2-6	68.4	81.7	86.0	90.6	97.0	98.1
Z2-8	68.9	78.8	83.7	89.3	96.1	98.1
Z3-3	75.7	84.7	89.3	92.7	96.8	98.1
Z3-4	68.2	77.5	82.6	87.3	92.5	95.1
Z3-6	68.2	77.9	83.9	89.3	95.7	97.0
Z3-8	70.8	81.8	85.8	91.4	96.6	97.4
Average	71.6	81.2	85.4	90.9	96.4	97.6

According to the results:

- The output of SVM network is the class number (1 to 16) and accordingly, this method could be useful in discrete mobile user tracking.
- The average value of correct classifications in the square areas for sizes of 100m, 200 m and 400m are 71.6%, 85.4% and 96.4%, respectively (Table III).
- 90% of the calls can be located correctly in a square area by the side of 500 meters and consequently, a hierarchical structure can improve accuracy (the next phase of research).
- The best feature vectors based on precision in the area size of 100m, 200m, 300m, and 400m are Z1-6, Z3-3, Z1-6 and Z1-4 (or Z2-4), respectively (Table III).
- Z1-6 and Z1-8 can estimate the location of mobile user more accurate than other vectors.

Finding the previous researches for comparing the results is difficult because the idea of *discrete* mobile user positioning is novel. The SVM classification results are compared with the FCC requirements and the result of [8] in Figure 2. In [8], two base stations which are installed out of the urban environment and 150 survey points per cell are taken into account. The results show that the SVM network can estimate the mobile user location better than the proposed method in [8], especially for the upper 200 m cell sizes. Also, it satisfies the FCC requirements. However, this method cannot estimate the user location for under 100m because of the discrete nature of estimation.

7. CONCLUSIONS

In this paper, a novel method based on the support vector machine technique is proposed to estimate the mobile user location. The algorithm takes advantage of time, angle and power features of the received signal to achieve an acceptable estimation. The simulation results indicate that the average error in location estimation is less than 100m in almost 72% of calls, which satisfies the FCC requirements in network-based solution. This method can be implemented without requiring any extra equipment for mobile terminals (handsets).

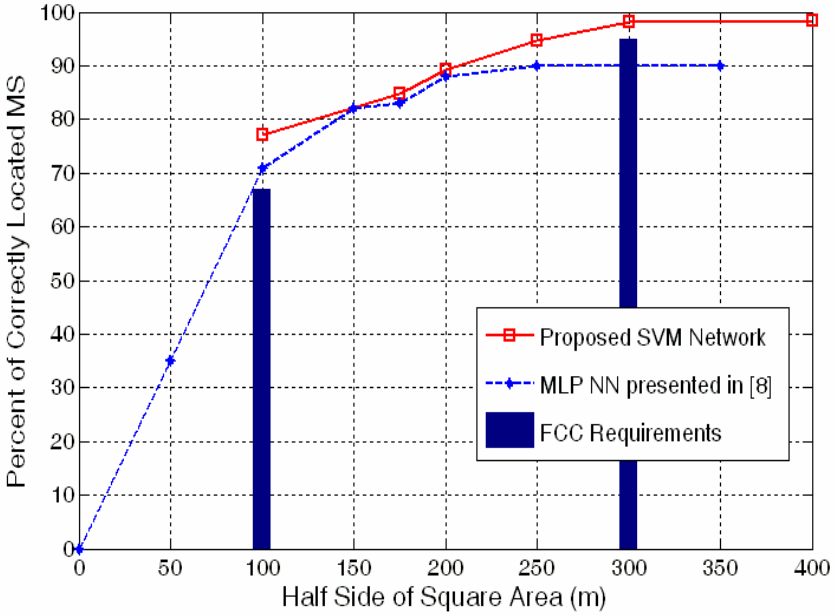

Figure 2. The SVM mobile user location estimation results compared with the results in [8] and the FCC requirements.

ACKNOWLEGEMENT

The authors appreciate partial support of this research by Iran Telecom Research Center.

REFERENCES

[1] Y. Zhao, "Mobile phone location determination and its impact on intelligent transportation systems," IEEE Trans. Intelligent Transportation Systems, vol. 1, no. 1, pp. 55 – 64, March 2000.

[2] http://www.fcc.gov/Bureaus/Engineering_Technology/Public_Notices/1999/da992130.html.

[3] 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, April 1998.

[4] M. McGuire, K. N. Plataniotis and A N. Venetsanopoulos, "Location of mobile terminals using time measurements and survey points," IEEE Trans. Veh. Technol., vol. 52, no. 4, pp. 999 – 1011, July 2003.

[5] R. I. Reza, Data Fusion for Improved TOA/TDOA Position Determination in Wireless Systems, M.S. Thesis, Virginia Polytechnic Institute and State University, 2000.

[6] S. Merigeault, M. Batariere and J. N. Patillon, "Data fusion based on neural network for the mobile subscriber location," Vehicular Technology Conference, IEEE VTS, vol. 2, pp. 536 – 541, 2000.

[7] M. McGuire, K. N. Plataniotis and A. N. Venetsanopoulos, "Location of mobile terminals using time measurements and survey points," IEEE Trans. Veh. Technol., vol. 52, no. 4, pp. 999 – 1011, July 2003.

[8] H. Zamiri-Jafarian, M. M. Mirsalehi, I. Ahadi-Akhlaghi and H. Keshavarz, "A neural network-based mobile positioning with hierarchical structure," Vehicular Technology Conference, VTC 2003. The 57th IEEE Semiannual, pp. 2003 - 2007 vol.3, April 2003.

[9] C. Chao-Lin and F. Kai-Ten, "An efficient geometry-constrained location estimation algorithm for NLOS environments," International Conf. Wireless Net., Comm. and Mobile Computing, vol.1, pp. 244 – 249, June 2005.

[10] M. Moghadam, Capasity Improvement by Rotatble Equal Sectorization Method in CDMA Cellular Systems, M.S. Thesis, Electrical Enginireeng Department, Ferdowsi University of Mashad, 2005.

[11] K. Bayat and R. S. Adve, "Joint TOA/DOA wireless position location using matrix pencil," Vehicular Technology Conference VTC2004, , vol. 5, pp. 3535–3539, Sept. 2004.

[12] N. Dharamdial, R. Adve and R. Farha, "Multipath delay estimations using matrix pencil," Wireless Communications and Networking, WCNC 2003, vol. 1, pp. 16-20, 2003.

[13] T. K. Sarkar, M. C. Wicks, M. Salazar-Pama and R. J. Bonneau, Smart Antennas, IEEE Press, 2003

[14] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," Data Mining and Knowledge Discovery Conf., vol. 2, pp. 955-974, 1998.