TRACKING OF MOBILE PHONE USING IMM IN CDMA ENVIRONMENT

Jihyo lee, H. Ko

Department of Electronics Engineering, Korea University
5Ka-1, Anam-dong, Sungbuk-ku, Seoul, 136-701, Korea.
Email : jhlee@ispl.korea.ac.kr, hsko@korea.ac.kr

ABSTRACT

This paper proposes an effective method to localize mobile phones in CDMA environment. This is to remedy the performance limitation inherent in the traditional localization algorithms, which make use of the present information only. If a Kalman filter is used that includes the previous information of location of a mobile unit, then the location error can be significantly reduced. Since the actual movement of a user is difficult to be represented by only one motion model, it will show better error performance if an interacting multiple model (IMM) that uses several Kalman filter models is applied in place of just one Kalman filter. Performance analysis of the location error between Kalman filter and IMM implementation confirm our postulation that IMM significantly reduces location error.

1. INTRODUCTION

Current techniques for determining the location of a mobile station (MS) are signal strength, AOA (Angle Of Arrival), TDOA (Time Difference Of Arrival) and TOA (Time Of Arrival). The localization algorithms require above three base stations that are receiving the transmit signal of a MS except AOA method. In the current CDMA environment where the power control is executed, a MS decreases the level of transmission power of the signal when it is located near a base station and vice versa when it is located further away. Sometimes, other base stations can't receive the signal from the MS due to the attenuation of the signal strength, unless the MS is located within the soft hand off region. It can't secure the base stations that are needed to execute localization algorithm of MS.

In order to complement these problems, a newly added PUF (Power Up Function) in IS-95B is used to increase the level of transmit signal power of the MS for a limited time through the reverse traffic channel. That is, to overcome the limitations of applying the current localization algorithm by enhancing the level of the signal power of the MS and to make it possible to secure the number of base stations needed for the localization of the MS.

The localization algorithms using the signal strength, TOA, and TDOA method with PUF applied are used in this paper. However, localization of a MS with respect to time does not include the relationship of the location of the MS at previous sampling time. Therefore, it will be possible to reduce the error of the localization of a MS if Kalman filter that includes considerations on the location at previous time is applied.

Kalman filter was used to reduce the localization error of a MS using the signal strength in the GSM environment [1]. However, there are limitations in describing the movement of an actual MS by using only one model. Therefore, errors can be reduced further if various models of constant-velocity and constant-acceleration are used together to detect the location of the target rather than applying Kalman filter that uses only one model. So, MS localization algorithm using IMM is proposed in this paper to reduce the location error.

2. LOCALIZATION ALGORITHM

In order to determine the location of a MS, information on the distance between base stations and MS is required. An adequate method can be chosen between signal strength and time, according to the method of acquiring the distance information.

When signal strength method is applied, power control between base station and MS must be considered because signal strength method uses the power of the signal. The distance between base station and MS can be computed by using path loss.

Time information is applied on methods such as TOA and TDOA. DLL is used for the synchronization of signal is applied in order to compute the time difference between base station and MS. The structure of the DLL used in the simulation is shown in Fig. 1.

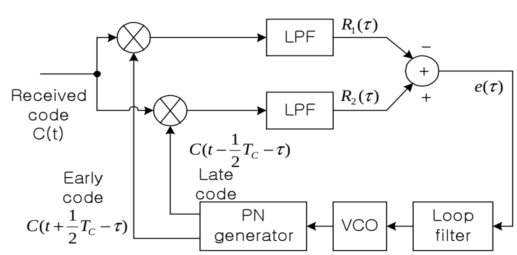

Fig. 1 Structure of DLL

After the distance information between base station and MS is obtained, location of MS is determined from localization algorithm. The same localization algorithm is used among signal strength and TOA since the only difference is their method of acquiring the distance information. Three methods were introduced in this paper. Method (1) is by using common chord of intersection of circles. Method (2) is by using the average value of three points of intersecting point among three circles. Method (3) is by using weighted distance value. If the measured distance from the base station 'i' is large, small weight is assigned in order to reduce the error of localization within the common region.

In the case of TDOA, a method using a hyperbola and a method using an oval are frequently used. However, hyperbola method revealed a defect that the point of intersection indicating the location of MS turned out to be more than two, even when the number of base stations were increased to use several hyperbolas. Therefore LOP (Line of Position) using longer axis of the oval was applied in the actual performance analysis for this paper.

3. TRACKING ALGORITHM

Location of MS can be determined by using localization algorithms mentioned in section 2. However, use of only localization algorithm has limitations.

If past distance information of MS is referred to determining current location, more accurate location will be found. In other words, when the error of the final location obtains from distance information between base station and MS is high at current time, past location of MS can be used to help determine more accurate location of MS at current state. Therefore, a method that determines the location of MS with respect to time using two parameters is necessary. The first parameter is the value of the location of MS obtained from distance information. The second parameter is a state value that estimates the movement of MS by assuming movement of a user as an equation of motion. The algorithm that can be applied to solve this problem is the Kalman filter. Kalman filter is the algorithm that determines the final location of the target by using state and measurement values derived from equations mentioned above. However, expressing the movement of an actual MS with an equation has limitations so that enhanced form of Kalman filter such as MM (Multiple Model) or IMM (Interactive Multiple Model) should be applied. IMM is selected in this paper since IMM is evaluated as better than MM due to its ability of transition between models.

Important point to notice in IMM algorithm is that interaction occurs among previous state values of each model for the calculation of the next state value under the assumption that transition between each model occurs with Markov Process. The structure of IMM is shown in Fig. 2. As the Fig. 2 shows, IMM is composed of three main parts. They are interaction, filtering and combination.

The interaction part determines the initial conditions of each Kalman filter at each sampling time. Previously determined state values and weighted sum of the mixing probability represent the interaction part[2][3].

$$\mu_{i|j}(k-1|k-1) = (1/\bar{c}_j)\, p_{ij}\mu_i(k-1) \tag{1}$$

$$\hat{x}_{0j}(k-1|k-1) = \sum_i \hat{x}_i(k-1|k-1)\mu_{i|j}(k-1|k-1) \tag{2}$$

$$\begin{aligned} P_{0j}(k-1|k-1) = \sum_i \{ & P_i(k-1|k-1) + [\hat{x}_i(k-1|k-1) - \\ & \hat{x}_{0j}(k-1|k-1)] \times [\hat{x}_i(k-1|k-1) - \\ & \hat{x}_{0j}(k-1|k-1)]^T \} \times \mu_{i|j}(k-1|k-1) \end{aligned} \tag{3}$$

$\mu_{i|j}(k-1|k-1)$ is the mixing probability using weight at time k-1, P_{ij} is the Markov model switching probability from model i at time k-1 to model j at time k. $\bar{c}_j$ is a normalizing factor and $\mu_i(k-1)$ is the probability about model j at time k. $\hat{x}_{0j}(k-1|k-1)$ and $P_{0j}(k-1|k-1)$ are the mixed initial condition for Kalman filter j at time k-1, and $\hat{x}_i(k-1|k-1)$, $P_i(k-1|k-1)$ are the state estimate and its covariance matrix in Kalman filter i at time k-1 [3].

The filtering part determines the state estimate $x_j(k|k)$ and its covariance matrix $p_j(k|k)$ by using the initial conditions derived from the iteration part. $\mu_j(k)$ is the probability of model j at time k which can be calculated using the likelihood function about model j.

$$\Lambda_j(k) = N(r_i(k); 0, S_j(k)) \tag{4}$$

$$\mu_j(k) = \frac{1}{c}\Lambda_j(k)\sum_i p_{ij}\mu_j(k-1) \tag{5}$$

$\Lambda_j(k)$ is the likelihood function of model j, c is a normalizing factor.

Finally, the combination part determines $x(k|k)$, $P(k|k)$. It is derived by the value of the state and covariance matrix determined at the Filtering part and weighted sum of the $\mu_j(k)$.

$$\hat{x}(k|k) = \sum_j \hat{x}_j(k|k)\mu_j(k) \tag{6}$$

$$\begin{aligned} P(k|k) = \sum_j \{ & P_j(k|k) + [\hat{x}_j(k|k) - \hat{x}(k|k)] \\ & \times [\hat{x}_j(k|k) - \hat{x}(k|k)]^T \}\mu_j(k) \end{aligned} \tag{7}$$

Fig. 3 is the final localization algorithm of MS in the IS-95B environment. The concept of MS tracking can be realized by applying localization with respect to time, Kalman filter or IMM algorithm.

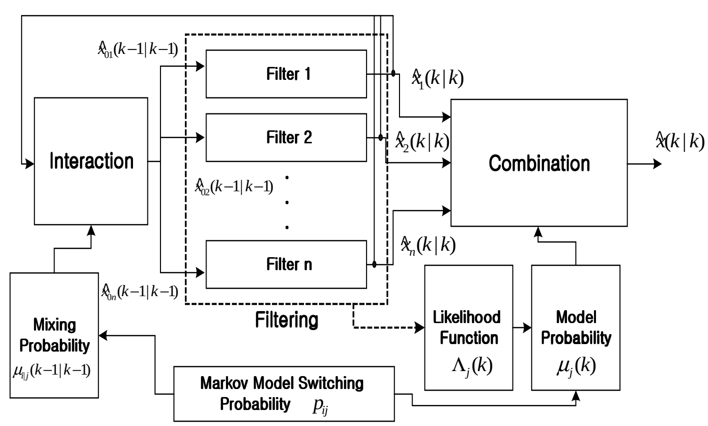

Fig. 2 Structure of IMM

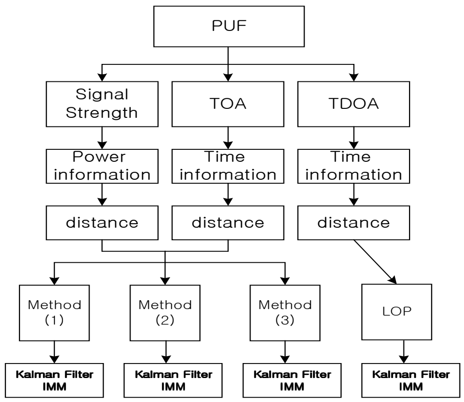

Fig. 3 Block diagram about tracking algorithm of MS

4. EXPERIMENT

We performed two experiments. In the first experiment, MS localization algorithms using signal strength, TOA and TDOA are compared and analyzed. In the second experiment, MS localization algorithms and tracking algorithms, Kalman filter and IMM, are performed.

Two scenarios are considered for experiment as shown in Fig. 4. The initial coordinate of a MS is (1800,2700) and the path of the MS movement is chosen to be within seven uniform cells that have a radius equaling R each. The velocity of the MS movement is 70Km/h. The total time of simulation taken for scenario 1 is 205 seconds and 300 seconds for scenario 2. The results after executing 200-run Monte Carlo simulation were taken for the analysis of the simulation.

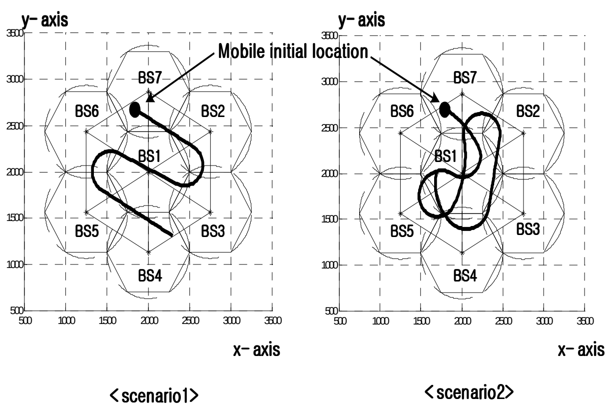

Fig. 4 Scenario for Simulation

4.1 Localization Algorithm

Based on the algorithms shown in section 2, experiment on the localization of a MS in the CDMA environment is performed in this section.

Table 1 shows the mean and variance of RMS error when the signal strength algorithm is used. The values are calculated from the actual location of MS and the measured location of MS. The measured location is the result from applying the three methods in section 2. As the Table 1 shows, method (1) is better in performance than method (2) or (3) regardless of the scenario being used. Table 2 shows the mean and variance of RMS error when the TOA and TDOA algorithm are used. In the case of TOA, the result is similar to Table 1.

Although the same localization algorithm is used among signal strength and TOA, they cannot be simply compared with each other because of the difference between the methods acquiring distance information. The localization algorithm using signal strength has a fatal defect. With the increment of the radius of the cell, the RMS error is also increased. This phenomenon is caused by nonlinear characteristic of pathloss equation.(see Table 3)

Table 1. RMS location error(meter) [signal strength]

Noise Variance $\sigma^2 = 1$ (w)				
	Scenario 1		Scenario 2	
	mean	variance	mean	variance
Method1	**133**	**262**	**131**	**270**
Method2	153	770	150	802
Method3	147	604	145	628

Table 2. RMS location error (meter) [time]

Noise Variance $\sigma^2 = 1.6 \times 10^{-7}$ (sec)				
	Scenario 1		Scenario 2	
	mean	Variance	mean	variance
Method1	**84**	**262**	**85**	**315**
Method2	110	1458	110	1580
Method3	105	1141	105	1275
LOP	75	409	74	419

Table 3. RMS location error according to increasing Radius (meter) [signal strength]

Noise Variance $\sigma^2 = 0.25$ (w), Scenario 1				
	Radius = 500m		Radius=1000m	
	mean	Variance	mean	variance
Method1	44	104	86	808
Method2	67	288	101	1970
Method3	62	250	116	2326

4.2 MS Tracking Algorithm

The Kalman filter applied to the simulation is a three dimensional kinematic model which is a discrete time constant-acceleration model. σ^2_v which is the parameter for the acceleration part of

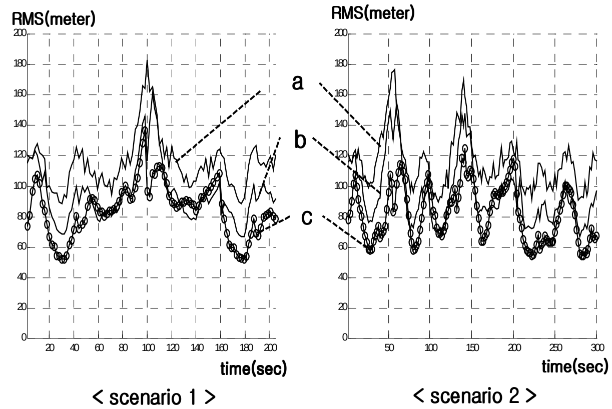

Fig. 5 Comparison between Kalman Filter and IMM [TOA]

Table 4. RMS error using tracking algorithm(meter) [TOA]

Noise Variance σ^2 (sec)	Scenario 1				Scenario 2			
	1.6×10^{-7}		2.3×10^{-7}		1.6×10^{-7}		2.3×10^{-7}	
	m	var	m	var	m	var	m	Var
Method1	85	283	**115**	**314**	85	301	**115**	**341**
KF	72	328	**95**	**368**	72	394	**95**	**424**
IMM	70	327	**84**	**316**	67	372	**82**	**332**

the process noise covariance is set to 30. A total of three models are applied in the case of IMM. The first model is a constant-velocity model with $\sigma^2{}_v = 5$ and other two models are constant-acceleration models with $\sigma^2{}_v = 30$, and $\sigma^2{}_v = 200$. [2] is used as a reference in assigning weights for the switching of each model.

Table 4 and 5 show the mean(m) and variance(var) of RMS error when the Kalman filer(KF) and IMM algorithm are applied in the case of TOA and TDOA. The mean and variance of the RMS error show that application of IMM leads to enhanced performance minimizing location error. As the result of the comparison between localization algorithm(method (1)) and IMM in Table 4, application of IMM results in performance improvement about 24m when noise variance is set to 2.3×10^{-7} sec. Comparing with Kalman filter, application of IMM obtains performance improvement about 11m. Comparing with LOP in Table 5, application of IMM obtains performance improvement about 35m when noise variance is set to 2.3×10^{-7} sec. Comparing with Kalman filter, application of IMM obtains performance improvement about 13m. Fig. 5 shows the result of Table 4. It is a plot of the result of applying Kalman filter and IMM when noise variance is set to 2.3×10^{-7} sec. 'a' represents the RMS error in the case of method(1), 'b' represents the RMS error when Kalman filter is applied and 'c' represents the RMS error when IMM is applied.

Fig. 6 shows the determined location of MS with respect to time using Kalman filter and IMM in the case of TDOA when noise variance is set to 1.6×10^{-7} sec.

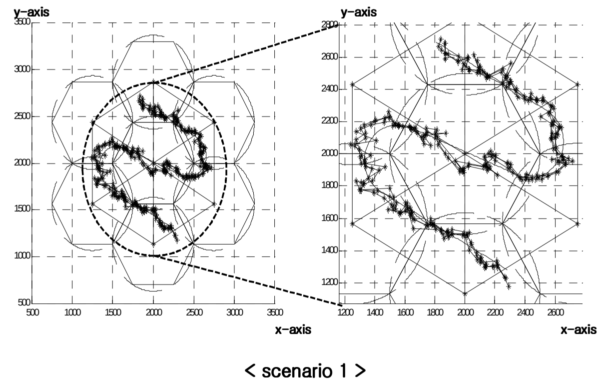

Fig. 6 MS tracking using the Kalman Filter and IMM [TDOA]

Table 5. RMS (meter) using tracking algorithm [TDOA]

Noise Variance σ^2 (sec)	Scenario 1				Scenario 2			
	1.6×10^{-7}		2.3×10^{-7}		1.6×10^{-7}		2.3×10^{-7}	
	m	Var	m	var	m	var	m	Var
LOP	75	409	**127**	**3899**	74	419	**131**	**5609**
KF	58	253	**101**	**2541**	56	236	**103**	**3552**
IMM	50	170	**83**	**1910**	49	154	**85**	**1102**

5. CONCLUSIONS

The simulation result showed that the method(1) gave the minimum error among the three localization algorithms, the method (1), (2),(3), in the case of signal strength and TOA.

The comparison analysis of the location error between localization algorithm and tracking algorithm showed that tracking algorithm obtain performance improvement. Especially, application of IMM could minimize the location error in CDMA environment. It is supported by experiment in section 4.2.

6. REFERENCES

[1] Martin Hellebrandt and Rudolf Mathar, "Localization Tracking of mobiles in Cellular Radio Networks", IEEE Transaction On Vehicular Technology, Vol.48, No 5, pp.1558-1562, September 1999.

[2] A.House and Y.Bar-shalom, "Multisensor Tracking of a Maneuvering Target in Clutter", IEEE Transactions On Aerospace and Electronic Systems, Vol. AES25, No 2, March 1989.

[3] E.Mazor, A.Averbuch, Y.Bar-shalom "Interacting Multiple Methods in Target Tracking", A Survey, IEEE Transactions On Aerospace and Electronic Systems, Vol. 34, No 1, January 1998.