Road-Constrained Mobile Station Tracking in GSM Networks in the Presence of NLOS Error

Miao Zhang, Stefan Knedlik, Otmar Loffeld
Center for Sensorsystems (ZESS), University of Siegen
Paul-Bonatz-Str. 9-11, D-57076 Siegen, Germany
zhang@zess.uni-siegen.de

BIOGRAPHY

Miao Zhang received the B. E. degree in industrial automation and the M. E. degree in pattern recognition and intelligent system from the Department of Automatic Control, Beijing Institute of Technology, P.R.China, in 2001 and 2004, respectively. She is currently pursuing her Ph.D. degree at the Center for Sensorsystems (ZESS), University of Siegen, Germany. Her primary research interests are multisensor data fusion, localization and positioning, target tracking and estimation theory.

Stefan Knedlik received the Diploma degree in electrical engineering and the Dr. Eng. degree from the University of Siegen, Germany, in 1998 and 2003, respectively. Since 1998, he has been a member of the Center for Sensorsystems (ZESS), University of Siegen, and a Researcher and Lecturer with the Department of Signal Processing and Communication Theory. Since 2002, he has also been the Executive Director of the International Postgraduate Programme IPP Multi Sensorics. Within the IPP Multi Sensorics he founded a research group on navigation. His current research interests include signal processing and applied estimation theory in navigation and synthetic aperture radar interferometry.

Otmar Loffeld received the Diploma degree in electrical engineering from the Technical University of Aachen in 1982, the Eng. Dr. degree, and the ‘habilitation’ in the field of digital signal processing and estimation theory in 1986, and 1989, respectively, both from the University of Siegen. In 1991 he was appointed as a professor for digital signal processing and estimation theory at the University of Siegen. In 1995 Prof. Dr. Loffeld became a member of the Center for Sensorsystems (ZESS) which is a central scientific research establishment at the University of Siegen. Since 2005 he is the Chairman of that Center. His current research interests comprise multi sensor data fusion, Kalman filtering techniques for data fusion, optimal filtering and process identification, SAR processing and simulation, SAR-interferometry, phase unwrapping, and baseline estimation. A recent field of interest is bistatic SAR processing. Prof. Loffeld is a member of the ITG/VDE and Senior Member of the IEEE/GRSS.

ABSTRACT

GSM network has the potential to provide position information. Using some attributes of the radio signals exchanged between a Mobile Station (MS) and multiple Base Transceiver Stations (BTSs), the location of the MS can be determined. However, using GSM network based on current specifications for MS tracking faces many difficulties, especially in the presence of the Non-Line-of-Sight (NLOS) error, which is a critical issue for mobile positioning in wireless communication environment. In this paper we will deal with the road-constrained MS tracking problem in the NLOS situation by adding the NLOS mitigation method. The performance comparison of the road-constrained approach and the road-free approach shows that incorporating the road information greatly improves the tracking accuracy. The tracking accuracy under different motions will be examined and the road-constrained approach is proved to be effective for different moving scenarios. Moreover, the road-constrained approach can provide a reliable position estimate in the case of only two NLOS measurements available.

1 INTRODUCTION

As a widely used mobile communication standard, the Global System for Mobil Communications (GSM) network has shown the potential of providing position information. Using some attributes of the radio signals exchanged between the Mobile Station (MS) and multiple Base Transceiver Stations (BTSs), the location of the MS can be determined. The most commonly used measurements for the location purpose are Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) and Received Signal Strength (RSS). Moreover, knowing the movement characteristics of the MS over a period of time, the position of the next time step can be predicted. This dynamic state estimation problem exists in many applications, such as automatic vehicle location, intelligent transport system, and fleet management.

However, using GSM network based on current specifications for MS tracking faces many difficulties. The resolution of the measurements from GSM network related to positioning is coarse and ambiguities of the position estimate arise when there are no sufficient measurements available. We have presented an extended Kalman filter (EKF) based algorithm of incorporating road constraints into the tracking process as pseudomeasurements to improve the estimation accuracy and it has been proved to be effective and robust [1]. However, the Non-Line-of-Sight (NLOS) problem has not been considered yet. Therefore, in this paper we will deal with the road-constrained MS tracking problem in the presence of NLOS error by adding the NLOS mitigation method.

The NLOS error is a critical issue for mobile positioning in wireless communication environment. Due to reflection and diffraction, the radio signal may travel extra path lengths in the order of hundreds of meters and there might be no direct path from the BTS to the MS. In such situation, if the algorithm for Line-of-Sight (LOS) condition is directly utilized, the position estimates will be greatly diverged from the true values. The NLOS error can be modeled as additive bias to the LOS measurement with known or unknown distribution [2]. Therefore, the NLOS problem is actually the estimation problem of biased measurement. Under this assumption, there are two main categories of the NLOS error mitigation methods. One is that the NLOS error can be first detected, which is referred to as NLOS identification, and then be removed, which is called LOS reconstruction. Wylie *et al.* [3] proposed a simple hypothesis test to determine if the measurement is in LOS or NLOS condition since the standard deviation of the TOA is much bigger in the case of NLOS than that in LOS situation. This group of methods requires the prior knowledge of the bias and it has a shortcoming of a delay of the estimation. Another category of methods models the biases as additional states and they are also estimated in the same time with the position and velocity of the MS. Nájar *et al.* [4] treated the TOA biases for each BTS as additional parameters to be estimated and a random walk process is used to model the time transition of the bias. Kim *et al.* [5] proposed a two-stage filter in which the bias-free estimates are first obtained and the biases are estimated from the residual of this bias-free estimator, then the bias-free estimates are updated using the bias estimates. In practice, the statistics of the NLOS error is usually unknown or known limitedly. Therefore, the second category of methods is more attractive for the MS tracking application. In this paper, the NLOS mitigation approach of estimating the NLOS biases as augmented states will be added into the road-constrained approach, and the tracking accuracy under different dynamic motions will be examined. The main purpose of this paper is to further demonstrate the benefits of the proposed road-constrained tracking algorithm in the presence of NLOS error.

The rest of the paper is organized as follows. In section 2, the main measurements related to positioning from GSM networks are introduced and the observation models in the presence of NLOS error are given. In section 3, the problem of ground target tracking is formulated and the NLOS mitigation method is presented. In section 4 the road constraints are described and the road-constrained approach is given. In section 5, the simulation results are illustrated and discussed. Finally, conclusions along with suggestions for future work are given in section 6.

2 MEASUREMENT MODEL IN THE PRESENCE OF NLOS ERROR

There are a variety of technologies available to provide position estimate in GSM networks. They can be loosely grouped into two basic classes depending on where the position information are mainly obtained: handset-based solution and network-based solution. The handset-based solution relies on the use of a handset that includes a specialized chipset capable of calculating its own position, e.g. a Global Positioning System (GPS) receiver. On the other hand, the network-based solution uses the attributes of the radio signals exchanged between the MS and multiple BTSs to determine the MS's location. The most important measurements from GSM networks are TOA, TDOA, AOA, and RSS. Considering that the handset-based solution requires significant modifications in the mobile phone, the network-based solution is the focus of this work.

Moreover, according to whether the position estimate is obtained directly from the received signals or from an intermediate estimate, such as TOA, TDOA, AOA, and RSS, the positioning can be categorized into direct positioning and two-step positioning [6]. In this work the two-step positioning is used for the sake of low complexity, where some position related parameters are extracted first from the signals, and then the position and velocity of the MS are estimated from these intermediate parameters as shown in Fig.1. We focus on the second step. In the following, the measurement models for the TOA, TDOA, AOA, and RSS in the NLOS situation are described.

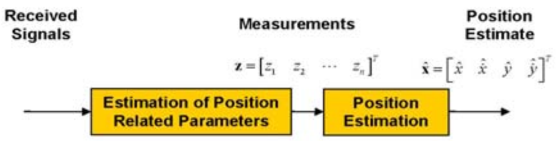

Fig.1 Two-Step Positioning

2.1 TOA

By measuring the transmission time that a signal takes to travel between a BTS and a MS, the distance between them can be calculated. However, this requires that the BTS and the MS are well synchronized or they know precisely the clock of each other. To avoid the synchronization problem, measuring the round trip time is more common utilized. Therefore, the measurement of TOA can be written as the distance between one MS and a certain BTS by a factor of the speed of light. Let (x, y) denote the position of the MS, $\mathfrak{B} = 1, 2, \cdots, n$ be the set of the BTSs and the position of the i^{th} BTS be (x_i, y_i). Assuming that NLOS errors exist for all BTSs in the BTS set $\mathfrak{B}$, the TOA measurement from the i^{th} BTS can be formulated as distance with noise.

$$z_{i,TOA}^{NLOS} = \sqrt{(x-x_i)^2 + (y-y_i)^2} + b_i + v_{i,TOA} \qquad (1)$$

where b_i is the positive bias induced by the NLOS propagation, the measurement noise $v_{i,TOA}$ can be assumed to be zero mean white Gaussian noise.

$$v_{i,TOA} \sim N(0, \sigma_{i,TOA}^2) \qquad (2)$$

Geometrically, one TOA measurement provides a circle. Using at least three BTSs to resolve the ambiguities in two dimensions, the intersection of circles provides the MS's position.

Timing Advance (TA) is such a TOA measurement in the GSM system. It is a parameter that a particular BTS sends to each MS according to the perceived round trip propagation delay BTS-MS-BTS. Then the MS advances its timing by this amount to compensate the propagation delay in order to avoid user time slot overlap and maintain the frame alignment, especially when the MS is far away from the BTS [7].

2.2 TDOA

Instead of the absolute time measurements, time difference measurements can be used to define hyperbolas. The intersection of hyperbolas provides the location of the MS. For two dimensional scenario, at least two TDOAs are required, i.e., three BTSs, to uniquely define a position. Similar as the TOA, the TDOA can be written as the difference of the distances. Assume that a BTS in the NLOS BTS set $\mathfrak{B}$ is chosen as the reference BTS $i = 0$, whose position is (x_0, y_0). For the i^{th} BTS of the rest BTSs, $i = 1, 2, \cdots, n-1$, the TDOA measurement relative to the reference BTS is modeled by

$$\begin{aligned} z_{i,TDOA}^{NLOS} = & \sqrt{(x-x_i)^2 + (y-y_i)^2} \\ & -\sqrt{(x-x_0)^2 + (y-y_0)^2} \\ & +(b_i - b_0) + v_{i,TDOA} \end{aligned} \qquad (3)$$

where b_i is the NLOS error of the i^{th} BTS and b_0 is the NLOS error of the reference BTS. The vector of the $n-1$ errors $v_{i,TDOA}$ is a multivariate Gaussian vector $N(\mathbf{0}, \Upsilon)$ [2].

$$\Upsilon = \begin{bmatrix} \sigma_1^2 + \sigma_0^2 & \sigma_0^2 & \cdots & \sigma_0^2 \\ \sigma_0^2 & \sigma_2^2 + \sigma_0^2 & \cdots & \sigma_0^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_0^2 & \sigma_0^2 & \cdots & \sigma_{n-1}^2 + \sigma_0^2 \end{bmatrix} \qquad (4)$$

The enhanced observed time difference (EOTD) method is such a TDOA approach in GSM network, which is based on three parameters: observed time difference (OTD), real time difference (RTD), and the TDOA, namely geometric time difference (GTD=RTD-OTD). They are used in GSM networks to improve the efficiency of handovers.

2.3 AOA

Using directive antennas or antenna arrays BTSs measure the AOA of a signal that is transmitted by the MS. For two-dimensional positioning, a minimum of two BTSs is required. The AOA measurement with NLOS error at the i^{th} BTS, $i = 1, 2, \cdots, n$, can be written as

$$z_{i,AOA}^{NLOS} = \arctan\frac{y - y_i}{x - x_i} + \varphi_i + v_{i,AOA} \tag{5}$$

where φ_i is a NLOS induced angle error and $v_{i,AOA}$ is a zero mean white Gaussian noise. Currently, it is mainly possible to use the rough sector information (e.g., 120 degree for a three-sector antenna). By using an antenna array for 3G systems, AOA accuracy can be improved.

2.4 RSS

The propagation loss between a MS and a certain BTS derived from RSS measurement is a logarithmic function of the distance between them. Therefore, if the propagation losses from three or more BTSs are available, we can estimate the MS's position in two dimensions based on trilateration techniques. The RSS measurement from the i^{th} BTS, $i = 1, 2, \cdots, n$, can be formulated in dB scale as

$$\begin{aligned} z_{i,RSS}^{NLOS} &= K + 10\beta \log\sqrt{(x - x_i)^2 + (y - y_i)^2} \\ &+ v_{i,RSS} \end{aligned} \tag{6}$$

where K and β are propagation constants depending on the environment characteristics, $v_{i,RSS}$ is a zero mean white Gaussian noise representing log-normal fading. The NLOS effects are implicitly included in the formulation. The above propagation model can be either empirical or theoretical, or a combination of these two. The empirical models are based on measurements, whereas the theoretical models deal with the fundamental principles of radio wave propagation phenomena. The COST 231-Walfisch-Ikegami-Model (COST-WI) [8] is an empirical path loss model based on extensive measurement campaigns in European cities, which has been used extensively in typical suburban and urban environment.

3. GROUND TARGET TRACKING WITH NLOS BIASES

For the target tracking problem, the state transition with respect to time and the relationship between the state vector $\mathbf{x}$ and the observation vector $\mathbf{z}$ are usually given by

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{f}\left[\mathbf{x}(k)\right] + \mathbf{G}(k)\mathbf{w}(k) \\ \mathbf{z}(k) &= \mathbf{h}\left[\mathbf{x}(k)\right] + \mathbf{v}(k) \end{aligned} \tag{7}$$

where k is the discrete-time index. $\mathbf{x}(k)$, $\mathbf{f}\left[\mathbf{x}(k)\right]$, $\mathbf{G}(k)$, $\mathbf{w}(k)$ are the target state vector, state transition function, noise Gain matrix and process noise sequence, respectively. $\mathbf{h}\left[\mathbf{x}(k)\right]$ and $\mathbf{v}(k)$ are the mapping of the states into the observation space (which is usually nonlinear) and the measurement noise sequence, respectively. $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are assumed to be zero mean white Gaussian noise and characterized by their covariance matrices.

$$\begin{aligned} \mathbf{w}(k) &\sim N\left(0, \mathbf{Q}(k)\right) \\ \mathbf{v}(k) &\sim N\left(0, \mathbf{R}(k)\right) \end{aligned} \tag{8}$$

where $\mathbf{Q}(k)$ is the covariance matrix of the process noise and $\mathbf{R}(k)$ is the covariance matrix of the measurement noise. Usually, Kalman filter addresses the general problem of estimating the state of a discrete-time controlled process that is described by a linear model. For the nonlinear system, EKF is utilized.

For simplicity, the measurements are three TOAs from three different BTSs. The NLOS biases of the three TOA measurements $\mathbf{b} = \left[b_1 \quad b_2 \quad b_3\right]^T$ can be modeled as random walks and incorporated into the system model as augmented states.

$$\mathbf{b}(k+1) = \mathbf{b}(k) + \mathbf{w}_b(k) \tag{9}$$

where each element in $\mathbf{w}_b = \left[w_{b_1} \quad w_{b_2} \quad w_{b_3}\right]^T$ is assumed to be zero mean white Gaussian noise. The dynamic model should be chosen according to the real trajectory. Assuming that a nearly constant velocity (CV) model is used, the augmented state vector is

$$\mathbf{x}' = \left[x \quad \dot{x} \quad y \quad \dot{y} \quad b_1 \quad b_2 \quad b_3\right]^T \tag{10}$$

which includes the position and velocity in two dimensions and the biases from three TOA measurements. Then the dynamic model is rewritten as

$$\mathbf{x}'(k+1) = \begin{bmatrix} \mathbf{F} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \mathbf{x}'(k) + \begin{bmatrix} \mathbf{G} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{w}(k) \\ \mathbf{w}_b(k) \end{bmatrix} \tag{11}$$

where

$$\mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{G} = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \tag{12}$$

The covariance matrix of the augmented process noise is $\mathbf{Q}' = diag(\sigma_x^2, \sigma_y^2, \sigma_{b_1}^2, \sigma_{b_2}^2, \sigma_{b_3}^2)$, where σ_x and σ_y represent the standard deviations of the acceleration noises $\mathbf{w} = \left[w_x \quad w_y\right]^T$, and $\sigma_{b_1}, \sigma_{b_2}$ and σ_{b_3} denote the standard deviations of the errors of the NLOS biases $\mathbf{w}_b$. The measurement model of the augmented states in the presence of the NLOS error is given by

$$\mathbf{z}'(k) = \mathbf{h}\left[\mathbf{x}(k)\right] + \mathbf{b}(k) + \mathbf{v}(k) \tag{13}$$

Then the Jacobian matrix with respect to the augmented states is

$$\mathbf{H}'(k) = \frac{\partial \mathbf{z}'(k)}{\partial \mathbf{x}'(k)} = \left[\mathbf{H} \quad \mathbf{I}\right]$$
$$= \begin{bmatrix} \frac{x-x_1}{d'_1} & 0 & \frac{y-y_1}{d'_1} & 0 & 1 & 0 & 0 \\ \frac{x-x_2}{d'_2} & 0 & \frac{y-y_2}{d'_2} & 0 & 0 & 1 & 0 \\ \frac{x-x_3}{d'_3} & 0 & \frac{y-y_3}{d'_3} & 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

where d'_i denotes the distance between the MS and the i^{th} BTS, $d'_i = \sqrt{\left(x-x_i\right)^2 + \left(y-y_i\right)^2}$. In EKF, the Jacobian matrix $\mathbf{H}'(k)$ is evaluated at the predicted state estimate $\hat{\mathbf{x}}^-(k)$.

4. ROAD CONSTRAINTS

Assuming that the MS is located on a ground vehicle, such as civil cars, trucks, and so on, they are strictly linked to the road network. Thus the MS can be assumed to be traveling on a given road segment. The following constraints exist: the position of the target lies on the road and the associated velocity is along with the direction of the road.

There is one important step before incorporating the road constraints into the estimation process, which is creating an analytical representation for a given road segment. The road network is usually represented by waypoints in the digital map database. Therefore, a linear road segment can be built by connecting the waypoints. On the other hand, if the road is a curve, it is represented by shape points in the database. A polynomial nonlinear function can be used to define the road. Let $s\left(x(t), y(t)\right) = 0$ denote the road segment function. Without loosing generality, we assume a polynomial function of second degree to represent a road segment.

$$\begin{aligned} s\left(x(t), y(t)\right) = a \cdot x(t)^2 + b \cdot y(t)^2 + c \cdot x(t)y(t) \\ + d \cdot x(t) + e \cdot y(t) + f \end{aligned} \tag{15}$$

where the parameters a, b, c, d, e, f are all *a priori* information and give a specific road segment. Then the road is incorporated into the estimation process as a pseudomeasurement. The road constraint can be rewritten as measurement model in discrete time

$$z_c(k) = h\left[\mathbf{x}(k)\right] + v_c(k) \tag{16}$$

where $z_c(k) = 0$, $h_c\left[\mathbf{x}(k)\right] = s\left(x(k), y(k)\right)$, and $v_c(k)$ is assumed to be zero mean white Gaussian noise, $v_c(k) \sim N\left(0, R_c(k)\right)$, which accounts for the uncertainty of the road constraint, such as road width, error of the road function, and so on. Then the original measurement model is augmented by the pseudomeasurement and KF can be ready to be applied [1]. When the road is linear, another constraint on the velocity can be also easily applied.

$$\mathbf{v}(t)^T \cdot \mathbf{n}_s(t) = 0 \tag{17}$$

where $\mathbf{v}$ is the velocity vector and $\mathbf{n}_s$ represents the normal vector of the road segment. The road constraints can be written in discrete time

$$\begin{aligned} \tan\theta \cdot x(k) - y(k) + c = 0 \\ \tan\theta \cdot \dot{x}(k) - \dot{y}(k) = 0 \end{aligned} \tag{18}$$

where θ is the road direction, c is the parameter to specify the linear road. Then they can be written as pseudomeasurement model

$$\mathbf{z}_c(k) = \mathbf{H}_c\mathbf{x}(k) + \mathbf{v}_c(k) \tag{19}$$

where $\mathbf{v}_c(k)$ is assumed to be zero mean white Gaussian noise.

The pseudomeasurement approach provides a convenient framework for incorporating such constraints without greatly increasing the computational cost. Since using the constraints removes some of the target dynamic uncertainty, the estimation performance will be improved. In addition, it has less computation complexity to incorporate the constraints into the measurement model rather than into the state transition model, especially in the case of nonlinear constraints.

5. SIMULATION RESULTS

The simulations are carried out in a simulated urban square area of 5 km × 5 km as shown in Fig.2. Within this area there are three BTSs, a , b , and c. It is supposed that the measurements are updated every 480 ms, i.e. T=0.48 s, which is a typical value for TA in GSM networks. Note that in current GSM networks only one TA is taken by the serving BTS. To obtain more TA measurements from other BTSs, handover should be implemented. According to the real measurements taken by Nokia in the GSM network, the mean and standard deviation of the range errors are in the order of 513 m and 436 m, respectively [3]. Therefore, in the simulations the standard deviation of the TOA measurement noise σ_{TOA} is chosen to be $\sigma_{TOA} = 400$ m. The NLOS bias in each BTS is modeled as a random walk (Eq.9). The initial values of the biases for three BTSs are supposed to be 500 m, respectively, and the standard deviations of the bias noises $\mathbf{w}_b$ are assumed to be 10 m, respectively.

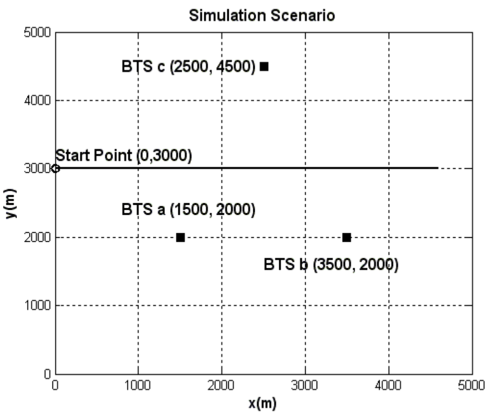

Fig.2 Simulation Scenario

It is assumed that a vehicle is equipped with a MS. The trajectory of the vehicle is generated by a first-order Euler discretization of the generic continuous-time curvilinear motion model from kinematics [9], which is called truth model since it represents the real trajectory for the simulations. The state vector $\mathbf{x}_t = \begin{bmatrix} x & y & v & \phi \end{bmatrix}^T$ includes the target position in two dimensions, speed and heading.

$$\mathbf{x}_t(k+1) = \mathbf{f}\left[\mathbf{x}_t(k)\right] + \mathbf{w}_t(k)$$
$$\mathbf{f}\left[\mathbf{x}_t(k)\right] = \begin{bmatrix} x(k) + Tv(k)\cos\left(\phi(k)\right) \\ y(k) + Tv(k)\sin\left(\phi(k)\right) \\ v(k) + Ta_t(k) \\ \phi(k) + Ta_n(k)/v(k) \end{bmatrix} \tag{20}$$

where a_t and a_n denote tangential (along-track) and normal (cross-track) accelerations, respectively. Through setting different values of a_t and a_n, we can simulate not only uniform motion, i.e., nonmaneuver motion, but also maneuver motion. The process noises $\mathbf{w}_t = \begin{bmatrix} w_x & w_y & w_v & w_\phi \end{bmatrix}^T$ are assumed to be zero mean white Gaussian noises.

In the following, different simulation scenarios, including uniform motion, maneuver motion and turn motion, are carried out to demonstrate the benefits of the road-constrained approach. For each simulation, all of the results are obtained by Monte Carlo simulations with 500 runs. Root Mean Square Errors (RMSEs) of different approaches are plotted and compared. The best achievable accuracy, Posterior Cramér Rao Lower Bound (PCRB) [10], is also drawn as a benchmark to evaluate the performance of the EKF.

5.1 Uniform Motion

In this simulation, the vehicle travels along a linear route started from the location (0 m, 3000 m) as shown in Fig.2. The direction of the road is 0° and the y coordinate is always 3000 m. The pseudomeasurement model for the linear road constraints (Eq.19) is specified by

$$\mathbf{z}_c(k) = \begin{bmatrix} -3000 \\ 0 \end{bmatrix}$$
$$\mathbf{H}_c(k) = \begin{bmatrix} 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix} \tag{21}$$

The covariance matrix of the pseudomeasurement noise $\mathbf{R}_c = diag\left[(10m)^2, (1m/s)^2\right]$. In the truth model, a_t and a_n are set to be 0 m/s^2, respectively, and the standard deviations of the process noises are set to be $w_x = 1\times10^{-4}$ m, $w_y = 1\times10^{-4}$ m, $w_v = 1\times10^{-5}$ m/s, and $w_\phi = 1\times10^{-6}$ rad. The initial velocity of the vehicle is (15 m/s, 0 m/s). The TOA measurement of the BTS a with NLOS error is illustrated in Fig.3.

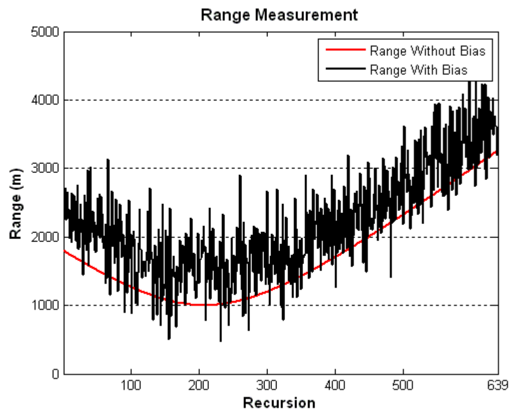

Fig.3 Range Measurement

The initial state estimates of the EKFs are set as following: The initial values of the velocity are assumed to be zero mean white Gaussian random variables with an associated standard deviation equal to half of the known maximum state values. The initial values of the position and NLOS biases are set to be the true values with zero mean white Gaussian noises, which have standard deviations of 400 m for positions, 10 m for biases, respectively. The dynamic model for the EKFs is CV model and the standard deviations of the process noises are set to be $\sigma_x = \sigma_y = 1\times10^{-4}$ m/s^2.

The RMSE performance of the road-free approach and the road-constrained approach in the presence of NLOS is shown in Fig.4. The RMSE of a EKF when there is no NLOS error is also given in Fig.4 to show the degradedness of the tracking accuracy if NLOS biases exist. It is observed that the road-constrained approach greatly improves the estimation accuracy. It can be also seen that the RMSEs achieve the corresponding PCRBs in this uniform motion.

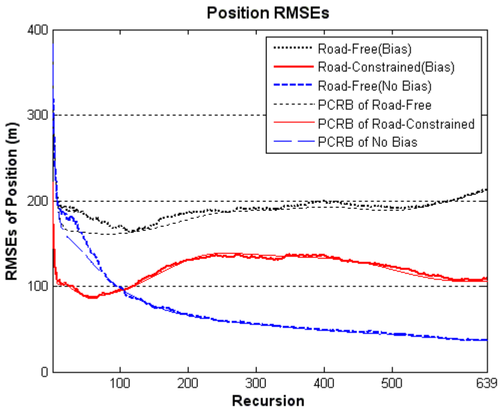

Fig.4 RMSEs for the Uniform Motion

5.2 Performance in the Case of Two NLOS Measurements

As is well known, to uniquely determine a position in two dimensions using trilateration technique, at least three base stations are required to solve the ambiguities. However, sometimes this condition can not be satisfied. In many areas of rural and suburban the cell size is large and the density of cells is low. Another situation is that in urban areas the blockage of high-rise buildings will introduce NLOS error and even there is no LOS available. Moreover, under current GSM specification TA measurement is only taken in the current serving BTS. In order to apply trilateration positioning, artificially forced hand over should be carried out, but it will degrade call quality and reduce system capacity. Therefore, in such situations the available number of BTSs might probably be less than three, or to obtain more measurements from other BTSs may cause more efforts and introduce errors. Using the pseudomeasurement approach to incorporate the road constraints can reduce the requirement, that at least three BTSs are required for two dimensional trilateration, to two BTSs [1]. Therefore, it is expected that the road-constrained approach using two measurements in the presence of NLOS error can still provide a reliable position estimate and has better performance than the road-free approach of using three measurements with NLOS error.

The simulated trajectory is the same as the last simulation. The performance of the road-constrained approach using three measurements, using two measurements and the road-free approach using three measurements in the presence of NLOS errors are given in Fig.5. The plots depict that the road-constrained approach using only two NLOS measurements greatly improves the RMSE accuracy compared with the road-free approach using three NLOS measurements. It can be concluded that the road-constrained approach of two measurements is an effective solution for the NLOS situation.

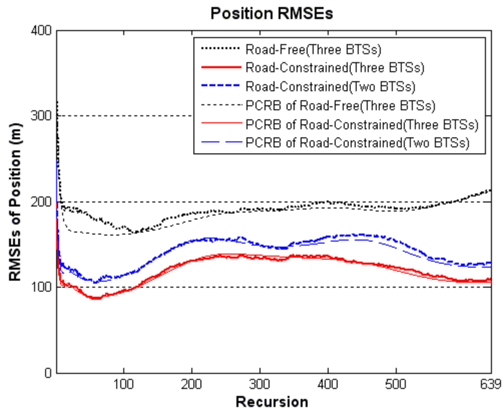

Fig.5 RMSEs for the Uniform Motion in the Case of Two NLOS Measurements

5.3 Maneuver Motion

The ground vehicle has a distinctive feature of high maneuverability. Due to the restriction of the terrain, road and traffic, the vehicle may frequently start, accelerate, decelerate, stop, or turn on the road. In this part of simulation, the trajectory of the vehicle, which travels along the same road as the uniform motion simulation (See Fig.2), is made of uniform motions and two maneuvers of only tangential accelerations, both of which are about 10 seconds. In the first maneuver, the vehicle accelerates under a_t = 3 m/s^2 and in the second maneuver the vehicle decelerates under a_t = -3 m/s^2. The initial position is (0 m, 3000 m) and the initial velocity is (5 m/s, 0 m/s). The dynamic model of the EKFs is still CV model. However, the standard deviations of the process noises are set to be $\sigma_x = \sigma_y$ = 3 m/s^2 to cover the maneuver time. The other parameters of the EKFs are the same as the uniform motion. The same linear road constraints specified by Eq.(21) is applied in the road-constrained approach.

The RMSE performance comparison is given in Fig.6. It is observed that the road-constrained approach achieves significantly improved accuracy compared with the road-free approach. Comparing the performance in the case of no NLOS biases with the performance in the NLOS situation, the state estimate in the presence of NLOS errors greatly degrades. The comparison of the RMSEs with the corresponding PCRBs depicts that for the maneuver motion the EKFs using a simple CV model cannot obtain the best achievable estimation accuracy. A better dynamic model, which matches the maneuver motion well, should be applied. Further, adaptive approaches, which adaptively update the dynamic model, can be utilized to improve the performance. The performance comparison in the case of only two NLOS measurements is given in Fig.7. The similar performance to the uniform motion is observed that the road-constrained approach is an effective solution in the case of only two measurements with NLOS error.

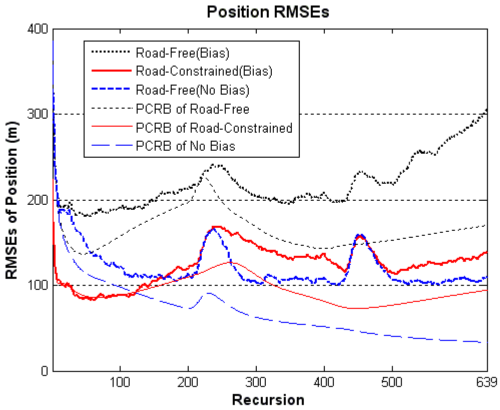

Fig.6 RMSEs for the Maneuver Motion

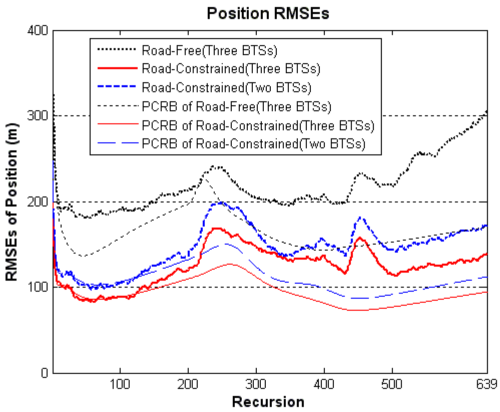

Fig.7 RMSEs for the Maneuver Motion in the Case of Two NLOS Measurements

5.4 Turn Motion

In this simulation the proposed road-constrained approach in the case of nonlinear road constraint is examined. It is assumed that the vehicle executes a coordinated turn motion along an arc route as shown in Fig.8.

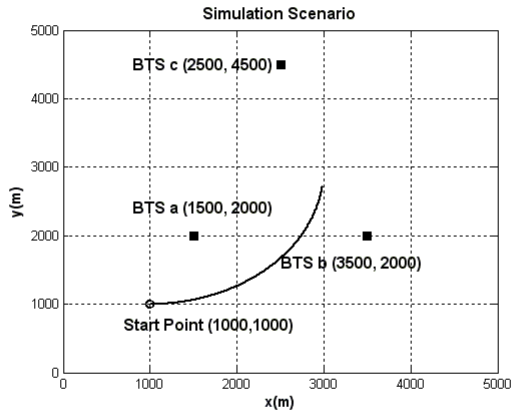

Fig.8 The Arc Route

The road constraint is specified by

$$r^2 = \left(x(k) - x_0\right)^2 + \left(y(k) - y_0\right)^2 \qquad (22)$$

where r denotes the radius of the road arc and (x_0, y_0) is the two-dimensional coordinate of the arc's centre, which are all known as *a priori* information. The start position is (1000 m, 1000 m) and the initial velocity is (20 m/s, 0 m/s). The normal acceleration is set to be a_n = 0.2 m/s^2 and the tangential acceleration is 0 m/s^2. The nonlinear equality constraints are fundamentally different from the linear equality constraints since the linearization errors arise, which includes truncation error resulting from neglecting the higher order terms of the Taylor series expansion in EKF and base point error due to the linearization around the predicted state estimate. The method of dealing with the nonlinear road constraint in the EKF estimator and the EKF design using a nearly coordinated turn (CT) model can be found in [1].

The RMSE performance is given in Fig.9. Similar conclusions as the uniform motion can be obtained that the road-constrained approach provides significantly improved estimation accuracy compared with the road-free approach. In Fig.10, the RMSE performance of the road-constrained approach in the case of only two NLOS measurements is shown. For the turn motion in this simulation, the designed EKFs using CT model do not achieve the corresponding PCRBs. This is because that in the road-constrained approach the nonlinear road constraint is incorporated at the initial stage with a high noise. This noise is reduced gradually as the estimation proceeds, which means that the estimator trust the constraint with an increasing weight. It also depicts that the proposed road-constrained approach in nonlinear case can be further improved to obtain the best achievable accuracy.

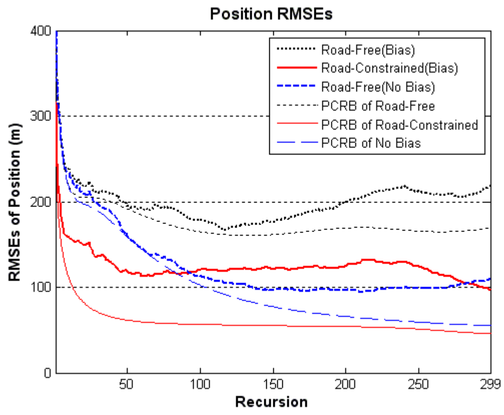

Fig.9 RMSEs of the Turn Motion

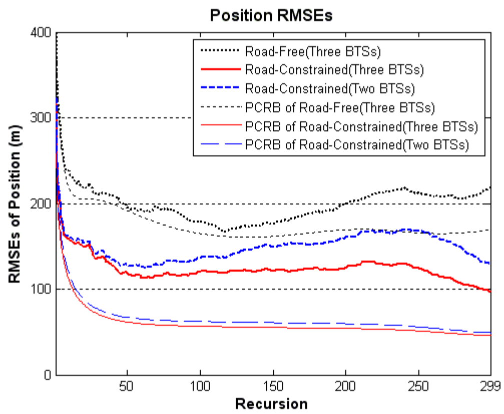

Fig.10 RMSEs of the Turn Motion in the Case of Two NLOS Measurements

6. CONCLUSIONS

In this paper, the performance of the proposed road-constrained approach for MS tracking is examined in the presence of NLOS error. The NLOS error is a critical issue for mobile positioning in wireless communication environment. It can be formulated as an additive bias to the noisy LOS measurement and the bias can be estimated as an augmented state using EKF. The simulation results of different dynamic motions demonstrate that the road-constrained approach, in which the road constraints are incorporated into the tracking process as pseudomeasurements, can significantly improve the estimation accuracy compared with the road-free approach. Moreover, integrating only two NLOS measurements and the road constraints provides an effective solution for the MS tracking in the presence of NLOS error.

In the future, the NLOS bias model should be further studied to have a better model representing the real NLOS error in GSM networks. Moreover, the proposed road-constrained approach in nonlinear case can be further improved.

REFERENCES

[1] M. Zhang, S. Knedlik, and O. Loffeld, "On nonlinear road-constrained target tracking in GSM networks", in *Proceeding of 2008 IEEE 67th Vehicular Technology Conference: VTC2008-Spring*, Singapore, May 2008, pp. 2026-2030.

[2] Y. Qi, H. Kobayashi, and H. Suba, "Analysis of wireless geolocation in a non-line-of-sight environment", *IEEE Transactions on Wireless Communications*, vol. 5, no. 3, pp. 672-681, Mar. 2006.

[3] M. P. Wylie and J. Joltzman, "The non-line of sight problem in mobile location estimation", in *Proceeding of 1996 5th IEEE International Conference on Universal Personal Communications*, Cambridge, MA, USA, Sep. 1996, vol.2, pp.827-831.

[4] M. Nájar and J. Vidal, "Kalman tracking for mobile location in NLOS situations", in *Proceeding of the 14th IEEE 2003 International Symposium on Personal, Indoor, and Mobile Radio Communication*, Beijing, China, Sep. 2003, Vol.3, 2203-2207.

[5] W. Kim, G. Jee and J. Lee, "Wireless location with NLOS error mitigation in Korean CDMA system", in *Proceeding of 2001 2nd International Conference on 3G Mobile Communication* Technologies, London, UK, Mar. 2001, pp. 134-138.

[6] S. Gezici, "A survey on wireless position estimation", *Wireless Personal Communications*, Springer Netherlands, vol. 44, no. 3, pp. 263-282, Feb. 2008.

[7] M. Pent, M. A. Spirito and E. Turco, "Method for positioning GSM mobile stations using absolute time delay measurements", *Electronics Letters*, vol. 33, no. 22, pp. 2019-2020, Nov. 1997.

[8] M. Zhang, S. Knedlik, P. Ubolkosold, and O. Loffeld, "A data fusion approach for improved positioning in GSM networks", in *Proc. of IEEE/ION Position, Location, And Navigation Symposium (PLANS) 2006*, San Diego, U.S.A., Apr. 2006, pp. 218-222.

[9] X. R. Li and V. P. Jilkov, "Survey of maneuvering target tracking. Part I: Dynamic models", *IEEE Transactions on Aerospace and Electronic Systems*, vol. 39, no. 4, pp. 1333-1364, Oct. 2003.

[10] P. Tichavský, C. H. Muravchik and A. Nehorai, "Posterior cramér-rao bounds for discrete-time nonlinear filtering", *IEEE Transactions on Signal Processing*, vol. 46, no. 5, pp. 1386-1396, 1998.