An Adaptive Road-Constrained IMM Estimator for Ground Target Tracking in GSM Networks

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Abstract—The Global System for Mobile Communications (GSM) networks can provide position information. However, a GSM positioning system based on current specifications faces many difficulties to yield accurate position estimate for ground target tracking. The additional information of the road network is very useful not only for restricting the target position inside the road but also for providing a potential constraint on the possible target motions. In this paper, we propose an Adaptive Road-Constrained Interacting Multiple Model (ARC-IMM) estimator, in which the road constraint is incorporated into a Variable Structure IMM (VS-IMM) mechanism as a pseudomeasurement. The module set of the ARC-IMM, not only the dynamic model but also the road constraint, is updated adaptively according to the estimated target position and the road network. In particular, the selection of the dynamic models depends also on the road constraint. The simulation results verify that the proposed approach significantly improves the estimation accuracy in comparison to an IMM estimator with only two measurements available demonstrates the efficiency and robustness of the proposed approach.

Keywords: Ground Target Tracking, Road Constraint, VS-IMM, GSM Network.

I. INTRODUCTION

Firstly driven by the requirement of localizing emergency calls, positioning in mobile cellular networks has become an exciting research area over the past few years. And as a widely used mobile communication standard around the world, the Global System for Mobile communications (GSM) network has shown the potential to provide position information. Besides emergency assistance, ground target tracking is also an important application of positioning a Mobile Station (MS), e.g., automatic vehicle location, intelligent transport system, and fleet management. However, a GSM positioning system based on current specifications faces many difficulties to yield an accurate position estimate for tracking applications. On one hand, due to the restriction of terrain, road and traffic, the ground target may frequently start, accelerate, decelerate, stop, or turn on the road, i.e., the state to be estimated may change dramatically. On the other hand, the resolution of the measurements in GSM networks related to positioning is coarse and ambiguities of the position estimate arise when there are not sufficient measurements available. Therefore, data fusion solutions which integrate more measurements and information are required to provide position estimation with better accuracy, reliability and coverage.

One of the natural characteristics for ground targets is the target motion uncertainty due to changing terrain and road conditions. The traditional dynamic models or motion models, which describe the evolution of the target state with respect to time, are nearly constant velocity model (CV), nearly constant acceleration model (CA), Singer model, and so on [1]. In recent years, Multiple Model (MM) methods have been generally considered as the mainstream approach for maneuvering target tracking under motion mode uncertainty, and the Interacting MM (IMM) estimator is one of the most efficient MM estimators, which was firstly proposed by Blom and Bar-Shalom [2], [3]. But most of the work on the IMM estimator considers only fixed mode sets. This requires that the estimator carries as many modes as necessary to handle the varying target motion characteristics during the entire tracking period, which will increase the computational load and may also degrade the estimation accuracy. It is possible to vary the set of models in the IMM estimator based on some criteria to yield better estimates, which results in Variable Structure IMM (VS-IMM) [4], [5]. The road network is such a promising a priori information.

Although the road network will cause the high maneuverability of ground targets, it has the advantage of additional knowledge on the target state. There are already many approaches of incorporating the road information into the tracking algorithm. Simon and Chia [6] proposed a method of projecting the unconstrained state estimate at each time step onto the state constraint surface. An approach of incorporating a kinematic constraint into the tracking process through a pseudomeasurement was firstly proposed in [7] and this approach could be also applied in road constraint. Other approaches include tuning the covariance of the process noise adaptively according to road maps [8], building the tracking filters upon the 1D representation of road segments [9], and so on. Moreover, there are also many research efforts which have been done to incorporate the road information into MM schemes. In [5], [10] the road constraint was handled using the concept of directional process noise. The target dynamics was modeled in one-dimensional road coordinates and mapped onto the ground coordinate in [11]. And the projection approach was applied within an VS-IMM filter in [12].

Recently, we expanded the pseudomeasurement approach
for road-constrained target tracking in GSM networks, including straight road [13] and nonlinear road [14]. And the benefits were demonstrated. In this paper, we will incorporate this road-constrained tracking approach into a VS-IMM mechanism, which results in an Adaptive Road-Constrained IMM (ARC-IMM) estimator. In this approach, the module set, not only the dynamic model but also the road constraint as a pseudomeasurement, is updated adaptively according to the estimated position of the target and the road network information as the estimation process proceeds. In particular, the selection of the dynamic models also depends on the road constraint. Comparative studies with utilizing an IMM estimator with directional noise, a standard IMM estimator and an extended Kalman filter (EKF) verify that the proposed approach significantly improves the tracking accuracy. In addition, the performance when there are only two measurements available is also discussed.

The rest of this paper is organized as follows. In section 2, the problem of ground target tracking on the road is introduced. In section 3, the measurements related with positioning in GSM networks is described. Section 4 presents the proposed ARC-IMM estimator. In section 5, simulation results are illustrated and discussed. Finally, conclusions along with suggestions for future work are given in section 6.

II. GROUND TARGET TRACKING ON THE ROAD

A. Maneuvering Ground Target Tracking

Different from air targets, ground targets may frequently accelerate, slow down, stop completely and turn depending on variable local conditions, e.g., terrain, road and traffic situations. Normally the target dynamics or motions are classified into two categories: nonmaneuver, which stands for the straight and level motion at a constant velocity, and maneuver, which includes all the other motions. The ground target motion has a unique nature of high maneuverability.

As is well known, Kalman filter performs well when the target dynamics matches the model used in the filter, which assumes the dynamics to be well modeled. But when a target maneuvers, it turns to be uncertain and time varying. In order to solve such uncertainty, adaptive filters have been developed to detect maneuvers and adapt the filter to the target dynamics in real time and especially MM approaches have been proposed [15]. The MM estimation algorithms assume the system to be in a finite number of modes. The state estimate is computed under each possible current model by running a set of filters, and then the output of those filters are fused for an overall estimate using different ways. Therefore, the problem of maneuvering ground target tracking can be described by a hybrid system, which is usually modeled by the equations:

\[ \mathbf{x}(k+1) = \mathbf{f}[k, \mathbf{x}(k), m(k+1)] \\
\quad + \mathbf{g}[k, \mathbf{x}(k), m(k+1), \mathbf{w}[k, \mathbf{x}(k), m(k+1)]](1) \]

\[ \mathbf{z}(k) = \mathbf{h}[k, \mathbf{x}(k), m(k)] + \mathbf{v}[k, \mathbf{x}(k), m(k)] \quad (2) \]

where \( \mathbf{x} \) is the target state vector, \( \mathbf{z} \) is the noisy measurement vector, and \( \mathbf{w}[-] \) and \( \mathbf{v}[-] \) are the state-dependent model-dependent process and measurement noise vectors, which are assumed to be white Gaussian noises. The \( \mathbf{f}[-] \), \( \mathbf{g}[-] \) and \( \mathbf{h}[-] \) are some vector-valued mapping functions. \( m(k) \) denotes the system mode at time \( k \), i.e., a pattern of the target behavior, which is assumed to be among the possible \( r \) modes \( m(k) \in \{M_j\}, j = 1, \ldots, r \) and it is assumed that the mode switching is a Markov chain with known mode transition probabilities

\[ p_{ij} = P\{m(k) = M_j|m(k-1) = M_i\} \quad (3) \]

As shown in (1) and (2), the hybrid system has both continuous uncertainties, i.e., the state, and discrete uncertainties, i.e., the mode. Thus, the hybrid estimation problem is to estimate the state and the mode based on the noisy measurements.

B. Road Constraint as Pseudomeasurement

Although the varying environmental conditions result in the high maneuverability of ground targets, they cause another nature of the ground targets, i.e., constrained motion. In this paper, the road restriction will be exploited, which provides a prior information for the estimation. The road constraint can be formulated as fictitious measurements. Accordingly, the original measurement model is augmented and the classic Kalman filter is ready to be applied.

Assuming that a target is traveling on a given road segment, the two-dimensional position of the target \( \{x(t), y(t)\} \) must lie on the road. Then the following constraint exists

\[ s(x(t), y(t)) = 0 \quad (4) \]

where \( s(\cdot) \) denotes the road segment and normally the road can be modeled as straight line, arc, or low-order polynomials. Without losing generality, we assume a polynomial function of second degree to represent a road segment as

\[ s(x(t), y(t)) = a \cdot x(t)^2 + b \cdot y(t)^2 + c \cdot x(t) y(t) + d \cdot x(t) + e \cdot y(t) + f \quad (5) \]

where the parameters \( a, b, c, d, e, f \) are all a priori information and define a specific road segment. The road constraint (5) can be rewritten as a pseudomeasurement model in discrete time

\[ z_r(k) = h_r[\mathbf{x}(k)] + v_r(k) \quad (6) \]

where \( z_r(k) = 0, h_r[\mathbf{x}(k)] = s(x(k), y(k)) \), and \( v_r(k) \) is assumed to be zero mean white Gaussian noise, which accounts for the uncertainty of the road constraint, such as road width, error of the road function, and so on.

\[ v_r(k) \sim \mathcal{N}(0, r_r(k)) \]

\[ r_r(k) = \sigma_r^2 \quad (7) \]

With the formulation of (6), EKF can be utilized. The pseudomeasurement model provides a convenient framework for incorporating such constraint without greatly increasing the computational cost. Since using the constraint removes some of the target dynamic uncertainty, the tracking performance will be improved. In addition, it has less computation complexity to incorporate constraints into the measurement model.
while not into the state transition model, especially in the case of nonlinear constraints.

III. MEASUREMENTS FROM GSM NETWORKS

The measurements in GSM networks are usually the attributes of the radio signals exchanged between the MS and multiple Base Transceiver Stations (BTSs), such as Timing Advance (TA), Enhanced Observed Time Difference (E-OTD), Received Signal Strength (RSS), Angle of Arrival (AOA), and so on. In this paper, we will use TA as an example and this road-constrained target tracking method can be also utilized for other measurements. TA 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 and maintain frame alignment in the GSM system. Therefore, TA is one time of arrival measurement, which can be written as the distance between one MS and a certain BTS. Let the position of the MS be \((x, y)\) and the position of the BTS be \((x_i, y_i)\), where \(i\) represents which BTS we define

\[
d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (8)
\]

For finding a position in two dimensions, at least three base stations are required, whose position coordinates are assumed to be \((x_{a_1}, y_{a_1}), (x_{a_2}, y_{a_2})\) and \((x_{a_3}, y_{a_3})\), respectively. Then the measurement model can be written as

\[
z(k) = \begin{bmatrix} d_{a_1}(k) \\ d_{a_2}(k) \\ d_{a_3}(k) \end{bmatrix} + \nu(k) \quad (9)
\]

where \(\nu(k)\) is the measurement noise vector which is assumed to be zero mean white Gaussian noise vector [16].

\[
\nu(k) \sim N(0, \mathbf{R}(k)) \\
\mathbf{R}(k) = \text{diag}(\sigma_1^2, \sigma_2^2, \sigma_3^2) \quad (10)
\]

The measurement function vector can be augmented by including more measurements. However, it should be noticed that under current GSM specification TA measurement is only taken in the current serving BTS. To get TAs from other BTSs will require the MS to be forced to attempt a handover to neighboring cells.

IV. ARC-IMM

MM approaches can be divided into two categories: one with a fixed set of models, and one with a variable structure. As been pointed out [4], the fixed mode set approach is not realistic since more models have to be used to cover all the possible target motions, which results in that not only computational load will be increased but also the performance will be degraded. Therefore, VS-IMM has been proposed to vary the set of models in the IMM estimator based on some criteria. E.g., the variations in the topography, which include targets entering and leaving roads, target motion at road junctions and target obscuration conditions, are considered to decide which models in the estimator are added or deleted at each revisit time [5].

In addition, the road network is also such information, which can be used to adaptively update the model set as the estimation process proceeds. Assuming that the road network can be modeled by a set of road segments \(\{s_l\}, l = 1, \ldots, n\) and each \(s_l\) can be described by a straight line, arc, or lower order polynomials as (5). At each time step, a neighboring road segment set of the target \(S(k) \triangleq \{s_o\} \in \{s_l\}, o = 1, \ldots, m\) can be obtained by examining the estimated target position and the road network. The road not only restricts the position of the target inside the road, but also has a potential constraint on the possible target motions corresponding to a specific road segment. E.g., on a straight road the target dynamic model might be a CV or a CA model, but can not be a nearly coordinated turn (CT) model. Therefore, if one road segment is selected into the neighboring road segment set, it has finite corresponding possible motion models. The principle of the proposed ARC-IMM estimator is based on a VS-IMM mechanism, where the module set will be updated adaptively according to the latest position estimate and the road network information. In particular, the road constraint is incorporated into the measurement model as a pseudomeasurement, and the modules of the estimator at each time step have not only different dynamic models but also different road constraints as pseudomeasurements, in which one or more dynamic models correspond to one road constraint. In the following, module \(M_j\), i.e., mode in MM approaches, stands for the different unit in the ARC-IMM, which includes a pair of dynamic model and road constraint.

Thus the hybrid system (1) and (2) can be written as:

\[
x(k + 1) = f_p[k, x(k)] + g_p[k, x(k), w_p(k)] \\
z_o(k) = h_o[k, x(k)] + v_o(k)
\]

where \(z_o(k)\) is the augmented measurement vector by the road constraint as a pseudomeasurement (6),

\[
z_o(k) = \begin{bmatrix} x(k) \\ z_o(k) \end{bmatrix}, \quad h_o[k, x(k)] = \begin{bmatrix} h_1[x(k)] \\ h_2[x(k)] \end{bmatrix}, \quad v_o(k) = \begin{bmatrix} \nu(k) \\ \nu_o(k) \end{bmatrix}
\]

and the subscript \(o\) denotes the neighboring road segment at time \(k\), and \(o = 1, \ldots, m\). The small letter in the dynamic model \(p\) denotes the different motion models corresponding to each \(o^{th}\) road segment. The module of the target \(M(k) \triangleq \{o, p\}\) is decided by the combination of different road constraints and different target motions. Unlike the fixed set IMM estimator, the module set at time \(k\), \(M(k) \triangleq \{M_j(k)\}, j = 1, \ldots, r\), and that at time \(k - 1\), \(M(k - 1) \triangleq \{M_i(k - 1)\}, i = 1, \ldots, s\), might be different. The module transition probability (3) is modified as

\[
p_{ij} \triangleq P\{M_j(k) \in M(k) | M_i(k - 1) \in M(k - 1)\}
\]

where \(p_{ij}\) depends on the module set \(M(k - 1)\) and \(M(k)\). One cycle of the ARC-IMM algorithm consists of the following five steps as illustrated in Fig. 1:

*Step 1: Module set update.*

The module set at time \(k\), \(M(k)\), is updated adaptively on the base of the latest estimated position, the neighboring road segments and corresponding possible target motions.
Fig. 1. Adaptive Road-Constrained IMM Estimator Consisting of Three Subfilters (One Cycle)

Step 1: Module Selection

Firstly, the neighboring road segment set is selected, which can be done by testing whether any segment of the road set \( s_i \) lies within a certain neighborhood ellipse centered at the predicted position \((\hat{x}, \hat{y})\) [5]. Then the corresponding target dynamic models of each road segment are chosen according to empirical knowledge. The modules of the estimator at one time step are illustrated in Fig.2. There are two road segments in the neighboring road set, \( s_1 \) and \( s_2 \). For the straight road \( s_1 \), the target might move at constant velocity or constant acceleration, and for the arc road \( s_2 \), the target might do coordinated turn. Therefore, three possible modules are chosen as shown in Fig.2. In this step, the measurement model will be augmented by the road constraint pseudomeasurement from the selected neighboring road segments.

Step 2: Calculation of the initial mixing condition for \( j = 1, \ldots, r \) filters.

The probabilities that module \( M_j \) was in effect at \( k-1 \) given that \( M_j \) is in effect at \( k-1 \) conditioned on \( z_i \) is

\[
\mu_{ij}(k-1|k-1) \triangleq P\{M_j(k-1)|M_j(k), z_i(k-1)\} = \frac{1}{\bar{c}_j} \mu_i(k-1), i \in M(k-1), j \in M(k)
\]

(14)

where \( \mu_i(k-1) \) is the probability about module \( i \) at time \( k-1 \), and \( \bar{c}_j \) is the normalizing constants, which is

\[
\bar{c}_j = \sum_{i=1}^{s} p_{ij}\mu_i(k-1), j = 1, \ldots, r
\]

(15)

Then starting with \( \hat{x}^0(k-1|k-1) \) one computes the mixed initial condition for the filter matched to \( M_j(k) \) as

\[
\hat{x}^{0j}(k-1|k-1) = \sum_{i=1}^{s} \mu_{ij}(k-1|k-1) \hat{x}^i(k-1|k-1)
\]

(16)

The corresponding covariance is

\[
P^{0j}(k-1|k-1) = \sum_{i=1}^{s} \mu_{ij}(k-1|k-1) \{P^i(k-1|k-1) + [\hat{x}^i(k-1|k-1) - \hat{x}^{0j}(k-1|k-1)] [\hat{x}^i(k-1|k-1) - \hat{x}^{0j}(k-1|k-1)]^T\}
\]

(17)

Step 3: Module-matched filtering for \( j = 1, \ldots, r \).

The estimate (16) and the covariance (17) are used as input to each filter, where EKF can be used, to yield \( \hat{x}^j(k|k) \) and \( P^j(k|k) \). The EKF with road constraint as pseudomeasurement in linear and nonlinear case refers to the previous works [13], [14]. The likelihood functions corresponding to the \( r \) filters...
are computed as
\[
\Lambda_j(k) = \mathcal{N}(\mathbf{e}^j(k); \mathbf{0}, \mathbf{S}^j(k))
\]
\[
= (2\pi)^{-\frac{d}{2}} ||\mathbf{S}^j(k)||^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} \mathbf{e}^j(k)^T \mathbf{S}^j(k)^{-1} \mathbf{e}^j(k) \right\}
\]
(18)
where \( \mathbf{e}^j(k) = \mathbf{z}(k) - \mathbf{h}[\hat{\mathbf{x}}^j(k|k-1)] \) is the residual and \( \mathbf{S}^j(k) \) is the residual covariance for filter \( j \) at time \( k \). Note that the real measurement model \( \mathbf{z}(k) \), not the augmented measurement model \( \mathbf{z}_h(k) \), is used to calculate the likelihood functions (18) considering the different road segment functions for each modules, i.e., straight line, arc or polynomial function.

**Step 4: Module probability update for \( j = 1, \ldots, r \).**

The module probability in effect at \( k \) is updated by
\[
\mu_j(k) = P(M_j(k)|\mathbf{x}(k)) = \frac{1}{c} \Lambda_j(k) \bar{e}_j
\]
(19)
where \( c \) is the normalization constant
\[
c = \sum_{j=1}^{r} \Lambda_j(k) \bar{e}_j
\]
(20)

**Step 5: Estimation and covariance combination.**

Combination of the module-conditioned estimate and covariance is done according to the mixture equations
\[
\hat{\mathbf{x}}(k|k) = \sum_{j=1}^{r} \mu_j(k) \hat{\mathbf{x}}^j(k|k)
\]
(21)
\[
\mathbf{P}(k|k) = \sum_{j=1}^{r} \mu_j(k) \left[ \mathbf{P}^j(k|k) + [\hat{\mathbf{x}}^j(k|k) - \hat{\mathbf{x}}(k|k)] \mathbf{P}^j(k|k)\hat{\mathbf{x}}^j(k|k) - \hat{\mathbf{x}}(k|k)]^T \right]
\]
(22)

The above five steps are similar with the VS-IMM algorithm, but the road constraint is incorporated into the estimation as a pseudomeasurement and the structure of the module set is selected and updated considering the neighboring road segments and corresponding possible target motions.

**V. SIMULATION RESULTS**

**A. Simulation Scenario**

The simulations are carried out in a simulated square area of 5km by 5km. Within this area there are three BTSs, a, b and c. As shown in Fig.3, it is assumed that a vehicle equipped with a MS, whose position and velocity are going to be estimated by three TA measurements from BTSs a, b and c, respectively, travels along a route D-E-F-G as an example to show the structure and performance of the proposed ARCS-IMM Estimator. There are three road segments: \( s_1(D-E) \) is a straight road, \( s_2(E-F) \) is an arc road, and \( s_3(F-G) \) is also a straight road. It is assumed that these three road segments are modeled as linear function or circle function as
\[
0 = \tan \theta \cdot x(k) - y(k) + c
\]
\[
r^2 = (x(k) - x_0)^2 + (y(k) - y_0)^2
\]
(23)
(24)
where \( \tan \theta \) is the slope of the straight roads, \( c \) stands for the \( y \)-intercept of the straight roads, \( r \) denotes the radius of the arc road and \((x_0, y_0)\) is the two-dimensional coordinate of the arc’s centre, which are all known parameters. Therefore they can be written as pseudomeasurement models
\[
z_{s_1}(k) = h_{s_1}(\mathbf{x}(k)) + v_{s_1}(k)
\]
(25)
\[
z_{s_2}(k) = h_{s_2}(\mathbf{x}(k)) + v_{s_2}(k)
\]
(26)
\[
z_{s_3}(k) = h_{s_3}(\mathbf{x}(k)) + v_{s_3}(k)
\]
(27)

The measurements update rate is \( T = 0.48s \), which is a typical value for a TA measurement update period in GSM networks. The standard deviation of the measurement noise (10) is assumed to be \( \sigma_d = 300m \).

It is assumed that the vehicle is moving on the road from D to G and the tracker starts to work at position D: \((1000m, 1000m)\) and at this time the velocity of the vehicle \((1000m, 1000m)\) and finally it has again constant velocity movement on the straight road \( s_3 \). The trajectory is generated by first-order Euler discretization of the generic continuous-time curvilinear motion model, which is called truth model since it represents the real trajectory for the simulations
\[
\mathbf{x}_t(k+1) = \mathbf{f}_t[\mathbf{x}_t(k)] + \mathbf{w}_t(k)
\]
\[
\mathbf{f}_t[\mathbf{x}_t(k)] = \begin{bmatrix} x(k) + Tv(k) \cos(\phi(k)) \\ y(k) + Tv(k) \sin(\phi(k)) \\ v(k) + Ta_n(k)/v(k) \end{bmatrix}
\]
(28)
where the state vector \( \mathbf{x}_t(k) = [x(k) \ y(k) \ v(k) \ \phi(k)]^T \) includes the target position in two dimensions, speed and heading. \( a_t \) and \( a_n \) denote tangential and normal accelerations, respectively, which are set to \( a_t = 0m/s^2, a_n = 0m/s^2 \) for the movement on \( s_1 \), \( a_t = 0m/s^2, a_n = 1m/s^2 \) for that on \( s_2 \), and \( a_t = 0m/s^2, a_n = 0m/s^2 \) for that on \( s_3 \). The process noises \( \mathbf{w}_t(k) = [w_x(k) \ w_y(k) \ w_v(k) \ w_\phi(k)]^T \) are assumed to
be zero mean white Gaussian noises
\[ w_t(k) \sim N(0, Q_t(k)) \]
\[ Q_t(k) = diag(\sigma_x^2, \sigma_y^2, \sigma_o^2, \sigma_\phi^2) \] (29)

where \( \sigma_x, \sigma_y, \sigma_o, \sigma_\phi \) are the standard deviations of the process noises set to the values of \( 10^{-4}\text{m} \), \( 10^{-4}\text{m} \), \( 10^{-5}\text{m/s} \), and \( 10^{-6}\text{rad} \), respectively.

The initial probability of each module is set to be 0.9 for module 1, and 0.05 for module 2 and 3, respectively. The initial values of the velocity \( \hat{x}^+(0) \) and \( \hat{y}^+(0) \) of the estimator are calculated by one point measurement [3], which uses a traditional least squares algorithm to achieve an initial position guess from three independent TA measurements at time step \( k = 0 \). And the initial values of the velocity \( \dot{x}^+(0), \dot{y}^+(0) \) are assumed to be zero mean Gaussian random variables with an associated standard deviation equal to half of the known maximum state values.

In order to evaluate the performance of the proposed approach, an IMM estimator with directional noise (IMM-DN), a standard IMM estimator, and a single model EKF estimator are also designed for the simulated scenario and the results are compared. The IMM-DN estimator comprises three models, one CV model for the road segment D-E, one CT model and one CV model for the road segment F-G. Since the target should have more uncertainty along the road than orthogonal to it, the variance of the corresponding process noise could be set as \( \sigma_a = 10^{-2}\text{m/s}^2, \sigma_o = 10^{-6}\text{m/s}^2, \sigma_\phi^2 \gg \sigma_\phi \). Then they need to be converted into a covariance matrix in the X-Y coordinate system.

\[ Q = \begin{bmatrix}
-\cos \varphi & \sin \varphi \\
\sin \varphi & -\cos \varphi
\end{bmatrix}
\begin{bmatrix}
\sigma_x^2 & 0 \\
0 & \sigma_o^2
\end{bmatrix}
\begin{bmatrix}
-\cos \varphi & \sin \varphi \\
\sin \varphi & -\cos \varphi
\end{bmatrix} \] (30)

where \( \varphi \) is the direction of the road segment D-E and E-F, respectively. The details of the directional noise design can be found in [5]. The mode transition probability matrix is the same with the ARC-IMM. The IMM estimator consists of two models, one CV model, in which the standard deviation of process noises \( \sigma_a = 10^{-2}\text{m/s}^2, \sigma_o = 10^{-6}\text{m/s}^2 \), and one CT model with process noises \( \sigma_a = 10^{-2}\text{m/s}^2, \sigma_o = 10^{-2}\text{m/s}^2 \). The mode transition probability matrix is assumed to be \( \begin{bmatrix} 0.99 & 0.01 \\ 0.02 & 0.98 \end{bmatrix} \) and the initial probability is set to be 0.9 for CV model, 0.1 for CT model. The dynamic model of the EKF is CV model, and the standard deviations of process noises are set to be \( \sigma_a = 3\text{m/s}^2, \sigma_o = 3\text{m/s}^2 \), which are designed to be big enough to track both the uniform motion and maneuver motion.

C. Performance Comparisons

The state estimate results of the proposed ARC-IMM estimator, the IMM-DN estimator, the IMM estimator and the single model EKF estimator are shown in Fig.4. It is observed that the performance of the ARC-IMM outperforms that of the other three approaches. The state estimates of the target yielded by the IMM-DN are close to the real state values. In particular, at the initial phase the estimates converge to the real values much quicker than in the other three approaches. And when the target maneuvers, i.e., when the target turns on the road, the proposed estimator can better track the change of the state than the others.

To further evaluate the estimation performance, the Root-Mean-Squared-Error (RMSE) performance is obtained from 1000 Monte Carlo simulations as shown in Fig.5. The comparison of the RMSEs verifies that the ARC-IMM significantly improves the estimation accuracy. During the uniform motion the ARC-IMM yields about 30m position RMSE reduction when comparing with the IMM and about 20m in comparison to the EKF. And the velocity RMSE is improved about 6m/s over the IMM and about 3m/s over the EKF. During the maneuver, the ARC-IMM has a peak error, but it decreases much faster than in the case of the other three estimators. By comparing the performance of IMM and EKF, it is shown that the IMM could not improve the estimation accuracy over the EKF even though an additional maneuver model is included, which is because the IMM estimator converges slowly in
this application with high measurement noises and relatively low velocities. And the comparison of the results from the IMM-DN and the IMM estimator shows that the IMM with directional noise has only a slightly better performance during the nonmaneuver period.

D. Performance in the Case of Two 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, some times this condition can not be satisfied in GSM networks. 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 None-Line-of-Sight error and even there is no Line-of-Sight available. Moreover, under current GSM specification TA 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 fewer than three, or to obtain more measurements from other BTSs may cause more effort and introduce errors. In this part of simulations the performance of different approaches, when there are only two measurements from two BTSs of a and b available, are compared. The RMSE performance based on 1000 Monte Carlo simulations is shown in Fig.6. It is observed that the proposed ARC-IMM yields the highest accuracy, and the performances of the other three approaches are greatly degraded. In the case of only two measurements the measurement model in the IMM-DN, the IMM and the EKF is only a two dimensional vector, which
results in that the ambiguity of the estimation arises. But in the ARC-IMM the incorporation of the road constraint as a pseudomeasurement augments the measurement model, thus the necessary number of measurements for trilateration in two dimensions is reduced to two. Therefore the proposed ARC-IMM can still provide stable and accurate estimates when there are only two measurements available.

VI. CONCLUSIONS

In this paper, an ARC-IMM estimator to track the ground target in GSM networks is proposed. The road constraint can be used not only to restrict the position of the target inside the road, but also as a criteria to select possible dynamic models. Similar as VS-IMM, the module set of the ARC-IMM is updated adaptively according to the estimated target position and the road network information. But the difference is that in the ARC-IMM the road constraint is incorporated into the estimator as a pseudomeasurement, and the module is specified by the dynamic model and the road constraint together. In particular, the selection of the dynamic model also depends on the road constraint. The performance comparison verified that the proposed ARC-IMM estimator is superior over an IMM with directional noise, a standard IMM estimator and a classic EKF estimator. And the results in the case of only two measurements available show that the approach is robust and efficient. In the future, the adaptive selection and update of the module set should be studied and the proposed estimator should be examined in different scenarios to further prove the benefits of applying the road constraint to improve the estimation performance.

REFERENCES