

# Ground Target Tracking with Road Map Support

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**Abstract:** Ground target surveillance is getting a more and more important task, for civil as for military applications. Ground targets may be bound to infrastructural constraints, like vehicles moving on roads. Therefore, incorporating road map information into the tracking process is a current topic of research. This paper presents a tracking algorithm, which considers the road information and is based on a Kalman filter approach. Beside crossings, narrow curves are also supported.

## 1 Introduction

Ground surveillance is getting more and more important, since several applications exist, like civil applications [Sc94], airport ground control and military surveillance applications [Ki00].

In difference to air target tracking, ground targets move on the earth surface and more clutter exists. In order to reduce ground clutter, MTI sensors like GMTI are widely used. In addition, targets may be hidden by topography structures, e.g. trees and hills.

Beside this, ground targets are often densely spaced (e.g. convoys) and infrastructural constraints may exist, like roads for example. Most of the vehicles move on roads and therefore it is a good choice to incorporate road maps into the tracking process.

There exist several filtering approaches in ground target tracking with road maps. Particle filters seem to be a good choice for this kind of application, since road map supported tracking leads to non-linear filter models [AS03, AG02]. In addition, velocity constraints can be applied easily. Disadvantage is the large computation time, which makes them demanding for real time applications.

Alternatively, Kalman filter based approaches are widely discussed in literature [Ki00, NC00, Pa04, Sh00, UI03]. Most of them deal with long straight roads only and use a Variable Structure Interacting Multiple Model (VS-IMM) approach to support crossings.

The work presented in this paper employs a Kalman filter based approach, which uses a one-dimensional on-road model. Since the update is done in the three-dimensional measurement space, equality constraints are applied to project the updated state back to the one-dimensional on-road state [SC02]. Crossings are supported by a Variable Structure Multiple Model (VS-MM) approach without interaction, since the interaction of the widely

used VS-IMM leads to bad estimations at crossings. Beside this, the presented approach considers narrow curved roads by further approximating the models with Gaussian sums similar to [UI03].

The paper is organized as follows: In section 2, the model and filtering process is described in more detail. Section 3 introduces support for crossings and narrow curves. Some experimental results are presented in section 4. Afterwards, the paper is summarized and a conclusion is given in section 5.

## 2 Model and filtering

The presented approach allows targets to move on roads only. These roads are represented by rectangles. Each road has its own coordinate system. Curves are represented by several small adjacent road segments.

The model of the road targets is defined in the coordinate system of the road, whereas the targets move on the centerline of the road only. The origin is the start point of the road. The state is given by  $\mathbf{x}_r = (x_r \ v_{x,r})^T$ , with  $r$  the road the target is currently moving on,  $x_r$  the distance from the start of the road and  $v_{x,r}$  the velocity of the target. The model uses a simple linear constant velocity, white noise acceleration model [BP03], i.e.

$$\mathbf{x}_r(k+1) = \begin{pmatrix} 1 & T \\ 0 & 1 \end{pmatrix} \mathbf{x}_r(k) + \boldsymbol{\nu}(k), \quad (1)$$

$\boldsymbol{\nu}(k)$  the process noise and  $T$  the sampling time, which leads to the covariance matrix

$$\mathbf{Q} = 2\tau\sigma_a^2 \begin{pmatrix} T^3/3 & T^2/2 \\ T^2/2 & T \end{pmatrix} \quad (2)$$

with  $\tau$  the target maneuver correlation time and  $\sigma_a$  the acceleration uncertainty.

The update uses converted measurements, which are defined in the three-dimensional coordinate system of the sensor. Therefore, the on-road state must be transformed to the coordinate system of the sensor. Since the on-road model is only one-dimensional, the road width and an altitude uncertainty of the road are assumed as additional noise to built up the appropriate covariance matrix.

The update itself is performed using regular Kalman filter update equations [BP03].

To gather the updated one-dimensional on-road state, the updated state in the coordinate system of the sensor is projected back to the road  $r$  by using state equality constraints as described in [SC02], where the road is assumed to be of infinite length.

## 3 Crossings and Curves

The model state is defined in the coordinate system of the corresponding road with a given length  $l_r$ . If the position  $x_r$  of the propagated or updated state is outside the corresponding

road  $r$ , i.e.  $x_r < 0$  or  $x_r > l_r$ , the state must be adjusted to the neighboring roads until the position is inside a road. Figure 1 illustrates this for the on-road position  $x_r$ .

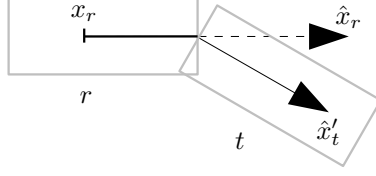


Figure 1: Adjustment of the on-road position  $x_r$ : Previous position  $x_r$  on road  $r$ , after propagation or update  $\hat{x}_r$ , after adjustment to the neighboring road  $t$ :  $\hat{x}'_t$ .

If the position passes a crossing during adjustment, a new model for each adjacent road is created. All models are handled using the Variable Structure Multiple Model (VS-MM) approach without an interaction. The weight for each model  $i$  is therefore calculated by

$$w_i(k+1) = \frac{w_i(k) \cdot \Lambda_i(k+1)}{\sum_j w_j(k) \cdot \Lambda_j(k+1)} \quad (3)$$

with innovation likelihood  $\Lambda_i(k) = p(\mathbf{z}(k)|\mathbf{Z}(k-1), i)$ .

The presented approach works well for long straight roads so far. If narrow curves should be supported, errors may occur, if the covariance of one of the on-road models is larger than the road itself (one sigma value of the estimated position). This leads to a bad association and bad estimation results. To overcome this problem, a large covariance of a model is further approximated by a Gaussian sum [U103] (see figure 2). As a result, the covariance fits the run of the roads much better.

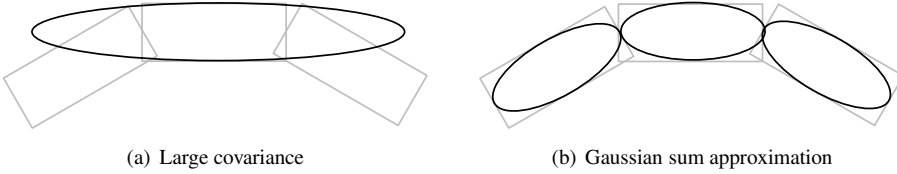


Figure 2: Gaussian Sum Approximation (b) for a long covariance of a model (a) (for better illustration, a two-dimensional covariance is shown).

Models subdivided by this means are added to the VS-MM, whereas the original model is removed. Models are dropped from the VS-MM according to their weight. In addition, similar models are merged to reduce the overall model number.

## 4 Results

Results are obtained from a GMTI simulation. The platform is flying to the south-east at an altitude of 10000 m starting in the north of the observation area at a distance of 100 km. The uncertainties of the measurements are assumed to be  $\sigma_R = 20$  m for the range,  $\sigma_{AZ} = 0.005$  for the azimuth and  $\sigma_{EL} = 0.005$  for the elevation angle. The target velocity is 10 m/s. The acceleration uncertainty is set to  $\sigma_a = 1$  m/s<sup>2</sup> and the correlation time to  $\tau = 10$  s. The sensor simulation accounts for a probability of detection, which depends on the range rate of the target and therefore suppresses targets moving at radial velocities close to the blind Doppler. Figure 3 shows the result from a run of the tracker.

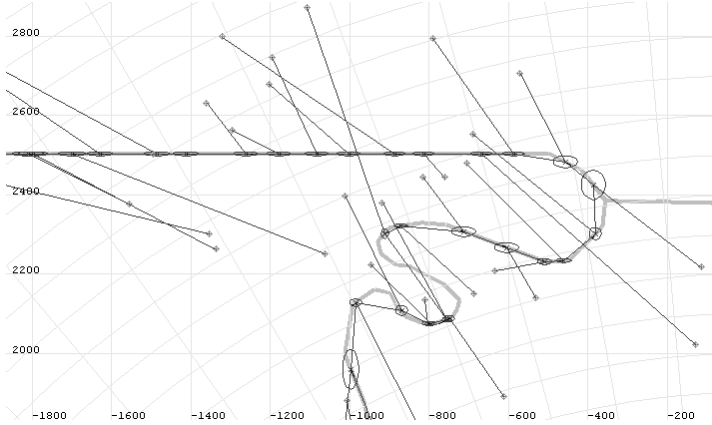


Figure 3: Results of a run: The crosses are the measurements, which are connected to the estimated state.

10000 Monte-Carlo runs were executed for the scenario shown in figure 3. The results are shown in figure 4. For comparison, a Kalman filter with a three-dimensional free mass, white noise acceleration model without road map support is also included in figure 4. As seen in figure 4, the road map supported tracker leads to much better estimation results in position and velocity as the free mass Kalman filter.

## 5 Summary

In this paper, an algorithm for tracking ground targets which move on roads was presented. In difference to many other publications, narrow curves are also supported by applying a Gaussian sum approximation to the on-road models, which expands over crossings as well. All models are kept in a VS-MM approach. The first results have shown, that this approach leads to good estimation results. In the next steps, the approach must be verified with real data and must be extended to multiple targets.

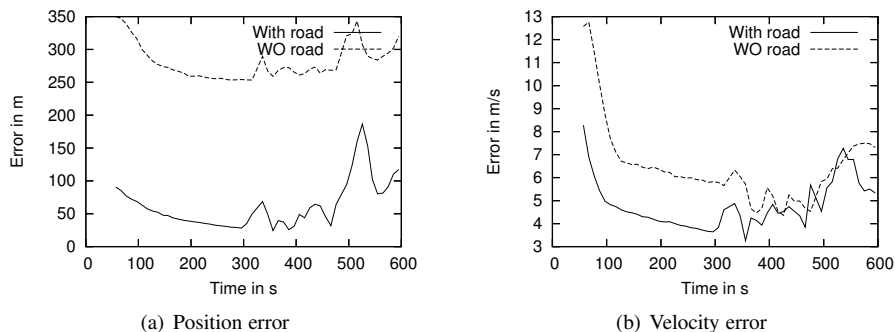


Figure 4: Simulation results: Position (a) and velocity errors (b), each with and without (WO) road map support.

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