A comparative study on the use of road network information in GMTI tracking

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Abstract - A key requisite to GMTI tracking is the use of road network to enhance the track quality and the track continuity. In this paper, we present a comparative study on the incorporation of such information in the GMTI tracking. We consider for this the particular scenario of tracking a target at road junctions or intersections. The goal of this study is to examine the performances of three tracking algorithms IMM, PMHT and DDIMM (Delayed Decision IMM) in this scenario. In this paper, we describe the GMTI tracking problem and some issues related to the integration of contextual information that need to be addressed. Furthermore, we give a brief description to the IMM, PMHT and DDIMM in the ground tracking framework. We emphasize on the particular approach of including the contextual information in the tracking algorithms: we consider that each road segment belonging to a junction or an intersection presents a different mode for the IMM and the DDIMM and a different hypothesis for the PMHT. The road segment selection test is done either sequentially or based on some batch processing. Before conclusion, some simulations results that evaluate the performances of the three filters are presented.

Keywords: GMTI tracking, data association, road network, IMM, PMHT.

1 Introduction

In GMTI tracking, the exploitation of the road network is becoming standard a priori information in the filtering process to improve the tracking quality. Kirubarajan et al. [1] consider a VS-IMM where the road network properties are considered in the definition of the dynamic models uncertainties. Off-road, the process noise has equal covariances in both road directions. For a target moving on a road, the noise is higher along the road due to the road constraint. In [2], Shea et al. use a VS-IMM estimation algorithm that has both off-road (unconstrained) motion models and on-road (constrained) motion models in addition to considering both length and width for each road segment. In paper [2], the problem of road intersection is dealt with by considering an off-road motion model as long as the uncertainty on the position of the target holds. In [3], and in addition to road constraint, Koch considers the Minimum Detectable Velocity (MDV) as a new constraint in target tracking. In the considered scenario, the road map information is equivalent to an additional range measurement. Another issue in GMTI tracking is the selection of a data association algorithm. Lately, the MHT has become quite popular because of the advances in computing hardware. In GMTI tracking, MHT has been combined with the IMM in [4]. In [2], Shea et al. represent the road segment as a Gaussian sum of ellipses to allow for comparison with track covariance ellipses during MHT and VS-IMM computations. In addition, they create a grid that is used to facilitate the road intersection hypothesis generation for the MHT algorithm. An alternative approach, that does not require the explicit expansion and evaluation of hypotheses is the assignment algorithms that choose a single best data association hypothesis or m-best hypotheses using multiple scans. Although there are differences in the specific steps, the assignment algorithms are all based upon Lagrangian relaxation. The main idea is to use the Lagrangian multipliers to move constraints into the cost to be minimized until the problem becomes a 2-D assignment problem which can be solved by algorithms such as the auction algorithm [9]. The assignment algorithm has been used in data association for GMTI tracking [1] and extended in a second paper [5] to deal with evasive targets (moving below the MDV). These association algorithms rely upon an evaluation of all the assignments of measurements to tracks. The PMHT has been developed by Streit and Luginbuhl [6] in order to perform tracking without an explicit association function. Instead of dealing with individual target states and individual measurements, this approach treats all targets and measurements as components of one system and estimates the system state directly without going through the separate steps of association and filtering. Although, it presents some problems, particularly at the level of initialization, the PMHT is still an attracting algorithm because of its straightforward implementation and its flexibility to handle target manoeuvre. In this paper, we present a comparative study on the performance of three filters. Under the assumption that the target is evolving on the road network and using a Bayesian approach, we study the performances of a PMHT, an IMM and a DDIMM for the particular scenario of a road junction. The IMM, a
widespread used filter, is computationally efficient with good performances when the tracked target is manoeuvring. The VS-IMM allows to improve the granularity of the track without degrading the whole performance of the filter. The adequate constrained motion models can be activated in real time according to the road constrained target positions. In defining the IMM and the DDIMM, we consider that to different road segments may correspond different target dynamics. Therefore, a set of dynamic models is associated to each road segment (constant velocity dynamic models where the process noises depend on the segment orientation in addition to the manoeuvrability of the target) in addition to a stop model when no reports are in the validation gate [7]. However, if the ground target approaches a junction, an ambiguity arises in adapting the constraint to the adequate road segment on which the target is evolving. Making the right road selection (i.e. the road chosen by the target) is very important in the definition of the IMM model set. We propose a sequential probability ratio test RSS-SPRT in order to select the road followed by the target t. This test is adapted to the VS-IMM algorithm in [8]. In the PMHT, we associate assignment indices to the different road segments, therefore to the different target dynamics. It follows that we can incorporate road segment switching and road segment manoeuvre as assignment parameter in the PMHT development.

This paper is organized as follows: In section 2, we give a brief description of the considered scenario and the problematic tracking at a road junction, in addition to a presentation of the general framework for the different tracking alternatives. In section 3, the PMHT algorithm is presented and a particular emphasis is given to the definition of the algorithm hypotheses. In section 4, we present the algorithm for a road constrained IMM in addition to a sequential probability ratio test (SPRT) used to select the target followed road segment at the junction. And finally, in section 5, we present some simulation results for the three filters and the conclusions drawn from these results.

# 2 Problem description

In the literature, the road intersection problem is dealt with either by considering all motion models associated to the different road segments present in the intersection [1] or by considering an off road dynamic model [2]. In the following, the road network, the stochastic target constrained motion model, and the measurement model are briefly described.

## 2.1 Representation of roads

We call road section a road delimited by junctions or a dead end and defined by a set of linear segments. These road segments are indexed with respect to the road section they belong to. All road coordinates are converted in a Topographic Coordinate Frame (TCF) before the actual ground surveillance operation. The TCF axes $X_{TCF}$, $Y_{TCF}$ and $Z_{TCF}$ are respectively oriented in the east local direction, the north local direction and the up local direction [7].

## 2.2 Target state under constraints

The target state at scan $t$ is defined in the local coordinate frame $(O, X_{TCF}, Y_{TCF})$ by:

$$x(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \\ y(t) \\ \dot{y}(t) \end{bmatrix},$$

where $(x(t), y(t))$ define the Cartesian coordinates of the target in $(O, X_{TCF}, Y_{TCF})$ and $(\dot{x}(t), \dot{y}(t))$ the corresponding velocities. We consider that the altitude component in the X-Y plane of the TCF is negligible. The dynamics of the target evolving on a road are modeled by a first order system. The target state constrained to the road segment $s$ is defined by $x_s(t) = [x_s(t), \dot{x}_s(t), y_s(t), \dot{y}_s(t)]^T$ where the target position $(x_s(t), y_s(t))$ belongs to the segment $s$ and the associated velocity vector is in the road segment $s$ direction. Therefore, the following constraint on the target state $x(t)$:

$$\begin{cases} 
  a \cdot x_s(t) + b \cdot y_s(t) + c = 0 \\
  \left[\begin{array}{c} x_s(t) \\ y_s(t) \end{array}\right] \cdot \hat{n}_s = 0 
\end{cases}
$$

where, the coefficients $a$, $b$ and $c$ are the parameters of the line equation associated to the road segment $s$ and $\hat{n}_s$ is the orthogonal vector to the segment $s$.

The constrained dynamics of the target are then defined by:

$$x_s(t) = F_s(\delta_s) \cdot x_s(t-1) + \Gamma(\delta_s) \cdot v_s(t)$$

Where $F_s(\delta_s)$ is the state transition matrix associated to the road segment $s$, and $v_s(t)$ is a white Gaussian process noise where the associated covariance matrix $Q_s(t)$ is built using the directional process noise [7]. The matrix $\Gamma(\delta_s)$ is defined by:
\[ \Gamma(\delta_t) = \begin{bmatrix} \frac{\delta_t^2}{2} & \delta_t & 0 & 0 \\ 0 & 0 & \frac{\delta_t^2}{2} & \delta_t \end{bmatrix} \]  

(3)

2.3 The measurement model

The GMTI reports are expressed in the platform polar coordinates frame:

\[ z(t) = [\rho(t) \ \theta(t)]^T \]  

(4)

Then, the measurements (4) are converted in the TCF with a debiased conversion such that:

\[ z_{TCF}(t) = H \cdot x_t(t) + v_{TCF}(t) \]  

(5)

where \( H = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} \) and \( v_{TCF}(t) \) is a zero-mean white Gaussian noise vector.

3 Basic PMHT algorithm description

The purpose of this section is to briefly describe the PMHT algorithm restricted to one sensor and for a batch formulation of the multi-target tracking problem. In the standard Bayesian approaches, or in the various hard assignment techniques, the assignment of a measurement to a track is considered as an unknown parameter of the problem. This parameter is subject to constraints, namely each target is allowed to form at most one measurement. In the PMHT, the assignment of each measurement is treated as a random process, with an associated probability mass function. Under the assumption that the association of measurements and sources is independent for different measurements, the problem of association and estimation then becomes a joint estimation process of two sets of random variables: target states and measurements assignments. It is possible to treat the tracking problem as an estimation problem with incomplete data. The incomplete data consists of the measurements, whereas complete data include the measurement assignments. This problem can be solved using the Expectation-Maximization (EM) algorithm. The (EM) algorithm provides a method for estimating the target states without estimating the assignments. This is achieved by maximizing the conditional expectation over the assignments of the joint log likelihood of the states, assignments, and measurements. The resulting algorithm is an iterative procedure that alternates between a data association step and a state estimation step. In the association step, the probability that each measurement belongs to each target is computed, using the state estimate from the previous iteration. In the estimation step, a new state estimate is produced by finding the maximum likelihood estimate of the state given measurements weighted by their association probabilities. The incorporation of clutter is done by adding an extra-model to the track list.

This algorithm is taken from Daveys’ thesis [6]. Assuming that at time \( T \), we have a set of cumulative measurements \( Z = (Z_1, ..., Z_T^T) \). For this batch length, we consider a set of \( M \) models of targets moving in the surveillance region in addition to the clutter. The temporal collection of model states over the batch for a model \( m \) is \( X^m = (x^m_0, x^m_1, ..., x^m_T) \). The total collection of all states is defined by \( X = (X^1, X^2, ..., X^m) \) and the vector of all states at time \( t \) \( X_t = (x^1_t, x^2_t, ..., x^m_t) \). For the \( rth \) measurement at scan \( t \), there is a corresponding assignment index \( k_{tr} \). The assignment index is an integer that takes value in the range \([1, M]\). The set of all assignment indices at scan \( t \) is defined by \( K_t = (k_{t1}, k_{t2}, ..., k_{tn_t}) \) where \( n_t \) defines the number of measurements at scan \( t \).

In the PMHT, the assignments are assumed to be i.i.d random variables. It allows each target to produce more than one measurement. \( \pi^m_t \) denotes the probability that the assignment index \( k_{tr} \), takes the value \( m \) at scan \( t \). We define the following sets \( \Pi_t = (\pi^1_t, \pi^2_t, ..., \pi^M_t) \) and \( \Pi = (\Pi_1, \Pi_2, ..., \Pi_T) \). The probability function of the measurement \( z_{tr} \) is then

\[ p(z_{tr} | X_t, k_{tr}) = \begin{cases} \pi^1_t (z_{tr} | x^1_t) & \text{if } k_{tr} = 1 \\ \vdots & \vdots \\ \pi^M_t (z_{tr} | x^M_t) & \text{if } k_{tr} = M \end{cases} \]  

(6)

Under the assumption that the measurements are in the TCF frame, the measurement probability density function is then given by

\[ \pi^m_t (z_{tr} | x^m_t) = \frac{1}{\sqrt{12\pi R_{tr}^m}} \exp \left\{ -\frac{1}{2} (z_{tr} - H^m_t x^m_t)^T R_{tr}^{-1} (z_{tr} - H^m_t x^m_t) \right\} \]  

(7)

The PMHT asymptotically approaches a local maximum of the EM auxiliary function by refining estimates of the states, \( X \), and the parameters \( \Pi \). The estimates \( X^{(t+1)} \) and
\(\Pi^{(i+1)}\) are obtained by maximizing the EM auxiliary function

\[
Q(X, \Pi^{x}/X^{(i)}, \Pi^{(i)}) = \sum_{i=1}^{T} \sum_{j=1}^{n_{i}} \sum_{k=1}^{M} \log P(X, K, Z; \Pi) P(K / X^{(i)}, Z; \Pi^{(i)})
\]  

(8)

The states of all models are assumed to be first order Markov random variables and are therefore independent of all other prior information when conditioned on the prior states. In addition to the assumption that the assignments are i.i.d, the measurements are i.i.d realizations of measurement processes as defined by the respective assignments. These independence assumptions combined with Bayes’ rule yield a decomposition of (8)

\[
Q(X, \Pi^{x}/X^{(i)}, \Pi^{(i)}) = \sum_{m=1}^{M} Q_{X}^{m}(X^{m} / X^{m(i)}, \Pi^{(i)}) + \sum_{i} Q_{\Pi^{x}}(\Pi^{x} / X^{(i)}, \Pi^{(i)})
\]  

(9)

The first term in (9) depends only on the model states and the measurements. This cost function can be maximized using a Kalman filter when the target measurement and evolution processes as defined by the respective assignments. This is equivalent to a maximum likelihood problem with weighted measurements. For linear Gaussian statistics, the likelihood function is the same as the likelihood function optimised by the Kalman smoother except that a modified measurement probability density is given by

\[
-\log p(z_{t} / x_{t}^{m(i)}) = \frac{1}{2} \log \left| R_{t} \right| - \frac{1}{2} (z_{t} - H_{t}^{m} x_{t}^{m(i)})^T R_{t}^{-1} (z_{t} - H_{t}^{m} x_{t}^{m(i)})
\]  

(12)

where \(z_{t}^{m(i)} = \frac{1}{n_{t} \pi^{m(i)}_{t}} \sum_{r=1}^{n_{t}} w_{mtr}^{(i)} z_{tr}^{m} \) defines the modified measurement centroid.

The PMHT algorithm is then the repeated application of equations (10) and (11) along with Kalman smoothing. At each iteration, the states and parameters are modified and this produces new weights through (11). When the algorithm converges, the changes in the estimates and weights become small.

The inclusion of multiple dynamics models for each target is done by considering the switching dynamic models used for manoeuvre tracking as a mixture model for the state evolution process.

Defining a target state probability density by :

\[
\Phi_{t}^{m}(x_{t} / x_{t-1}^{m(i)}) = \begin{cases} 
\phi_{t1}^{m1}(x_{t} / x_{t-1}^{m1}) & \text{if } \mu_{t}^{m} = 1 \\
\phi_{t2}^{m2}(x_{t} / x_{t-1}^{m2}) & \text{if } \mu_{t}^{m} = 2 \\
\vdots & \vdots \\
\phi_{tN}^{mN}(x_{t} / x_{t-1}^{mN}) & \text{if } \mu_{t}^{m} = N 
\end{cases}
\]  

(13)

where \(\mu_{t}^{m} \in [1 \cdots N] \) denotes the component of the mixture distribution present at scan \(t\). Each of the \(\phi_{t}^{m}(x_{t} / x_{t-1}^{m(i)})\) is a known function.

The manoeuvre model index, \(\mu_{t}^{m}\), is modelled as a Markov chain with known transition matrix. In PMHT, the index is treated as an additional missing data. Under the assumption that manoeuvre models can be presented by constant velocity models with different process noise
covariance matrices, then the resulting PMHT can be implemented using a scalar multiple of $Q$ in the same way as done for modified measurements.

### 4 Delayed Decision IMM

By using the notation $M^i(t)$ to define the $i$th motion model (constant velocity dynamics characterized by the process noise ($\sigma_d, \sigma_n$) at the current time $t$), the state probability density function given the measurement set $Z'$ and the event that the target is following the $M^i(t)$ dynamics is denoted by:

$$p\{x(t)\mid Z', M^i(t)\}$$

(14)

The state $x(t)$ is a Gaussian random variable defined by its estimated mean $\hat{x}^i(t/t)$ and its estimated covariance $P^i(k|k)$ (both obtained using a $M^i$ model based filter [7]). We consider now the new event that the target is following $M^i(t)$ dynamics on the road segment $s$ presented by $M^i(t)\cap e_s(t)$. Under the road constraint, the estimated state $\hat{x}^i(t/t)$ is therefore the state obtained by the maximization of pdf (14) given the event $M^i_s(t)$. It follows that:

$$\hat{x}_s^i(t/t) = \arg\max_{\hat{x}(t)}\left(p\{x(t)\mid Z', M^i_s(t)\}\right)$$

(15)

Given the fact that the event of the target evolving on the road segment $s$ (denoted $e_s(t)$) can be considered as an equality constraint then by using the Lagrangian approach and the Gaussian assumption we obtain:

$$\hat{x}_s^i(t/t) = \arg\min_{\hat{x}(t)\in e_s(t)}\left(\|x(t) - \hat{x}^i(t/t)\|_{P^{i(t/i)}^{-1}}^2\right)$$

(16)

where the notation $\|\|_{P^{i(t/i)}^{-1}}$ defines the Mahanalobis distance. The equality constraint $e_s(t)$ is expressed by (1). Consequently, in order to obtain a target state estimate for each model $M^i(k)$ under the road segment $s$ constraint, we must predict the state according to the dynamics (3) and pseudo project the updated state (15). The pseudo projected local estimate analytic expression (state and covariance) are given in 7:

$$\hat{x}_s^i(t/t) = \hat{x}_s^i(t/t) - P^i(t/t) \cdot \tilde{D} \cdot (\tilde{D} \cdot P^i(t/t) \cdot \tilde{D}^\top)^{-1} \cdot (\tilde{D} \cdot \hat{x}_s^i(t/t) - L)$$

(17)

$$P^i_s(t/t) = (\text{Id}(4) - W(t)) \cdot P^i(t/t) \cdot (\text{Id}(4) - W(t))^T$$

(18)

where the matrix $\text{Id}(4)$ is the identity matrix of dimension $4\times4$, and $W(t) = \text{P}(t/t) \cdot \tilde{D} \cdot (\tilde{D} \cdot \text{P}(t/t) \cdot \tilde{D}^\top) \cdot \tilde{D}$.

For a manoeuvring target, we consider three motion models $M^1_s(t)$, $M^2_s(t)$ and $M^3_s(t)$ which are respectively a constant velocity model with a low uncertainty $V_s(t)$, a constant velocity model with a high uncertainty reflected by a strong noise $V_s(t)$, and a stop model when the target is assumed to have a zero velocity. The transition between the models is a Markovian process. It is evident that when the target moves from one segment to the next, the set of dynamic models changes. However, when the target is making the transition from one segment to another the problem is to choose the segments with the corresponding motion models that can better fit the target dynamics. The IMM proposed in [8] suggests a decomposition cycle in five steps:

**Step 1:** Under the assumption of three possible dynamic models for segment $s$ as defined in the previous paragraph, the mixing probabilities are given by:

$$(\forall i, j \in \{0,1,2\}),$$

$$\mu_{ij}(t-1|t-1) = P\{M^i_s(t-1)\mid M^j_s(t), Z^{t-1}\}$$

(19)

$$\mu_{ij}(t-1|t-1) = \frac{p_{ij} \cdot \mu_i(t-1)}{e_j}$$

(20)

The model switching depends on the Markov chain according to the transition probability $p_{ij} = P\{M^i(s)\mid M^j(s-1)\}$. Note that the transition probability does not depend on the constraint $s$.

**Step 2:** The mixing probabilities above are used to weight the initial state estimates in order to present to the model filters the mixed estimates. We define the probability density function of the state according to the observation and the model under road segment $s$ constraint by:
\[ p\{x(t-1)|M^j_s(t), Z^{t-1}\} = \]

\[ \sum_{i=0,1,2} p\{x(t-1)|M^i_s(t-1), Z^{t-1}\} \cdot P\{M^i_s(t-1)|M^j_s(t), Z^{t-1}\} \]  

(21)

The mixed estimate under road segment constraint is given by:

\[ \hat{x}^0_{s,j}(t-1|t-1) = \arg \max_{x(t-1)} p\{x(t-1)|M^j_s(t), Z^{t-1}\} \]  

(22)

Given the relation (16) and the Fubini theorem, we found the following expression:

\[ \hat{x}^0_{s,j}(t-1|t) = \sum_{i=0,1,2} \hat{x}^i_{s,j}(t-1|t-1) \cdot \mu_j(t-1|t-1) \]  

(23)

The mixed estimate, input to the jth model filter (state and covariance \( P^0_{s,j}(t-1|t-1) \)), does not necessarily belong to the road segment \( S \) because it is obtained by a weighted sum. That is why we propose to make the pseudo projection, equation (9), of the mixed estimate (17). It comes:

\[ \hat{x}^0_{s,j}(t-1|t) = \hat{x}^0_{s,j}(t-1|t-1) - P^0_{s,j}(t-1|t-1) \cdot \hat{D} \cdot (\hat{D} \cdot P^0_{s,j}(t-1|t-1) \cdot \hat{D}^T)^{-1} \]

(24)

The constrained covariance \( P^0_{s,j}(t-1|t) \) is obtained according to relation (18).

Step 3: Model update

The motion models are constrained to the associated road segment. Each constrained mixed estimate (23) is predicted and then associated to one new segment or several (intersection case) new ones therefore the modification in the dynamics according to the new segments. Each constrained predicted state is updated based on the MTI report used also to calculate the corresponding likelihood:

\[ \Lambda_j(t) = p\{z(t)|M^j_s(t), Z^{t-1}\} \]  

(26)

According to (9), the obtained state estimate \( \hat{x}^i(t|t) \) is pseudo projected on the most probable road segment \( s_j \).

The technique used to select the most probable road segment \( s_j \) is described in [7].

Step 4: The model probability updates

The model probability is defined by:

\[ \mu_j(t) = p\{M^j_s(t)|Z^t\} \]  

(27)

This is the model probability and not the probability to belong to road segment \( s \).

\[ \mu_j(t) = \frac{1}{c} \cdot \Lambda_j(t) \cdot \bar{c}_j \]  

(28)

The coefficient \( c \) is a normalization coefficient.

Step 5: The constrained global state estimate

The combined state estimate called global state estimate is the sum of each constrained local state estimate weighted by the model probability.

In the previous paragraph, we have proposed a technique for the activation of constrained motion models in order to build the IMM model set structure. However, if the ground target approaches a junction, an ambiguity arises in adapting the constraint to the adequate road segment on which the target is evolving. Making the right road selection (i.e. the road chosen by the target) is very important in the definition of the IMM model set. In paper [7], a sequential probability ratio test named RSS-SPRT is proposed in order to select the road chosen by the target. This test is adapted to the VS-IMM in [8]. For this, we consider that an hypothesis corresponds to one road section at the intersection. If there are \( N \) roads at the intersection, we consider \( N \) hypotheses. So for each hypothesis, or road section, there is one IMM with an appropriate constrained motion model set. The IMM outputs are sequentially evaluated. Here, for each IMM, we have three likelihoods associated to the corresponding constrained model filters. We define the global likelihood function obtained by combining the three likelihoods

\[ \left( \forall h \in \{1, \ldots, N\} \right) \Delta_h(t) = p\{z(t)|Z^{t-1}, \bigcup_{j=0,1,2} M^j_{s_h}\} \]  

(29)

Under the assumption that the events \( M^j_{s_h} \) are disjoints for \( j \in \{0,1,2\} \), the previous expression can be written as follows:
(\forall h \in \{1, \ldots, N\}) \Delta_h(t) = \frac{1}{C} \prod_{j=0,1,2} \Lambda_j(t) \quad (30)

Where the parameter C is a normalization constant and the likelihood \( \Lambda_j(t) \) is defined in (24). The probability \( \mu_h(t) \) is defined according to the road section probability [7] by:

(\forall h \in \{1, \ldots, N\}) \quad \mu_h(t) = \Delta_h(t) \cdot \sum_{\vec{r}_a \in [1, \ldots, N_{\vec{r}_a}] \setminus \{h\}} \Omega_{\vec{r}_a,h}(t-1) \cdot \mu_{\vec{r}_a}(t-1) \quad (31)

The matrix component \( \Omega_{\vec{r}_a,h}(t-1) \) represents the probability transition between the roads associated respectively to the hypotheses \( \vec{r}_a \) and \( h \). The probability \( \mu_{\vec{r}_a}(t-1) \) is the probability according to the hypothesis \( \vec{r}_a \) at the time \( t-1 \). The sequential probability ratio test to choose the adequate road section and activate the correct constrained motion model set is therefore 0the following:

(\forall (h, h') \in \{1, \ldots, N\}^2) \quad \mu_h(t) \mu_{h'}(t) \geq B

Accept hypotheses \( h \) if \( \frac{\mu_h(t)}{\mu_{h'}(t)} \geq B \)

Reject hypotheses \( h \) if \( \frac{\mu_h(t)}{\mu_{h'}(t)} \leq A \)

Go to the next cycle for one more measurement and continue the test until just one hypothesis holds.

The thresholds A and B are given in [7].

5 Simulations: scenario and results

In this section, we consider an illustrative scenario of the road intersection problem in GMTI tracking. The purpose of this paper is only to compare the performances of the proposed algorithms in this context and under the assumption that the present targets are already being tracked. To start, we consider first the case of one target getting to a road intersection in the presence of false alarms. False alarms are Poisson distributed, with spatial density \( \lambda \) whose value will depend on the simulation. The road intersection consists of a junction of three road sections which form an angle of \( \pi/4 \) with respect to each other. In this particular scenario, we consider that each road section may correspond to different target dynamics. Therefore, to one road section corresponds one dynamic model or more depending on the target if it is manoeuvring or not. In the PMHT definition, one important assumption is that measurements at a given scan can all originate from the same target. Following this assumption, we consider that the assignment index denotes the model that gave rise to the measurement. It follows that the assignment index denotes the road section on which the target is evolving and the received measurements can all originate from one road section.

We consider a sliding batch for the PMHT. The performances of the proposed algorithms are measured in terms of the number of scans, or the length of the batch for the PMHT, needed to reach a decision on the followed road section. The needed number of scans is evaluated for each algorithm for different values of \( \lambda \) (false alarms). The receiver for the purpose of simulations is considered static and at 40 km from the road intersection. Measurements are received at a sampling rate of \( T = 5 \) sec. The sensor accuracies of the measurements in the Cartesian frame are \( \sigma_x = \sigma_y = 500 \) m. The target moves at a constant speed. At the road intersection, and depending on the followed road segment, it moves at \( v_x = 5 \) m/s, \( v_y = 0 \), \( v_x = 10 \) m/s, or \( v_x = 5 \) m/s, \( v_y = 0 \). The surveillance volume is taken equal to 2.5x10^4 m^3.

<table>
<thead>
<tr>
<th>( \lambda )</th>
<th>PMHT</th>
<th>IMM</th>
<th>DD-IMM</th>
</tr>
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<tbody>
<tr>
<td>10^{-5}</td>
<td>Lost track</td>
<td>Lost track</td>
<td>8 scans</td>
</tr>
<tr>
<td>0.5x10^{-3}</td>
<td>20 scans</td>
<td>Lost track</td>
<td>4 scans</td>
</tr>
<tr>
<td>10^{-4}</td>
<td>10 scans</td>
<td>Tracking</td>
<td>4 scans</td>
</tr>
<tr>
<td>10^{-5}</td>
<td>5 scans</td>
<td>Tracking</td>
<td>4 scans</td>
</tr>
<tr>
<td>10^{-6}</td>
<td>5 scans</td>
<td>Tracking</td>
<td>4 scans</td>
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</table>

Table 1: simulation results: number of scans needed to maintain the track for different levels of false alarm density.

The obtained preliminary results show that the DD-IMM presents the best performances for different levels of false alarms. It shows also reasonable performances for the PMHT. These results were obtained after introducing a certain gating because the number of false alarms was too high to get processed as additional measurements by the PMHT. The obtained results demonstrate the importance of considering the road network even at the level of a road intersection. They reveal also comparative performances in the case of one target for two algorithms, one dealing
directly with the data association problem and the second tracking without data association.

Following these preliminary results, we plan to extend the study to the multi-target scenario and to include the computation time in the comparison between the algorithms.

In summary, in this paper, we have presented some preliminary performances of a new algorithm, DDIMM, and an unexplored algorithm, the PMHT in the GMTI tracking framework. The obtained results are promising but need further exploitation for a clear algorithmic strategy in GMTI tracking at road intersections. Moreover the PMHT as an initialization algorithm should be further studied in GMTI critical scenarios (several possible road sections to follow).

6 References


