Improvement of Multiple Ground Targets Tracking with GMTI Sensor and Fusion of Identification Attributes

Benjamin Pannetier, Jean Dezert, Evangeline Pollard
ONERA - The French Aerospace Lab
Information Processing and Modeling Department
29 Avenue de la Division. Leclerc,
92322 Châtillon, France.
benjamin.pannetier@onera.fr,jean.dezert@onera.fr

Abstract—Multiple ground targets (MGT) tracking is a challenging problem in real environment because of partial observations, high traffic density, the maneuverability of targets, the clutter and the low target detection probabilities. Most of current MGT trackers use GMTI (Ground Moving Target Indicator) sensor, since this sensor provides the range-rate measurement (Doppler) aside classical position measurements. This helps the tracking algorithms and the preliminary ground target classification. Advanced algorithms include exogeneous information like road network and terrain topography. In this paper, we develop a new improved VS-IMM (Variable Structure Interacting Multiple Model) algorithm for GMTI tracking which includes the stop-move target maneuvering model, contextual information (on-off road model, road network constraints), and identification information arising from classifiers coupled with the GMTI sensor. The identification information is integrated to the likelihood of each hypothesis of our SB-MHT and allows to solve efficiently most of ambiguities that can arise mainly at road intersections or after a target maneuver when leaving the road, or with undetected ground targets after few scans. We maintain aside each target track a set of ID hypotheses with their committed beliefs which are updated on real time with classifier decisions through target type tracker based on a proportional conflict redistribution fusion rule. The advantage of such a new approach is to deal precisely and efficiently with the identification attribute information available as it comes by taking into account its inherent uncertainty/non-specificity and possible high auto-conflict.

Table of Contents

1-4244-1488-1/08/$25.00

1. Introduction

Tracking ground targets with a GMTI sensor is strategic in order to establish the threat assessment on the battlefield. Since several years ground targets tracking algorithms have been studied and integrated in fusion stations. The main challenge is to develop new ground target tracking algorithms or to adapt those used in aerial surveillance domain. Contrariwise to air-target tracking algorithms, ground-target tracking algorithms are used in a more complex environment due to: high traffic density and large number of false alarms, which increases significantly the amount of data to process, fast and high maneuverability of the targets which yields to difficult data association problems, and terrain topography which can generate occulted zones where ground targets cannot be detected at all during period of time where there are moving or stopping in.

In a GMTI surveillance context, we propose to fuse the contextual information with MTI reports in order to improve track quality (estimation precision and track continuity). Based on road segments positions, dynamic motion models under road constraint are built and an optimized projection technique of the estimated states is proposed to keep each target position and heading on the road. A VS-IMM filter is built using this projection approach [4]. The set of models used in the filter is adjusted sequentially according to target positions and to road network configuration. The markov process is used to select the most probable motion models set which depends on the road feature.

In a multiple target context, we have adapted SB-MHT (Structured Branching - Multiple Hypotheses Tracking) [19] to take into account target manoeuvres and detection probability of each ground target. This algorithm, called VS-IMMC SB-MHT, is very efficient when targets are always detectable by the sensor.

Despite of track continuity improvement resulting from the VS-IMMC SB-MHT algorithm, an ambiguity arises in a multi-target context when several targets approach a junction (*i.e.* a crossroad) at the same time. In fact, according to motion models uncertainties and the number of roads involved

in the crossroad, the associations between all constrained predicted states are compromised if we only consider the measurement location. However, in the STANAG 4607 [7], each MTI segment is associated to a classification information with the estimated probability that the target identity (ID) is correctly classified. The new idea proposed in this work is to maintain aside each target track a set of ID hypotheses with their committed belief which are revised on real time with the classifier decision through a very recent and efficient fusion rule based on proportional conflict redistribution [17]. The advantage of such new approach is to deal precisely and efficiently with the identification attribute information available as it comes taking into account its inherent uncertainty/non-specificity and possible high auto-conflict. This approach is appealing since it doesn't require the introduction of extra ad-hoc assumption on probability distribution model always necessary in a pure classical Bayesian approach.

After a detailed presentation of our improved SB-MHT algorithm, we focus the second part of this paper on our simulation results and performance evaluation on a complex Multiple Ground Targets Tracking scenario within a real environment.

2. Motion and measurement models

Introduction

Usual target tracking algorithms are based on the Kalman filter. Since several years, in ground target tracking domain, the Kalman filter has been improved to take into account the contextual information in the tracking process. For instance, Kirubarajan *et al.* proposed to use the road segment location in order to modelize the dynamic of a target moving on the road [8]. The road network is considered here as *a priori* information to be integrated in the tracking system. The map information comes from a GIS (Geographic Information System) which contains information about the road network location and the DTED (Digital Terrain Elevation Data). In the following, the GIS description is given in addition to the stochastic target constrained and the measurement descriptions.

GIS description

The GIS used in this work contains the following information: the segmented road network and DTED. Each road segment is expressed in the WGS84 system. The road network is connex and each road segment is indexed by the road section they belong to. A road section $Ro\,(p)$ is defined by a connected road segments set delimited by a road end or a junction in the manner that $Ro\,(p) = \{s_0, s_1, \cdots\}$.

At the beginning of a surveillance battlefield operation, a Topographic Coordinate Frame (denoted *TCF*) and its origin *O* are chosen in the manner that the axes *X*, *Y* and *Z* are respectively oriented in the east, north and up local directions. The target tracking process is carried out in the *TCF*.

Target state under constraint

Constrained motion model—The target state at the current time *k* is defined in the local coordinate frame by (*TCF*):

$$x\,(k) = \left[\begin{array}{cccc} \mathrm{x}\,(k) & \dot{\mathrm{x}}\,(k) & \mathrm{y}\,(k) & \dot{\mathrm{y}}\,(k) \end{array}\right]' \tag{1}$$

where the couples $(\mathrm{x}\,(k)\,, \mathrm{y}\,(k))$ and $(\dot{\mathrm{x}}\,(k)\,, \dot{\mathrm{y}}\,(k))$ define respectively the target location and velocity. The dynamics of the targets evolving on the road network are modelized by a first-order system. The target state under the road segment s is defined by $x_s\,(k)$ where the target position $(\mathrm{x}_s\,(k)\,, \mathrm{y}_s\,(k))$ belongs to the road segment and the corresponding velocity vector $(\dot{\mathrm{x}}_s\,(k)\,, \dot{\mathrm{y}}_s\,(k))$ is in the road segment s direction. Therefore, the target constraint state $x_s\,(k)$ is defined by the following constraint:

$$\left\{\begin{array}{l} a \cdot \mathrm{x}_s\,(k) + b \cdot \mathrm{y}_s\,(k) + c = 0 \\ \left\langle \left[\begin{array}{cc} \dot{\mathrm{x}}\,(k) & \dot{\mathrm{y}}\,(k) \end{array}\right]' \middle| \vec{n}_s \right\rangle = 0 \end{array}\right. \tag{2}$$

where the indexes *a*, *b* and *c* are the coefficients of the line associate to the road segment s and $\overrightarrow{n}_s$ is the normal vector to the road segment s . The constraint can be expressed as follows:

$$\tilde{D} \cdot x_s\,(k) = L \tag{3}$$

with $\tilde{D} = \left[\begin{array}{cccc} a & 0 & b & 0 \\ 0 & a & 0 & b \end{array}\right]$ and $L = \left[\begin{array}{c} -c \\ 0 \end{array}\right]$.

The event that the target is on the road segment s is noted $e_s\,(k) = \{x\,(k) \in s\}$. Knowing the event $e_s\,(k)$ and according to a motion model M_i the dynamics of the target can be improved by considering the road segment s. Due to the precision of the GMTI sensor and the long time scan period, the chosen motion models are quite simple. They consist in *r* constant velocity motion models having different process noise statistics (standard deviations). However the proposed approach is valid for much more complicated motion models like the constant acceleration or coordinated turn ones. It follows that :

$$x_s\,(k) = F_{s,i}\,(\Delta_k) \cdot x_s\,(k-1) + \Gamma\,(\Delta_k) \cdot \nu_{s,i}\,(k) \tag{4}$$

where Δ_k is the time of sampling, the matrix $F_{s,i}$ is the state transition matrix associated to the road segment *s* (described in [9]) and is adapted to a motion model M_i, the variable $\nu_{s,i}\,(k)$ is a white noise Gaussian process and its associated covariance $Q_{s,i}\,(k)$ is built in the manner that the standard deviation σ_n along the road segment is higher than the standard deviation σ_d in the orthogonal direction. Consequently the covariance matrix $Q_{s,i}$ is defined by :

$$Q_{s,i}\,(k) = R_{\vartheta_s} \cdot \left[\begin{array}{cc} \sigma_d^2 & 0 \\ 0 & \sigma_n^2 \end{array}\right] \cdot R_{\vartheta_s}^T \tag{5}$$

where the matrix R_{ϑ_s} is the rotation matrix associate to the s road segment direction ϑ_s defined in the plane (O, X, Y). The matrix $\Gamma\,(\delta_k)$ is defined in [10]. The predicted target state and covariance are defined respectively by:

$$\hat{x}_{s,i}\,(k\,|k-1\,) = F_{s,i}\,(k) \cdot \hat{x}_{s,i}\,(k-1\,|k-1) \tag{6}$$

$$P_{s,i}(k|k-1) = F_{s,i}(k) \cdot P_{s,i}(k-1|k-1) \cdot F_{s,i}(k)^T + Q_{s,i}(k) \quad (7)$$

Adjustment of the process noise at the road extremities—For notation convenience, the event $\theta^{k,l}$ denotes the occurence of the lth sequence of measurements $Z^{k,l}$ which represents a possible set of measurements generated by the target up to time k (*i.e.*, there exists a subsequence *n* and a measurement *i* in the manner that $Z^{k,l} = \{Z^{k-1,n}, ..., z_j(k)\}$) associated with the track $T^{k,l}$. At the current time *k* the track $T^{k,l}$ is represented by the estimated states sequence. $z_j(k)$ is the jth measurement available at time k among $m(k)$ validated measurements around the target measurement prediction. We recall that a track is a sequence of state estimates.

Since the previous constraint on the motion model is specific only to a given segment s, it does not take into account the whole road network[1] and thus it omits the possibility for the target to switch onto another road segment when reaching the extremity of the segment it is moving on. Such modeling is too simplistic and the ground-target tracking based on it provides in general poor performances. To improve modeling for targets moving on a road network, we propose to adapt the level of the dynamic model's noise depending on the length of the road segment s and on the location of the target on this segment with respect to its extremities. This allows to relax gradually the *on-segment* constraint as soon as the target approaches the extremity of the road segment and/or a junction. If we omit the road segment length in the motion model, the tracking algorithm may not associate the predicted track with a measurement when the predicted state is near the road segment extremity. In fact, if a measurement is originated from a target moving on the road segment $s+1$, the measurement won't be in the validation gate (defined in [19]), because of the road segment s constraint that generates a directive predicted covariance with a small standard deviation in the road segment s orthogonal direction. That is why, we propose to increase the standard deviation σ_d when the target approaches the road extremity, in the manner that the standard deviation in the orthognal road segment direction becomes equal to the standard deviation in the road segment direction. For this, we use the *prior* probability $P\{e_s(k)|Z^{k-1,n}\}$ in order to relax the constraint when the target approaches the road segment s extremity. The white noise Gaussian process $\nu_{s,i}(k)$ in (4) is modified in the manner that the covariance $Q_{s,i}$ is replaced by $\tilde{Q}_{s,i}$:

$$\tilde{Q}_{s,i}(k) = R_{\vartheta_s} \cdot \begin{bmatrix} \sigma_d^2 & 0 \\ 0 & q_{22} \end{bmatrix} \cdot R_{\vartheta_s}^T \quad (8)$$

where

$$q_{22} = \sigma_n^2 \cdot P\{e_s(k)|Z^{k-1}\} + \sigma_d^2 \cdot (1 - P\{e_s(k)|Z^{k-1}\}).$$

[1] i.e. the possibility of several other road segments connected at extremity of each road segment of the network.

The probability that the target belongs to the road segment s is based on the derivations proposed by Ulmke and Koch [11] and Herrero *et al.* [12], but we do not consider the road width and our modelization is done in the 2D space only. So the predicted road segment s belonging probability is expressed as:

$$P\{e_s(k)|Z^{k-1,n}\} = P\{\Pi_s(x) \leq l_s \mid Z^{k-1,n}\} \quad (9)$$

where $\Pi_s(x)$ is the projection operator on the road segment s modulo the road segment length l_s. According to the Gaussian assumption, the probability can be rewritten as follows:

$$P\{x(k) \in s | Z^{k-1,n}\} = \int_0^{l_s} N(u, \Pi_s(x), \sigma_s^2) du = \frac{1}{2} \cdot f\left(\frac{l_s - \prod_s(x)}{\sqrt{2 \cdot \sigma_s^2}}\right) \quad (10)$$

The variance σ_s^2 is the variance obtained after the projection Π_s on the road segment s and is given in [11]. The function $f(.)$ is the integral of the Gaussian distribution with 0 mean and variance of 1/2

$$f(t) = erf(t) = \frac{2}{\sqrt{\pi}} \cdot \int_0^t e^{-t^2} dt \quad (11)$$

Finally, we obtain a constrained motion model which takes into account the uncertainty that the target belongs to the road segment. This uncertainty is modelized by an additive noise process.

Constrained state estimation— We define $M_s^i(k) = \{M^i(k) \cap e_s(k)\}$ the event that the target is following a dynamic according to the motion model M^i and moves on the road segment s. So, the state probability density function (*i.e.* pdf) given the measurements set Z^k and the event $M_s^i(k)$ is denoted :

$$p\{x(k) | Z^k, \theta^{k,l}, M_s^i(k)\} \quad (12)$$

The state $x_i(k)$ is a Gaussian random vector defined by its estimated mean $\hat{x}_i(k|k)$ and its estimated covariance $P_i(k|k)$ (both obtained using a model based filter). Under the road constraint, the estimated state $\hat{x}_{s,i}(k|k)$ is therefore obtained by the maximization of pdf (12) given the event M_s^i. Finally, under the Gaussian assumption of the Kalman filter, the analytic expression of the constrained estimate state associate with the motion model M^i is obtained by calculating the Lagrangian of (12) under the constraint (3). The expressions of the constrained estimated state and it covariance are given in [4].

Since the road network is composed of several road segments and a ground target has several motion models, we consider an IMM (Interacting Multiple Model) with a variable structure [19], [23] to adapt the constraint motion models set to the road network configuration. This VS-IMMC is presented in the following section.

Measurement model

MTI report—According to the NATO GMTI formats, the MTI reports are expressed in WGS84 coordinates system [3]. All

MTI reports are converted for each tracking station into the *TCF*. A MTI measurement z at the current time k is given in the *TCF* by:

$$z(k) = \left[\begin{array}{ccc} \mathrm{x}(k) & \mathrm{y}(k) & \dot{\rho}_m(k) \end{array} \right]' \tag{13}$$

where $(\mathrm{x}(k), \mathrm{y}(k))$ are the x and y MTI coordinates in the local frame (*0*,*X*,*Y*) and $\dot{\rho}_m$ is the associated modified range-rate measurement expressed in the *TCF*:

$$\dot{\rho}_m(k) = \frac{\mathrm{x}(k) \cdot \dot{\mathrm{x}}(k) + \mathrm{y}(k) \cdot \dot{\mathrm{y}}(k)}{\sqrt{\mathrm{x}^2(k) + \mathrm{y}^2(k)}} \tag{14}$$

We don't consider the range-rate $\dot{\rho}$ obtained directly in the sensor frame because it is correlated to the MTI location components. In litlerature, there exist several techniques to uncorrelate the range-rate from the location components like for example, the SEKF from Wang *et al.* [13] based on Cholesky's decomposition. Nevertheless, we prefer to use the AEKF (Alternative Extended Kalman Filter) presented by Bizup and Brown [14]. This last one is very simple to compute because the authors propose only to use an alternative linearization of the EKF (Extended Kalman Filter). For our problem, the alternative linearization of the observation function is verified only if we consider the range-rate in the local frame TCF. Then, the measurement equation is given according to the AEKF, by:

$$z(k) = H(k) \cdot x(k) + \nu(k) \tag{15}$$

with $\nu(k)$ a zero-mean white Gaussian noise vector and $H(k)$ defined by:

$$H(k) = \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{\partial \dot{\rho}_m(k)}{\partial \mathrm{x}} & 0 & \frac{\partial \dot{\rho}_m(k)}{\partial \mathrm{y}} \end{array} \right] \tag{16}$$

The explicit expression of (16) is given in [14].

Classification segment—An issue to improve the multiple target tracking algorithm is to combine the kinematic data association with the attribute data association. In the STANAG 4607 [7], each MTI report is associated to the location and velocity information (described in the previous part) in addition to the attribute information with its probability that it is correct. We denote $C = \{c_0, c_1, \ldots, c_u\}$, the frame of discernement of our target classification problem. C is assumed to be constant over time (*i.e* target ID does not change with time) and consists in a finite set of u exhaustive and exclusive elements representing the possible states of the world for target classification. In the STANAG 4607 the set C is defined by :

$$C = \left\{ \begin{array}{l} No\ Information, \\ Tracked\ Vehicle, \\ Wheeled\ Vehicle, \\ Rotary\ Wing\ Aircraft, \\ Fixed\ Wing\ Aircraft, \\ StationaryRotator, \\ Maritime, \\ Beacon, \\ Amphibious \end{array} \right\} \tag{17}$$

In addition to the classification or attribute information, the STANAG allows to use the probability $P\{c_a\}$, $a = 1, \ldots, 9$, but it does not specify the way these probabilities are obtained because $P\{c_a\}$ are actually totally dependent on the algorithm chosen for target classification. In this paper, we do not focus on the classification algorithm itself, but rather on how to improve multiple ground targets tracking with attribute information and target classification. Hence, we consider the probabilities $P\{c_a\}$ as input parameters of our tracking systems characterizing the global performances of the classifier. In other words, $P\{c_a\}$, $a = 1, \ldots, 9$, represent the diagonal terms of the confusion matrix C_a of the classification algorithm assumed to be used. The modified/extended measurement $\mathbf{z_j}(\mathbf{k})$ among $m(k)$ measurements including both kinematic part and (classification) attribute part is defined as:

$$\mathbf{z}_j(k) = \{z_j(k), c_a, P\{c_a\}\} \tag{18}$$

3. VS-IMM WITH ROAD CONSTRAINTS (VS-IMMC)

IMM with only one road segment constraint

The IMM is an algorithm for combining states hypotheses from multiple filter models to get a better state estimate when the target is maneuvering. IMM is near optimal with a reasonable complexity. In section 2, a constrained motion model i to segment s, noted $M_s^i(k)$, is defined. Here we extend the segment constraint to the different dynamic models (among a set of $r+1$ motion models) that a target can follow. The model indexed by $r = 0$ is the stop model. 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. In a conventionnal IMM estimator [18], [20], the likelihood function of a model i is given, for a track $T^{k,l}$, associated with the j-th measurement, $j \in \{0, 1, \ldots, m(k)\}$ by:

$$\Lambda_i(k) = p\{z_j(k) | M_s^i(k), Z^{k-1,n}\}, \quad i = 0, 1, \ldots, r \tag{19}$$

where $Z^{k-1,n}$ is the subsequence of measurements associated with the track $T^{k,l}$.

Using the IMM estimator with a stop motion model, we get the likelihood function of the moving target mode for $i = 1, \ldots, r$ and for $j \in \{0, 1, \ldots, m(k)\}$ by:

$$\begin{aligned} \Lambda_i(k) = \quad & P_D \cdot p\{z_j(k) | M_s^i(k), Z^{k-1,n}\} \cdot (1 - \delta_{m_j,0}) \\ & + (1 - P_D) \cdot \delta_{m_j,0} \end{aligned} \tag{20}$$

while the likelihood of the stopped target mode (*i.e.* $r = 0$) is:

$$\Lambda_0(k) = p\{z_j(k) | M_0^i(k), Z^{k-1,n}\} = \delta_{m_j,0} \tag{21}$$

where $\delta_{m_j,0}$ is the Kronecker function defined by $\delta_{m_j,0} = 1$ if $m_j = 0$ and $\delta_{m_j,0} = 0$ whenever $m_j \neq 0$.

The combined/global likelihood function $\Lambda(k)$ of a track in-

cluding a stopped model is then given by:

$$\Lambda(k) = \sum_{i=0}^{r} \Lambda_i(k) \cdot \mu_i(k|k-1) \tag{22}$$

where $\mu_i(k|k-1)$ is the predicted model probabilities [20].

The steps of the IMM under road segment s constraint are the same as for the classical IMM :

1. Step 1. Under the assumption of several possible models for segment s as defined previously, the mixing probabilities are given for i and j in $\{0, 1, \ldots, r\}$ by:

$$\mu_{i|j}(k-1|k-1) = \frac{p_{ij} \cdot \mu_i(k-1)}{\bar{c}_j} \tag{23}$$

where $\bar{c}_j$ is a normalizing factor. The probability of model switch depends on the Markov chain according to the transition probability p_{ij}. It is important to note that the transition probability does not depend on the constraint s.

2. 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. The mixed estimated of the target state under the road segment s constraint is defined for $i = 0, 1, \ldots, r$ by:

$$\hat{x}^0_{i,s}(k-1|k-1) = \sum_{j=0}^{r} \hat{x}_{j,s}(k-1|k-1) \cdot \mu_{i|j}(k-1|k-1) \tag{24}$$

The covariance corresponding to the estimation error is:

$$\begin{aligned} &P^0_{i,s}(k-1|k-1) = \\ &\textstyle\sum_{j=0}^{r} \mu_{i|j}(k-1|k-1) \cdot [P^0_{j,s}(k-1|k-1) + \\ &(\hat{x}_{j,s}(k-1|k-1) - \hat{x}^0_{i,s}(k-1|k-1)) \cdot \\ &(\hat{x}_{j,s}(k-1|k-1) - \hat{x}^0_{i,s}(k-1|k-1))^T] \end{aligned} \tag{25}$$

Despite of the constraint on local estimated states, the mixed estimated states do not belong to the road section s. Nevertheless, the state transition (4) matrix projects the mixed estimate on the road section.

3. Step 3. The motion models are constrained to the associated road segment. Each constrained mixed estimate (24) is predicted and then associated to one new segment or several (in crossroad case) new ones therefore the modification in the dynamics according to the new segments. The mixed estimates (24) and (25) are used as inputs to the filter matched to M^i_s, which uses the MTI report associated to the track $T^{k,l}$ to yield $\hat{x}^l_{i,s}(k|k)$, $P^l_{i,s}(k|k)$ and the corresponding likelihood (22).

4. Step 4. The model probability update is done for $i = 0, 1, \ldots, r$ as follows:

$$\mu_i(k) = \frac{1}{c} \cdot \Lambda_i(k) \cdot \bar{c}_i \tag{26}$$

where c is a normalization coefficient and $\bar{c}_i$ is given in (23).

5. Step 5. The combined state estimate, called global state estimate, is the sum of each constrained local state estimate weighted by the model probability, i.e.

$$\hat{x}^l(k|k) = \sum_{i=0}^{r} \mu_i(k) \hat{x}^l_{i,s}(k|k) \tag{27}$$

Here, one has presented briefly the principle of the IMM algorithm constrained to only one road segment s. However, a road section is composed with several road segments. When the target is making a 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 choice of a segment implies the construction of the directional process noise. That is why the IMM motions model set varies with the road network configuration and VS-IMM offers a better solution for ground target tracking on road networks as explained in next sections.

Variation of the set of constrained motion models

In the previous subsection, we have proposed an IMM with a given/fixed motion model set. We have noted that the predicted state could give a local estimate under another road segment than the segment associated to the motion model (a road turn for example). The change to another road segment causes the generation of a new constrained motion models. In literature, several approaches are proposed to deal with the constrained motion models [8], [15]. In [4], we have proposed an approach to activate the most probable road segments sets. Based on the work of Rong Li [18], we consider $r+1$ oriented graphs which depends on the road network topology. For each graph i, $i = 0, 1, \ldots, r$, each node is a constrained motion model M^i_s. The nodes are connected to each other according to the road network configuration. For instance, if we consider a road section composed by three road segments s_1, s_2, s_3, the ith associated graph is composed by three nodes ($M^i_{s_1}$, $M^i_{s_2}$ and $M^i_{s_3}$) where the nodes $M^i_{s_1}$ and $M^i_{s_3}$ are connetced with the node $M^i_{s_2}$. In [4], the activation of the motion model at the current time depends on the local predicted states $\hat{x}^l_{i,s}(k|k-1)$ location of the track $T^{k,l}$. Consequently, we obtain a finite set of $r+1$ motion models constrained to a road section Ro_p (we recall that a road section is a set of connected road segments).

However, an ambiguity arises when there are several road sections (*i.e.* the target approach a crossroad). In fact, the number of constrained motion models grows up with the number of road sections present in the crossroad/junction. If we consider the $r+1$ graphs, the activation of the constraint motion model is done according to the predicted states location. Consequently the number of motion models increases with the number of road sections. We obtain several constrained motion model sets. Each set is composed of $r+1$ models constrained to road segments which belong to the road section. In order to select the most probable motion model set

(*i.e.* in order to know on which road section the target is moving on), a sequential probability ratio test named RSS-SPRT is proposed in [4] in order to select the road section taken by the target.

We consider that a hypothesis corresponds to one road section involved in the crossroad. At the current time k, if there are N_k road sections Ro_p at the intersection, we consider all N_k hypotheses. So for each hypothesis h, associated to a given road section, there is one IMM with an appropriate constrained motion models set. The IMM outputs are sequentially evaluated. However, one measurement iteration is not sufficient to choose the right hypothesis. The probability $\mu_h(k)$ of h is derived based on the likelihood function and the transition matrix between the road segments. The combined likelihood (22) of a constrained models set and for a hypothesis h, $h = 1, \ldots, N_k$ is denoted Λ_h. Mathematically, $\mu_h(k)$ is defined according to the road section probability [4] for $h = 1, \ldots, N_k$ by:

$$\mu_h(k) = \frac{1}{c} \cdot \Lambda_h(k) \cdot \sum_{\bar{h} \in \{1,\ldots,N_{k-1}\}} \Omega_{\bar{h},h}(k-1) \cdot \mu_{\bar{h}}(k-1) \quad (28)$$

The matrix component $\Omega_{\bar{h},h}$ represents the probability transition between the roads associated respectively to the hypotheses h and $\bar{h}$. In fact if the road section is a highway and the road section is an highway also the transition probability is high. On the contrary, if the road is a highway and the road section is a byway the transistion probability is small. The probability $\mu_{\bar{h}}(k-1)$ is the probability of hypothesis $\bar{h}$ at the time $k-1$ (i.e. the probability of the previous road section where the target was moving on). Wald's sequential probability ratio test [21], [22] (SPRT) for choosing the adequate road segment and activate the correct constrained motion model set at current time k is the following:

- Accept hypothesis h if for all $h' \neq h$, $h' \in \{1, \ldots, N_k\}$:

$$\frac{\mu_h(k)}{\mu_{h'}(k)} \geq B \quad (29)$$

- Reject hypothesis h if for all $h' \neq h$, $h' \in \{1, \ldots, N_k\}$:

$$\frac{\mu_h(k)}{\mu_{h'}(k)} \leq A \quad (30)$$

- Go to the next cycle and wait for one more measurement and continue the test until one hypothesis is accepted by the SPRT. The thresholds A and B are given in [21], [22], [19]. For a faster test see the MSP-SPRT [23] based on a probabilities classification.

VS-IMMC within the SB-MHT

We briefly describe the main steps of the VS-IMMC SB-MHT. More details you can be found in chapter 16 of [19].

1. The first functional block of the SB-MHT in figure 1 is the track confirmation and the track maintenance. When the new set $Z(k)$ of measurements is received, a standard gating procedure [20] is applied in order to determine the viable MTI reports to track pairings. The existing tracks are updated with VS-IMMC and extrapolated confirmed tracks are formed. When the track is not updated with MTI reports, the stop motion model is activated.

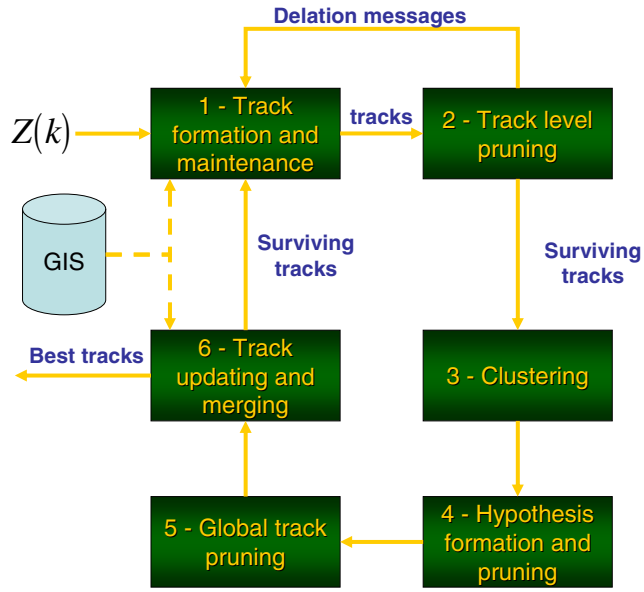


Figure 1. Track-oriented MHT logic flowchart with GIS

2. In order to palliate the association problem, we need a probabilistic expression for the evaluation of the track formation hypotheses that includes all aspects of the data association problem. It is convenient to use the log-likelihood ratio (LLR) or track score which can be expressed at current time k in the following recursive form [20]:

$$L(k) = L(k-1) + \Delta L(k) \quad (31)$$

with

$$\Delta(k) = \ln\left(\frac{\Lambda(k)}{\lambda_{fa}}\right) \quad (32)$$

and

$$L(0) = \ln\left(\frac{\lambda_{fa}}{\lambda_{fa} + \lambda_{nt}}\right) \quad (33)$$

where λ_{fa} and λ_{nt} are respectively the false alarm rate and the new target rate per unit of surveillance volume. After the track score calculation of the track $T^{k,l}$, the SPRT is used to set up the track status either as deleted, tentative or confirmed track. The tracks that fail the test are deleted and the surviving tracks are kept for the next stage.

3. The process of clustering is the collection of all tracks that are linked by a common measurement. The clustering technique is used to limit the number of hypotheses to generate and therefore to reduce the complexity. The result of clustering is a list of tracks that are interacting. The next step is to form hypotheses of compatible tracks.

4. For each cluster, in the fourth level, multiple coherent hypotheses are formed to represent the different compatible tracks scenarios. Each hypothesis is evaluated according to the track score function associated to the differents tracks. Then, a technique is required in order to find the hypotheses set that represents the most likely tracks collection. The unlikely hypotheses and associated tracks are deleted by a pruning process and only the N_Hypo best hypotheses are conserved.

5. For each track, the *a posteriori* probability is computed and a well known *N-Scan* pruning approach [19] is used to select and delete the confirmed tracks. With this approach the most likely track is selected to reduce the number of tracks. But the *N-Scan* technique combined with the constraint implies that other tracks hypotheses (*i.e.* constrained on other road segments) are arbitrary deleted. That is why, we must modify the *N-Scan* pruning approach in order to select the N_k best tracks on each N_k road sections.

6. Wald's SPRT proposed in Section 3 is used to delete the unlikely hypotheses among the N_k hypotheses. The tracks are then updated and projected on the road network. In order to reduce the number of track to keep in the memory of the computer, a merging technique (selection of the most probable tracks which have common measurements) is also implemented.

4. TARGET TYPE TRACKING

In this section we briefly present the approach for tracking target ID and explain the methodology for improving the VS-IMMC SB-MHT with target ID information. The basic idea is to modify the (kinematic-based) likelihood function of each set of data association sequence involved in SB-MHT with some attribute-based likelihood. Attribute-based likelihood estimates the probability that the current target ID corresponds to the expected target ID of the track under consideration. Some investigations based on this approach have already been sucessfully applied in aerial MTT domain [17], [1] Chapter 12. The mechanism for tracking the target type/ID is based on the sequential combination (fusion) of the predicted belief of the type of the target under track with the current "belief measurement" obtained from the target classifier decision and the quality of the classifier characterized by its confusion matrix (assumed to be known at least partially as specified by STANAG). The motivation and justification for using the so called Proportional Conflict Redistribution rule no 5 (PCR5) developed in the DSmT (Dezert Smarandache Theory) framework comes from its ability for dealing efficiently with (potentially high) conflicting information and managing uncertainty with respect to the well-known established fusion rules. Dezert et al. have recently proved the usefulness of PCR5 for target type tracking [2], [17] over other main combination rules. This choice is motivated in this typical application because in dense traffic scenarios, the VS-IMMC SB-MHT based only on kinematic information is not always able to track correctly all ground targets specially during maneuvers and crossroads. With enrichment of VS-IMMC SB-MHT with target attribute information, we expect to alleviate some data association ambiguities and thus improve the overall performances of our multiple ground target tracking system. Before presenting the derivation of enriched track score with target attribute likelihood, it is necessary to briefly recall how PCR5 combination rule works.

PCR5 combination rule

Let $\Theta = \{\theta_1, \ldots, \theta_n\}$ be a discrete finite set of n exhaustive elements and two distinct bodies of evidence providing basic belief assignments [16] (bba's) $m_1(.)$ and $m_2(.)$ defined on the power-set[2] of Θ. The idea behind the Proportional Conflict Redistribution (PCR) rules [17] is to transfer (total or partial) conflicting masses of belief to non-empty sets involved in the conflicts proportionally with respect to the masses assigned to them by sources as follows:

1. calculation the conjunctive rule of the belief masses of sources;
2. calculation the total or partial conflicting masses;
3. redistribution of (total or partial) conflicting masses to the non-empty sets involved in the conflicts proportionally with respect to their masses assigned by the sources.

The way the conflicting mass is redistributed yields actually several versions of PCR rules. These PCR fusion rules work for any degree of conflict, for any DSm models (Shafer's model, free DSm model or any hybrid DSm model [16]) and both in DST 'Dempster Shafer Theory) and DSmT frameworks for static or dynamical fusion situations. PCR5 is the most sophisticated proportional conflict redistribution rule since it redistributes the partial conflicting mass to the elements involved in the partial conflict, considering the conjunctive normal form of the partial conflict. PCR5 does the most mathematically exact redistribution of conflicting mass to non-empty sets following the logic of the conjunctive rule. It does a better redistribution of the conflicting mass than Dempster's rule since it goes backwards on the tracks of the conjunctive rule and redistributes the conflicting mass only to the sets involved in the conflict and proportionally to their masses put in the conflict. PCR5 preserves the neutral impact of the vacuous belief assignment because in any partial conflict, as well in the total conflict (which is a sum of all partial conflicts), the conjunctive normal form of each partial conflict does not include Θ since Θ is a neutral element for intersection (conflict), therefore Θ gets no mass after the redistribution of the conflicting mass. We have also proved in [17] the continuity property of the PCR5 result with continuous variations of bba to combine. The general PCR5 formula for $s \geq 2$ sources is given in [17]. For the combination of only

[2] In our GMTI-MTT applications, we will assume Shafer's model for the frame Θ of target ID which means taht elements of Θ are assumed truly exclusive. This assumption can be relaxed in DSmT [16], [17].

two sources, it is given by $m_{PCR5}(\emptyset) = 0$ and $\forall X \in 2^{\Theta} \backslash \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in 2^{\Theta} \backslash \{X\} \\ X \cap Y \equiv \emptyset}} \frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \sum_{\substack{Y \in 2^{\Theta} \backslash \{X\} \\ X \cap Y \equiv \emptyset}} \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)} \quad (34)$$

where $m_{12}(X)$ corresponds to the conjunctive consensus on X between the two sources and where all denominators are different from zero (see [17] for details and examples). If a denominator is zero, that fraction is discarded.

The Target Type Tracking Problem can be simply stated as follows [2]:

- Let $k = 1, 2, ..., k_{max}$ be the time index and consider M possible target ID $T_i \in \Theta = \{\theta_1, \ldots, \theta_M\}$ in our environment (for example $\Theta = C$ as given in (17).
- at each instant k, a target of true type $T(k) \in \Theta$ (not necessarily the same target) is observed by an attribute-sensor (we assume a perfect target detection probability here).
- the attribute measurement of the sensor is then processed through a classifier which provides a decision $c_a(k)$ on the type of the observed target at each instant k with its associated probability $P\{c_a(k)\}$.
- The sensor is in general not totally reliable and is characterized by a $M \times M$ confusion matrix

$$\mathbf{C} = [\mathbf{c_{ij}} = \mathbf{P}(\mathbf{c_a} = \mathbf{T_j} | \mathbf{TrueTargetType} = \mathbf{T_i})]$$

To estimate the true target type $T(k)$ at current time k from the sequence of declarations done by the unreliable classifier up to time k, i.e. to build an estimator $\hat{T}(k) = f(c_a(1), c_a(2), \ldots, c_a(k))$ of $T(k)$, we proceed according the Target Type Tracker (TTT) developed in [2] which consists in the following sequential steps:

- a) Initialization step (*i.e.* $k = 0$). Select the target type frame $\Theta = \{\theta_1, \ldots, \theta_M\}$ and set the prior bba $m^-(.)$ as vacuous belief assignment, i.e $m^-(\theta_1 \cup \ldots \cup \theta_M) = 1$ since one has no information about the first target type that will be observed.
- b) Generation of the current bba $m_{obs}(.)$ from the current classifier declaration $c_a(k)$ based on attribute measurement. At this step, one takes $m_{obs}(c_a(k)) = P\{c_a(k)\} = C_{c_a(k)c_a(k)}$ and all the unassigned mass $1 - m_{obs}(c_a(k))$ is then committed to total ignorance $\theta_1 \cup \ldots \cup \theta_M$.
- c) Combination of current bba $m_{obs}(.)$ with prior bba $m^-(.)$ to get the estimation of the current bba $m(.)$. Symbolically we will write the generic fusion operator as $\oplus$, so that $m(.) = [m_{obs} \oplus m^-](.) = [m^- \oplus m_{obs}](.)$. The combination $\oplus$ is done according to the PCR5 rule (*i.e.* $m(.) = m_{PCR5}(.)$).
- d) Estimation of True Target Type is obtained from $m(.)$ by taking the singleton of Θ, *i.e.* a Target Type, having the maximum of belief (or eventually the maximum Pignistic Probability[3] [16]).
- e) set $m^-(.) = m(.)$; do $k = k + 1$ and go back to step b).

It is important to emphasize that both rules of DST and TBM (Transferable Belief Model) do not respond to new information as soon as the mass committed to empty set becomes one at a previous temporal fusion step (see examples in [17]), whereas PCR5 rule always reacts very quickly to any mistaken target ID switches and therefore it offers a very good behavior for quickly readapt to bad target ID estimation in cases of closely crossing targets in high cluttered environements. To make DST and/or TBM working properly in such cases which arises very quickly in practice, it is necessary to introduce ad-hoc temporal discounting techniques which are not necessary to introduce if PCR5 is adopted. If there are good reasons to introduce temporal discounting, there is obviously no difficulty to still apply PCR5 fusion of these discounted sources. Let's now present in the next section how the track likelihood is improved for taking into account attribute information arising from the target type tracker just described above.

Data attributes in the VS-IMMC SB-MHT

The posterior (or updated) probability of a target being in class c_a, is given by the pignistic probability. The Classical Pignistic Transformation (CPT) is described by:

$$P\{c_a(k)\} = \sum_{X \in 2^{\Theta}} \frac{|X \cap c_a(k)|}{|X|} \cdot m(X) \quad (35)$$

In equation (35), $|X|$ represents the classical cardinality of a set X.

At each time, the TTT takes a decision on the target type according to the maximum of Pignistic Probabilities (35). The estimated target type at the time $k-1$ is noted $\bar{c_a}(k-1)$. So the target type $\bar{c_a}(k-1)$ is associated to a track $T^{k-1,n}$. To improve the target tracking process, the introduction of the target type probability is done in the likelihood calculation. For this, we consider the measurement $\mathbf{z}_j(k)$ described in (18). With the assumption that the kinematic and classification observations are independant it is easy to prove that the new combined likelihood Λ_N associated with a track is the product of the kinematic likelihood (22) with the classification probability in the manner that:

$$\Lambda_N(k) = \Lambda(k) \cdot Pr\{c_a(k) | \bar{c_a}(k-1)\} \quad (36)$$

where the the probability $Pr\{c_a(k) | \bar{c_a}(k-1)\}$ is the pignistic probability value on the target type $\bar{c_a}(k-1)$.

Finally, the new combined likelihood (36) is used to calculate the combined log likelihood ratio (32) of the track $T^{k,l}$ and

[3] We don't provide here the results based on Pignistic Probabilities since in our simulations the conclusions are unchanged when working with max. of belief or max. of Pign. Proba.

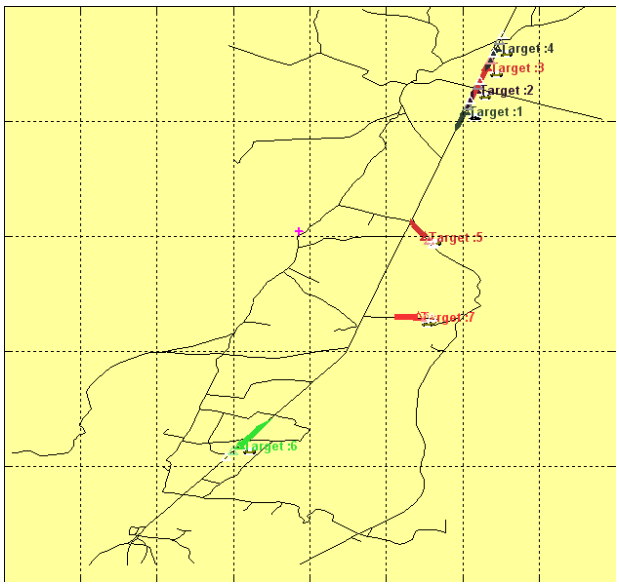


Figure 2. Real situation at time 155 + t_0.

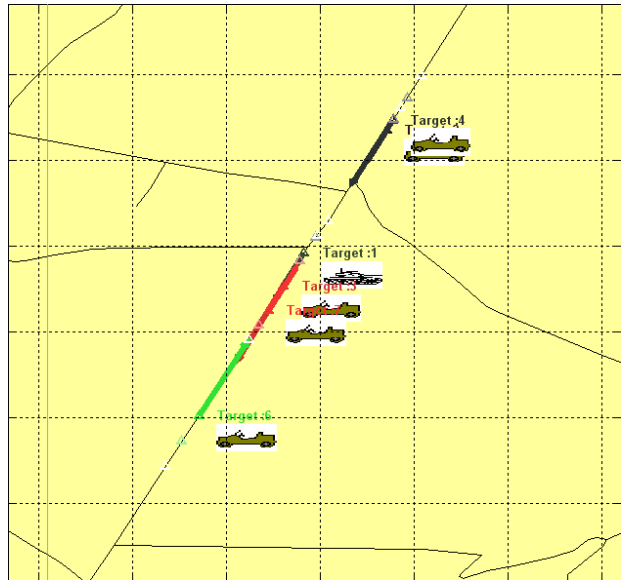


Figure 3. Real situation at time 365 + t_0.

to improve the data association process in the SB-MHT with the integration of the target class information. For the dummy measurement the attribute probability in (36) is equal to the last updated attribute probability.

5. Simulations and results

Scenario description

To evaluate the VS-IMMC SB-MHT improvement by tacking into account the attribute type, we consider 7 targets which are maneuvering on the road network (figure 2). In the preliminary results presented here, we only consider 3 target types:

$$C = \left\{ \begin{array}{l} Tracked\ Vehicle, \\ Wheeled\ Vehicle, \\ Rotary\ Wing\ Aircraft \end{array} \right\} \tag{37}$$

Among the 7 targets, 5 targets are tracked vehicles (*i.e.* civilian vehicule) and the targets 1 and 2 are wheeled vehicules (*i.e.* military vehicules). When the target 1 is approaching a junction (figure 3), in the same time, the target 3 passes this wheeled vehicule and the target 7 is crossing both (*i.e.* targets 1 and 3). The goal of the simulation is to increase the association complexity with the road network configuration.

The 7 targets are tracked by a GMTI sensor at 7 seconds with 20 m, 0.0008 rad and 1 $m \cdot s^{-1}$ range, cross-range and range-rate measurement standard deviation respectively. The detection probability P_D is equal to 0.9 and the MDV (Minimal Detectable Velocity) fixed at 1 m/s. The sensor is located at (40 *km*,40 *km*) from the *TCF* origine at 4000 *m* in elevation and moves in the west direction. On figures 2 and 3, one shows the cumulated MTI reports. The confusion matrix of

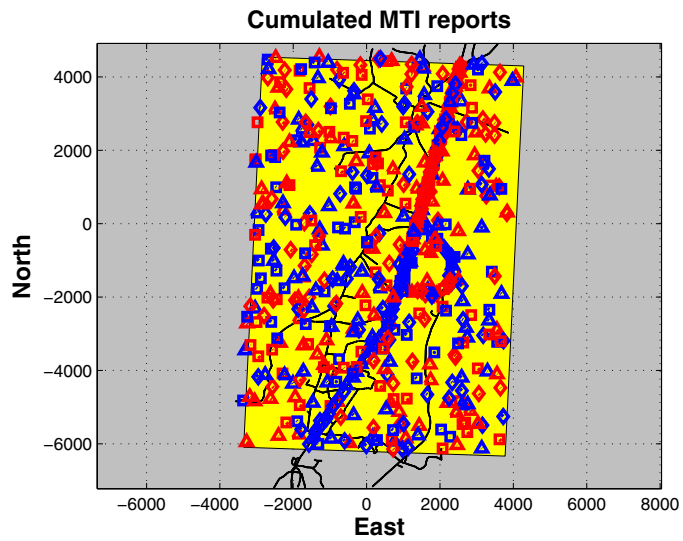


Figure 4. Cumulated MTI reports.

the sensor described in the part 4 is given by:

$$\mathbf{C} = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \tag{38}$$

We recall that the confusion matrix is only used to simulate the target type probability.

VS-IMMC SB-MHT parameters

We consider three motion models (*i.e.* $i \in \{0, 1, 2\}$) which are respectively a stop model M_0 when the target is assumed to have a zero velocity, a constant velocity model M_1 with a low uncertainty, and a constant velocity model M_2 with a high uncertainty (modeled by a strong noise). The parameters

of the IMM are the following: for the motion model M_1, the standard deviation along and orthogonal to the road segment are equals to 0.05 $m \cdot s^{-2}$), the constrained constant velocity model M_2 has a high standard deviation to adapt the dynamic to the target manoeuvre (the standard deviation along and orthogonal to the road segment are respectively equal to 0.8 $m \cdot s^{-2}$ and 0.4 $m \cdot s^{-2}$) and the stop motion model M_0 has a standard deviation equal to zero. Those generics constrained motion models must be adapted following the road network topology. The transition matrix $p_{i,j}(\forall i, j \in \{0, 1, 2\}^2)$ used in (23) is equal to:

$$[p_{i,j}] = \begin{bmatrix} 0.5 & 0.02 & 0.48 \\ 0.005 & 0.9 & 0.095 \\ 0.05 & 0.3 & 0.65 \end{bmatrix} \tag{39}$$

The SB-MHT parameters are those taken in [19]. The validation gate probability is equal to 0.99. The false alarm rate λ_{fa} and the new target rate λ_{nt} are respectively equal to $1.4877 \cdot 10^{-9}$ and $1.4877 \cdot 10^{-10}$ per unit of volume. The best hypothesis number N_Hypo is equal to 4. The *N-Scan* number for the pruning process is equal to 3.

Preliminary results

For each confirmed track given by the VS-IMMC SB-MHT, a test is used to associate a track to the most probable target. So, several tracks can belong to only one target.

The target tracking goal is to track as long as possible the target with one track. Then, in order to evaluate the track maintenance we use the track length ratio criterion for a target *n* between the true target trajectory length l_n and the associated track length L_n obtained in a simulation. According to 50 Monte-Carlo runs, we obtain for each track the averaged track length ratio ($\forall n \in \{1, ..., 7\}$):

$$R_n = \sum_{k=1}^{100} \frac{l_n}{100 \cdot L_n} \tag{40}$$

In addition to the track length ratio criterion, we calculte the averaged root mean square error (noted ARMSE) for each target, the track purity and the type purity (only for the tracks obtained with PCR5). The ARMSE is the root mean square error averaged on the time. The track purity is the ratio between the sum of correct association number on the track length and the type purity is the ratio between the sum of true type decision number on the track length.

The track length ratio of the target 1 and 3 is better with the PCR5 (figure 6) than without (figure 5). In fact, when the target 3 is passing the target 1 or 2 (the wheeled vehicules), the VS-IMMC SB-MHT without the PCR5 can associate track of target 2 to the measurement of target 3. Then, the track of target 3 is lost and a new track is built for this target. That is why the track purity of the target 3 is bad (see table 1). Sometimes, the association between target 2 and 3 is good (the passing is detected). However, when target 3 is passing

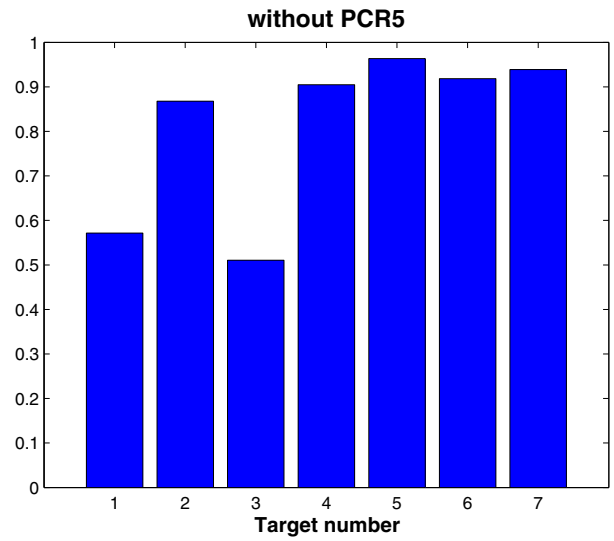


Figure 5. Track length ratio without PCR5

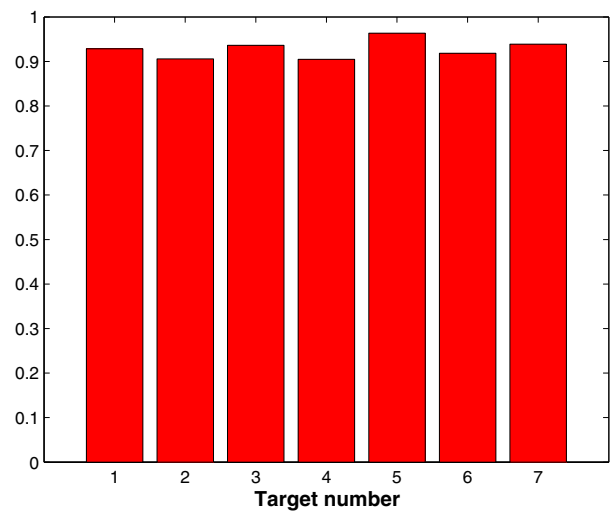


Figure 6. Track length ratio with PCR5

Target #	ARMSE	Track Purity	Type Purity
1	73.89	0.38	None
2	32.71	0.72	None
3	46.36	0.32	None
4	28.20	0.76	None
5	35.15	0.85	None
6	28.25	0.80	None
7	16.91	0.78	None

Table 1. Averaged track results without PCR5.

Target #	ARMSE	Track Purity	Type Purity
1	16.60	0.82	0.93
2	26.75	0.77	0.83
3	29.12	0.70	0.91
4	25.18	0.81	0.90
5	35.15	0.85	0.96
6	28.25	0.80	0.92
7	16.91	0.78	0.94

Table 2. Averaged track results with PCR5.

target 1 in the junction, the algorithm is weakened in the manner that the correct association is disturbed by the manoeuver of the targets and the road network configuration. On the contrary, when the PCR5 is taking into account in the VS-IMMC SB-MHT, the passing of targets 1 and 2 by target 3 is well detected. That is why the track purity of the target 1, 2 and 3 is better with PCR5 (table 2) than the track purity of the algorithm without PCR5 (table 1). So, the PCR5 improves the track association when the road network is complex (case of road intersection) and the target type is different. If there is no type distinction, the performances of both algorithms are the same. Yet, we can remark that there is no performance distinction with both algorithms for the target 4, 5, 6 and 7 because there is no interaction between the targets expected for the target 4. Despite the crossing of the target 4 with the targets 1, 2 and 3, the track purity or the track length ratio are not disturbed. This is due to the fact that in our simulation, the crossing is done during a short time contrariwise to the passing. So, the short time interaction between the targets combined with the road network taking into account in the algorithm improves significantly the track association.

6. Conclusions

In this paper, we have presented an approach to improve the VS-IMMC SB-MHT by introducing the type information defined in the STANAG 4607 in the data association process. Our tracking algorithm combines efficiently the kinematic information with the attribute information expressed by the pignistic probability of Target ID. The estimation of the Target ID probability is done from the updated/current attribute belief function using the Proportional Conflict Redistribution rule no. 5 (PCR5) developed in DSmT framework and according to the Target Type Tracker (TTT) recently developed by the authors. The Target ID probability once obtained is then introduced in the track score computation in order to improve the likelihoods of each data association hypothesis of the SB-MHT. Our preliminary results show a significant improvement of the performances of the VS-IMMC SB-MHT when the type information is processed by our PCR5-based Target Type Tracker. In particular, the road ambiguity is reduced at a junction with the PCR5 when several targets of different types approach the junction.

The evaluations and comparisons of the performances of our new target tracking algorithm with the one based on Dempster-Shafer's Target Type Tracker are currently under investigation. Our preliminary results and analysis have shown that the passing of targets is a very difficult association problem whenever the targets have the same type. That is why we will investigate the possibility in using the High Range Radial Resolution given by the GMTI sensor coupled with our PCR5-based Target Type Tracker. Finally, the type information must be extended with heterogeneous sensors by using a taxonomy.

References

[1] J. Dezert, A. Tchamova, L. Bojilov and P. Konstantinova, "Performance evaluation of tracking algorithm incorporating attribute data processing via DSmT", *Proc. of Int. Workhop on Advances and Applications of DSmT for Plausible and Paradoxical Reasoning for Information Fusion* organized by the Bulgarian IST Centre of Competence in 21st Century, December 14, 2006, Bulg. Acad. of Sciences, Sofia, Bulgaria.

[2] J. Dezert, A. Tchamova, F. Smarandache and P.Konstantinova, "Target Type Tracking with PCR5 and Dempster's rules: A Comparative Analysis", *Proceedings of International Conference on Information Fusion 2006*, Firenze, Italy, Jul. 2006.

[3] http://en.wikipedia.org/wiki/WGS84

[4] B. Pannetier, K. Benameur, V. Nimier and M. Rombaut, "VS-IMM using road map information for a ground target tracking", *Proceedings of International Conference on Information Fusion 2005*, vol. 1, Jul. 2005.

[5] T. Kirubarajan and Y. Bar-Shalom, "Tracking evasive move-stop-move targets with an MTI radar using a VS-IMM estimator", *IEEE Transactions on aerospace and electronic systems*, vol. 39, no. 3, pp. 1098–1103, Jul. 2003.

[6] B. Pannetier, M. Rombaut, "Terrain Obscuration Management for Multiple Ground Target Tracking", *Proceedings of International Conference on Information Fusion 2007*, Jul. 2007.

[7] NATO, "STANAG 4607 JAS (Edition 2) - NATO ground moving target indicator GMTI) format",*NSA0749(2007)-JAS/4607*, Aug. 2007.

[8] T. Kirubarajan, Y. Bar-Shalom, K.R. Pattipati and I. Kadar, "Ground target tracking with topography-basd variable structure IMM estimator", *Proceedings of SPIE, signal and data processing of small targets*, vol. 3373, pp. 222–233, Jul. 1998.

[9] B. Pannetier, K. Benameur, V. Nimier and M. Rombaut, "Ground target tracking with road constraint", *Proceedings of SPIE, sensor fusion and target recognition XIII*, volume 5429, Apr. 2004.

[10] Y. Bar Shalom and D. Blair, *Multi-Target Multi-Sensor tracking: Applications and Advances* , Artech House,

Vol. III, 2000.

[11] M. Ulmke and W. Koch, "Road-map assisted ground moving target tracking", *IEEE Transactions, on aerospace and electronic systems*, Vol. 42, n4,pp. 1264-1274, Oct. 2006.

[12] J. G. Herrero, J. A. B. Portas and J. R. C. Corredara, "Use of Map Information for target tracking on airport surface", *IEEE Transactions, on aerospace and electronic systems*, Vol. 39, n2, pp. 675-693, Apr. 2003.

[13] J. G. Wang, T. Long and P.K. He, "A New Method of Incorporating Radial Velocity Measurement into Kalman Filter" ,*Proccedings of signal Processing*, no. 18, pp. 414–416, 2002.

[14] D.F. Bizup and D.E. Brown, "The over extended Kalman filter – Don't use it !", *Proceedings of the International Conference on Information Fusion 2003*, Jul. 2003.

[15] P.J. Shea, T. Zadra, D. Klamer, E. Frangione and R. Brouillard, "Improved state estimation trough use of roads in ground tracking", *Proceedings of SPIE, Signal and Data Processing of Small Targets*, Volume 4048, pp. 321-332, Jul. 2000.

[16] F. Smarandache and J. Dezert (Editors), "Applications and Advances of DSmT for Information Fusion (Collected works)", Vol.1, *American Research Press*, Rehoboth, 2004. http://www.gallup.unm.edu/~smarandache/DSmT-book1.pdf.

[17] F. Smarandache and J. Dezert (Editors), "Applications and Advances of DSmT for Information Fusion (Collected works)", Vol.2, *American Research Press*, Rehoboth, 2006. http://www.gallup.unm.edu/~smarandache/DSmT-book2.pdf.

[18] X. R. Li, "Multitarget/Multisensor Tracking Applications and Advances Volume III", *Chapter X, Yaakov Bar-Shalom, Artech House Publishers*, Oct. 2000.

[19] S.S. Blackman and R. Popoli, *Design and analysis of modern tracking systems* , Artech House, 1999.

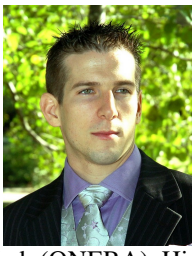
[20] Y.Bar-Shalom, X. R. Li and T. Kirubarajan, *Estimation with applications to tracking and navigation : algorithms and softaware for information extraction* , New York, Wiley, 2001.

[21] A. Wald, *Sequential Analysis*, John Wiley, New York, 1947.

[22] A. Wald and J. Wolfowitz, *Optimum character of the sequential probability ratio test*, Ann. Math. Stat., Vol. 19, pp. 326-339, 1948.

[23] Y. Bar-Shalom and D. Blair, *Multitarget multisensor tracking : Applications and Advances*, *Vol. III, Artech House*, pp. 523, 2000.

BIOGRAPHY



Benjamin Pannetier was born in Paris on November 30th, 1979. He received his B.S. mathematical degree from the University of Marne la Vallée, and his Ph.D. in Automatic Control and Signal Processing from the University of Grenoble in 2006. Since 2005, he is a research engineer at the French Aerospace Lab (ONERA). His research interests include target tracking, detection/estimation theory and data fusion for the battlefield surveillance systems for the french army. With Professor Rombaut (University of Grenoble) he is working on a new approach for the abnormal behaviour detection.

Jean Dezert was born in l'Hay les Roses, France, on August 25th, 1962. He got his Ph.D from the University Paris XI, Orsay in 1990, in Aut. Cont. and Sign. Proc. During 1986-1990 he was with the Syst. Dept. at the French Arerospace Research Lab (ONERA), Châtillon, France and did research in multisensor multitarget tracking (MS-MTT). During 1991-1992, he visited the Dept. of Electrical and Syst. Eng., UConn, Storrs, U.S.A. as an European Space Agency Postdoc Research Fellow. During 1992-1993 he was teaching assistant in EE Dept. at the Univ. of Orléans, France. Since 1993, he is senior research scientist in the Information Modelling and Proc. Dept. at ONERA. His current research interests include estimation theory and its applications to MS-MTT, and information fusion. Dr. Dezert developed with Prof. Smarandache a new theory for information fusion (DSmT) and has edited two textbooks in 2004 and 2006 (collected works) freely downloadable on the web. He is member of IEEE and of Eta Kappa Nu, serves as reviewer for different Int. Journals and he collaborates for the development of the Int. Soc. of Information Fusion (ISIF - http://www.isif.org) since 1998. He has served as Local Arrangements Organizer for Fusion 2000 Conf. in Paris. He has been involved in the Tech. Prog. Committees of Fusion 2001-2007. Since 2001, he serves in the ISIF executive board and was executive vice-president of ISIF in 2004. In 2003, he organized with Prof. Smarandache, the first special session devoted to DSmT at Fusion 2003, Cairns, Australia and also a panel discussion and a special session at Fusion 2004 and Fusion 2006. Dr. Dezert gave several invited seminars and lectures on Data Fusion and Tracking during past yearst. He is member of Tech. Committee of last Fuzzy Set and Tech. Conf. and Associate Editor of the ISIF Journal of Advances in Information Fusion (JAIF). Recent advances on DSmT can be found at http://www.gallup.unm.edu/ smarandache/dsmt.htm.

Evangeline POLLARD was born in Roubaix on July 27th, 1984. She got her signal and image processing M.S. Degree in 2007 from the University of Lyons. That same year she graduated from the ”CPE-Lyons” engineer school in Electronics, Telecommunications and Informatics. During 2005-2006, she worked at the German aerospace laboratories (DLR) in Munich for the TerraSAR-X processor. Since 2007, she is a PhD student at the French Aerospace Lab (ONERA). With Prof. Rombaut (University of Grenoble) and Dr. Pannetier, she is working on a new approach for the abnormal behaviour detection.