

# GMTI and IMINT data fusion for multiple target tracking and classification

Benjamin Pannetier, Jean Dezert

ONERA, Information Fusion Systems

29 avenue de la Division Leclerc

92322 Châtillon, France.

[benjamin.pannetier@onera.fr](mailto:benjamin.pannetier@onera.fr), [jean.dezert@onera.fr](mailto:jean.dezert@onera.fr)

**Abstract** – *In this paper, we propose a new approach to track multiple ground target with GMTI (Ground Moving Target Indicator) and IMINT (IMagery INtel-ligence) reports. This tracking algorithm takes into account road network information and is adapted to the out of sequence measurement problem. The scope of the paper is to fuse the attribute type information given by heterogeneous sensors with DSMT (Dezert Smarandache Theory) and to introduce the type results in the tracking process. We show the ground target tracking improvement obtained due to better targets discrimination and an efficient conflicting information management on a realistic scenario.*

**Keywords:** Multiple target tracking, heterogeneous data fusion, DSMT.

## 1 Introduction

Data fusion for ground battlefield surveillance is more and more strategic in order to create the situational assessment or improve the precision of fire control system. The challenge of data fusion for the theatre surveillance operation is to know where the targets are, how they evolve (manoeuvres, group formations,...) and what are their identities.

For the first two questions, we develop new ground target tracking algorithms adapted to GMTI (Ground Moving Target Indicator) sensors. In fact, GMTI sensors are able to cover a large surveillance area during few hours or more if several sensors exists. However, ground target tracking algorithms are used in a complex environment due to the high traffic density and the false alarms that generate a significant data quantity, the terrain topography which can provoke occlusion areas for the sensor and the high maneuverability of the ground targets which yields to the data association problem. Several references exist for the MGT (Multiple Ground Tracking) with GMTI sensors [1, 2] whose fuse contextual informations with MTI reports. The main results are the improvement of the track precision

and track continuity. Our algorithm [6] is built with several reflexions inspired of this literature. Based on road segment positions, dynamic motion models under road constraint are built and an optimized projection of the estimated target states is proposed to keep the track on the road. A VS-IMM (Variable Structure Interacting Multiple Models) filter is created with a set of constrained models to deal with the target maneuvers on the road. The set of models used in the variable structure is adjusted sequentially according to target positions and to the road network topology.

Now, we extended the MGT with several sensors. In this paper, we first consider the centralized fusion between GMTI and IMINT (IMagery INtel-ligence) sensors reports. The first problem of the data fusion with several sensors is the data registration in order to work in the same geographic and time referentials. This point is not presented in this paper. However, in a multisensor system, measurements can arrive out of sequence. Following Bar-Shalom and Chen's works [3], the VS-IMMC (VS-IMM Constrained) algorithm is adapted to the OOSM (Out Of Sequence Measurement) problem, in order to avoid the reprocessing of entire sequence of measurements. The VS-IMMC is also extended in a multiple target context and integrated in a SB-MHT (Structured Branching - Multiple Hypotheses Tracking). Despite of the resulting track continuity improvement for the VS-IMMC SB-MHT algorithm, unavoidable association ambiguities arise in a multi-target context when several targets move in close formation (crossing and passing). The associations between all constrained predicted states are compromised if we use only the observed locations as measurements. The weakness of this algorithm is due to the lack of good target state discrimination.

One way to enhance data associations is to use the reports classification attribute. In our previous work [5], the classification information of the MTI segments has been introduced in the target tracking process. The idea was to maintain aside each target track a set of ID

hypotheses. Their committed belief are revised in real time with the classifier decision through a very recent and efficient fusion rule called proportional conflict redistribution (PCR). In this paper, in addition to the measurement location fusion, a study is carried out to fuse MTI classification type with image classification type associated to each report. The attribute type of the image sensors belongs to a different and better classification than the MTI sensors. The counterpart is the short coverage of image sensors that brings about a low data quantity. In section 2, the motion and measurement models are presented with a new ontologic model in order to place the different classification frames in the same frame of discernment. After the VS-IMMC description given in section 3, the PCR fusion rule originally developed in DSMT (Dezert-Smarandache Theory) framework is presented in section 4 to fuse the target type information available and to include the resulting fused target ID into the tracking process. The last part of this paper is devoted to simulation results for a multiple target tracking scenario within a real environment.

## 2 Motion & observation models

### 2.1 GIS description

The GIS (Geographical Information System) used in this work contains both the segmented road network and the DTED (Digital Terrain Elevation Data). Each road segment expressed in WGS84 is converted in a Topographic Coordinate Frame (denoted  $TCF$ ). The  $TCF$  is defined according to the origin  $O$  in such a way that the axes  $X$ ,  $Y$  and  $Z$  are respectively oriented towards the local East, North and Up directions. The target tracking process is carried out in the  $TCF$ .

### 2.2 Constrained motion model

The target state at the current time  $t_k$  is defined in the local horizontal plane of the  $TCF$ :

$$\mathbf{x}(k) = [x(k) \dot{x}(k) y(k) \dot{y}(k)]' \quad (1)$$

where  $(x(k), y(k))$  and  $(\dot{x}(k), \dot{y}(k))$  define respectively the target location and velocity in the local horizontal plane. The dynamics of the target evolving on the road are modeled by a first-order differential system. The target state on the road segment  $s$  is defined by  $\mathbf{x}_s(k)$  where the target position  $(x_s(k), y_s(k))$  belongs to the road segment  $s$  and the corresponding heading  $(\dot{x}_s(k), \dot{y}_s(k))$  is in its direction.

The event that the target is on road segment  $s$  is noted  $e_s(k) = \{\mathbf{x}(k) \in s\}$ . Given the event  $e_s(k)$  and according to a motion model  $M_i$ , the estimation of the target state can be improved by considering the road segment  $s$ . It follows:

$$\mathbf{x}_s(k) = \mathbf{F}_{s,i}(\Delta(k)) \cdot \mathbf{x}_s(k-1) + \mathbf{\Gamma}(\Delta(k)) \cdot \mathbf{v}_{s,i}(k) \quad (2)$$

where  $\Delta(k)$  is the sampling time,  $\mathbf{F}_{s,i}$  is the state transition matrix associated to the road segment  $s$  and adapted to a motion model  $M_i$ ,  $\mathbf{v}_{s,i}(k)$  is a white Gaussian random vector with covariance matrix  $\mathbf{Q}_{s,i}(k)$  chosen in such a way that the standard deviation along the road segment is higher than the standard deviation in the orthogonal direction. It is defined by:

$$\mathbf{Q}_{s,i}(k) = \mathbf{R}_{\theta_s} \cdot \begin{pmatrix} \sigma_d^2 & 0 \\ 0 & \sigma_n^2 \end{pmatrix} \cdot \mathbf{R}'_{\theta_s} \quad (3)$$

where  $\mathbf{R}_{\theta_s}$  is the rotation matrix associated with the direction  $\theta_s$  defined in the plane  $(O, X, Y)$  of the road segment  $s$ . The matrix  $\mathbf{\Gamma}(\Delta_k)$  is defined in [8].

To improve the modeling for targets moving on a road network, we proposed in [5] to adapt the level of the dynamic model's noise based on the length of the road segment  $s$ . The idea is to increase the standard deviation  $\sigma_n$  defined in (3) to take into account the error on the road segment location. After the state estimation obtained by a Kalman filter, the estimated state is then projected according to the road constraint  $e_s(k)$ . This process is detailed in [6].

### 2.3 GMTI measurement model

According to the NATO GMTI format [7], the MTI reports received at the fusion station are expressed in the WGS84 coordinates system. The MTI reports must be converted in the  $TCF$ . A MTI measurement  $z$  at the current time  $t_k$  is given in the  $TCF$  by:

$$\mathbf{z}(k) = [x(k) y(k) \dot{\rho}(k)]' \quad (4)$$

where  $(x(k), y(k))$  is the location of the MTI report in the local frame  $(O, X, Y)$  and  $\dot{\rho}(k)$  is the associated range measurement expressed by:

$$\dot{\rho}(k) = \frac{(x(k) - x_c(k)) \cdot \dot{x}(k) + (y(k) - y_c(k)) \cdot \dot{y}(k)}{\sqrt{(x(k) - x_c(k))^2 + (y(k) - y_c(k))^2}} \quad (5)$$

where  $(x_c(k), y_c(k))$  is the sensor location at the current time in the  $TCF$ . Because the range radial velocity is correlated to the MTI location components, the use of an extended Kalman filter (EKF) is not adapted. In the literature, several techniques exist to uncorrelate the range radial velocity from the location components. We prefer to use the AEKF (Alternative Extended Kalman Filter) proposed by Bizup and Brown in [9], because the implementation is easier by using the alternative linearization than another algorithms to decorrelate the components. Moreover, AEKF working in the sensor referential/frame remains invariant by translation. The AEKF measurement equation is given by:

$$\mathbf{z}_{MTI}(k) = \mathbf{H}_{MTI}(k) \cdot \mathbf{x}(k) + \mathbf{w}_{MTI}(k) \quad (6)$$

where  $\mathbf{w}_{MTI}(k)$  is a zero-mean white Gaussian noise vector with a covariance  $R_{MTI}(k)$  (given in [5]) and

$\mathbf{H}_{MTI}(k)$  is defined by:

$$\mathbf{H}_{MTI}(k) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{\partial \hat{\rho}(k)}{\partial \hat{x}} & 0 & \frac{\partial \hat{\rho}(k)}{\partial \hat{y}} \end{pmatrix} \quad (7)$$

Each MTI report is characterized both with the location and velocity information and also with the attribute information and its probability that it is correct. We denote  $C_{MTI}$  the frame of discernment on target ID based on MTI data.  $C_{MTI}$  is assumed to be constant over the time and consists in a finite set of exhaustive and exclusive elements representing the possible states of the target classification. In this paper, we consider only 3 elements in  $C_{MTI}$  defined as:

$$C_{MTI} = \left\{ \begin{array}{l} c_1 \triangleq \textit{Tracked vehicle} \\ c_2 \triangleq \textit{Wheeled vehicle} \\ c_3 \triangleq \textit{Rotary wing aircraft} \end{array} \right\} \quad (8)$$

We consider also the probabilities  $P\{c(k)\}$  ( $\forall c(k) \in C_{MTI}$ ) as input parameters of our tracking systems characterizing the global performances of the classifier. The vector of probabilities  $[P(c_1) P(c_2) P(c_3)]$  represents the diagonal of the confusion matrix of the classification algorithm assumed to be used. Let  $\mathbf{z}_{MTI}^*(k)$  the extended MTI measurements including both kinematic part and attribute part expressed by the herein formula:

$$\mathbf{z}_{MTI}^*(k) \triangleq \{\mathbf{z}_{MTI}(k), c(k), P\{c(k)\}\} \quad (9)$$

## 2.4 IMINT motion model

For the imagery intelligence (IMINT), we consider two sensor types : a video EO/IR sensor carried by a Unmanned Aerial Vehicle (UAV) and a EO sensor fixed on a Unattended Ground Sensor (UGS).

We assume that the video information given by both sensor types are processed by their own ground stations and that the system provides the video reports of target detections with their classification attributes. Moreover, a human operator selects targets on a movie frame and is able to choose its attribute with a HMI (Human Machine Interface). In addition, the operator is able with the UAV to select *several targets* on a frame. On the contrary, the operator selects *only one target* with the frames given by the UGS. There is *no false alarm* and a target cannot be detected by the operator (due to terrain mask for example). The video report on the movie frame is converted in the *TCF*. The measurement equation is given by:

$$\mathbf{z}_{video}(k) = \mathbf{H}_{video}(k) \cdot \mathbf{x}(k) + \mathbf{w}_{video}(k) \quad (10)$$

where  $\mathbf{H}_{video}$  is the observation matrix of the video sensor

$$\mathbf{H}_{video} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \quad (11)$$

The white noise Gaussian process  $\mathbf{w}_{video}(k)$  is centered and has a known covariance  $\mathbf{R}_{video}(k)$  given by the ground station.

Each video report is associated to the attribute information  $c(k)$  with its probability  $P\{c(k)\}$  that it is correct. We denote  $C_{video}$  the frame of discernment for an EO/IR source. As  $C_{MTI}$ ,  $C_{video}$  is assumed to be constant over the time and consists in a finite set of exhaustive and exclusive elements representing the possible states of the target classification. In this paper, we consider only eight elements in  $C_{video}$  as follows:

$$C_{video} = \left\{ \begin{array}{l} \textit{civilian car} \\ \textit{military armoured car} \\ \textit{wheeled armoured vehicule} \\ \textit{civilian bus} \\ \textit{military bus} \\ \textit{civilian truck} \\ \textit{military armoured truck} \\ \textit{copter} \end{array} \right\} \quad (12)$$

Let  $\mathbf{z}_{video}^*(k)$  be the extended video measurements including both kinematic part and attribute part expressed by the following formula ( $\forall c(k) \in C_{video}$ ):

$$\mathbf{z}_{video}^*(k) \triangleq \{\mathbf{z}_{video}(k), c(k), P\{c(k)\}\} \quad (13)$$

For notation convenience, the measurements sequence  $\mathbf{Z}^{k,l}$  represents a possible set of measurements generated by the target up to time  $k$  (*i.e.*, there exists a subsequence  $n$  and a measurement  $i$  such that  $\mathbf{Z}^{k,l} = \{\mathbf{Z}^{k-1,n}, \dots, \mathbf{z}_j^*(k)\}$ ) associated with the track  $T^{k,l}$ . At the current time  $k$ , the track  $T^{k,l}$  is represented by a sequence of the state estimates.  $\mathbf{z}_j^*(k)$  is the  $j^{th}$  measurement available at time  $k$  among  $m(k)$  validated measurements around the target measurement prediction.

## 3 Tracking with road constraints

### 3.1 VS IMM with a road network

The IMM is an algorithm for combining state estimates arising from multiple filter models to get a better global state estimate when the target is under maneuvers. In section 2.2, a constrained motion model  $i$  to a road segment  $s$ , noted  $M_s^i(k)$ , was 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. It is evident that when the target moves from one segment to the next, the set of dynamic models changes. In a conventional IMM estimator [1], the likelihood function of a model  $i = 0, 1, \dots, r$  is given, for a track  $T^{k,l}$ , associated with the  $j$ -th measurement,  $j \in \{0, 1, \dots, m(k)\}$  by:

$$\Lambda_i^l(k) = p\{\mathbf{z}_j(k) | M_s^i(k), \mathbf{Z}^{k-1,n}\} \quad (14)$$

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

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

$$\Lambda_i^l(k) = P_D \cdot p\{\mathbf{z}_j(k) | M_s^i(k), \mathbf{Z}^{k-1,n}\} \cdot (1 - \delta_{m_j,0}) + (1 - P_D) \cdot \delta_{m_j,0} \quad (15)$$

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

$$\Lambda_0^l(k) = p\{\mathbf{z}_j(k) | M_0^i(k), \mathbf{Z}^{k-1,n}\} = \delta_{m_j,0} \quad (16)$$

where  $P_D$  is the sensor detection probability,  $\delta_{m_j,0}$  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  $\Lambda^l(k)$  of a track including a stop model is then given by:

$$\Lambda^l(k) = \sum_{i=0}^r \Lambda_i(k) \cdot \mu_i(k|k-1) \quad (17)$$

where  $\mu_i(k|k-1)$  is the predicted model probabilities [8].

The steps of the IMM under road segment  $s$  constraint are the same as for the classical IMM as described in [8].

In real application, the predicted state could also appear onto another road segment, because of a road turn for example, and we need to introduce new constrained motion models. In such case, we activate the most probable road segments sets depending on the local predicted state  $\hat{x}_{i,s}^l(k|k-1)$  location of the track  $T^{k,l}$  [5, 1]. We consider  $r+1$  oriented graphs which depend on the road network topology. For each graph  $i$ ,  $i = 0, 1, \dots, r$ , each node is a constrained motion model  $M_s^i$ . The nodes are connected to each other according to the road network configuration and one has a finite set of  $r+1$  motion models constrained to a road section. The selection of the most probable motion model set, to estimate the road section on which the target is moving on, is based on a sequential probability ratio test (SPRT).

### 3.2 OOSM algorithm

The data fusion that operates in a centralized architecture suffers of delayed measurement due to communication data links, time algorithms execution, data quantity, ... In order to avoid reordering and reprocessing an entire sequence of measurements for real-time application, the delayed measurements are processed as out-of-sequence measurements (OOSM). The algorithm used in this work is described in [3]. In addition, according to the road network constraint, the state retrodiction step is done on the road.

### 3.3 Multiple target tracking

For the MGT problem, we use the SB-MHT (Structured Branching Multiple Hypotheses Tracking) presented in [10]. When the new measurements set  $\mathbf{Z}(k)$  is received, a standard gating procedure is applied in order to validate MTI reports to track pairings. The existing tracks are updated with VS-IMMC and the extrapolated and confirmed tracks are formed. More details can be found in chapter 16 of [10]. 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 a track score of a track  $T^{k,l}$  which can be expressed at current time  $k$  in the following recursive form:

$$L^l(k) = L^s(k-1) + \Delta L^l(k) \quad (18)$$

with

$$\Delta L^l(k) = \log \left( \frac{\Lambda^l(k)}{\lambda_{fa}} \right) \quad (19)$$

and

$$L(0) = \log \left( \frac{\lambda_{fa}}{\lambda_{fa} + \lambda_{nt}} \right) \quad (20)$$

where  $\lambda_{fa}$  and  $\lambda_{nt}$  are respectively the false alarm rate and the new target rate per unit of surveillance volume and  $\Lambda^l(k)$  is the likelihood given in (17).

## 4 Target type tracking

In [4], Blasch and Kahler fused identification attribute given by EO/IR sensors with position measurement. The fusion was used in the validation gate process to select only the measurement according to the usual kinematic criterion and the belief on the identification attribute. Our approach is different since one uses the belief on the identification attribute to revise the LLR with the *posterior* pignistic probability on the target type. We recall briefly the Target Type Tracking (TTT) principle and explain how to improve VS-IMMC SB-MHT with target ID information. TTT is based on the sequential combination (fusion) of the predicted belief of the type of the track with the current "belief measurement" obtained from the target classifier decision. Results depends on the quality of the classifier characterized by its confusion matrix (assumed to be known at least partially as specified by STANAG). The adopted combination rule is the so-called Proportional Conflict Redistribution rule no 5 (PCR5) developed in the DSMT (Dezert Smarandache Theory) framework since it deals efficiently with (potentially high) conflicting information. A detailed presentation with examples can be found in [12, 11]. This choice is motivated in this typical application because in dense traffic scenarios, the VS-IMMC SB-MHT only based on kinematic information can be deficient during maneuvers and crossroads. Let's recall first what the PCR5 fusion rule

is and then briefly the principle of the (single-sensor based) Target Type Tracker.

#### 4.1 PCR5 combination rule

Let  $C_{Tot} = \{\theta_1, \dots, \theta_n\}$  be a discrete finite set of  $n$  exhaustive elements and two distinct bodies of evidence providing basic belief assignments (bba's)  $m_1(\cdot)$  and  $m_2(\cdot)$  defined on the power-set<sup>1</sup> of  $C_{Tot}$ . The idea behind the Proportional Conflict Redistribution (PCR) rules [11] 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. The way the conflicting mass is redistributed yields actually several versions of PCR rules, but PCR5 (i.e. PCR rule # 5) does the most exact redistribution of conflicting mass to non-empty sets following the logic of the conjunctive rule and is well adapted for a sequential fusion. It does a better redistribution of the conflicting mass than other rules 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. The PCR5 formula for  $s \geq 2$  sources is given in [11]. For the combination of only two sources (useful for sequential fusion in our application) when working with Shafer's model, it is given by  $m_{PCR5}(\emptyset) = 0$  and  $\forall X \in 2^{C_{Tot}} \setminus \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in 2^{C_{Tot}} \setminus \{X\} \\ X \cap Y = \emptyset}} \left[ \frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)} \right] \quad (21)$$

where  $m_{12}(X)$  corresponds to the conjunctive consensus on  $X$  between the two sources (i.e. our a prior bba on target ID available at time  $k - 1$  and our current observed bba on target ID at time  $k$ ) and where all denominators are different from zero. If a denominator is zero, that fraction is discarded.

#### 4.2 Principle of the target type tracker

To estimate the true target type  $type(k)$  at time  $k$  from the sequence of declarations  $c(1), c(2), \dots, c(k)$  done by the unreliable classifier<sup>2</sup> up to time  $k$ . To build an estimator  $\widehat{type}(k)$  of  $type(k)$ , we use the general principle of the Target Type Tracker (TTT) developed in [12] which consists in the following steps:

- a) Initialization step (i.e.  $k = 0$ ). Select the target type frame  $C_{Tot} = \{\theta_1, \dots, \theta_n\}$  and set the

<sup>1</sup>In our GMTI-MTT applications, we will assume Shafer's model for the frame  $C_{Tot}$  of target ID which means that elements of  $C_{Tot}$  are assumed truly exclusive.

<sup>2</sup>Here we consider only one source of information/classifier, say based either on the EO/IR sensor, or on a video sensor by example. The multi-source case is discussed in section 4.3.

prior bba  $m^-(\cdot)$  as vacuous belief assignment, i.e.  $m^-(\theta_1 \cup \dots \cup \theta_n) = 1$  since one has no information about the first observed target type.

- b) Generation of the current bba  $m_{obs}(\cdot)$  from the current classifier declaration  $c(k)$  based on attribute measurement. At this step, one takes  $m_{obs}(c(k)) = P\{c(k)\} = C_{c(k)c(k)}$  and all the unassigned mass  $1 - m_{obs}(c(k))$  is then committed to total ignorance  $\theta_1 \cup \dots \cup \theta_n$ .  $C_{c(k)c(k)}$  is the element of the known confusion matrix  $\mathbf{C}$  of the classifier indexed by  $c(k)c(k)$ .
- c) Combination of current bba  $m_{obs}(\cdot)$  with prior bba  $m^-(\cdot)$  to get the estimation of the current bba  $m(\cdot)$ . Symbolically we write the generic fusion operator as  $\oplus$ , so that  $m(\cdot) = [m_{obs} \oplus m^-](\cdot) = [m^- \oplus m_{obs}](\cdot)$ . The combination  $\oplus$  is done according to the PCR5 rule (i.e.  $m(\cdot) = m_{PCR5}(\cdot)$ ).
- d) Estimation of True Target Type is obtained from  $m(\cdot)$  by taking the singleton of  $\Theta$ , i.e. a Target Type, having the maximum of belief (or eventually the maximum Pignistic Probability).

$$\widehat{type}(k) = \underset{A \in C_{Tot}}{\operatorname{argmax}} (BetP\{A\}) \quad (22)$$

The Pignistic Probability is used to estimate the probability to obtain the type  $\theta_i \in C_{Tot}$  given the previous target type estimate  $\widehat{type}(k - 1)$ .

$$BetP\{\theta_i\} = P\{\widehat{type}(k) = \theta_i | \widehat{type}(k - 1)\} \quad (23)$$

- e) set  $m^-(\cdot) = m(\cdot)$ ; do  $k = k + 1$  and go back to step b).

Naturally, in order to revise the LLR in our GMTI-MTT systems for taking into account the estimation of belief of target ID coming from the Target Type Trackers, we transform the resulting bba  $m(\cdot) = [m^- \oplus m_{obs}](\cdot)$  available at each time  $k$  into a probability measure. In this work, we use the classical pignistic transformation defined by [13]:

$$BetP\{A\} = \sum_{X \in 2^{C_{Tot}}} \frac{|X \cap A|}{|X|} m(X) \quad (24)$$

#### 4.3 Working with multiple sensors

Since in our application, we work with different sensors (i.e. MTI and Video EO/IR sensors), one has to deal with the discernment frames  $C_{MTI}$  and  $C_{video}$  defined in section 2. Therefore we need to adapt the (single-sensor based) TTT to the multi-sensor case. We first adapt the frame  $C_{MTI}$  to  $C_{video}$  and then, we extend the principle of TTT to combine multiple bba's (typically here  $m_{obs}^{MTI}(\cdot)$  and  $m_{obs}^{Video}(\cdot)$ ) with prior target ID bba  $m^-(\cdot)$  to get finally the updated global bba  $m(\cdot)$  at each time  $k$ . The proposed approach can

be theroretically extended to any number of sensors. When no information is available from a given sensor, we take as related bba the vacuous mass of belief which represents the total ignorant source because this doesn't change the result of the fusion rule [11] (which is a good property to satisfy). For mapping  $C_{MTI}$  to  $C_{video}$ , we use a (human refinement) process such that each element of  $C_{MTI}$  can be associated at least to one element of  $C_{video}$ . In this work, the delay on the the type information provided by the video sensor is not taking into account to update the global bba  $m(\cdot)$ . All type information (delayed or not provided by MTI and video sensors) are considered as bba  $m_{obs}(\cdot)$  available for the current update. The explicit introduction of delay of the out of sequence video information is under investigations.

#### 4.4 Data attributes in the VS IMMC

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  $\mathbf{z}_j^*(k) (\forall j \in \{1, \dots, m_k\})$  described in (9) and (13). With the assumption that the kinematic and classification observations are independant, it is easy to prove that the new combined likelihood  $\Lambda_N^l$  associated with a track  $T^{k,l}$  is the product of the kinematic likelihood (17) with the classification probability in the manner that:

$$\Lambda_N^l(k) = \Lambda^l(k) \cdot P\{\widehat{type}(k)|\widehat{type}(k-1)\} \quad (25)$$

where the the probability  $P\{\widehat{type}(k)|\widehat{type}(k-1)\}$  is chosen as the pignistic probability value on the declared target type  $\widehat{type}(k)$  given  $\widehat{type}(k-1)$  derived from the updated mass of belief  $m(\cdot)$  according to our target type tracker.

## 5 Simulations and results

### 5.1 Scenario description

To evaluate the performances of the VS-IMMC SB-MHT with the attribute type information, we consider 10 maneuvering (acceleration, deceleration, stop) targets on a real road network. The 10 target types are given by (12). The target 1 is passing the military vehicles 2, 3, 4 and 7. Targets 2, 3, 4 and 7 start from the same starting point. The target 2 is passing the vehicles 3 and 7 in the manner that it places in front of the convoy. The targets 5, 6, 9 and 10 are civilian vehicles and are crossing the targets 1, 2, 3 and 7 at several junctions. The goal of this simulation is to reduce the association complexity by taking into account the road network topology and the attribute types given by heterogeneous sensors. In this scenario, we consider one GMTI sensor located at  $(-50km, -60km)$  at 4000m in elevation and one UAV located at  $(-100m, -100m)$  at 1200m in elevation and 5 UGS distributed on the

ground. The GMTI sensor tracks the 10 targets at every 10 seconds with  $20m$ ,  $0.0008rad$  and  $1m \cdot s^{-1}$  range, cross-range and range-rate measurements standard deviation respectively. The detection probability  $P_D$  is equal to 0.9 and the MDV (Minimal Detectable Velocity) fixed at  $1m \cdot s^{-1}$ . The false alarms density is fixed ( $\lambda_{fa} = 10^{-8}$ ). The confusion matrix described in part 4.2 is given by:

$$\mathbf{C}_{MTI} = diag([ 0.8 \quad 0.7 \quad 0.9 ]) \quad (26)$$

This confusion matrix is only used to simulate the target type probability of the GMTI sensor. The data obtained by UAV are given at 10 seconds with 10m standard deviation in  $X$  and  $Y$  direction from the  $TCF$ . The time delay of the video data is constant and equal to 11 seconds. The detection probability  $P_D$  is equal to 0.9. The human operator only selects for each video report a type defined by (12). In our simulations, the target type probability depends on the sensor resolution. For this, we consider the volume  $V_{video}$  of the sensor area surveillance on the ground. The diagonal terms of the confusion matrix  $\mathbf{C}_{video}$  are equal to  $P\{c(k)\}$  where  $P\{c(k)\}$  is defined by:

$$P\{c(k)\} = \begin{cases} 0.90 & \text{if } V_{video} \leq 10^6 m^2 \\ 0.75 & \text{if } 10^6 m^2 < V_{video} \leq 10^8 m^2 \\ 0.50 & \text{if } V_{video} > 10^8 m^2 \end{cases} \quad (27)$$

For the UGS, the target detection is done if only the target is located under the minimal range detection (MRD). The MRD is fixed for the 5 UGS at 1000 m and each sensor gives delayed measurement every seconds. The time delay is also equal to 11 seconds. The UGS specificity is to give only one target detection during 4 seconds in order to detect another target. We recall that there is no false alarms for this sensor. Based on [4], the target type probability depends on  $\alpha$  (*i.e.* the target orientation towards the UGS). The more the target orientation is orthogonal to the sensor line of sight, the more the target type probability increases. The diagonal terms of the confusion matrix  $\mathbf{C}_{UGS}$  are equal to  $P\{c(k)\}$  where  $P\{c(k)\}$  is defined by:

$$P\{c(k)\} = \begin{cases} 0.90 & \text{if } \frac{5\pi}{6} \leq \alpha \leq \frac{\pi}{6} \\ 0.50 & \text{otherwise} \end{cases} \quad (28)$$

For each detected target, a uniform random number  $u \sim U([0, 1])$  is drawn. If  $u$  is greater than the true target type probability of the confusion matrix, a wrong target type is declared for the ID report and used with its associated target type probability. The targets are scanned at different times by the sensors (figure 1).

### 5.2 Filter parameters

We consider three motion models (*i.e.*  $i \in \{0, 1, 2\}$ ) which are respectively a stop model  $M_0$  when the target

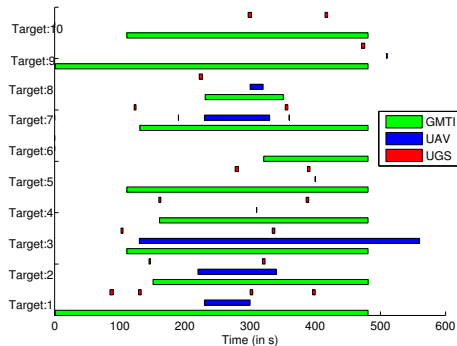


Figure 1: Target's sensor illumination.

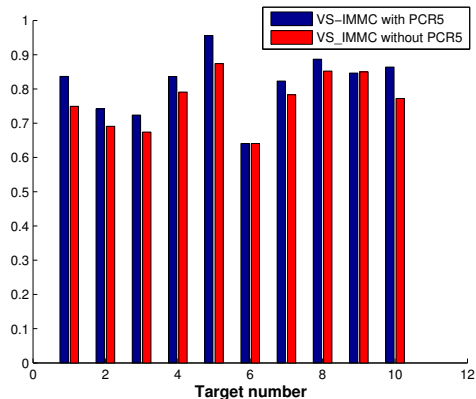


Figure 2: Track length ratio.

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  $0.05 \text{ m} \cdot \text{s}^{-2}$ , the constrained constant velocity model  $M_2$  has a high standard deviation to adapt the dynamics to the target manoeuvre (the standard deviation along and orthogonal to the road segment are respectively equal to  $0.8 \text{ m} \cdot \text{s}^{-2}$  and  $0.4 \text{ m} \cdot \text{s}^{-2}$ ) and the stop motion model  $M_0$  has a standard deviation equals to zero. These constrained motion models are however adapted to follow the road network topology. The transition matrix and the SB-MHT parameters are those taken in [5].

### 5.3 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. The target tracking goal is to track as long as possible the target with one track. To evaluate the track maintenance, we use the track length ratio criterion, the averaged root mean square error (noted ARMSE) for each target and the track purity and the type purity (only for the tracks obtained with PCR5) [5]. These measures of performances are averaged on 50 Monte-Carlo runs.

On figure 2, one sees that the track length ratio becomes better with the PCR5 than without as expected for the target 6. When the targets 1 and 2 are passing the targets 3, 4 and 7, an association ambiguity arises to associate the tracks with the correct measurements. This is due to the close formation between targets with the GMTI sensor resolution and the road network configuration with junctions. Sometimes tracks are lost with the VS IMMC SB-MHT without the PCR5. Then new tracks for each targets are built. That is why, the track purity of the VS IMMC SB-MHT without PCR5 (Table 1) is smaller than the the track purity with

Target	ARMSE	Track purity	Type purity
1	14.82	0.70	none
2	16.62	0.62	none
3	15.61	0.61	none
4	22.54	0.77	none
5	16.25	0.85	none
6	18.68	0.64	none
7	14.45	0.72	none
8	17.51	0.84	none
9	19.23	0.85	none
10	17.40	0.75	none

Table 1: Tracking results (VSIMMC without PCR5).

Target	ARMSE	Track purity	Type purity
1	14.37	0.78	0.64
2	15.77	0.66	0.62
3	15.60	0.61	0.59
4	21.10	0.81	0.81
5	15.88	0.94	0.55
6	18.68	0.64	0.02
7	14.22	0.76	0.76
8	17.38	0.87	0.87
9	19.20	0.85	0.05
10	17.17	0.83	0.46

Table 2: Tracking results (VSIMMC and PCR5).

PCR5 (Table 2). So, the track precision, given by the ARMSE criterion, is better with the PCR5. For the target 6 results, this target is only scanned by the GMTI sensor and its associated performances are equivalent for both algorithms. Then, if there is no IMINT information and no interaction between targets, the performances of the algorithm with PCR5 are the same than without PCR5.

Despite of the PCR5 improvement on the target tracking, the difference of performances between the algorithms is not significant. If there is an interaction be-

tween IMINT and GMTI information, we can see a gain on the track length ratio or track purity of 10% with PCR5. This small difference is due to the good constrained state estimation. The estimated target states have a good precision because the target tracking is done by taking into account the road segments location and the good performances of the OOSM approach. So, it implies a substantial improvement of the target-to-track association. In addition, on Table 2, the type purity based on PCR5 is derived from the maximum of  $BetP$  criterion. But  $BetP$  is computed according the set  $C_{video}$  (12) and if the track receives only MTI reports the choice on the target type is arbitrary for the tracked vehicles of  $C_{MTI}$  (8). In fact, a tracked vehicle can be 6 elements of (12). So the probability  $BetP$  on the 6 tracked vehicles of (12) is equivalent. The selection of the maximum of  $BetP$  has no meaning because in such case and the maximum becomes arbitrary. This explains the bad track purity of targets 6 and 9.

## 6 Conclusion

In this paper, we have presented a new approach to improve VS IMMC SB-MHT by introducing the data fusion with several heterogeneous sensors. Starting from a centralized architecture, the MTI and IMINT reports are fused by taking into account the road network information and the OOSM algorithm for delayed measurements. The VS IMMC SB-MHT is enlarged by introducing in the data association process the type information defined in the STANAG 4607 and an IMINT attribute set. The estimation of the Target ID probability is done from the updated/current attribute mass of belief using the Proportional Conflict Redistribution rule no. 5 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 an improvement of the performances of the VS-IMMC SB-MHT when the type information is processed by our PCR5-based Target Type Tracker. In this work, we did not distinguish undelayed from delayed sensor reports in the TTT update. This problem is under investigations and offers new perspectives to find a solution for dealing efficiently with the time delay of the information type data and to improve performances. One simple solution would be to use a forgetting factor of the delayed type information but other solutions seem also possible to explore and need to be evaluated. Some works need also to be done to use the operational ontologic APP-6A for the heterogeneous type information. Actually, the frame of the IMINT type information is bigger than the one used in this paper and the IMINT type information can be given at different granularity levels. As a third perspective, we

envisage to use both the type and contextual information in order to recognize the tracks losts in the terrain masks which represent the possible target occultations due to the terrain topography in real environments.

## References

- [1] T. Kirubarajan, and Y. Bar-Shalom, "Tracking evasive move-stop-move targets with an MTI radar using a VS-IMM estimator", *IEEE Tran. on AES*, Vol. 39, No. 3, pp. 1098–1103, Jul. 2003.
- [2] M. Ulmke and W. Koch, "Road-map assisted ground moving target tracking", *IEEE Tran. on AES*, Vol. 42, No. 4, pp. 1264–1274, Oct. 2006.
- [3] Y. Bar-Shalom and H. Chen, "IMM estimator with out-of-sequence measurements", *IEEE Tran. on AES*, Vol. 41, No. 1, pp. 90–98, Jan. 2005.
- [4] E. Blash, B. Kahler, "Multiresolution EO/IR target tracking and identification", *Proc. of Fusion 2005*, Jul. 2005.
- [5] B. Pannetier, J. Dezert and E. Pollard, "Improvement of multiple ground targets tracking with GMTI sensors and fusion identification attributes", *Aerospace Conference, 2008 IEEE*, Mar. 2008.
- [6] B. Pannetier, V. Nimier and M. Rombaut, "Multiple ground target tracking with a GMTI sensor", *Proc. of MFI 2006*, Sept. 2006.
- [7] NATO, "STANAG 4607 JAS (Edition 2) - NATO ground moving target indicator GMTI format", *NSA0749(2007)-JAS/4607*, Aug. 2007.
- [8] Y. Bar-Shalom and D. Blair, *Multitarget multi-sensor tracking : Applications and Advances*, Vol. III, Artech House, pp. 523, 2000.
- [9] D.F. Bizup and D.E. Brown, "The over extended Kalman filter – Don't use it !", *Proc. of Fusion 2003*, Jul. 2003.
- [10] S.S. Blackman and R. Popoli, *Design and analysis of modern tracking systems*, Artech House, 1999.
- [11] F. Smarandache, J. Dezert, (Editors), *Advances and Applications of DSMT for Information Fusion (Collected Works)*, Vol. 2, American Research Press, Rehobooth, U.S.A, 2006.
- [12] J. Dezert, A. Tchamova, F. Smarandache and P. Konstantinova, "Target Type Tracking with PCR5 and Dempster's rules: A Comparative Analysis", *Proc. of Fusion 2006*, Jul. 2006.
- [13] Ph. Smets, "Data Fusion in the Transferable Belief Model", *Proc. of Fusion 2000*, Jul. 2000.