

Multiple ground target tracking and classification with DSMT

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Abstract: Based on our previous work we propose to track multiple ground targets with GMTI (Ground Moving Target Indicator) sensors as well as with imagery sensors. The scope of this 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 to improve its performances.

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. For this, 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 evolve on the same operational theatre. Several references exist for the MGT (Multiple Ground Tracking) with GMTI sensors [?, 8] 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. The proposed VS-IMMC (Variable Structure Interacting Multiple Models) filter is extended in a multiple target context and integrated in a SB-MHT (Structured Branching - Multiple Hypotheses Tracking).

One way to enhance data associations is to fused data obtained by several sensors. The most easily approach is to consider the centralized fusion between two or more GMTI sensors. Another way is to introduce heterogeneous sensors in the centralized architecture in order to improve the data associations (by using the reports in location and its classification attribute) and palliate the poor GMTI sensor classification. In our previous works [6], the classification information of the MTI segments and IMINT segments (IMagery INTelligence) 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, we illustrate on a complex scenario our approach to fuse MTI classification type with image classification type associated to each report.

2 Motion & observation models

2.1 Constrained motion model

The target state $\mathbf{x}(k)$ at the current time t_k is defined in a local horizontal plane (O, X, Y) of a Topographic Coordinate Frame denoted TCF . 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 . The constrained motion model M_i^s is build in such a way that the predicted state is on the road segment s and the gaussian noise is defined under the road segment constant [6]. 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].

2.2 GMTI measurement model

According to the NATO GMTI format [5], 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 . Each MTI report is characterized both with the location and velocity information (range radial velocity) 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 $C_{MTI} = \{Tracked\ vehicle, Wheeled\ vehicle, Rotary\ wing\ aircraft\}$.

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:

$$\mathbf{z}_{MTI}^*(k) \triangleq \{\mathbf{z}_{MTI}(k), c(k), P\{c(k)\}\} \quad (1)$$

2.3 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 IMINT reports $\mathbf{z}_{video}(k)$ at the current time t_k are expressed in the reference frame (O, X, Y) and give a location information and type

target. 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. For the last point, a human operator selects targets on a movie frame and is able to choose its attribute with a HMI (Human Machine Interface). Based on the military symbology called 2525C [3], we build the frame of discernment for an EO/IR source denoted C_{video} . Each video report is associated to the attribute information $c(k) (\forall c(k) \in C_{video})$ with its probability $P\{c(k)\}$ that it is correct. 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.

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

$$\mathbf{z}_{video}^*(k) \triangleq \{\mathbf{z}_{video}(k), c(k), P\{c(k)\}\} \quad (2)$$

The attribute type of the image sensors belongs to a different and better classification than the MTI sensors.

2.4 Taxonomy

In our work, the symbology 2525C [3] is used to describe the links between the different classification sets C_{MTI} and C_{video} . Figure 1 represents a short part of the 2525C used in this paper. The red elements underlined in italic style are the atomic elements of our taxonomy. Each element of both sets can be placed in 1. For example, the “wheeled vehicle” of the set C_{MTI} is placed at the level “Armoured \rightarrow Wheeled” or the “Volkswagen Touareg” given by the video is placed at the levels “Armoured \rightarrow Wheeled \rightarrow Medium” and “Civilian Vehicle \rightarrow Jeep \rightarrow Medium”.

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 2.1, a constrained motion model i to a road segment s , noted $M_s^i(k)$, was defined. 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 according to the road network configuration. The steps of the IMM under road segment s constraint are the same as for the classical IMM as described in [1].

In real applications, 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.

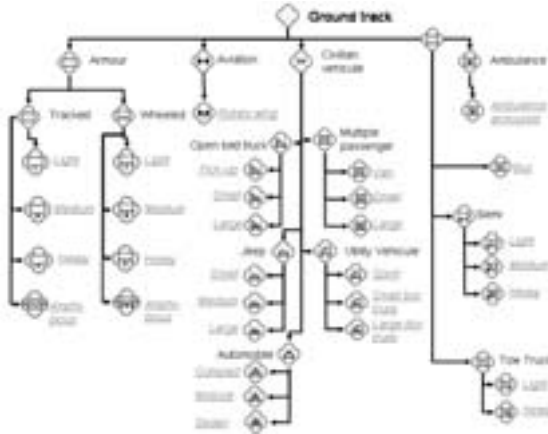


Figure 1: 2525C (light version).

In such case, we activate the most probable road segments sets depending on the local predicted state/location of the track $T^{k,l}$ [6]. 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 Wald's sequential probability ratio test (SPRT) [9].

3.2 Multiple target tracking

For the MGT problem, we use the SB-MHT (Structured Branching Multiple Hypotheses Tracking) presented in [2]. 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 [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) $L^l(k)$ or a track score of a track $T^{k,l}$ expressed at current time t_k .

4 Target type tracking

Our approach consists to use 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. 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 [4, 7].

4.1 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 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 [4] which consists in the following steps:

1. Initialization step (*i.e.* $k = 0$). Select the target type frame $C_{Tot} = \{\theta_1, \dots, \theta_n\}$ and set the 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.
2. 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 C of the classifier indexed by $c(k)c(k)$.
3. Combination of current bba $m_{obs}(\cdot)$ with prior bba $m^-(\cdot)$ to get the estimation of the current bba $m(\cdot)$.
4. Estimation of True Target Type is obtained from $m(\cdot)$ by taking the singleton of Θ , *i.e.* a Target Type, having the maximum of belief (or eventually the maximum Pignistic Probability).
5. Set $m^-(\cdot) = m(\cdot)$; do $k = k + 1$ and go back to step 2).

Naturally, in order to revise the LLR in our GMTI-MTT system 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.

4.2 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 (1) and (2). With the assumption that the kinematic and classification observations are independent, it is easy to prove that the new combined likelihood Λ_N^l associated with a track $T^{k,l}$ is the product of the kinematic likelihood.

5 Illustration

In the extended version of this paper, we will illustrate our algorithm by using a complex scenario generated with a powerful simulator developed at ONERA. The area of interest is located in a fictive country called North Atlantis. In this scenario, the goal is to detect and track several targets with 2 GMTI sensors (JSTARS, SIDM), 18 UGS and 4 UAV (SDTI), in order to build the situation assessment and evaluate the threat in order to protect the coalition forces. On the operation theater, 250 targets evolve, they can maneuver on and out the road network. The set of target type is significant, we can have for instance civilian vehicles (as 4x4, cars, bus, truck,...) and military vehicles as well (T-62, AMX 30, Kamakov,...). Illustrations and conclusion of our algorithm will be presented in the extended version of this paper.

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