

# Track segment association with classification information

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**Abstract**—We propose a new method to track maneuvering ground targets and correct the ground tactical situation. The method developed in this work improves the performances of Structured-Branching Multiple Hypothesis Tracker (SB-MHT) and reduces the incorrect track deletions in tracks maintenance with a new Track Segment Association (TSA) algorithm taking into account both kinematic and classification information. The performances of this method are quantified on a realistic simulated scenario involving twenty maneuvering ground targets observed by an airborne with a Ground Moving Target Indicator (GMTI) sensor and Unattended Ground Sensor (UGS).

## I. INTRODUCTION

Ground tracking algorithms are used in a special environment: the high traffic density and the large number of false alarms, that brings about a significant data quantity, the strong and fast target maneuvers which compromise target tracking due to the association problem and the terrain elevation that generates undetected areas in which ground targets cannot be detected. In a Ground Moving Target Indicator (GMTI) surveillance context, we propose to use the road network information as a prior information in order to improve the tracking quality. Under the assumption that the targets are evolving on the road network and using a Bayesian approach, the event that the target state belongs to a road segment (*i.e.* the position is on the road segment and the velocity in the road segment direction) can be taken into account in the tracker as proposed in [1].

Because of the ground target proximity and the sensor precision, the kinematic discrimination is usually not sufficient to maintain the correct association between tracks and measurement and that is why the classification information (when good enough) based on target identification features is also useful to improve the tracking performances [2]–[5]. The adaptation of Bar-Shalom’s and Gokberk approach [6] to the Structured-Branching Multiple Hypothesis Tracker (SB-MHT) [2] has been proposed in [7] with the use of Dezert-Smarandache Theory (DSmT) to update and to modify the assignment cost where the feature information was provided by an aerial EO/IR system.

In applications, the use of the tracker is always limited in time due to the Unnamed Aerial Vehicle (UAV) performances (maneuvers, autonomy, ...) and the classification information given by the GMTI sensor. Usually, the proportion of well-classified tracks obtained after the fusion between GMTI tracks and EO/IR UAV detections is very small. To palliate the track breakage and the weak track classification, we propose

in this paper a new approach to solve the Track Segment Association (TSA) problem presented recently by Zhang and Bar-Shalom in [8] by using classification information obtained with several Unattended Ground Sensor (UGS) distributed over a big area surveillance that are able to provide a well-classification information about targets.

## II. MOTION AND OBSERVATION MODELS

### A. Constrained motion model

The target state at the current time  $t_k$  is defined in the local horizontal plane of the Topographic Coordinate Frame (TCF) by the vector:

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

The target state of a target moving on the road segment  $s$  is  $\mathbf{x}_k^s$  and follow a dynamic model  $\mathcal{M}_i$  as explained in [9] and we adapt the level of the dynamic model’s noise based on the length of the road segment  $s$ , see [10], [11] for a detailed presentation of our ground target tracking algorithms on road networks.

### B. MTI and UGS observation models

1) *MTI report segment*: The Moving Target Indicator (MTI) measurement  $\mathbf{z}_k^{MTI}$  at the current time  $t_k$  is given in the TCF by Bizup and Brown Alternative Extended Kalman Filter (AEKF) measurement equation [12]

$$\mathbf{z}_k^{MTI} = [x_k \ y_k \ \dot{\rho}_k]' = \mathbf{H}_k^{MTI} \cdot \mathbf{x}_k + \mathbf{w}_k^{MTI} \quad (2)$$

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 radial velocity measurement, and the observation matrix is

$$\mathbf{H}_k^{MTI} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{\partial \dot{\rho}_k}{\partial x} & 0 & \frac{\partial \dot{\rho}_k}{\partial y} \end{pmatrix} \quad (3)$$

and where  $\mathbf{w}_k^{MTI}$  is a zero-mean white Gaussian noise vector with a covariance  $\mathbf{R}_k^{MTI}$  approximated by

$$\mathbf{R}_k^{MTI} = \begin{pmatrix} \sigma_x^2 & \sigma_{xy}^2 & 0 \\ \sigma_{xy}^2 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_{\dot{\rho}}^2 \end{pmatrix} \quad (4)$$

$\sigma_{\dot{\rho}}^2$  is the standard deviation of the modified range radial velocity and  $\sigma_{xy}^2$  is the cross-covariance.

Each MTI report is characterized both with the location and velocity information and also with the attribute information and the probability that it is correct. We denote  $C_{MTI}$  the frame of discernment on target ID based on MTI data which 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,  $C_{MTI}$  is defined as  $\{\text{Tracked vehicle, Wheeled vehicle, Rotary wing aircraft}\}$ . We denote by  $\mathbf{z}_k^{MTI*}$  the extended MTI measurements including both kinematic part and attribute part defined by  $\mathbf{z}_k^{MTI*} \triangleq \{\mathbf{z}_k^{MTI}, c_k, P(c_k)\}$ , where  $P(c_k)$  represent the diagonal terms of the “confusion matrix”  $\mathbf{C}_k = [c_k^{i,j}]$  of the classification algorithm assumed to be used with  $c_k \in C_{MTI}$ . The element  $c_k^{i,j}$  of  $\mathbf{C}_k$  matrix is the likelihood of the true class  $i$  when the classifier output is  $j$ , see [6] for details. Generally in practice, only the diagonal elements of  $\mathbf{C}_k$  are known, and so the off-diagonal terms of  $\mathbf{C}_k$  are chosen at a same value in  $[0; 1]$  such that the sum of each column of  $\mathbf{C}_k$  is equal to one.

2) *UGS report segment*: We use a video EO/IR sensor and an acoustic sensor fixed on a Unattended Ground Sensor (UGS). The UGS measurement  $z_k^{UGS}$  at the current time  $t_k$  is given in the TCF by the equation

$$\mathbf{z}_k^{UGS} = [x(k) \ y(k)]' = \mathbf{H}_k^{UGS} \cdot \mathbf{x}(k) + \mathbf{w}_k^{UGS} \quad (5)$$

with the video sensor observation matrix given by

$$\mathbf{H}_k^{UGS} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \quad (6)$$

The white noise Gaussian process  $\mathbf{w}_k^{UGS}$  is centered and has a known covariance  $\mathbf{R}_k^{UGS}$  given by the ground station.

We denote  $\mathbf{z}_k^{UGS*}$  the extended video measurements including both kinematic part and attribute part defined  $\forall c_k \in C_{UGS}$  by  $\mathbf{z}_k^{UGS*} \triangleq \{\mathbf{z}_k^{UGS}, c_k, P(c_k)\}$ . The attribute type of the Unattended Ground Sensor (UGS) sensors allow to achieve a better (refined) classification than the Moving Target Indicator (MTI) sensors and that is why the size of the classification frame  $C_{UGS}$  is bigger than the size of the frame  $C_{MTI}$ . The frames of discernments for target classifications are based on a taxonomy presented in the following subsection.

### C. Taxonomy for target classification

The symbology 2525C [13] is used to describe the links between the different classification sets  $C_{MTI}$  and  $C_{UGS}$ . We use the same taxonomy presented in the paper [7].

For notation convenience, the measurements sequence  $Z^{k,l} = \{Z^{k-1,n}, \mathbf{z}_k^j\}$  represents a possible set of measurements generated by the target up to time  $k$ .  $Z^{k,l}$  consists in a subsequence  $Z^{k-1,n}$  of measurements up to time  $k-1$  and a validated measurement  $\mathbf{z}_k^j$  available at time  $k$  associated with the track  $\mathcal{T}^{k,l}$ . At the current time  $k$ , the track  $\mathcal{T}^{k,l}$  is represented by a sequence of the state estimates.

### D. Multiple ground target tracker

The main steps of Structured-Branching Multiple Hypothesis Tracker (SB-MHT) (see Chap.16 of [2]) coupled with Variable Structure Interacting Multiple Model under Constraint (VS IMMC) [1] are

- 1) Track confirmation and the track maintenance of SB-MHT: when the new set of measurements is received, a standard gating procedure [2] is applied validate MTI reports for 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-model is activated.
- 2) Track Score: The Log-Likelihood Ratio (LLR) used as the track score of a track  $\mathcal{T}^{k,l}$  is  $L_{k,l} = L_{k-1,n} + \Delta L_{k,l}$  where  $\Delta L_{k,l}$  and  $L(0)$  are given in [2], [7]. The Sequential Probability Ratio Test (SPRT) [14] is then used to set up the track status (tentative, confirmed or deleted).
- 3) Track Clustering: all the tracks that are linked by a common measurement are put in a same cluster to limit the number of hypotheses and to reduce the complexity of tracking system. The result of the clustering process is a list of tracks that are interacting.
- 4) Track Pruning: For each track, the *a posteriori* probability is computed and a classical *N-Scan* pruning approach [2] is used to select the confirmed and delete the most unlikely tracks. In the constrained ground target tracking context, a modified *N-Scan* pruning approach is necessary in order to select the  $N_k$  best tracks on each road section.
- 5) Track Deletion: SPRT is used to delete the unlikely hypotheses among the  $N_k$  hypotheses. The tracks are then updated and projected on the road network. A merging technique selecting the most probable tracks with common measurements is used to reduce the memory storage.

### E. Target type tracker

The target type tracker [6] is used to improve the performance of the data association in the SB-MHT. The principle consists to compute the posterior class probability vector at time  $t_k$  using the classifier output by

$$\beta_{k,l} = \frac{P_J \otimes \beta_{k-1,n}}{P'_J \beta_{k-1,n}} \quad (7)$$

where  $P_J$  is the likelihood function of the subset  $J$  corresponding to the list of attributes that characterize the element  $c_k$  of the frame  $C_{MTI}$ ,  $\beta_{k-1,n}$  is the prior probability provided by the previous updated track  $\mathcal{T}^{k-1,n}$  and  $\otimes$  is the Schur-Hadamard product. At time  $t_0$ , one takes  $\beta_0 = P_J$ . In assuming kinematic and classification observations independent, the augmented LLR for  $\mathbf{z}_k^{MTI*}$  or  $\mathbf{z}_k^{UGS*}$  is given by  $L_{k,l} = L_{k-1,n} + \Delta L_{k,l} + \Delta L_{k,l}^c$  with  $\Delta L_{k,l}^c = \log(\frac{P'_J \beta_{k-1,n}}{P'_J \beta_e})$  and where  $e$  defines an extraneous target.  $\Delta L_{k,l}^c = 0$  if the track is not associated to a measurement at the current time  $t_k$ . Finally the updated target type  $\hat{c}_{k,l}$  of the track  $\mathcal{T}^{k,l}$  is

chosen as the maximum probability of updated classification vector (7). However, if this probability is not superior to 0.7, we use the taxonomy 2525C presented in [7] to choose the target class that satisfies this condition.

### III. TRACK SEGMENT ASSOCIATION

#### A. Problem formulation

In TSA problem, we want to associate a current track with an old track set in presence of false tracks (the tracker is not perfect and false tracks can appear in dense clutter area). Based on previous works on [8], [15], we propose to solve the track segment association by taking into account the road network and an Interacting Multiple Model (IMM)-smoother. Two track sets are considered: an old track set  $\mathcal{O}_k$  which contains the terminated track (“dead” or “stopped” tracks) at time  $t_k$  due to lack of measurement, and a current track set  $\mathcal{C}_k$  which contains current updated tracks (the stop model is not activated) at time  $t_k$ . The sets  $\mathcal{O}_k$  and  $\mathcal{C}_k$  are updated at each sensor scan time by the following TSA process summarized in [8]:

- 1) Track sets selection: we select the set  $\mathcal{C}_k$  of current tracks and the tracks set  $\mathcal{O}_k$ .
- 2) Smoothing: the tracks contained in  $\mathcal{O}_k$  and in  $\mathcal{C}_k$  are smoothed.
- 3) Track correlation: a retrodiction and prediction process are respectively done on tracks contained in  $\mathcal{C}_k$  and old tracks contained in  $\mathcal{O}_k$ . At each scan time, track segments are associated based on a cost function.
- 4) Track assignment: the Auction algorithm [2] is used to solve the track segment association problem.

#### B. TSA Algorithm without target classification

1) *Track sets selection*: An updated track  $\mathcal{T}^{k,l}$  at time  $t_k$  is defined by  $\mathcal{T}^{k,l} \triangleq \{\hat{\mathbf{x}}_{t|t}^l, \mathbf{P}_{t|t}^l, t = k_i^l, \dots, k\}$ . Its initialization time is noted  $t_{k_i^l}$ . Starting from the empty set, the set  $\mathcal{C}_k$  of confirmed tracks is built sequentially. In the set  $\mathcal{O}_k$ , there are all terminated tracks since the beginning of the surveillance mission the deleted tracks  $\mathcal{T}^{k_e^m, m}$ , are defined with a termination time  $t_{k_e^m}$  and a start time  $t_{k_i^m}$ . An old track is defined by  $\mathcal{T}^{k_e^m, m} \triangleq \{\hat{\mathbf{x}}_{t|t}^l, \mathbf{P}_{t|t}^l, t = k_i^m, \dots, k_e^m\}$ . The times  $t_{k_e}$  and  $t_{k_i}$  are not necessarily the same for each track contained in  $\mathcal{O}_{k-1}$ . The current old track set  $\mathcal{O}_k$  is based on the previous set  $\mathcal{O}_{k-1}$  updated with the current deleted tracks. The tracks deleted by the SB-MHT at the current time  $t_k$  are added to set  $\mathcal{O}_k$ . To palliate the track discontinuity due to the stop-model activation, we also add to  $\mathcal{O}_k$  all the stopped tracks. If a stopped track present in  $\mathcal{O}_{k-1}$  is moving at time  $t_k$ , it is withdrawn from  $\mathcal{O}_k$  and added to  $\mathcal{C}_k$ . In our simulation, a track is declared as “stopped” if the confirmed track has a stop-model probability greater than 0.9.

2) *IMM fixed-lag smoother*: To improve tracking performances and to take into account all the measurements of a track available in a sliding window, we use a Rauch Tung Striebel (RTS) IMM smoothing algorithm. The forward recursion is performed using the VS IMMC algorithm. The backward recursion keeps the selected model set of the track

and imitates the IMM estimator in the forward direction. See [10], [16], [17] for details.

#### 3) Track correlation:

a) *Retrodiction and association*: From each starting time  $t_{k_i^l}$  of each track  $\mathcal{T}^{k,l}$ , we use a back propagation equation of a constant velocity model. For each track  $\mathcal{T}^{k,l}$ , a sequence of retrodicted states is obtained at previous times for each deleted tracks of  $\mathcal{O}_k$ . The set of candidate track pairs for TSA is obtained according to a two-steps procedure:

- Step 1 (velocity gating): we associate the current track with old tracks if the maximum ground target speeds are below  $v_{max}$ . The set of pairing tracks satisfying this condition is defined by

$$\Phi_v = \{(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) \mid \frac{|\hat{x}_{k_c|k_i^l}^l - \hat{x}_{k_c|k_o}^m|}{t_{k_i^l} - t_{k_o}} \leq v_{max}, \text{ and } \frac{|\hat{y}_{k_c|k_i^l}^l - \hat{y}_{k_c|k_o}^m|}{t_{k_i^l} - t_{k_o}} \leq v_{max}\} \quad (8)$$

where  $\mathcal{T}^{k,l} \in \mathcal{C}_k$ ,  $\mathcal{T}^{k_o, m} \in \mathcal{O}_k$ ,  $t_{k_i^l} < t_{k_o} < t_{k_e^m}$  with  $t_{k_c} = \frac{t_{k_i^l} - t_{k_o}}{2}$ .  $(\hat{x}_{.|k_i^l}^l, \hat{y}_{.|k_i^l}^l)$  is the retrodicted location of the track  $\mathcal{T}^{k,l}$  and  $(\hat{x}_{k_c|k_o}^m, \hat{y}_{k_c|k_o}^m)$  is the predicted location of the track  $\mathcal{T}^{k_o, m}$ . This is the approach used in [8] where the track pairing of the old track  $\mathcal{T}^{k_e^m, m}$  is done at each time  $\{t_{k_i^m}, \dots, t_{k_e^m}\}$  and not only at the time end  $t_{k_e^m}$ .

• Step 2: A  $\chi_n^2$  test ( $n$  being the state vector dimension) is used to select the pairs in  $\Phi_v$  to reduce the complexity. At time  $t_{k_c}$  the difference between the retrodicted tracks of  $\mathcal{T}^{k_i^l, l}, (\mathcal{T}^{k,l} \in \mathcal{C}_k)$  and predicted tracks of  $\mathcal{T}^{k_o, m}, (\mathcal{T}^{k_e^m, m} \in \mathcal{O}_k)$  is defined by  $\Delta_{k_c}^{l,m} = \hat{x}_{k_c|k_i^l}^l - \hat{x}_{k_c|k_o}^m$  with the covariance  $\mathbf{P}_{k_c}^{l,m} = \mathbf{P}_{k_c|k_i^l}^l - \mathbf{P}_{k_c|k_o}^m$ . The new set of track pairing candidate is defined as

$$\Phi_s = \{(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) \text{ such that } (\Delta_{k_c}^{l,m})^T [\mathbf{P}_{k_c}^{l,m}]^{-1} (\Delta_{k_c}^{l,m}) \leq \chi_n^2 (1 - Q)\} \quad (9)$$

with  $(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) \in \Phi_v$ ,  $t_{k_i^l} < t_{k_o} < t_{k_e^m}$ , and  $t_{k_c} = \frac{t_{k_i^l} - t_{k_o}}{2}$ , and where  $Q$  is a fixed tail probability.

b) *Track assignment*: After applying the gating (9), we obtain a set of track pairs candidates between current track in  $\mathcal{C}_k$  and deleted or stopped tracks in  $\mathcal{O}_k$ . The association is formulated as a 2-D assignment problem with the binary assignment variables

$$a(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) = \begin{cases} 1 & \text{track } \mathcal{T}^{k_i^l, l} \text{ originates from } \mathcal{T}^{k_o, m} \\ 0 & \text{otherwise.} \end{cases} \quad (10)$$

The track segment association cost  $c(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m})$  is

$$c(\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) = \begin{cases} -\log \frac{\mathcal{N}(\Delta_{k_c}^{l,m}; 0, \mathbf{P}_{k_c}^{l,m})}{\mu}, & (\mathcal{T}^{k_i^l, l}, \mathcal{T}^{k_o, m}) \in \Phi_s \\ -\log(1 - P_{D_s}), & \text{otherwise.} \end{cases} \quad (11)$$

where  $\mu$  is given by the spatial density of the extraneous tracks in the state space and  $P_{D_s}$  is the probability that a target is

tracked [8]. The optimal set of track pairs (optimal assignment) is obtained by minimizing the cost

$$C = \sum_{l=1}^{M_c} \sum_{m=1}^{N_o} a(\mathcal{T}^{k_i^l}, \mathcal{T}^{k_o, m}) c(\mathcal{T}^{k_i^l}, \mathcal{T}^{k_o, m}) \quad (12)$$

under the constraints:

$$\begin{cases} \sum_{l=1}^{M_c} a(\mathcal{T}^{k_i^l}, \mathcal{T}^{k_o, m}) = 1, m = 1, \dots, N_o \\ \sum_{m=1}^{N_o} a(\mathcal{T}^{k_i^l}, \mathcal{T}^{k_o, m}) = 1, l = 1, \dots, M_c \end{cases} \quad (13)$$

where  $M_c$  and  $N_o$  are respectively the number of current associated tracks and the number dead associated tracks. This assignment problem is solved by the Auction algorithm [2].

### C. TSA Algorithm with target classification

We introduce the track classification information in the Track Segment Association (TSA) process to increase the discrimination between the old and current tracks. Two methods are presented for such purpose.

1) *Track classification gating*: this first method is the easiest. We propose to add a new test in the track pairing test (9). This test consists to validate only the track with the same classification level between a current track  $\mathcal{T}^{k_i^l}$  and a old track  $\mathcal{T}^{k_e^m, m}$ . So, we add the following new condition  $\widehat{\text{Class}}_{k_i^l} = \widehat{\text{Class}}_{k_e^m, m}$  in (9). In practice, it is more efficient to choose the updated type at the current time  $t_k$  for the track  $\mathcal{T}^{k_i^l}$  even if the kinematic test is done on the initial smoothed state at time  $t_{k_i^l}$ .

2) *Track classification scoring*: the second method consists to modify the cost association presented in (11) by introducing a track classification cost. After the pairing test (9) between the current track  $\mathcal{T}^{k_i^l}$  and the old track  $\mathcal{T}^{k_e^m, m}$ , the track class vectors  $\beta_{k_i^l}$  and  $\beta_{k_e^m, m}$  are compared based on the Bhattacharyya distance  $c(\beta_{k_i^l}, \beta_{k_e^m, m}) = -\log \sum \sqrt{\beta_{k_i^l} \cdot \beta_{k_e^m, m}}$ . The expression of the global cost association is same as in (11), except that the term  $-\log(\mathcal{N}(\Delta_{k_e}^{l, m}; 0, \mathbf{P}_{k_e}^{l, m})/\mu)$  is replaced by  $-\log(\mathcal{N}(\Delta_{k_e}^{l, m}; 0, \mathbf{P}_{k_e}^{l, m})/\mu) + c(\beta_{k_i^l}, \beta_{k_e^m, m})$  if  $(\mathcal{T}^{k_i^l}, \mathcal{T}^{k_o, m}) \in \Phi_s$ .

## IV. SIMULATION AND RESULTS

Here we show the impact of the classification information in the TSA algorithm for multiple ground target tracking. Our results are based on a Monte-Carlo simulation with 100 runs. The scenario duration is limited to 10 minutes.

### A. Measures of performance

The classical Measures Of Performance (MOP) have been used in simulations to evaluate the TSA algorithm: the Track Segment Purity (TSP), the Mean Track Life (MTL) and the Percentage of Correct Classification (PCC) which are defined by  $\text{TSP} = (1/N) \sum_{l=1}^N n(\mathcal{T}^{k_i^l})/n_T$ ,  $\text{MTL} = (1/N) \sum_{l=1}^N l(\mathcal{T}^{k_i^l})/n_T$ ,  $\text{PCC} = (1/N) \sum_{l=1}^N n_c(\mathcal{T}^{k_i^l})/l(\mathcal{T}^{k_i^l})$  where  $N$  is the number of tracks associated to the same target,  $n(\mathcal{T}^{k_i^l})$  is the number of measurements of the track  $\mathcal{T}^{k_i^l}$  generated by the target associated to the track,  $n_T$  is the number of measurements in the track  $\mathcal{T}^{k_i^l}$ ,  $l(\mathcal{T}^{k_i^l})$  is

length of the track  $\mathcal{T}^{k_i^l}$  associated to the target, and  $l_T$  is the length of the target trajectory,  $n_c(\mathcal{T}^{k_i^l})$  is the number of correct classification of the track  $\mathcal{T}^{k_i^l}$  associated to a target, and  $l_{\mathcal{T}^{k_i^l}}$  is the length of the track  $\mathcal{T}^{k_i^l}$ .

### B. Scenario description

1) *Targets description*: We consider 20 targets that are able to maneuver (acceleration, deceleration, stop), pass and cross the others targets. The relations between target type, the target classification set and the taxonomy 2525C are given in the table I. We recall that the frame of discernment  $C_{UGS}$  is similar to  $C_{2525C}$ .

Target	Target type	Target class in $C_{MTI}$	Target class in $C_{2525C}$
1	TWINGO	Wheeled	Compact Automobile
2	Citroen xsara	Wheeled	Midsize Automobile
3	Small Bus	Wheeled	Small Bus
4	Renault Scenic	Wheeled	Sedan Automobile
5	Peugeot 206	Wheeled	Compact Automobile
6	Laguna II	Wheeled	Midsize Automobile
7	Van	Wheeled	Van
8	Large Bus	Wheeled	Large Bus
9	4x4 TOYOTA	Wheeled	Jeep Medium
10	civilian heavy truck	Wheeled	Large Box Truck
11	Midsize Bus	Wheeled	Small Bus
12	civilian heavy truck	Wheeled	Large Box Truck
13	VBL	Wheeled	Light Wheeled
14	VAB	Tracked	Medium Tracked
15	VAB	Tracked	Medium Tracked
16	Renault Scenic	Wheeled	Sedan Automobile
17	AMX-30	Tracked	Heavy Tracked
18	AMX-30	Tracked	Heavy Tracked
19	TWINGO	Wheeled	Compact Automobile
20	Military Van	Wheeled	Bus

Table I: Correspondence between target type and target classification in  $C_{MTI}$  and  $C_{2525C}$ .

2) *Sensor parameters*: The GMTI sensor is located at  $(-40km, 40km)$  in the TCF and is moving at  $5km$  in altitude. The sampling period is fixed at  $0.25Hz$  (i.e. 4 seconds), the azimuth standard deviation is  $0.001rad$ , the range standard deviation is  $10m$  and the range rate standard deviation is  $1m.s^{-1}$ . The detection probability is fixed to 0.9 with a Minimal Detectable Velocity (MDV) equal to  $1m.s^{-1}$ . The false alarm probability is equal to  $10^{-7}$ . The diagonal elements of confusion matrix of each class of  $C_{MTI}$  are 0.8, 0.7 and 0.9. Fig. 1 shows the cumulated MTI reports.

Every 3 minutes, the UAV changes its trajectory and cut-off the GMTI sensor during 40 seconds. The parameters of the UGS are simplified and characterized by a standard deviation equal to  $2m$ , a false alarm probability fixed to  $10^{-9}$ , and a sampling time fixed to  $1Hz$ . An illustration of the sensor area coverage is given on the figure 2. The UGS are always activated. Each detection is provided with the diagonal element of the confusion matrix  $C_{UGS}$  equal to 0.8. The other terms of the column are equi-distributed in the manner that the sum without the diagonal element is equal to 0.2.

### 3) Filter parameters of VS IMMC SB-MHT:

a) *VS IMMC parameters*: We use two constant velocity (CV) models: a CV model  $\mathcal{M}^{s,1}$  with plant noise parameters  $\sigma_d = 0.1m.s^{-2}$ ,  $\sigma_n = 0.1m.s^{-2}$  to track targets moving on the road, a CV model  $\mathcal{M}^{s,2}$  with parameters  $\sigma_n = 1m.s^{-2}$ ,  $\sigma_d = 0.5m.s^{-2}$  to palliate the target maneuvers, and a stop-model  $\mathcal{M}^{s,0}$  with parameters  $\sigma_d = 0.1m.s^{-2}$ ,  $\sigma_n = 0.05m.s^{-2}$  for  $\mathcal{M}^{s,0}$ . For the unconstrained motion models

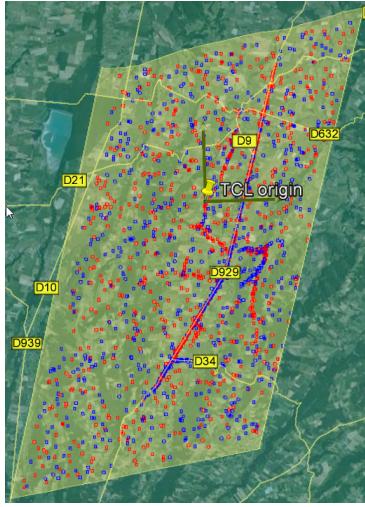


Figure 1: Cumulated MTI reports.



Figure 2: Cumulated reports of the UGS 7, 8, 9 and 10.

$\mathcal{M}^1$ ,  $\mathcal{M}^2$  and  $\mathcal{M}^0$ , we use the parameters  $\sigma = 0.1m.s^{-2}$ ,  $\sigma = 2m.s^{-2}$  and  $\sigma = 0.5m.s^{-2}$  respectively. The initial model probabilities is  $\mu(0) = [0.9 \ 0.1 \ 0]^T$  and the transition probability matrix

$$\pi = \begin{pmatrix} 0.9 & 0.095 & 0.005 \\ 0.3 & 0.65 & 0.15 \\ 0.1 & 0.6 & 0.3 \end{pmatrix} \quad (14)$$

b) *SB-MHT parameters:*

- For the track initialisation: each MTI report at every scan is considered as a new track. The initialised track is declared as “tentative track”. The MTI reports are validated with a classical gating procedure (a Chi2 test with a probability of gating equal to  $P_g = 0.95$ ).
- For the track termination step, a track is declared as “deleted track” if the probability of the stop-model is greater than 0.9, and if the track is not associated to measurements during 30seconds.
- For the track association step: a track is associated to a report if the MTI report is validated according the previous test (with a gating probability equal to  $P_g = 0.95$  for unconstrained tracks and  $P_g = 0.99$  for constrained tracks), and if the maximum velocity allowed for a ground target is less than  $35m.s^{-1}$ .
- In the hypothesis generation step of the Multiple Hypothesis Tracker (MHT): the threshold used to keep a track

Algo.	Target	1	2	3	4	5	6	7	8	9	10	
		TSP	PCC									
TSA alone		0.56	0	0.77	0	0.68	0	0.67	0	0.92	0	0.64
		0	0	0	0	0	0	0	0	0	0	0
TSA scoring		0.70	0.41	0.80	0.61	0.88	0.47	0.90	0.29	0.69	0.37	0.87
		0.62	0.45	0.61	0.44	0.61	0.45	0.31	0.29	0.79	0.43	0.81
TSA gating		0.74	0.45	0.89	0.62	0.83	0.35	0.84	0.31	0.93	0.58	0.86
		0.62	0.45	0.88	0.62	0.83	0.35	0.86	0.31	0.93	0.55	0.88
Algorithm	Target	11	12	13	14	15	16	17	18	19	20	
TSA alone		0.50	0.59	0.85	0.60	0.59	0.58	0.79	0.58	0.76	0.65	0.53
		0	0	0	0	0	0	0	0	0	0	0
TSA scoring		0.90	0.44	0.88	0.40	0.79	0.21	0.81	0.67	0.76	0.41	0.68
		0.70	0.44	0.87	0.40	0.78	0.21	0.82	0.67	0.77	0.41	0.65
TSA gating		0.93	0.62	0.87	0.42	0.86	0.40	0.82	0.61	0.96	0.55	0.68
		0.70	0.62	0.87	0.42	0.86	0.40	0.82	0.61	0.96	0.55	0.68
		0.62	0.62	0.87	0.42	0.86	0.40	0.82	0.61	0.96	0.55	0.68

Table II: MOP of the TSA algorithm without class information.

hypothesis is fixed to 0.01, and the track is maintained if its global track probability is greater than 0.1. The number of scans before the N-Scan pruning process is equal to 3.

- For the TSA algorithm, the smoothing process is realized every minute.

### C. Analysis of the results

To evaluate the impact of the classification information introduced in the TSA algorithm, we test the VS IMMC SB-MHT with three TSA versions: the first version is a TSA algorithm without classification information represented in red color, the second version is a TSA algorithm including the classification distance in the cost function (presented in III-C2) represented in blue color, and the third version is a TSA algorithm including the classification gating procedure (presented in III-C1) represented in yellow color. We recall the results are based on a 100 runs Monte-Carlo simulation.

The figure 3 represents the average MTL of each target. We observe that globally the introduction of classification information improves the performance of the track segment association algorithm because the length of tracks with respect to the length trajectory of the associated target is greater with the classification information (blue and yellow bars) than without (red bars).

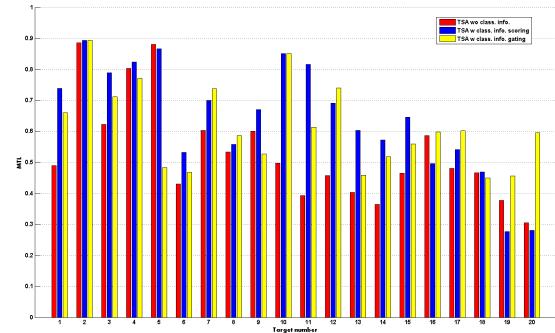


Figure 3: Mean Track Life (MTL) of each target.

We observe also a large difference of performances between the tracks associated to the targets 19 and 20. This difference

is due to the UGS illumination of the targets. In fact, the UGS provide a better classification information and the target 20 is illuminated by this sensor type during 15 seconds. According the UGS sampling time, the illumination duration is very sufficient to obtain a good and precise estimation of the class. The target 19 is never illuminated by the UGS sensor but it evolves at the proximity of the target 20. So, when the TSA algorithm is executed, the targets 19 and 20 are well discriminated in class information. A similar remark applies for the targets that have a correct class estimator due to a long illumination time by UGS sensors. However, the gating procedure doesn't take into account the sensor type uncertainty. We reveal also the limits of the gating procedure because the MTL of the TSA algorithm with the gating procedure is inferior to TSA algorithm with the scoring procedure. In addition, the table II shows the TSP and PCC of tracks associated to each target. Introduction of the classification information improves the association between tracks and measurements originated from the corresponding target. In fact, the TSP of the TSA algorithm without class information is inferior to the TSA algorithms with scoring and gating class information expected for the targets 16, 19 and 20. The TSP values for those targets are higher than TSP values with scoring technique. This phenomenon is due to bad classification results because the target type is not discriminant, or because the targets are not illuminated sufficiently by a UGS. The introduction of the class cost decreases the performances of the TSA algorithm if the class likelihood can't select the good class or discriminate the targets in the same cluster. So, if an ambiguity occurs on the track class, or if the tracks are not illuminated by UGS we recommend to not use the class information in the cost function, otherwise the TSA performances will degrade.

## V. CONCLUSIONS

We have presented a complete process to track multiple ground targets with airborne GMTI sensors. The first step is to track maneuvering targets in a complex ground environment with the only information in target location and range radial velocity. We have proposed, in the first part, to adapt the Interacting Multiple Model (IMM) algorithm by taking into account the road network and the Structured-Branching Multiple Hypothesis Tracker (SB-MHT) to obtain several association scenarii in road intersection. In this paper, we focus on the Track Segment Association (TSA) algorithm in order to associate the track segments obtained by after several fly paths. In fact, when the airborne GMTI sensors observes an area of interest, the Unnamed Aerial Vehicle (UAV) maneuvers after few minutes to obtain a new trajectory in order to conserve its capacity to observe its surveillance area. During the maneuvers and due to sensor constraint the GMTI sensor is shut down. The tracker is reinitialized to avoid track association errors. To improve the track continuity we have studied and developed a Track Segment Association (TSA) algorithm. However, due to the ground targets density and targets proximity, the Track Segment Association (TSA) algorithm is perfectible because the cost function is based only on kinematic information. That

is why it appears interesting to deploy Unattended Ground Sensor (UGS) sensors and to develop methods to deal with the uncertain and imprecise identification information of the observed target. We have proposed to modelize the classification information for each sensor type and introduce the classification information in the log-likelihood function in the Structured-Branching Multiple Hypothesis Tracker (SB-MHT) and also in the cost function of the Track Segment Association (TSA) algorithm. Our results show that the introduction of classification improves the track segment association and the track continuity between several fly paths whenever the target are well illuminated by Unattended Ground Sensor (UGS) when several targets evolve in close formation. Our future research works will consist to: 1) use other cost functions for the TSA algorithm by introducing the entropic distance and evaluate the performances obtained, 2) detect the conflicts between the segment association and let the operator to take a decision, 3) use the conflict detector and the UGS location to automatically differ the TSA algorithm execution, 4) study the problem of UGS deployment by taking into account the contextual information, and 5) work on the signal processing to improve the GMTI classification information.

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