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Extended and multiple target tracking: evaluation of an hybridization solution

Benjamin Pannetier, Jean Dezert
ONERA - The French Aerospace Lab
F-91761 Palaiseau, France
Email: benjamin.pannetier@onera.fr, jean.dezert@onera.fr

***Abstract*—In the usual multiple target tracking systems, detections associated to the targets are considered as issued from a single point source. This hypothesis is true if the size of the sensor resolution cells is bigger than the size of the target and if there is only one target in the resolution cell. Due to the increasing resolution capabilities of modern sensors this hypothesis is considered valid for the small targets (like ground vehicles). However, in real situations observed with modern GMTI (Ground Moving Target Indicator) sensors we cannot neglect the sensor resolution phenomenon: for littoral surveillance applications, the large targets (or extended targets) can generate more than one detection at a time; in addition for ground surveillance applications the distance between the individual targets can often be less than the size of the resolution cell which produces only one detection for a group of targets. On those considerations, we must adapt our individual targets' tracking algorithm with the extended and group tracking algorithms. In this paper, we test a very simple hybridization between a multiple target tracking algorithm and the recent bayesian approach for extended object tracking and group tracking represented by a random symmetrical positive definite matrix.**

Keywords: Group tracking, data association, Kalman filtering, GMTI sensor.

I. Introduction

Most of the trackers developed in ground stations are based on the assumption that the tracked objects are considered as point sources. It implies that the size of the target (or extension) is neglected with respect to the sensor resolution. Thanks to modern sensors, the resolution increases (i.e. the size of resolution cells diminishes) and the previous assumption is no longer valid; because of the short range applications, different scattering centers can be associated to the same targets. As an example, in maritime surveillance applications, super-tankers can generate several detections and a different number of detections at each scan. The relative scattering centers location can vary as well. On the other hand, the limited sensor resolution results in a fluctuating number of detections for a group where the targets evolve within a closed space. Therefore, the tracking of individual targets based on single measurement association is no an efficient solution since we cannot estimate the state of a target with a fluctuating number of validated detections. The new challenge is to deal with extended targets, groups of targets as well as individual targets as the same time maintaining the track continuity with an acceptable precision.

Several Bayesian solutions exist in the literature to address the data association problem with extended targets or convoys. In the paper [1], the authors propose a sensor resolution model and consider this as another association hypothesis which is naturally evaluated with a classical MHT (Multiple Hypotheses Tracker). Another approach has been presented recently in [2] to extend the resolution model, given for two partially unresolved targets, for the case of an arbitrary number of targets. In [3], the authors introduced a tracking algorithm that captures group tracks by using an IMM-JPBDAF (intercating multiple model with a joint probabilistic and believe data association filter) approach and a multiple validation gate model with road networks to distinguish group members based on movements, while the group JBPDAF approach used target IDs to capture group tracks. On the other hand, the PHD (Probability Hypothesis Density) filter is described in [4] as a method for tracking a large number of targets with an unknown number of targets moving in a closely space. This work has been adapted in [5] to track individual targets in a close formation by taking into account the road network information. Starting from these approaches, we have also proposed a solution [6] to hybridize the MHT with a GMCPHD (Gaussian Mixture Cardinalized Probability Hypothesis Density) filter in order to track the targets with an airborne GMTI (Ground Moving Target Indicator) sensor and to detect the convoys in civilian traffic. We must cite also the research works based on sequential Monte-Carlo methods, for example in [7], for tracking targets in close formation.

In this paper, we are interested by tracking both extended targets and individual targets based on GMTI sensor for ground battlefield and maritime surveillance. Airborne GMTI sensors are able to cover a large surveillance area for a few hours or more if several sensors are in activity. Several references exist for the MGT (Multiple Ground Target tracking) using contextual information with MTI reports for GMTI sensors [8], [9]. The main results are the improvement of the track precision and track continuity. Our algorithm [10] is built with several concepts inspired by 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 used to maintain the track on the road. A VS-IMM (Variable Structure Interacting Multiple Models) filter is set up with a set of constrained models to deal with the target's 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.

This paper is organized as follows: we start with a short presentation of the motion and measurement models. Then we describe quickly the Bayesian extended object formulation. A short description of our multiple target tracking algorithm and its basic hybridization with the group tracking algorithm is also presented. The paper is completed by illustrations obtained with simulated data for a ground scenario and real GMTI data for a maritime scenario.

II. Motion and measurement models

A. GIS description

The GIS (Geographical Information System) used in this work contains both the segmented transportation network (road and railway) 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*.

B. Constrained motion model

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

$$\mathbf{x}(k) = (x(k)\ \dot{x}(k)\ y(k)\ \dot{y}(k))' \tag{1}$$

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 modelled by a first-order differential system. The target state on the road segment s is defined by $\mathbf{x}_s(k)$ where $(x_s(k), y_s(k))$ and $(\dot{x}_s(k), \dot{y}_s(k))$ are respectively the target position and velocity on the road segment s

The event that the target is on road segment s is noted by $e_s(k) = \{\mathbf{x}(k) \in s\}$. 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:

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

where T is the sampling time, $\mathbf{F}_{s,i}$ is the state transition matrix associated with 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:

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

where $\mathbf{R}_{\theta_s}$ is the rotation matrix associated with the direction θ_s defined in the plane (O, X, Y) of the road segment s. The matrix $\mathbf{\Gamma}(T)$ is defined in [11]. If $s = 0$ the model is unconstrained.

To improve the modeling for targets moving on a road network, we have proposed in [10] 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 σ_n defined in (3) to take into account the error on the road segment location. After the state estimation by a Kalman filter, the state estimate is then projected according to the road constraint $e_s(k)$. This process is detailed in [10].

C. GMTI measurement model

According to the NATO GMTI format [12], 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:

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

where $(x(k), y(k))$ is the location of the MTI report in the local frame (O, X, Y). $\dot{\rho}(k)$ is the associated range radial velocity measurement. Because the range radial velocity is correlated to the MTI location components, the use of an extended Kalman filter (EKF) is not suitable. We use an alternative form of the EKF (called AEKF) presented in [13]. The AEKF measurement equation is given by:

$$\mathbf{z}(k) = \mathbf{H}_2(k) \cdot \mathbf{x}(k) + \mathbf{w}_2(k) \tag{5}$$

where $\mathbf{w}_2(k)$ is a zero-mean white Gaussian noise vector with a covariance $\mathbf{R}(k)$ (given in [10]) and $\mathbf{H}_2(k)$ is defined by:

$$\mathbf{H}_2(k) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & \frac{\partial \dot{\rho}(k)}{\partial \dot{\mathrm{x}}} & 0 & \frac{\partial \dot{\rho}(k)}{\partial \dot{\mathrm{y}}} \end{pmatrix} \tag{6}$$

Because Doppler ambiguities arise in cluster (generated by a convoy for example) we adapt the previous observation model with the observation matrix $\mathbf{H}_1(k)$ and the associated noise $\mathbf{w}_1(k)$ if the tracked target belongs to the target clusters.

$$\mathbf{H}_1(k) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \tag{7}$$

For notational convenience, the measurement sequence $\mathcal{Z}^{k,l}$ represents a possible set of measurements generated by the target up to time k (*i.e.*, there exists a subsequence n and a measurement j such that $\mathcal{Z}^{k,l} = \{\mathcal{Z}^{k-1,n}, ..., \mathbf{z}^j(k)\}$) 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. $\mathbf{z}^j(k)$ is the j^{th} measurement available at time k among m_k validated measurements around the target measurement prediction.

D. Modelling of the extended object measurement

A Bayesian approach proposed by Koch in [14] for tracking extended objects and group of targets considers both: the kinematic state of the centroid, and the extension $\mathbf{X}(k)$ which is a symmetric positive definite random matrix. According to the extension $\mathbf{X}(k)$ of dimension 2×2, we are able to obtain at the current time t_k the shape, size and orientation of the extended object. Let $\mathbf{Y}(k) = \{z^j(k), \forall j \in \{1, \ldots, n_k\}$ be the set of n_k measurements generated by the extended target at time t_k. The centroid measurement set $\bar{\mathbf{z}}(k)$ and the corresponding scattering matrix $\bar{\mathbf{Z}}(k)$ are given by:

$$\bar{\mathbf{z}}(k) = \frac{1}{n_k}\sum_{j=1}^{n_k}\mathbf{z}^j(k) \tag{8}$$

$$\bar{\mathbf{Z}}(k) = \sum_{j=1}^{n_k}(\bar{\mathbf{z}}(k) - \mathbf{z}^j(k))(\bar{\mathbf{z}}(k) - \mathbf{z}^j(k))' \tag{9}$$

The likelihood of the set $\mathbf{Y}(k)$ is obtained by taking into account the kinematic part, the extension, and the number of measurements:

$$p(\mathbf{Y}(k)|n_k, \mathbf{x}_k, \mathbf{X}_k) = \prod_{j=1}^{n_k}\mathcal{N}(\mathbf{z}^j(k), \mathbf{x}(k), \beta\mathbf{X}_k + \mathbf{R}(k)) \tag{10}$$

where $\mathcal{N}$ denotes the normal density and β is a scaling factor. $\mathbf{x}(k)$ is the kinematic centroid state given in (1). We see that the covariance measured extension depends on the predicted extension and the sensor error. In fact we choose immediately this way as described in [15], because:

- the extension could not be sufficient to compensate for the maneuver due to the agility of the tracked object;
- we have, in critical cases, extended targets generating only two measurements ($n_k \leq 2$) and if we respect the extended covariance (9) the measurement's error cannot be ignored.

So, in contrary to Koch's initial work [14], it appears that no conjugate prior can be found for the likelihood of $\mathbf{R}(k)$. Thus we will propose in the next part some approximations.

III. Bayesian extended object tracking

In this section, we present the predicted and updated equations of an extended target. The details of the hypotheses and approximations necessary to understand the approach are not detailed in this paper, the reader can refer to the papers [14], [15] for further details.

A. Kinematic update step

As described in [15], the updated estimate of the unconstrained centroid $\mathbf{x}_0(k)$ is calculated by using a standard Kalman filter. The equations are obtained by considering that the object extension $\mathbf{X}(k)$ is known and is replaced by its prediction $\mathbf{X}(k|k-1)$. Hence, we have

$$\hat{\mathbf{x}}_0(k|k) = \hat{\mathbf{x}}_0(k|k-1) + \mathbf{K}(k)(\bar{\mathbf{z}}(k) - \mathbf{H}_1(k)\mathbf{x}(k|k-1)) \tag{11}$$

$$\mathbf{P}_0(k|k) = \mathbf{P}_0(k|k-1) - \mathbf{K}(k)\mathbf{S}(k)\mathbf{K}'(k) \tag{12}$$

with the innovation covariance matrix

$$\mathbf{S}(k) = \mathbf{H}_1(k)\mathbf{P}(k|k-1)\mathbf{H}_1'(k) + \frac{\mathbf{Z}(k|k-1)}{n_k} \tag{13}$$

and with Kalman gain

$$\mathbf{K}(k) = \mathbf{P}(k|k-1)\mathbf{H}_1'(k)\mathbf{S}^{-1}(k) \tag{14}$$

The predicted covariance of a single measurement is given by

$$\mathbf{Z}(k|k-1) = \bar{\mathbf{Z}}(k) + \mathbf{R}(k) \tag{15}$$

B. Extension update step

To update the extension (the random matrix $\mathbf{X}$), we must use Cholesky factorization of the predicted extension in order to maintain the symmetric positive definite structure.

$$\mathbf{X}(k|k-1) = \mathbf{X}(k|k-1)^{1/2}(\mathbf{X}(k|k-1)^{1/2})' \tag{16}$$

By denoting $\mathbf{N}(k|k-1)$ the covariance associated with the centroid location, one introduces the fact that the extension depends on the predicted extension, the covariance $\hat{\mathbf{N}}(k|k-1)$, and the covariance $\hat{\mathbf{Z}}(k|k-1)$ in such a way that:

$$\mathbf{X}(k|k) = \frac{1}{\alpha_{k|k}}(\alpha_{k|k-1}\mathbf{X}(k|k-1) + \hat{\mathbf{N}}(k|k-1) + \hat{\mathbf{Z}}(k|k-1)) \tag{17}$$

with

$$\begin{aligned}\hat{\mathbf{N}}(k|k-1) = &\mathbf{X}(k|k-1)^{1/2}\mathbf{S}(k|k-1)^{-1/2}\mathbf{N}(k|k-1) \\ &(\mathbf{S}(k|k-1)^{-1/2})'(\mathbf{X}(k|k-1)^{1/2})'\end{aligned} \tag{18}$$

where

$$\begin{aligned}\mathbf{N}(k|k-1) = &(\bar{\mathbf{z}}(k) - \mathbf{H}_1(k)\hat{\mathbf{x}}_0(k|k-1)) \\ &(\bar{\mathbf{z}}(k) - \mathbf{H}_1(k)\hat{\mathbf{x}}_0(k|k-1))'\end{aligned} \tag{19}$$

and

$$\begin{aligned}\hat{\mathbf{Y}}(k|k-1) = &\mathbf{X}(k|k-1)^{1/2}\mathbf{Z}(k|k-1)^{-1/2}\bar{\mathbf{Z}}(k|k-1) \\ &(\mathbf{Z}(k|k-1)^{-1/2})'(\mathbf{X}(k|k-1)^{1/2})'\end{aligned} \tag{20}$$

The extension parameter α is assumed to follow the equation

$$\alpha_{k|k} = \alpha_{k|k-1} + n_k \tag{21}$$

From the innovation matrix $\mathbf{N}(k|k-1)$ it is possible to estimate an unknown measurement error covariance, even in the case of point-source targets or with extension of a completely unresolved group of targets (i.e. when $n_k \leq 1$).

C. Prediction step

It is assumed that the estimates for centroid kinematics and extension are independent. We recall that the centroid of the extension is unconstrained. The predicted equations of the centroid and covariance are respectively given for the motion model M_{ex} by:

$$\hat{\mathbf{x}}_0(k|k-1) = \mathbf{F}_{0,ex}(T)\hat{\mathbf{x}}_0(k-1|k-1) \tag{22}$$

$$\begin{aligned}\mathbf{P}_0(k|k-1) = \mathbf{F}_{0,ex}(T)\mathbf{P}_0(k-1|k-1)\mathbf{F}_{0,ex}(T)' \\ + \mathbf{Q}_{0,ex}(k)\end{aligned} \tag{23}$$

The motion model M_{ex} is specially adapted to modelling the extension dynamics. If we assume that the extension does not change over time, we can take

$$\mathbf{X}(k|k-1) = \mathbf{X}(k-1|k-1) \tag{24}$$

In [15] the authors remark that the variance of the extension is proportional to $1/(\alpha_{k|k} - 2)$ for very large $\alpha_{k|k}$ as well as when $\alpha_{k|k}$ becomes close and greater to 2. The authors assume an exponential increase of the variance according to

$$\alpha_{k|k-1} = 2 + \exp(-T/\tau)(\alpha_{k-1|k-1} - 2) \tag{25}$$

where τ denotes a time constant related to the agility in which the target could change its extension over time.

D. Data association

The goal of this work is to study Koch's Bayesian extended object tracking algorithm in a real context where the extended target evolves in a cluttered environment with multiple ground targets. The data association problem between the measurements arises naturally in such a difficult context. In a first approach, we propose to extend the NNSF (Nearest Neighbour Standard Filter) applied to measurement subset data association. In [16], a more robust approach using a PMHT (Probabilistic Multi-Hypothesis Tracking) and the estimation of the ellipsoidal shape and kinematics of each target is proposed.

The convoy is manually initialised by the selection of a measurement subset. Then, for all measurement validated by a statistical test (gating), we build all possible measurements subsets according to the maximal distance of resolution d_{res} (see figure 1). The set $\mathcal{Z}_v(k)$ of validated measurements at the current time is composed of p measurement subsets such that $\mathcal{Z}_v(k) = \{S_1 \cup S_2 \cup \ldots \cup S_p\}$. Starting from those subsets, we calculate the likelihood (26) of the extended object for each partition $(\{S_1\}, \{S_1 \cup S_2\}, \ldots, \{S_1 \cup S_2 \cup \ldots \cup S_p\})$. This likelihood and the terms $\mathrm{Var}[\Delta_{k|k-1}]$ and $\Delta_{k|k-1}$ are detailed in [15]. It is a combination between the statistical distance of the extended object state and the measurement centroid, and the statistical distance of the predicted extension and the measured extension. Afterwards, the most probable partition of subsets is chosen as the most representative measurement subsets of the extended object. The likelihood of S_i is mathematically given by [15] to be :

$$\begin{aligned}\Lambda_{S_i} \propto\ & \mathcal{N}(\bar{z}(k), \mathbf{H}_1(k)\hat{\mathbf{x}}_0(k|k-1), \mathbf{S}(k)) |2\pi \mathrm{Var}[\Delta_{k|k-1}]|^{-\frac{3}{4}} \\ & \times \mathrm{etr}(-\frac{1}{2}\Delta'_{k|k-1}\mathrm{Var}[\Delta_{k|k-1}]^{-1}\Delta_{k|k-1})\end{aligned} \tag{26}$$

In the case where the extension grows we assume that the convoy is separating. So for each measurement subset contained in the most probable partition, new extended objects are automatically created.

A flowchart of the extended target tracking algorithm (called ETT) is given in the upper part of figure 2.

IV. Multiple target tracking algorithm

In this section, we describe quickly our MGT tracker used for tracking multiple ground targets. It is based on an IMM (Interacting Multiple Model) for tracking maneuvering targets by taking into account the contextual information. This algorithm with a variable structure is well adapted to track several targets in cluttered environments.

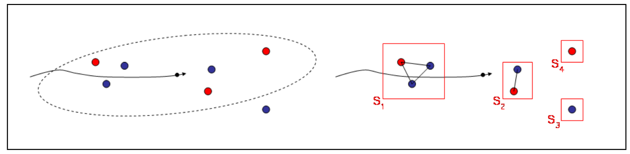

Figure 1. Validation and measurement subsets creation according to the resolution distance d_{res}.

A. VS IMM under Constraint

The IMM is an algorithm for combining state estimates arising from multiple models filter to get a better global state estimate when the target is in a maneuver mode. In section II-B, a constrained motion model i to a road segment s, noted M_s^i, 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 $r = 0$ corresponds to the stop model. When the target moves from one segment to the next, the set of dynamic models usually changes. In a conventional IMM estimator [8], the likelihood of a possible track l up to time k, denoted $\mathcal{T}^{k,l}$, is given by

$$\Lambda^l(k) = \sum_{i=0}^{r} p\{\mathbf{z}_j(k)|M_s^i(k), \mathcal{Z}^{k-1,n}\} \cdot \mu_i(k|k-1) \tag{27}$$

where $j = \{0, 1, \ldots, m_k\}$ is the index of the current measurement, $i = \{0, 1, \ldots, r\}$ is the index of the possible modes, $\mathcal{Z}^{k-1,n}$ is the subsequence of measurements associated with the track $\mathcal{T}^{k,l}$ and $\mu_i(k|k-1)$ is the predicted model probabilities [11]. The motion model likelihood contained in the sum function of (27) takes into account the perception of the target respecting the contextual information (terrain obscuration, Doppler blindness,...). Its expression is given in [17].

The steps of the IMM under road segment constraint are the same as for the classical IMM as described in [11].

Despite the road segment constraint, the predicted state could give a local estimate under another road segment than the segment associated with the motion model (a road turn for example). The change to another road segment causes the generation of a new constrained motion model. In [10], we have proposed an approach to activate the set of most probable road segments. We consider $r+1$ oriented graphs which depend on the road network topology. For each graph i, $i = \{0, 1, \ldots, r\}$, each node is a constrained motion model M_s^i. The nodes are connected to each other according to the road network configuration. In [10], the activation of the motion model at the current time depends on the position in the local predicted states $\hat{x}_{i,s}^l(k|k-1)$ of the track $\mathcal{T}^{k,l}$. Consequently, we obtain a finite set of $r+1$ motion models constrained to a road section (we recall that a road section is a set of connected road segments).

B. Multiple target tracking

For the MGT problem, we use the TO-MHT (Track Oriented Multiple Hypotheses Tracking) presented in [18]. When the new measurements set $\mathcal{Z}(k)$ 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 (Variable Structure - Interacting Multiple Model under Constraint) and the extrapolated and confirmed tracks are formed. More details can be found in chapter 16 of [18]. In order to address 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 $\mathcal{T}^{k,l}$ which can be expressed at current time k in the following recursive form:

$$L^l(k) = L^s(k-1) + \Delta L^l(k) \tag{28}$$

with

$$\Delta L^l(k) = \log\left(\frac{\Lambda^l(k)}{\lambda_{fa}}\right) \tag{29}$$

and

$$L(0) = \log\left(\frac{\lambda_{fa}}{\lambda_{fa} + \lambda_{nt}}\right) \tag{30}$$

where λ_{fa} and λ_{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 (27). The LLR of each track is used to evaluate all compatible scenarios generated in each cluster. The tracks are pruned according to the association scenario probability and the global track probability. Surviving constraint tracks are tested to select (if SPRT - Sequential Probability Ratio Test - is satisfied) the most probable constrained tracks. Surviving tracks are updated and presented to the operator. A flowchart of the MGT is represented in the bottom part of figure 2.

C. Basic hybridization solution

In order to take into account both the extended target tracking algorithm and the multiple target tracking algorithm, we propose a basic approach based on the assumption that an individual target is not detected if it is in same resolution cell as the extended object. So each measurement that belongs to the most probable partition (validated by the track of the extended object) is considered as the detection of the extended object. Then, no individual track is initialized with those measurements and the existing individual tracks score are modified. In fact, for each track present in the same resolution cell as the extended track, we modify its perception probability and therefore its track score (28). The modification of the track score brings a modification of the track association scenario. The interactions between the ETT and MGT algorithms are represented by the red arrows in figure 2.

V. Illustrations on simulated and real data

We test our simple hybridization approach with simulated GMTI data (for the ground scenario) and real GMTI data (for the maritime scenario).

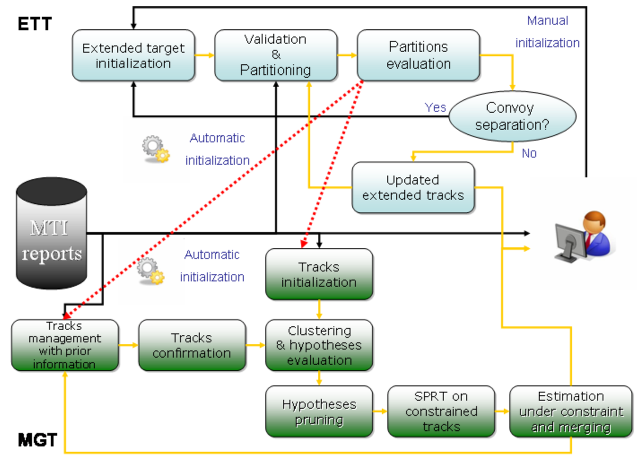

Figure 2. Design of an hybridization approach.

A. Illustration on simulated data

In the scenario, we try to track a convoy in civilian traffic. For this, we consider that the convoy is composed of 9 targets (1 to 9). It is moving on the road network and maneuvre at each intersection (deceleration, turn and acceleration). The distance between each vehicle of the convoy varies and can be up to 150 m. At the end of the scenario, the convoy separates into sub-convoys which leave the road network to stop on several strategic positions (figure 3). The rest of the 20 individual vehicles are moving on the road network (acceleration, deceleration and stop). The GMTI sensor is moving at 10 km away from the centre of the area (figure 3). The sampling interval is $T = 5s$, with $10m$, $0.001rad$ and $1m \cdot s^{-1}$ range, cross-range and range-rate measurement standard deviation respectively. The false alarm rate is high 10^{-6} false alarm per unit of volume. The detection probability is fixed at 0.9 expected for the targets in the convoy where it is fixed at 0.7 to simulate the sensor resolution. The occlusion masks due to terrain elevation or Doppler obscuration (the minimal detectable velocity is $1m \cdot s^{-1}$) are taken into account.

The VS-IMMC TO-MHT has good performances for tracking all individual manoeuvring targets on the road network (figure 4)and is a well known result with this algorithm. The convoy, called “Group : 2”, is manually initialized and the hybrid algorithm tracks the convoy with a variable number of detections (figure 5). The ellipse in blue represents the extension of the object. Despite the complex scenario in which one ground target is passing the convoy with another target in the proximity of the end of the convoy and the convoy is manoeuvring at each intersection (deceleration, acceleration), the algorithm chooses the correct partition of measurements. Track 82 at time $t = 291s$ is approaching the convoy (figure 6). According to the modification of the perceivability probability of the track 82 and the good selection of measurement partition for the convoy, the continuity of track 82 is maintained (figure

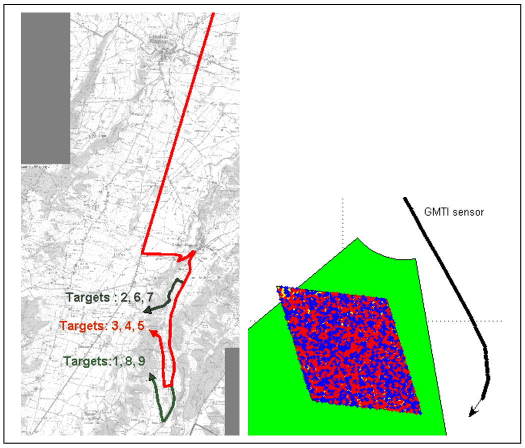

Figure 3. Trajectory of the convoy (left) and sensor trajectory and surveillance area with cumulated MTI reports (right).

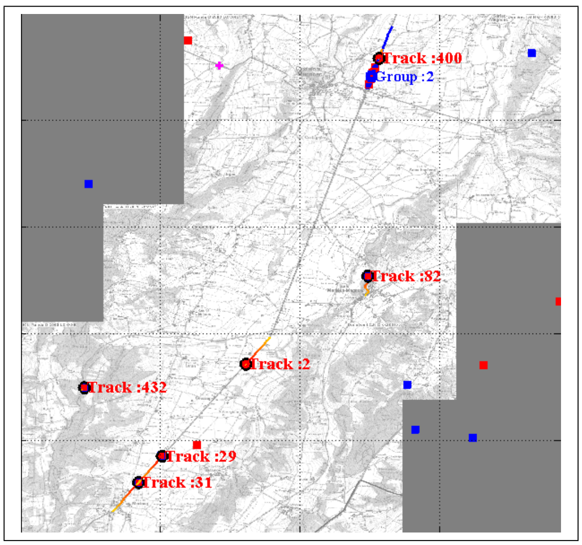

Figure 4. Tactical situation at time $t = 156s$.

7). The same observation can be made for tracks 29 and 31 which pass the convoy. The group is well tracked despite of the big group maneuvre in the map center (figure 8). However we observe a weakness in the algorithm when the convoy is separating. The separation is quick and the main sub-convoy, has the same direction and extension direction than previously. So the most probable partition is the measurement subset of the main sub-convoy and 2 individual tracks (because of ground target proximity) are initialized for the 3 vehicles of the other sub-convoy.

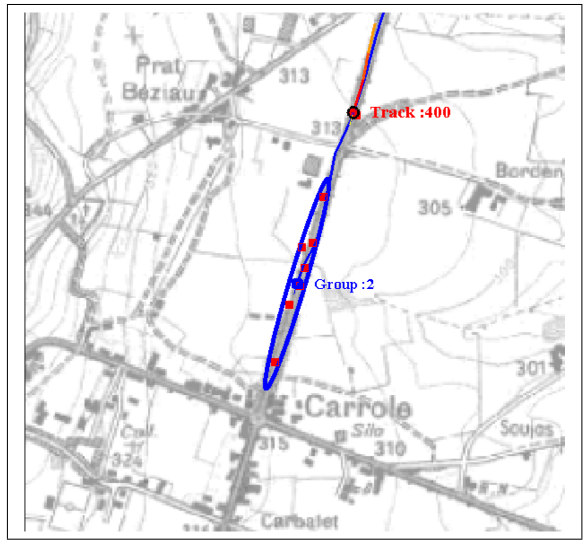

Figure 5. Convoy initialization and tracking at time $t = 156s$.

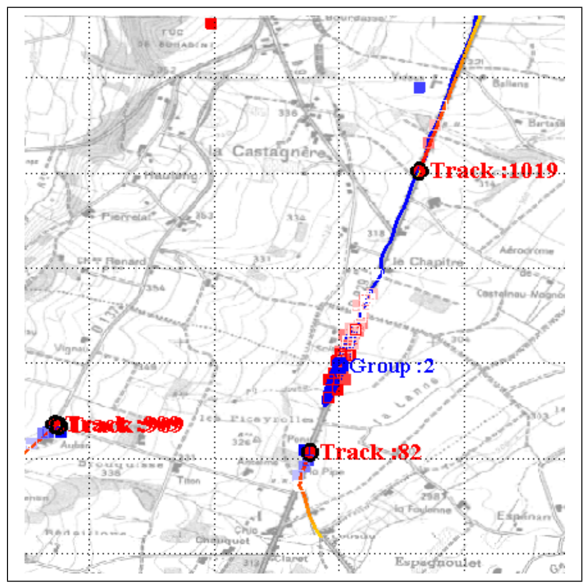

Figure 6. Tactical situation at time $t = 291s$.

B. Validation on real data

In this section, we test the previous approach on real data obtained with an operational airborne GMTI sensor. The GMTI sensor is moving away from its area of interest and observes for two minutes the tactical situation assessment (Figure 9). Several remarks must be made on the observed MTI reports as shown in Figure 10:

1) the chosen scenario is not convenient for a GMTI sensor because the area on the upper part of the map is an industrial area which causes a high number of false alarms, building occlusion result in many missed detection.
2) the operational need is also to analyse the maritime threat assessment. So we can see, according the cumu-

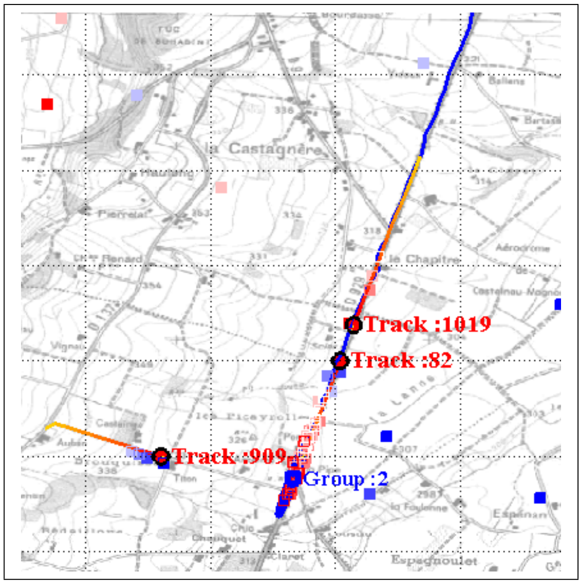

Figure 7. Tactical situation at time $t = 331s$.

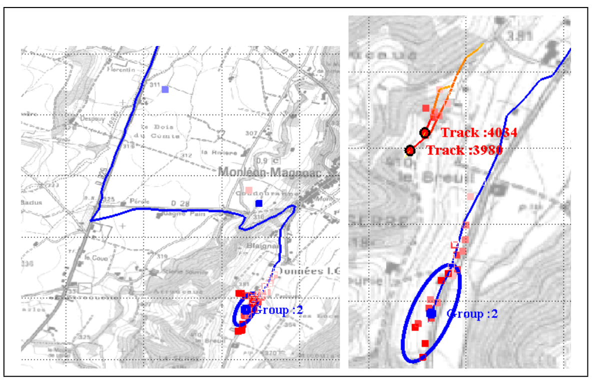

Figure 8. Tactical situation at time $t = 751s$ (left part) and at time $t = 796s$ (right part).

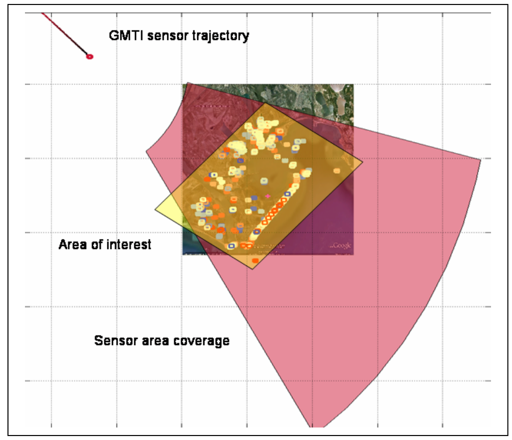

Figure 9. Sensor trajectory and surveillance area.

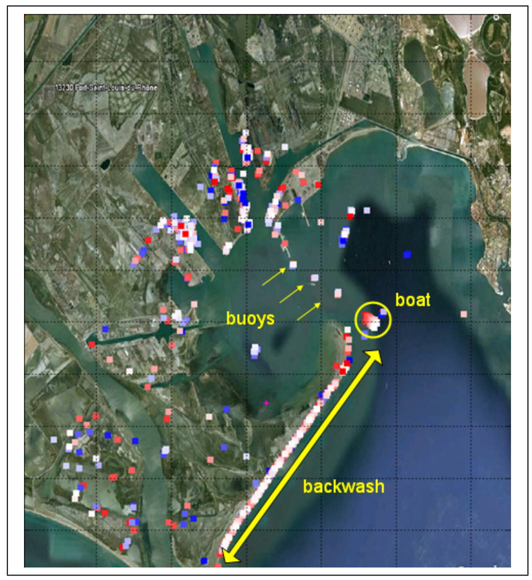

Figure 10. Cumulated MTI reports.

lated MTI reports, a boat arriving in the harbour. This boat is an extended target because we detect, regularly, at most two MTI reports for this target.

3) we observe a large number of false alarms on the coast due to the backwash. We can also see that the movement of buoys generates detections in the harbour.

In this scenario, we keep the parameters used in the previous section. We have initialized manually the track associated with the boat entering the harbour and a track of a group of targets issued from the localized set of false alarms generated by the backwash. We obtain the following results: the boat is well-tracked in a critical case where the number of associated MTI reports does not exceed 2 at each scan (see Figure 11). The ellipse in white represents the extension of the object. When two MTI reports are associated with the extended target, we take into account the measurement matrix $\mathbf{R}(k)$ for updating the extension matrix $\mathbf{X}(k|k)$. If there is only one MTI report associated to the target, we use the mean of the innovation matrix $\mathbf{N}(k|k-1)$ described in III-A. On figure 11, we compare our results for tracking this extended target based on our hybrid approach with respect to the MTT approach. The tracking of a small extended target (*small* with respect to the sensor resolution cell) is not satisfying because the MTT algorithm tries to obtain the most probable sequence of measurements with the assumption that the target generates at most one measurement. We recall that the backwash is considered as a group of targets. The size of the false alarm area generated by the backwash is well-estimated as shown in figure 12. We observe also a weak variation of the movement of this group. Comparing with the MTT approach (figure 13), we observe that the extension used in this paper destroys all new tracks initialized by the MTT. The buoys are tracked as

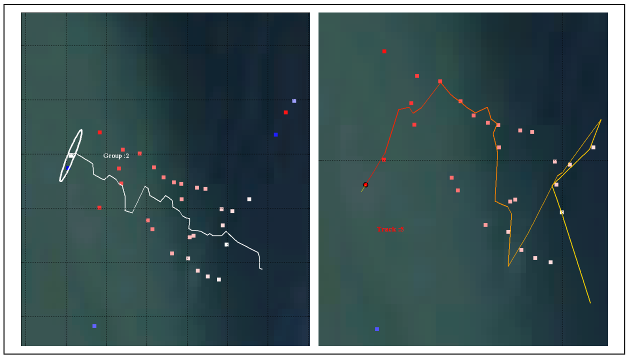

Figure 11. Comparison of the boat tracking with the extension approach (left part) and the MTT approach (right part).

a static object with the usual MTT.

VI. CONCLUSION

This paper evaluates the feasibility of an hybridization solution between an usual MTT and the extended target tracking approach proposed initially by Koch. The results obtained on simulated data and real data show that the proposed algorithm could be a satisfactory approach to track extended targets (as well as localized clusters of false alarms) and individual targets and to avoid the excessive track generation in a cluster. However, more investigations are required to develop a more robust approach to evaluate and maintain several association scenarios for the extended object. In addition a better hybridization solution to update the individual tracks in a convoy could be proposed based on the work in [2]. In future work, we will evaluate the performances of our approach with measures of performance based on Monte-Carlo simulations and real ground data for the technical validation. In addition, a more ambitious project should consider additional information, such as HRRR (High Range Radar Resolution) or video attributes (correlated with MTI reports), in order to refine the hypotheses evaluation and correct the current situation.

Figure 12. Track of the backwash with the extension approach.

Figure 13. Track of the backwash with the MTT.

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