Convoy detection processing by using the hybrid algorithm (GMCPHD/VS–IMMC–MHT) and dynamic bayesian networks

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Abstract – *Convoys are military objects of interests in certain applications like battlefield surveillance, that is why it is important to detect and track them in the midst of civilian traffic as part of the situation assessment. Our purpose is a process in two steps. The first is an original tracking algorithm appropriate for Ground Moving Target Indicator (GMTI) data based on the hybridization of a labeled GMCPHD (Gaussian Mixture Cardinalized Probability Hypothesis Density) and the VS-IMMC-MHT (Variable Structure - Interacting Multiple Model with Constraints - Multiple Hypothesis Tracking): one is very efficient to estimate the number of targets and the other for the state estimates. Then, by using algorithm outputs and other data like video or SAR if they are available, vehicle aggregates are detected and their characteristic are introduced into a Dynamic Bayesian Network which processes the probability for an aggregate to be a convoy. Finally, the number of targets belonging to the convoy is evaluated. This process is tested on a complex simulated scenario, our tracking algorithm is compared to classical ones and used to compute the probability to have convoys.*

Keywords: Multitarget Tracking, GMTI, Convoy detection, GMCPHD, VS-IMMC-MHT, dynamic bayesian network

1 Introduction

In the battlefield surveillance domain, ground target tracking is a first challenging task to assess the situation [1]. Data used for tracking comes from Ground Moving Target Indicator (GMTI) sensors which detect moving targets only by measuring their Doppler frequency. The goal is to have a real ground picture: the number of targets, their dynamics, their relationship... in order to discover military events of interests. In this article, we focus on convoy detection.

Some studies on convoy detection based on GMTI signatures already exist [2, 3, 4], but our purpose is convoy detection by using target tracks. In this context, two steps are proposed : (1) process a hardy multi-target tracking algorithm in order to detect vehicle aggregates with precision in term of cardinality and state estimation, (2) check if the detected aggregates are convoys or not, by introducing other data types (Synthetic Aperture Radar (SAR), video,. . .) and by using a data fusion method. This purpose is summarized in Figure 1.

Very efficient tracking algorithms exist today and they have to be adaptated to the very complex ground environment. First, the traffic density is very high and generates a large number of measurements. This characteristic eliminates, in our application, Monte-Carlo techniques [5, 6, 7]. Moreover measurements are noisy and can contain many false alarms. Also vehicles on the ground are usually quite manoeuvrable over short periods of time according to the sensor scanning time T. Finally, vehicles are detected by the sensor with probability P_D and according to the sensor resolution. In other words, when vehicles are very close together, one measurement can be missing generating the *spawned targets*. This phenomena added to the problem of data association make the classical algorithms, like SD-assignment [8] or MHT [9] less efficient to track convoys.

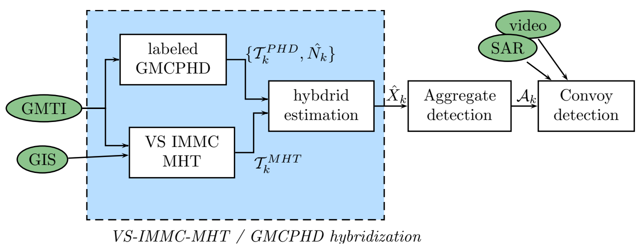


Figure 1: Convoy detection process

However, recently, a new filter class appears, opening a lot of opportunities. The Probability Hypothesis Density (PHD) Filter was developped by Ronald Mahler by using his work on FInite Set STatistics [10] (FISST) and Random Sets. This filter leads to a new class of algorithms [11] based on the study of joint density probability of the Random Finite Sets (RFS) describing target dynamics and measurements. The first order moment of this RFS, called the intensity function, is the function whose the integral in any region on state space is the expected number of targets in that region. Points with highest density are then expected targets. To improve the number of targets estimation, Mahler proposes a generalization of the PHD called the CPHD [12], which jointly propagates the intensity function and the entire probability distribution of the number of targets. Under Gaussian assumptions on target dynamics and birth process, Vo proposes a CPHD recursion called the Gaussian Mixture Cardinalized PHD [13, 14] (GMCPHD). This approach gives very encouraging results, in particular for the estimation of the number of targets and seems adaptated to convoy tracking.

Nevertheless, as we will show in Table 7, with manoeuvring targets, the GMCPHD has problems with velocity estimation. From this point of view, the GMCPHD and the IMM-MHT can be seen as complementary algorithms: the first for the estimation of the number of targets and for an approximate position estimation, and the latter can be used to specify state estimation. The proposed hybridization is described in Figure 1. In this approach, we use a special version of the MHT: the VS-IMMC-MHT [15] (Variable Structure - Interacting Multiple Model with Constraints - Multiple Hypothesis Tracking) which uses road segment position from Geographical Information System (GIS) to improve the state estimation. Other authors proposed to combine a PHD filter with other filters [16]. By using outputs of our algorithms, we are able to detect aggregates with precision. The second step is to define if they are convoys or not.

Before discuss our approach, we define a convoy as a group of vehicles, evolving on the road, having the same dynamics and generally composed of more than two military vehicles. The distance between two vehicles depends on the environment, but most of the time it is over 100m. Giving these restrictions, we want to produce a general convoy model, able to discriminate convoys from a group of vehicles. We use the Dynamic Bayesian Network (DBN) formalism which seems adaptated to this problematic [17].

The paper is organized as follows: Section 2 is a description of the existing GMCPHD filter, Section 3 details how we use this algorithm in a hybrid version, Section 4 explains how DBNs are used for convoy detection. Finally Section 5 describes our simulation and compares results before we conclude in Section 6.

2 Background on the GMCPHD filter

2.1 The PHD filter

A Random Finite Set (RFS) is a finite-set valued random variable which can be generally characterized by a discrete probability distribution and a family of joint probability densities representing the existence probabilities of the target set. Considering the RFS of survival targets $S_{k|k-1}$ between iterations $k-1$ and k, the RFS of spawned targets $B_{k|k-1}$ and the RFS of spontaneous birth targets σ_k, the global RFS characterizing the multitarget set can be written as:

$$X_k = \left[\bigcup_{\zeta \in X_{k-1}} S_{k|k-1}(\zeta) \right] \cup \left[\bigcup_{\zeta \in X_{k-1}} B_{k|k-1}(\zeta) \right] \cup \sigma_k \tag{1}$$

In the same manner, the multitarget set observation Z_k can be seen as a global RFS composed by the RFS of measurements originally from the targets X_k and by the RFS of false alarms K_k:

$$Z_k = \left[\bigcup_{x \in X_k} \Theta_k(x) \right] \cup K_k \tag{2}$$

The PHD traditionally evolves in two steps: prediction and estimation that propagate the multitarget posterior density of the target RFS also called the intensity function v. The prediction state is based on the *a posteriori* intensity function v_{k-1} at the previous time $k-1$, the probability P_S for a target to survive between times $k-1$ and k, the transition function $f_{k|k-1}(.|\zeta)$ given the previous state ζ and the intensity of target birth γ_k.

$$v_{k|k-1}(x) = \left(\int P_s(\zeta).f_{k|k-1}(x|\zeta).v_{k-1}(\zeta)d\zeta \right) + \gamma_k(x) \tag{3}$$

Knowing the measurement random set Z_k, it is possible to update the intensity function as follows:

$$v_k(x) = (1-P_D)v_{k|k-1}(x) + \sum_{z \in Z_k} \frac{P_D.g(z|x)v_{k|k-1}(x)}{\kappa_k(z) + \int P_D.g(z|\zeta)v_{k|k-1}(\zeta)d\zeta} \tag{4}$$

where $g(z|x)$ is the likelihood of a measurement z knowing the state of a target x, κ_k is the clutter intensity which is modeled by a Poisson process.

2.2 The GMCPHD filter

The GMCPHD, proposed by Vo [13], combines a Gaussian mixture model for the intensity function with the Cardinalized generalization of the PHD filter. That means that the posterior target intensity can be written as a Gaussian mixture:

$$v_k(x) = \sum_{i=1}^{J_k} w_{k,i} \mathcal{N}(x; m_{k,i}, P_{k,i}) \tag{5}$$

where $w_{k,i}$, $m_{k,i}$ and $P_{k,i}$ are the weight, mean and covariance of the current Gaussians and J_k is their number.

Moreover, added to the operations (3) and (4), the probability to have n targets is predicted and estimated in the same way, as, $\forall n \in \mathbb{N}^\star$,

$$p_{k|k-1}(n) = \sum_{j=0}^{n} p_\Gamma(n-j)\times \sum_{l=j}^{\infty} C_j^l \frac{\langle P_s, v_{k-1}\rangle^j \langle 1-P_s, v_{k-1}\rangle^{l-j}}{\langle 1, v_{k-1}\rangle^l} p_{k-1}(l) \quad (6)$$

with $p_\Gamma(n-j)$ the birth probability of $(n-j)$ target and C_j^l the binomial coefficient with parameters (n,j). Following the Bayes theorem, the estimated cardinality distribution $p_{k|k}$ can be written as a likelihood ratio:

$$p_{k|k}(n) = \frac{\mathcal{L}(Z_k|n)}{\mathcal{L}(Z_k)} p_{k|k-1}(n) \quad (7)$$

where $\mathcal{L}(Z_k|n)$ is the likelihood of the measurements set Z_k knowing that there are n targets and $\mathcal{L}(Z_k)$ is a normalizing constant.

3 The VS-IMMC-MHT / GM-CPHD hybridization

3.1 The labeled GMCPHD

In the classical version of the GMCPHD, the problem of track labeling is not considered. Yet, this step is quite important for complex multitarget scenario. Clark and Panta [18, 19] proposes method but not adaptated to Gaussian mixture and to a large number of targets. Also, we propose, as an alternative, using the track score for the track initialization and in addition to the statistical distance between peak and predicted track to take into account the global weight for the peak to track association.

Let $\mathcal{G}$ be the Gaussian set given by the GMCPHD written:

$$\mathcal{G}_k = \{w_{k,i}, m_{k,i}, P_{k,i}\}_{i\in\{1,\dots,N_k^{\mathcal{G}}\}} = \left\{\mathcal{G}_{k,1}, \dots, \mathcal{G}_{k,N_k^{\mathcal{G}}}\right\} \quad (8)$$

where $N_k^{\mathcal{G}}$ is the number of Gaussians ($N_k^{\mathcal{G}} > \hat{N}_k$) at time k. A track can be defined as a sequence of estimated states describing the dynamics of one target. The goal of tracking is to offer a list of tracks corresponding to all of the targets. That is why this labeling step is necessary in order to provide a track set chosen amongst the Gaussian set $\mathcal{G}_k$. A track $\mathcal{T}_{k,i}$ is defined at time k by a state $\hat{x}_{k,i}$, a covariance $P_{k,i}$ and a score $s_{k,i}$:

$$\mathcal{T}_{k,i} = \{\hat{x}_{k,i}, P_{k,i}, s_{k,i}\}_{i\in\{1,\dots,\hat{N}_k\}} \quad (9)$$

The track set is finally written:

$$\mathcal{T}_k = \left\{\mathcal{T}_{k,1}, \dots, \mathcal{T}_{k,\hat{N}_k}\right\} \quad (10)$$

with $\hat{N}_k$ the estimation of the number of targets given by the GMCPHD.

We define a set of association matrices A_k of size $\hat{N}_k \times N_k^{\mathcal{G}}$ to associate the Gaussian set to the tracks. $\forall(m,n) \leq (\hat{N}_k, N_k^{\mathcal{G}})$, an association matrix $A_{k,i}$ is written as:

$$A_{k,i}(m,n) = \begin{cases} 1 & \text{if } \mathcal{G}_{k,n} \text{ can be associated to } \mathcal{T}_{k|k-1,m} \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

with $\mathcal{T}_{k|k-1,m}$ the predicted track m and knowing that a track is associated at most to one Gaussian. A Gaussian peak n is said associable to a track m if it satisfies a gating test around the predicted position of the track.

We define a weight matrix W_k of size $\hat{N}_k \times N_k^{\mathcal{G}}$ defined as follows, $\forall(m,n) \leq (\hat{N}_k, N_k^{\mathcal{G}})$:

$$W_k(m,n) = \begin{cases} w_{k,n} & \text{if } \mathcal{G}_{k,n} \text{ can be ass. to } \mathcal{T}_{k|k-1,m} \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

If $\hat{N}_k > \hat{N}_{k-1}$, one or more new tracks must be initialized and each Gaussian is a potential new track. In matrix W_k, $\forall m \in \{1,\dots,N_k^{\mathcal{G}}\}, \forall l \in \{\hat{N}_{k-1}+1,\dots,\hat{N}_k\}$,

$$W_k(m,l) = w_{k,l} \quad (13)$$

In the same way, if $\hat{N}_k < \hat{N}_{k-1}$, some tracks must be deleted. Weakly weighted tracks cannot be deleted because of the detection probability, which is why tracks with the lowest score are deleted.

Finally, we compute the set of global weight of an association:

$$W_k^g = \sum_{m=1}^{\hat{N}_k} \sum_{n=1}^{N_k^{\mathcal{G}}} A_k(m,n).W_k(m,n) \quad (14)$$

And the association matrices which maximize the weight are written as:

$$A_k^\star = \underset{A_k}{\operatorname{argmax}}\, W_k^g \quad (15)$$

Similarly, the cost matrix C_k of size $\hat{N}_k \times N_k^{\mathcal{G}}$ is written as, $\forall(m,n) \setminus (\hat{N}_k, N_k^{\mathcal{G}})$,

$$C_k(m,n) = \begin{cases} c(m,n) & \text{if } \mathcal{G}_{k,n} \text{ can be ass. to } \mathcal{T}_{k|k-1,m} \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

with $c(m,n)$ the cost of the association of the predicted track m with the Gaussian n written as the negative Napierian logarithm of the likelihood ratio, $\forall(m,n) \in (\hat{N}_k, N_k^{\mathcal{G}})$,

$$c(m,n) = -\ln\left(\frac{P_D.\Lambda(\mathcal{G}_{k,n}|\mathcal{T}_{k|k-1,m})}{\beta_{FA}}\right) \quad (17)$$

with β_{FA} the spatial false alarm density and $\Lambda(\mathcal{G}_{k,n})$ the likelihood of the Gaussian n knowing the predicted position of the track m, calculated as a Gaussian density.

Finally, the global association cost is computed as:

$$C_k^g = \sum_{m=1}^{\hat{N}_k} \sum_{n=1}^{N_k^{\mathcal{G}}} A_k^\star(m,n).C_k(m,n) \tag{18}$$

And the best association $A^{\star\star}$ is computed like the minimal cost matrix:

$$A_k^{\star\star} = \underset{A_k^\star}{\operatorname{argmin}}\, C_k^g \tag{19}$$

3.2 The hybridization

The GMCPHD produces a reliably estimation of the number of targets, whereas the VS-IMMC-MHT is effective to give a good estimation of the target state by introducing road coordinates when targets are not close together, because of the problem for MHT algorithm to evaluate the number of targets. We propose therefore to use these two algorithms as complementary filters: the first estimates the number of targets and the approximate target position and the second increases the accuracy for the target state estimation. The two algorithms are running simultaneously. Then, a gating process is applied around the target position given by the GMCPHD, to select MHT tracks. Finally, MHT tracks which have the highest score are selected. If a PHD track is not associated to any MHT track, the GMCPHD track is kept.

This approach combines the advantages of the different algorithms without increasing the processing time:

- Robust to target maneuvers by using IMM
- Good precision for state estimation by using road coordinates
- Good estimation of the number of targets
- No performance decrease when targets are close together

Different algorithms performances are compared in Section 5 in a complex scenario. But before let us define the proposed convoy detection method.

4 Description of a convoy

4.1 Some definitions

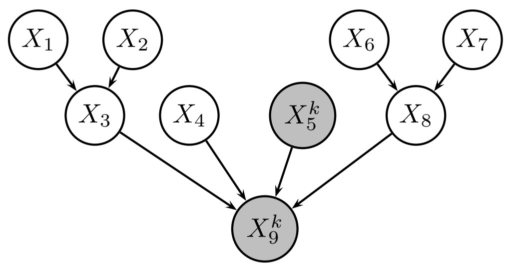
A convoy is defined as a vehicle set evolving approximatively with the same dynamics during a long time. These vehicles are moving on the road under a limited velocity (<20m/s). They must stay at sight with almost constant distances between them (mostly 100m). Criteria describing a convoy are manifold and of different natures, moreover variables are discrete. That is why, bayesian networks represent an interesting formalism in our application as in similar thematics [20, 21, 17, 22].

A Bayesian Network (BN) is a graphical model for representing dependency relation between a set of random variables. Graphically, each variable is represented by a node and an arc, from a node X_i to a node X_j, means that X_i "causes" X_j, $\forall (i,j) \in \{1,\dots,N\}^2$. Finally, the joint probability is computed as:

$$P(X_1,\dots,X_N) = \prod_{i=1}^{N} P(X_i|Pa(X_i)) \tag{20}$$

where $Pa(X_i)$ are parent nodes of X_i.

The Dynamic Bayesian Networks (DBN) are an extension of BN, which take into account the time evolution of random variables. The convoy detection approach is bounded to the time evolution as shown in Figure 2. For example, variable X_5 is time depending, because the type information can come from heterogeneous sources (SAR, video, ...) with different scanning times, and variable X_9 is confirmed with time.



X_1: Velocity < 80km/h $\{yes, no\}$
X_2: Constant velocity $\{yes, no\}$
X_3: Velocity criteria $\{yes, no\}$
X_4: On the road $\{yes, no\}$
X_5^k: Military vehicles $\{yes, no\}$
X_6: Constant distance between vehicles $\{yes, no\}$
X_7: Constant convoy length over time $\{yes, no\}$
X_8: Distance criteria $\{yes, no\}$
X_9^k: Convoy $\{yes, no\}$

Figure 2: *Dynamic bayesian network for convoy detection. The gray nodes represent states depending on their previous state.*

4.2 Conditional Probability Distribution evaluation

If independency relation between variables can be very intuitively established, one difficulty with DBN is to evaluate the Conditional Probability Distribution (CPD) of each node given its parents. If data sets are available, these prior probabilities can be learned, but in our case, they are evaluated by experts, according to a certain weight to each parameters. For example, if a convoy is detected at time $k-1$, the probability to detect one at time k is high and the prior probability given to this parameter must be "relatively" high. As

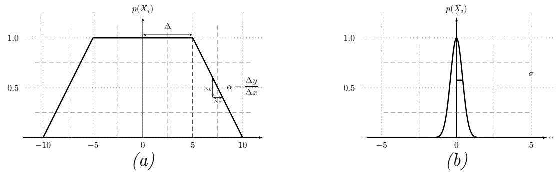


Figure 3: *Examples of transformation*

described in [23], we propose heuristic rules to represent relationships between variables :

$$5 \times X_9^{k-1} + 1.5 \times X_3 + X_4 + X_5 + 1.5 \times X_8 = X_9^k \quad (21)$$

As said, this rule means that the probability to have a convoy at time k is half-depending on the fact to have a convoy at time $k-1$, and that we care more criteria on distance and velocity than criteria "on road" or "vehicle type".

4.3 Probability transformation

Another difficulty is the transformation of numerical data (number of targets, target position and velocity, road position) into a probability. This step is done by using probability distributions or fuzzy transformations like linear transformation (*cf.* Fig 3 (a)) or Gaussian transformation (*cf.* Fig 3 (b)):

- $p(X_1)$ is computed according to a Rayleigh distribution.
- $p(X_2)$ is following a fuzzy linear transform using the difference between velocity mean at time k and at previous times.
- $p(X_4)$ is computed according to a χ^2 distribution.
- $p(X_6)$ is computed using a fuzzy gaussian transformation by studding the distribution of distances between vehicles of the aggregate.
- $p(X_7)$ is computed using a fuzzy linear transformation by examining the variation of the convoy length over time

4.4 Inference

The next step consists to propagate the information through the network. It is called the inference. Many algorithms exist like JLO [24] from the names of its authors or Expectation-Maximization (EM) algorithm. We choose arbitrarily the JLO algorithm adaptated to discrete nodes and available in the Murphy's Bayes net toolbox [25].

4.5 Targets number estimation

Computing the probability $p(X_9)$ for an aggregate to be a convoy is a first step (*cf.* Figure 9), but it is possible to take into account the average number of targets belonging to the convoy. First, we know the number of targets in the aggregate and moving in the same direction. If for instance at time k, we detect $N(k) = 5$, while there was 4 until there, we have to propagate the information and to compute simultaneously the probability to have a convoy with 5 vehicles, and a convoy with the 4 best located target tracks. Mathematically, it means we compute $p(X_9, N^{\mathcal{C}})$, with $N^{\mathcal{C}}$ the set of different values taken by N^k, where $N^k = \{N(1), \ldots, N(k)\}$ is the sequence of mean number of targets in the aggregate, moving in the same direction.

However, as shown in Figure 11, it is not easy to discriminate certain cases, here the cases $N^{\mathcal{C}} = 5$ and $N^{\mathcal{C}} = 6$ (the reality is $N^{\mathcal{C}} = 6$). If, at the beginning of the simulation, we detect $N^{\mathcal{C}} = 5$, we must continue to compute the probability to have a 5 target convoy, because we are possibly in the case of an overtaking, but it is not realistic, to support this assumption against the 6 target convoy if the sequence of measurement never gives again $N(k) = 5$. That is why we introduce the local estimated cardinality of the Gaussian mixture on the aggregate surface, computed as $N_k^{\mathcal{C}} = \sum_{i=1}^{N_{max}} i.p_{k|k}^{\mathcal{C}}(i)$ knowing the sequence of average number of targets.

Finally, the probability becomes:

$$p(X_9^k, N^{\mathcal{C}}, \hat{N}_k^{\mathcal{C}} | N^k) = p(X_9, N^{\mathcal{C}}).p(\hat{N}_k^{\mathcal{C}} | N^k) \quad (22)$$

By considering a Markovian assumption and Bayes theorem, the probability is computed as:

$$p(\hat{N}_k^{\mathcal{C}} | N^k) = p(N(k) | \hat{N}_k^{\mathcal{C}}, N(k-1)).p(\hat{N}_k^{\mathcal{C}} | N(k-1)).\frac{1}{c} \quad (23)$$

with c a normalization constant, $p(\hat{N}_k^{\mathcal{C}} | N^{k-1}) = \mathcal{N}(\hat{N}_k^{\mathcal{C}}; N^{k-1}, \sigma_N^2)$ is computed as the normal density with mean N^{k-1} and variance σ_N^2, and $p(N(k) | \hat{N}_k^{\mathcal{C}}, N^{k-1})$ is computed by using a linear transformation.

5 Simulation and results

In the following, we present some simulation results that illustrate the performances of the proposed hybridization. These are compared to the performances of a classical IMM-MHT, a labeled GMCPHD, a VS-IMMC-MHT and an hybridization GMCPHD/IMM-MHT. Then we present some results on the convoy detection.

5.1 Scenario

The GMTI sensor has a linear trajectory, its velocity is 30m/s and its altitude is 4000m. The typical measurement error is 20m in range and 0.008rad in azimuth. The sensor scan time is $T = 10$s. Scenario time is limited to 500s. The false alarm density is $\beta_{FA} = 8.92.10^{-9}$ and the detection probability is $P_D = 0.9$. Target trajectories are illustrated in Figure 4, while cumulated MTI reports are shown in Figure 5. In the scenario, one 6 target convoy (Target 1-6) is moving on the main road with a constant velocity of 10m/s from South to North. An independant target (Target 7) is moving on the same road in the same direction but with a constant velocity of 15m/s and overtakes the convoy between time t=150s and t=350s approximately.

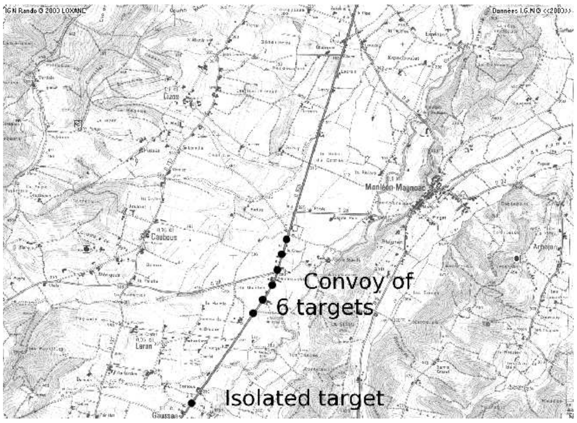


Figure 4: *Scenario*

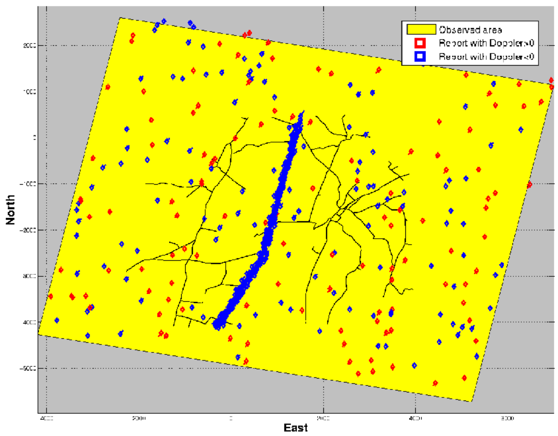


Figure 5: *Cumulated MTI reports*

The simulation parameters are presented in Tables 1 to 5.

Name	Value
CV model noise 1	$0.05m.s^{-2}$
CV model noise 2	$0.8m.s^{-2}$
Model noise 3 (STOP)	$0m.s^{-2}$

Table 1: The IMM parameters

5.2 Results

The performances of tracking algorithms have been compared for 100 independent Monte Carlo runs. Figure 6 shows the average RMSE (Root Mean Square Error) of each target in position, Figure 7 average RMSE in velocity and Figure 8 is the track length ratio of each target. The IMM-MHT offers acceptable performances in state estimation, while the VS-IMMC-MHT improves highly position estimation. The GMCPHD produces lower performances in term of state estimation, but the track length ratio is close to 1. The hybrid version (Hybrid 1 is the hybridization of IMM-MHT and GMCPHD, Hybrid 2 is the hybridization of VS-IMMC-IMM-MHT and GMCPHD) is a good compromise between the two sorts of algorithms. The track length ratios have similar values as the GMCPHD, whereas, the state estimation are similar for Hybrid 1 to the IMM-MHT and for Hybrid 2 to the VS-IMMC-MHT.

Name	Value
Birth target density	$8.92.10^{-9}$
Threshold for track confirmation	10^{-4}
Threshold for track deletion	10^{-1}
Threshold for hypothesis deletion	10^{-2}
Number of branches to keep	2
Threshold for gloabl track probability	50
Number of scans before pruning	50
Gating probability	0.95

Table 2: The MHT parameters

Name	Value
Survival probability	0.98
Initial Gaussian weight	10^{-3}
Pruning threshold	10^{-2}
Merging threshold	20
Maximum number of targets	50
Maximum number of Gaussians	50
Average number of birth	0.6
Model noise	2
Maximum velocity	20

Table 3: The GMCPHD parameters

Name	Value
CV model noise 1 in normal direction	0.1
CV model noise 1 in orthogonal direction	0.1
CV model noise 2 in normal direction	0.6
CV model noise 2 in orthogonal direction	0.4
Maximum value for off road velocity	$9m.s^{-1}$

Table 4: The VS-IMMC parameters

Name	Value
Number of iterations for score calculation	3
Weight threshold for new track	0.8

Table 5: The hybridization parameters

Concerning the convoy probability, $p(X_9)$ is evolving progressively from 0.5 to 0.6 (*cf.* Figure 9) with some picks which indicate a change of cardinality in the aggregate. By introducing $N^{\mathcal{C}}$, we begin to estimate the number of targets in the aggregate (*cf.* Figure 11). We discriminate the case $N^{\mathcal{C}} = 7$, but we cannot decide between $N^{\mathcal{C}} = 5$ or 6. Finally, by introducing $\hat{N}_k^{\mathcal{C}}$ knowing N^k (*cf.* Figure 10), the case $N^{\mathcal{C}} = 6$ appears as the

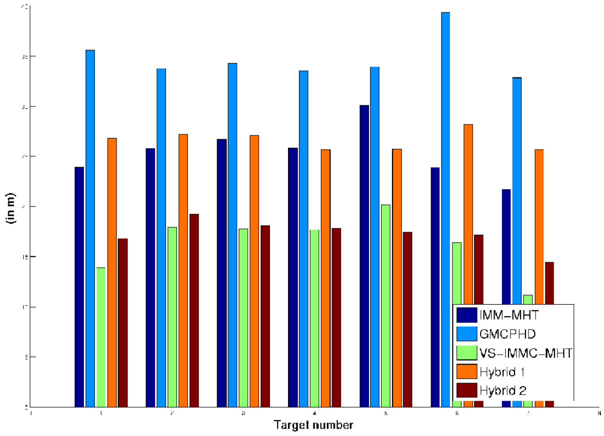


Figure 6: *Average RMSE in position of each target*

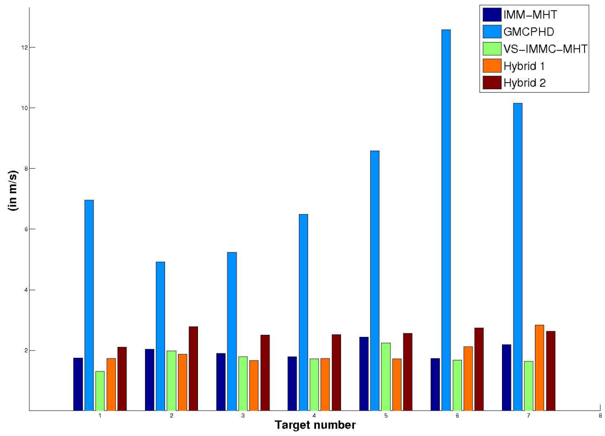


Figure 7: *Average RMSE in velocity of each target*

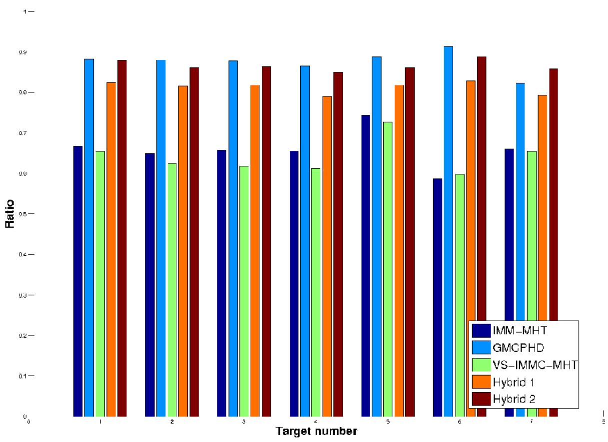


Figure 8: *Track length ratio*

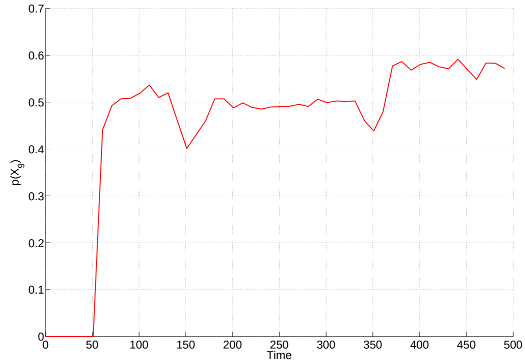


Figure 9: $p(X_9)$

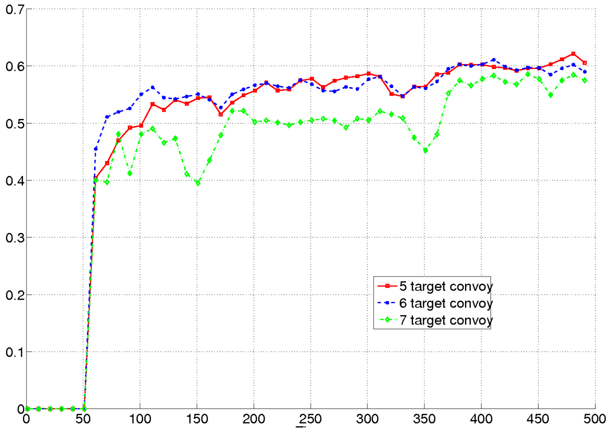


Figure 10: $p(X_9, N^{\mathcal{C}})$

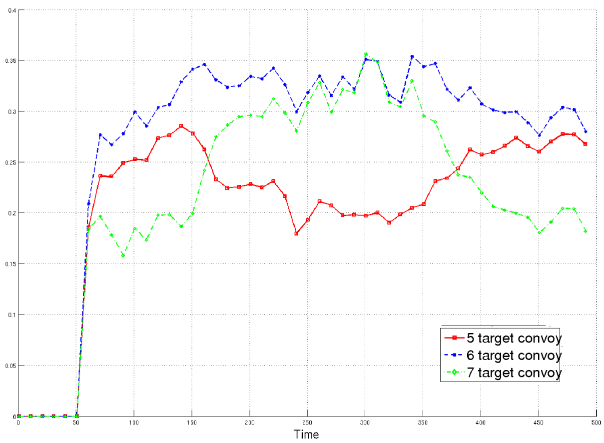


Figure 11: $p(X_9^k, N^{\mathcal{C}}, \hat{N}_k^{\mathcal{C}} | N^k)$

most likely.

6 Conclusion

The new approach for convoy detection has shown its efficiency on a complex multitarget scenario. Several theoretical contributions have been proposed. The first one concerns the labeled version of the GMCPHD that allows to differentiate the tracks. The second contribution concerns the hybridization of the GMCPHD algorithm to the VS-IMMC-MHT algorithm in order to improve the performances, specially for group of closely spaced objects. Finally, the third contribution concerns the convoy model by using DBN that proposes an original answer to convoy detection process. This has been tested on several scenarios not presented in the paper. The next step is now the problem of make a decision which stays entire.

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