Performances in Multitarget Tracking for Convoy Detection over Real GMTI data

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Abstract – *A convoy is defined as a group of vehicles traveling together for mutual support and protection. It constitutes an object of high military interest in the context of the situation assessment. However, it is a challenging task to track and evaluate because convoy targets are very close of each other. In this view, the Onera recently developed a new two step convoy detection process. The first is an original tracking algorithm appropriate for Ground Moving Target Indicator (GMTI) data based on the hybridization of two classical multitarget tracking algorithms, and adapted to closely spaced target tracking. Then, by using algorithm outputs and other data, vehicle aggregates are detected and their characteristics are introduced into a Dynamic Bayesian Network (DBN) which processes the probability for an aggregate to be a convoy. This process gives encourageous results with simulated data. In this paper, we validate this process by showing real data results.*

Keywords: real GMTI data, multitarget tracking, convoy detection

1 Introduction

In the last ten years, MTI sensors demonstrated their necessity as part of the battlefield surveillance in a multi-platform context [1, 2]. Indeed, this kind of sensors offer the possibility to detect and track moving vehicles on a large area. However, multitarget tracking algorithms have to deal with the high target density and many birth and dead process at each iteration. Some other difficulties like the high clutter density or the presence of hidden zones for the sensor due to the terrain elevation or a detection probability lower than one have to be taken into account. Therefore, the use of a reliable automatic multitarget tracking is indispensable to assess the situation.

In some previous works, an original approach was presented for multitarget tracking and for convoy detection and evaluation in [3, 4]. Some results were presented with simulated data. To summarize, the approach is in two step. Firstly, we elaborated a new hybrid algorithm combining the advantages of the Multiple Hypothesis Tracker (MHT) and the Cardinalized Probability Hypothesis Density (CPHD) filter. Then, we modeled the convoy by using Dynamic Bayesian Network (DBN). The goal is now to validate this approach by obtaining similar results as previously with real GMTI data, where the goal is to evaluate the sensor operational ability and to validate the use of an airborne multisensor observation system.

In this paper, we first describe our convoy detection process before we show some performances obtained with real data in order to validate the presented approach.

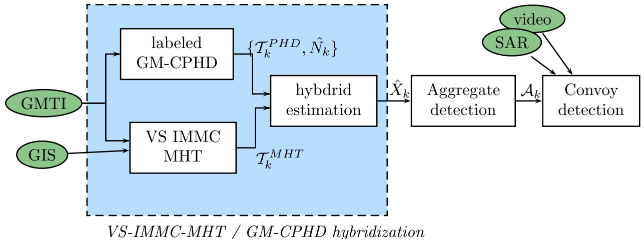


Figure 1: Convoy detection process

2 Convoy detection processing description

In some recent works, we developed a new convoy detection processing. As the goal of this publication is to show some performances on real data, we just summarized in this part the main principle of the convoy detection. Readers should refer to [3, 4] for more details.

In this convoy detection purpose, we propose a process in two main steps as shown in figure 1. We first use GMTI data for aggregate detection and then we process Dynamic Bayesian Network for convoy detection and evaluation.

2.1 Step 1: a new hybrid algorithm to track very close targets together as well as independent targets

The MHT, combined with a Multiple Model approach and road projection, is a very reliable multitarget algorithm, but it has weaknesses when targets are close of each other. From another point of view, the CPHD filter estimates very precisely the number of targets on a scene, even if targets are moving in a close formation, but does not produce an estimation for target velocity. That is why, the two algorithms are combined into a hybrid version described in this part.

2.1.1 Background on the CPHD 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 [5]. 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:

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

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.

Moreover, in the Cardinalized PHD recursion [6], added to the operations (3) and (4), the probability of having n targets is predicted and estimated in the same way as $\forall n \in \mathbb{N}^\star$,

$$\begin{aligned} p_{k|k-1}(n) = \sum_{j=0}^{n} p_\Gamma(n-j) \times \\ \sum_{l=j}^{\infty} C_j^l \frac{\langle P_s, v_{k-1}\rangle^j \langle 1-P_s, v_{k-1}\rangle^{l-j}}{\langle 1, v_{k-1}\rangle^l} p_{k-1}(l) \end{aligned} \tag{5}$$

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

$$p_{k|k}(n) = \frac{\mathcal{L}(Z_k|n)}{\mathcal{L}(Z_k)} p_{k|k-1}(n) \tag{6}$$

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

The GM-CPHD, proposed by Vo [7], 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:

$$v_k(x) = \sum_{i=1}^{J_k} w_{k,i} \mathcal{N}(x; m_{k,i}, P_{k,i}) \tag{7}$$

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. $\mathcal{N}$ represent the normal distribution.

2.1.2 The GM-CPHD labelization

As the problem of track labeling is not considered in the classical implementation of the GM-CPHD, we proposed a new one. The GM-CPHD outputs a set of Gaussian components and a very accurate estimation of the number of targets. The principle of track labeling is to specify amongst the Gaussian component set, which components can be associated to tracks. We propose to label Gaussian components by taking the Gaussian set which maximizes the Gaussian weights and minimizes the distance between the predicted track position and the Gaussian position.

2.1.3 The hybridization

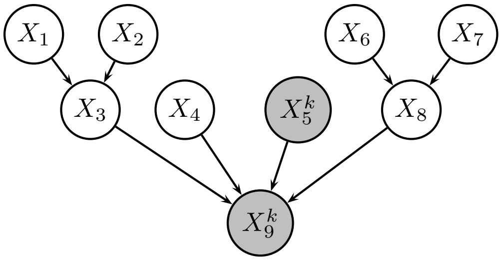
The GM-CPHD produces a reliably estimation of the number of targets, whereas the Multiple Hypothesis Tracker (MHT) is effective to give a good estimation of the target state (specially by introducing Multiple Model and road coordinates as in [8]) when targets are not close together, because of the problem for MHT algorithm to evaluate the number of targets. We therefore propose to use these two algorithms as complementary filters; the first algorithm 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 GM-CPHD 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 GM-CPHD track is kept.

This approach benefits of both algorithms without increasing the processing time:

- Robust to target maneuvers by using Multiple Model approach (IMM)
- Good precision for state estimation by using road coordinates (MHT with road constraints)
- Good estimation of the number of targets (CPHD)
- No performance decrease when targets are close together (CPHD)

2.2 Second step: convoy model by using the DBNs

A convoy is defined as a vehicle set evolving approximately with the same dynamics over a long period of time. These vehicles are moving on the road at a limited velocity (<20m/s). They must stay within sight of each other 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 [9], as shown in figure 2.



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: DBN for convoy detection. *The gray nodes represent states depending on their previous state.*

The DBNs are an interesting and intuitive formalism for our application. However it requires some processings for :

- Conditional probability distribution evaluation: this step is done by an expert.
- Raw data transformation in probability: by using classical distribution (like Rayleigh or χ^2 distribution) or fuzzy transformation.
- The inference step: we use a JLO algorithm [10], available in Murphy's Bayes net toolbox [11].
- The number of targets estimation in the convoy.

3 Experimental results

In this part, we present tracking results as well as convoy detection and evaluation results for data, which combine real GMTI data with simulated GMTI data generated from a ground truth. Before showing numerical results, let us describe preprocessing steps.

3.1 Data preprocessing

Before tracking, some preprocessing steps are done:

- Road network extraction by using High resolution optical image from Google earth and Digital Terrain Elevation Data (DTED).
- Coordinate transformation: the GMTI data (MTI reports and sensor position) are given in the World Geodetic System 84 (WGS84), whereas the tracking is done in a local two dimensional Cartesian coordinates. Consequently, GMTI data must first be transformed in local coordinates.
- Spatial bias correction: MTI report resampling by using road coordinates
- Temporal bias correction between GPS time and GMTI measurement time: in addition to the one hour delay for GMTI data due to clock change in winter, a few second delay is visible and corrected by minimizing the estimation error with different time delay.
- Data simulation: sensor parameters for simulated data are similar to the real sensor parameters. Finally, figures 3 and 4 illustrate how heterogeneous scanning times are processed.

3.2 Scenario description

The mission consists of more than 500 scans, separated by a varying time interval. Since the Doppler MTI measurements are not reliable, it is not processed in the tracking algorithms.

The scenario takes place between time 2:17 PM and 3:48 PM. Military vehicles are generally equipped with

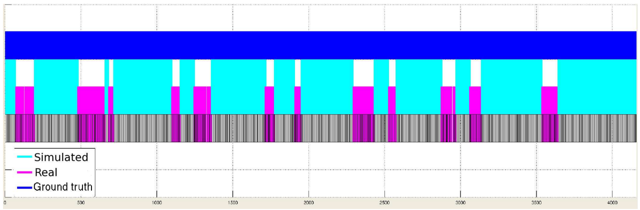


Figure 3: Sensor sampling

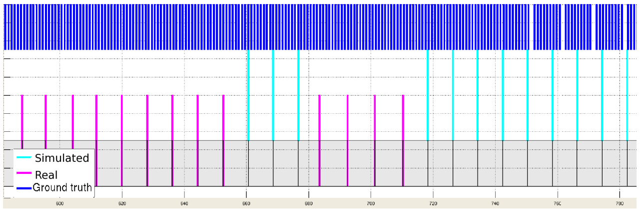


Figure 4: Sensor sampling zoom.
Blue lines represent GPS acquisition time - Pink line represents real scanning time - Cyan lines represent the simulated scanning time to compensate data lack - Black lines represent algorithm scanning time

a GPS device, providing their position in WGS84 with a time interval of about 5-30s. Amongst them, about 50 vehicles are moving. The vehicles are classified into different types including tanks and armored personnel carriers called vab in French. This is worth noting that not every vehicle is equipped with a GPS device, as noticed by comparing accumulated MTI reports and accumulated GPS reports. We estimated, by looking at MTI measurements, that a lot of GPS are missing. Moreover, sensors cover civilian area with unknown traffic.

3.3 Interpretation

Every numerical figure has a colored background. If it is blue, it means that the scene is observed by the simulated sensor, and if it is yellow it means that the scene is observed by the real sensor. Now, some numerical performances are shown as the completeness, ratio of redundant track, ratio of false track and Root Mean Square Error (RMSE).

3.3.1 Multitarget tracking results

The figure 5 illustrates global numerical performances by showing:

- The completeness defined as the number of validated tracks under the number of real targets. During sensor scanning time, an expert evaluates the number of targets which do not produce a GPS signal. However this number is generally underestimated, that is why the completeness decreases. During simulated scanning time, the completeness is very close to one.

- The false track rate is the number of tracks which are not associated to a real target over the number of validated tracks. This rate is quite low except during iteration 120 to 160 where the number of real targets is very low (until only one).

- The redundant track rate is the number of validated tracks over the number of targets associated to at least one tracks. This rate is quite low and increases between iteration 370 and 470 where the number of closely spaced targets increases.

- The cardinality estimation is quite good by observing the many target birth and death processes. However, during the scanning time of the real sensor, it is more difficult to evaluate the exactitude of the estimation of the number of targets.

Measure of performances like OSPA distance cannot be calculated because the ground reality is incomplete.
Figures 6 and 7 illustrate individual tracking performances for a vab (Target 533) and a tank (Target 510). Each figure is made of 4 sub-figures.

- For the first sub-figure, the black lines indicate the detection times. A target is undetectable if its velocity is lower that the minimum velocity threshold and if it is outside the zone of interest. The detection value is one if a measurement can be associated to the target and is zero if not. If the target is undetectable, no value is assigned.

- The RMSE in position is calculated for MHT algorithm with road constraints (in green), labeled GM-CPHD (in blue) and hybrid algorithm (in red). When the value is zero with a black cross marker, the target is not tracked and no RMSE can be calculated.

- The RMSE in velocity operates like the RMSE in position.

- The true velocity is the norm of the velocity calculated from the GPS position. The black line indicates the minimum velocity detection threshold.

Target 533 is known as a vab. It is moving from iteration 240 to 330 in the North-East. In figure 6, the cyan line illustrates the real trajectory of this target, the red squares are the associated measurements and the other colored lines are the 3 different tracks associated to target 533. Some difficulties for tracking at the beginning and at the end appear. In spite of many unassociated measurements and target maneuvers, the tracking continuity is maintained (with the hybrid algorithm, the track length ratio is 0.87). Globally, the hybrid algorithm offers better performances for this target, RMSE in position as well as in velocity are lower that for the GM-CPHD and the track length ratio is better that for the MHT algorithm.

The target 510 is an interesting case of move-stop-move-stop target. The target is continually accelerating and decelerating and, due to its velocity, the target status is constantly changing from detectable to undetectable. Consequently, the target is really difficult to detect and track. But due to a quicker track initialization, GM-CPHD and hybrid algorithm show their superiority with this kind of targets. This case is very interesting because it is a typical tank behavior, that we find many times in this scenario and that we could detect as such.

3.3.2 Convoy detection results

We study a convoy case, coming from an interesting sequence for situation assessment. A group of vehicles is moving from the start point to the stop point describing nearly a loop. The group is composed of two head vehicles (target 533 and 440, vab and tank), one intermediate vehicle further (target 470, vab), two additional tanks further (target 410 and 413), and a group of 3 tanks (target 420, 400 and 433) which is joined by a vab (target 433). Our study concerns this last group a vehicles. When available, the probability to have a convoy is quite interesting. The first sub-figure, represents the probability of having a convoy of N_c targets. It is calculated for the value $N_c = \{3, 4, 5\}$. Most of the time, with this figure, it is not possible to distinguish the case $N_c = 3$ and $N_c = 4$, which have both a high probability. However, by introducing the sequence of the number of targets in the aggregate, as in the second sub-figure, it is possible to see, that, progressively, the probability of having a convoy of 4 targets becomes higher that the probability to have a convoy of 3 targets, while the vab is integrated in the convoy.

4 Conclusion

This article is a short presentation of our approach for convoy tracking and detection based on real data. Our algorithm is both able to track multiple targets by tacking into account contextual information and to track aggregates with a GM-CPHD. The first case has been studied with real GMTI data presented in this paper and we have observed some weaknesses to track the convoy. However, the use of a GM-CPHD improves the convoy tracking but decreases the performances of the individual estimated tracks (in location and velocity). The proposed hybridization shows an improvement of the convoy tracking and convoy detection. Those results has been first observed on simulated data and now confirmed on real data.

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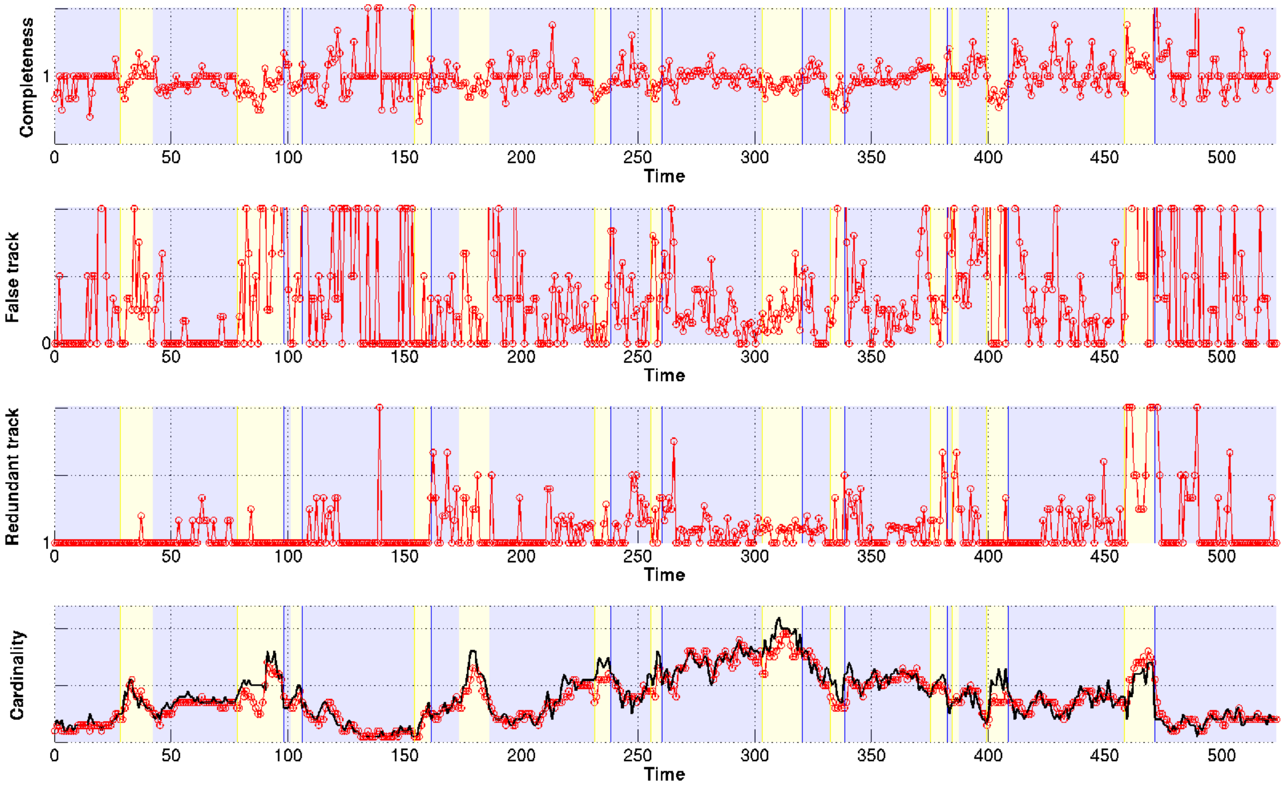

Figure 5: Completeness, False track rate, Redundant track rate, Cardinality - *Red lines represent estimated value with the hybrid algorithm and black line represents the ground truth for cardinality.*

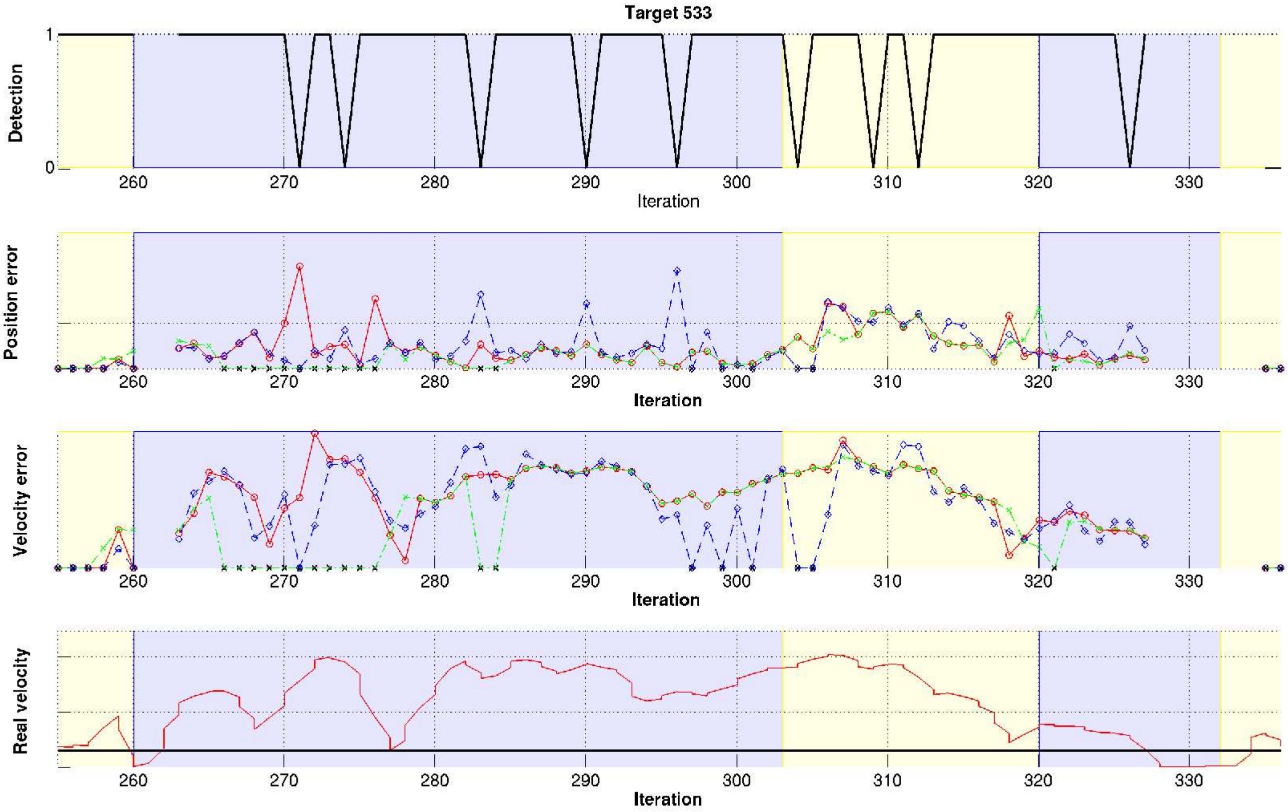

Figure 6: Tracking performances with an armored personnel carrier

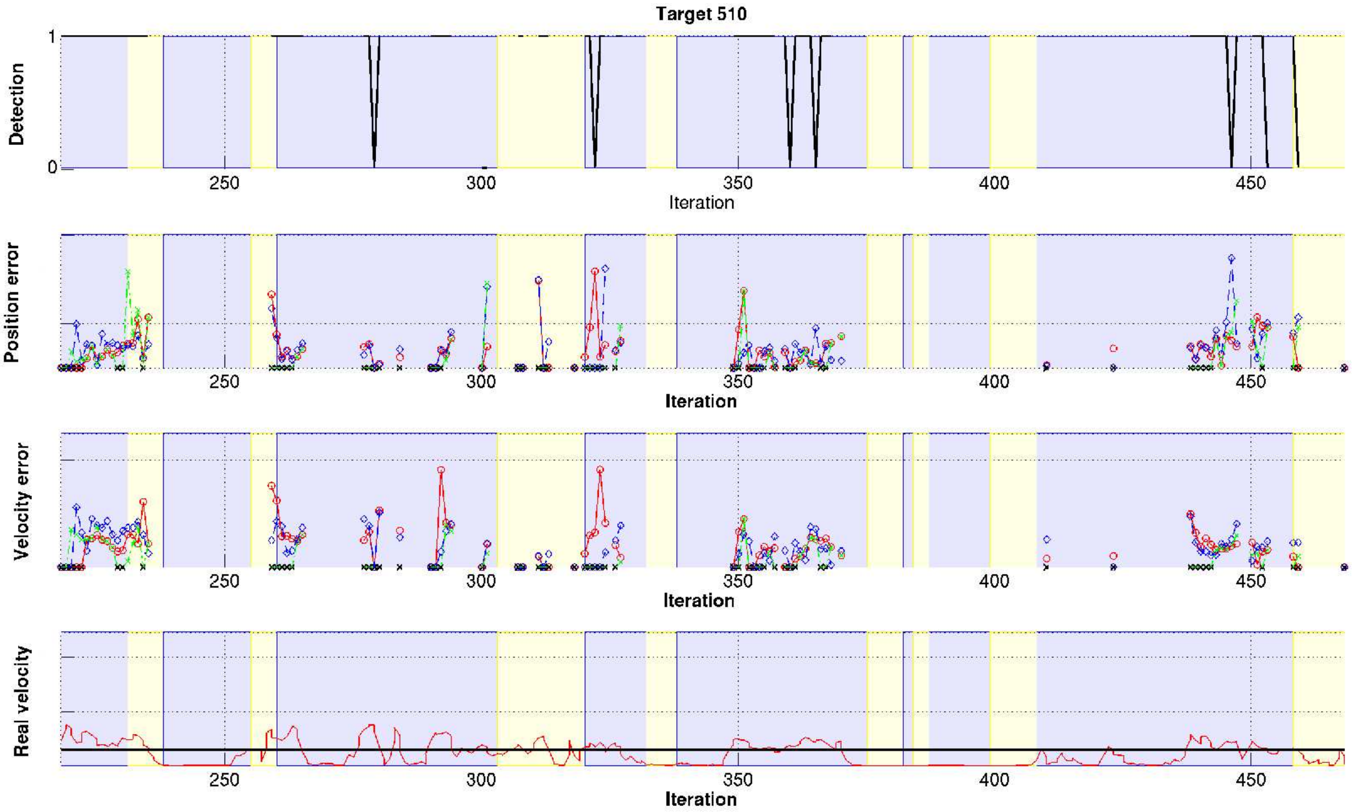

Figure 7: Tracking performances with a move-stop tank

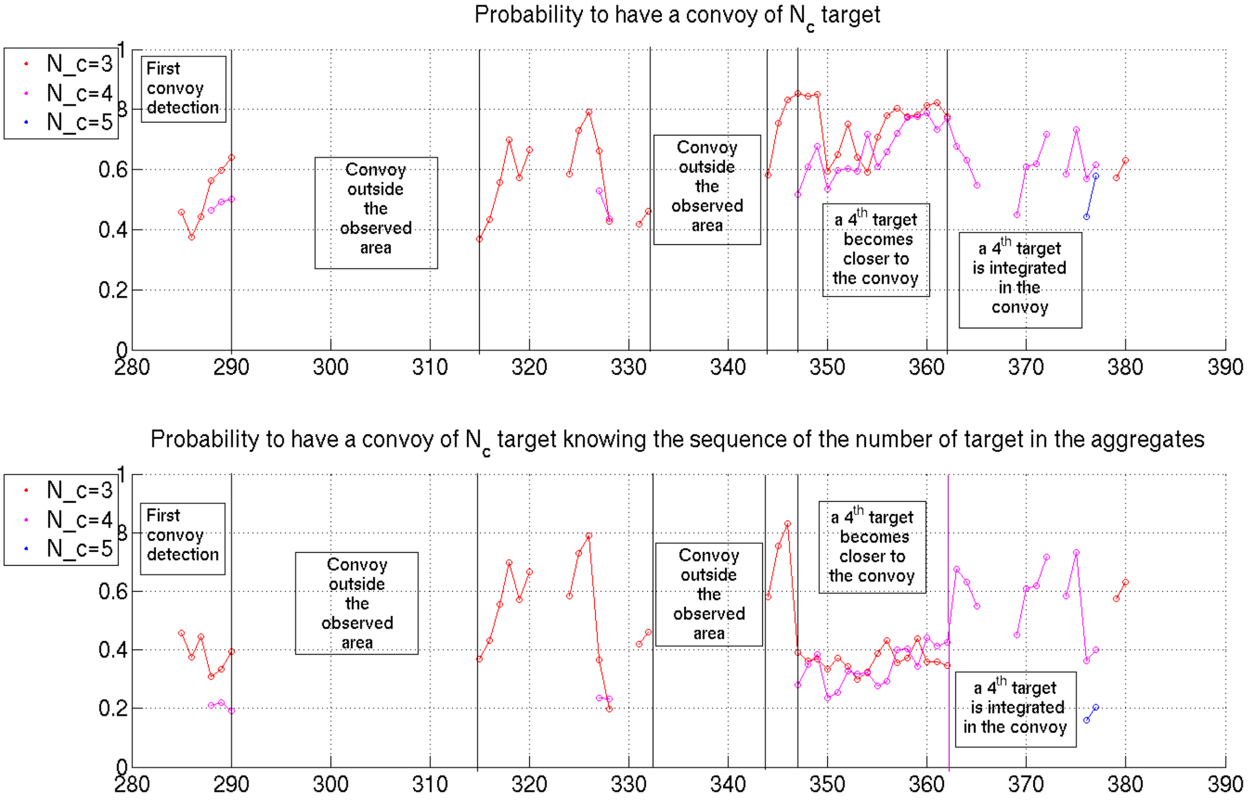

Figure 8: Convoy probabilities