A particle filtering approach for convoy tracking in the midst of civilian traffic

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A Particle-Filtering Approach to Convoy Tracking in the Midst of Civilian Traffic

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ABSTRACT

In the battlefield surveillance domain, ground target tracking is used to evaluate the threat. Data used for tracking is given by a Ground Moving Target Indicator (GMTI) sensor which only detects moving targets. Multiple target tracking has been widely studied but most of the algorithms have weaknesses when targets are close together, as they are in a convoy. In this work, we propose a filtering approach for convoys in the midst of civilian traffic. Inspired by particle filtering, our specific algorithm cannot be applied to all the targets because of its complexity. That is why well discriminated targets are tracked using an Interacting Multiple Model-Multiple Hypothesis Tracking (IMM-MHT), whereas the convoy targets are tracked with a specific particle filter. We make the assumption that the convoy is detected (position and number of targets). Our approach is based on an Independent Partition Particle Filter (IPPF) incorporating constraint-regions. The originality of our approach is to consider a velocity constraint (all the vehicles belonging to the convoy have the same velocity) and a group constraint. Consequently, the multitarget state vector contains all the positions of the individual targets and a single convoy velocity vector. When another target is detected crossing or overtaking the convoy, a specific algorithm is used and the non-cooperative target is tracked down an adapted particle filter. As demonstrated by our simulations, a high increase in convoy tracking performance is obtained with our approach.

Keywords: GMTI, convoy tracking, particle filter, IMM-MHT

1. INTRODUCTION

In the battlefield surveillance domain, ground target tracking is used to evaluate tactical situation. Data used for tracking comes from a Ground Moving Target Indicator (GMTI) sensor which detects moving targets only by measuring their Doppler effect. Tracking algorithms were originally elaborated for airborne targets in the 1970's. Ground target tracking is widely inspired of these techniques[1], but they were adapted because the ground environment is much more complex than aerial environment. For example, they have to take into account the very high density of ground traffic which generates an important number of measurements, ground elevation (mountain, hill,...) which create hidden zones for sensor and also sensor limitations (false alarms, detection probability, resolution,...). Moreover, measurements are noisy and ambiguous and ground targets highly manoeuvrable.

In spite of these difficulties, very efficient algorithms for single or multitarget tracking[2–4] based on Kalman filtering exist today. However, most of these algorithms have weaknesses when targets are close together as they are in a convoy, because of the problem of targets-GMTI measurement association. Yet the goal of tracking is to evaluate ground situation by taking objects of interest, such as convoys, into account. Multiple target tracking has been widely studied for many years. Conventional approaches such as the Multiple Hypothesis Tracking[2–5] (MHT) or the Joint Probabilistic Data Association Filter[2–5] (JPDAF) use a Gaussian mixture representation of probability density of the state vector. Yet, in the convoy tracking case, this assumption is not verified. Moreover, convoy measurements are very close together and, as measurements used to update MHT and JPDAF

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are chosen in a given neighborhood, finding the right one is a very challenging task. That is why it is necessary to develop local algorithms which are able to track each target belonging to a convoy.

One solution proposed by Williams[6] is to use a Gaussian mixture reduction with a MHT. Therefore, a MHT algorithm is very efficient, particularly with regards to the enormous quantity of data produced by GMTI sensor. Another interesting alternative for non linear, non Gaussian tracking of multiple targets is the particle filtering but it is very time consuming. Since on the battlefield, the number of convoys is limited, we propose to use the particle filtering approach locally.

The paper is organized as follows: Section 2 describes the multi target motion model. Section 3 reviews existing particle filters. Our specific algorithm for convoy tracking is described in Section 4 and finally Section 5 explains how the local particle filtering algorithm is integrated into a classical multitarget tracking method: the Interacting Multiple Model-Multiple Hypothesis Tracking Algorithm (IMM-MHT). This method proves very efficient in tracking uncorrelated targets.

2. CONSTANT VELOCITY MOTION MODEL

Target tracking is done in a local two-dimensional plane. We consider M targets moving in this plane. The state vector for the t^{th} target, $(\forall t \in \{1, \ldots, M\})$, is given by:

$$x_t(k) = [\mathrm{x}_t(k), \dot{\mathrm{x}}_t(k), \mathrm{y}_t(k), \dot{\mathrm{y}}_t(k)]^T \tag{1}$$

where $(\mathrm{x}_t(k), \mathrm{y}_t(k))$ corresponds to the position and $(\dot{\mathrm{x}}_t(k), \dot{\mathrm{y}}_t(k))$ to the velocity of the t^{th} target at time k in the Cartesian model.

Assuming that the target motion is linear in the Cartesian coordinate system, the state equation of a target can be written as:

$$x_t(k+1) = F_i(k).x_t(k) + \Gamma(k).\nu_i(k) \tag{2}$$

where $F_i(k)$ is the state transition matrix which depends on the motion model M^i $(\forall i \in \{1, \ldots, r\})$. Generally, a constant velocity model M^i is used with the sampling interval T:

$$F_i(k) = \begin{pmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{3}$$

and $\nu_i(k)$ is a zero-mean, white Gaussian process with the known covariance matrix Q_i which models the target acceleration:

$$Q_i = E[\nu_i(k).\nu_i(k)^T] = q_i \Gamma(k).\Gamma(k)^T \tag{4}$$

with q_i the model noise and $\Gamma(k)$ as defined by Bar-Shalom[7].

The sensor gets a measurement vector $Z(k) = [z_1(k), \ldots, z_{m_k}(k)]$ with m_k the number of measurements at each iteration k. Each measurement $z(k)$ corresponds to the observed position vector and is given by:

$$z(k) = H.x_t(k) + b(k) \tag{5}$$

where $b(k)$ is a white Gaussian noise with a known covariance matrix $R(k) = E[b(k), b(k)^T]$. According to the state vector $x_t(k)$, the matrix H can be written as:

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \tag{6}$$

3. PARTICLE FILTERING

Before detailing the proposed approach, we will briefly review standard particle filters described in the literature[8–12] for single target, multitarget and convoy targets.

3.1 Single target particle filtering

Particle filtering is a method for approximately solving the state prediction and updating equations of the model by simulation. The interest of this approach is that there is no analytic representation of the density. Samples from the target density, written $X_{part}(k) = \{X_1(k), \dots, X_{N_{part}}(k)\}$ with N_{part} the number of particles and $X_p(k)$ the particle state, are used to represent the density and are propagated through time. To implement a single target particle filter, the estimation state is approximated by a set of weighted samples as follows:

$$\hat{x}(k|k) \approx \sum_{p=1}^{N_{part}} w_p(k) X_p(k) \tag{7}$$

$$P(k|k) \approx \sum_{p=1}^{N_{part}} w_p(k).[(\hat{x}(k+1|k) - \hat{x}(k|k)).(\hat{x}(k+1|k) - \hat{x}(k|k))^T] \tag{8}$$

where $w_p (\forall p \in \{1, \dots, N_{part}\})$ is the weight of each particle. This weight can be computed as the likelihood of the position measurement z knowing the position X_p of the particle p:

$$w_p(k) = w_p(k-1) \times p(z(k)|X_p(k)) = \frac{1}{\sqrt{2\pi|R|}} exp(-\frac{1}{2}[z(k) - \mathrm{X}_p(k)]^T R^{-1} [z(k) - \mathrm{X_p}(k)]) \tag{9}$$

where $R(k)$ is the measurement noise, $z(k)$ is the measurement associated to the target (defined by a Nearest-Neighborhood method for example) and $\mathrm{X}_p(k)$ is the particle position at time k. For further information, the reader can see[13].

But in practice, the particle cloud is composed in majority of weakly weighted particles and in minority of strongly weighted particles, which are more informative. This creates a problem, because after several iterations the cloud spreads and the filter diverges, due to the state covariance matrix increasing. This problem is solved by a resampling, when necessary, like the Sampling Importance Resampling (SIR) proposed and demonstrated by Kong[14].

3.2 Sampling Importance Resampling

The principle of resampling is to delete weakly weighted particles and to duplicate strongly weighted ones. Yet, since resampling is time consuming, it is important to measure the filter degeneration in order to use a resampling only when necessary. Kong Liu and Wong[14] introduced a criterion to define the effective number of particles in order to quantify the global information due to the particles. This criterion is based on variance, because diffuse clouds imply weakly weighted degenerated particles. Let N_{eff} be the effective number of particles at time k, defined as follows:

$$N_{\text{eff}} = \frac{N_{part}}{1 + Var(w_p^\star(k))} \tag{10}$$

where $Var(w_p^\star(k))$ designs the actual weight variance which can only be approximated. Finally $\hat{N}_{\text{eff}}$ is written as:

$$\hat{N}_{\text{eff}} = \frac{1}{\sum_{p=1}^{N_{part}} w_p(k)} \tag{11}$$

When $\hat{N}_{\text{eff}}$ is greater than a given threshold N_{th} (Kong proposed empirically $N_{th} = 2\hat{N}_{\text{eff}}/3$), Sampling Importance Resampling is operated.

3.3 Multitarget Particle Filter

The previous algorithm described for a single target, can be simply adapted to a multitarget tracking case. Let M be the number of tracked targets. The multitarget state vector X_p is the concatenation of each single target state vector $X_{p,t}$ named partition, so the state of the p^{th} particle at time k is composed of the concatenation of M partitions:

$$X_p(k) = [X_{p,1}(k), \ldots, X_{p,M}(k)]^T \tag{12}$$

The likelihood of a particle p becomes the product of each partition likelihood $X_{p,t}(k)$:

$$w_p(k) = w_p(k-1) \prod_{t=1}^{M} p(z(k)|X_{p,t}(k)) \tag{13}$$

where $z(k)$ is the closest validated measurement for partition t.

This algorithm has very good performances but it involves the use of a number of particles increasing proportionally to the number of tracked targets. This is why a lot of versions of this algorithm exist like the Independent Partition Particle Filter (IPPF).

3.4 Independent Partition Particle Filter

Orton[15] proposes a new particle algorithm called Independent Partition Particle Filter (IPPF), which assumes the targets sufficiently separated in regards to the sensor resolution. This results in an uncorrelated measurement likelihood. The principle is to optimize the resampling step by constructing particles independently proposing partitions for each particle. This efficiently reducts the number of particles as compared to proposing all partitions simultaneously. Therefore, particle weight is not simply calculated as the product of partition likelihoods, indeed a bias appears. The weight of the particle p ($\forall p \in \{1, \ldots, N_{part}\}$) can also be written as:

$$w_p(k) = w_p(k-1) \times \frac{p(Z(k)|X_p(k))}{\prod_{t=1}^{M} w_{p,t}(k)} \tag{14}$$

where $w_{p,t}(k)$ is the partition weight for target t, at time k.

This method is very efficient when targets are well discriminated. Although if a doubt concerning the target-measurement association exists (as in a convoy), it can lead to the partition clouds merging and consequently only one target is tracked. This method is not directly transposable to the application addressed in this paper.

3.5 Particle Filter using a convoy model

Most multitarget tracking algorithms make the assumption that all considered targets have independent motion. Yet we can consider that this is not the case when targets move in a convoy. The main characteristic is that they have the same velocity. On this assumption, we can write, as Gordon[8], the convoy state vector $X^c(k)$ and the particle state vector $X_p^c(k)$ at time k as:

$$X^c(k) = \begin{pmatrix} \mathrm{X}_1^c(k) \\ \vdots \\ \mathrm{X}_M^c(k) \\ \dot{\mathrm{X}}^c(k) \end{pmatrix} \tag{15}$$

$$X_p^c(k) = \begin{pmatrix} \mathrm{X}_{p,1}^c(k) \\ \vdots \\ \mathrm{X}_{p,M}^c(k) \\ \dot{\mathrm{X}}_p^c(k) \end{pmatrix} \tag{16}$$

where $\mathrm{X}_t^c(k)(\forall t \in \{1, \ldots, M\})$ represents the position (x, y) of the target t of the convoy in Cartesian coordinates at time k and $\dot{\mathrm{X}}^c(k)$ the global convoy velocity $(\dot{\mathrm{x}}^c, \dot{\mathrm{y}}^c)$. M is the number of targets in the convoy.

Target position and global convoy velocity are supposed to follow both linear and Gaussian model. This can be written as:

$$p(\mathrm{X}_{p,t}^c(k)|\mathrm{X}_{p,t}^c(k-1), \dot{\mathrm{X}}_p^c(k-1)) = \mathcal{N}(\mathrm{X}_{p,t}^c(k-1) + T.\dot{\mathrm{X}}_{p,t}^c(k-1), Q_t) \tag{17}$$

$$p(\dot{\mathrm{X}}_p^c(k)|\dot{\mathrm{X}}_p^c(k-1)) = \mathcal{N}(\dot{\mathrm{X}}_p^c(k-1), Q_v) \tag{18}$$

where Q_v and Q_t are the covariance matrices for the velocity and for the position of a target t. Combining equations (17) and (18), we can write:

$$p(X_p(k)|X_p(k-1)) = \mathcal{N}(F_c.X_p(k-1), Q_c) \tag{19}$$

where F_c is the state transition matrix for a convoy of dimension $2 \times (M+1)$ and Q_c is the model covariance written:

$$F_c = \begin{pmatrix} I_2 & 0 & \dots & 0 & T.I_2 \\ 0 & I_2 & & & T.I_2 \\ \vdots & & \ddots & & \vdots \\ 0 & & & I_2 & T.I_2 \\ 0 & 0 & \dots & 0 & I_2 \end{pmatrix} \tag{20}$$

$$Q_c = \begin{pmatrix} Q_t & 0 & \dots & & 0 \\ 0 & Q_t & & & \\ \vdots & & \ddots & & \vdots \\ 0 & & & Q_t & 0 \\ 0 & 0 & \dots & 0 & Q_v \end{pmatrix} \tag{21}$$

where $Q_t = Q_v = q.I_2$ with q the model noise which represents the acceleration uncertainty and I_2 is the 2 dimensional identity matrix.

4. CONVOY TRACKING

Literature on convoy tracking is not very extensive[4,16], probably because of its recent feasibility, with sensor resolution improvement. Nevertheless, Koch[17] proposes a method based on information fusion, Kyriakides[18] uses constraint regions to adapt the IPPF, and Gordon[8] proposes a convoy state vector. In this section, we propose a method inspired of all these authors.

4.1 Convoy initialization

We make the assumption that at time t_d, a convoy is detected and this information comes from a HUMINT (Human Intelligence) or a IMINT (Image Intelligence). So the initial position of each target in the convoy and the number of targets that compose the convoy may be considered to be known.

4.2 Constraint regions

Constraint regions are now introduced to limit the data association problem. Let $\Pi_l(k) = [\pi_{1,l}(k), \dots, \pi_{M,l}(k)]$ be one combination of target-measurement association ($\forall l \in \{1, \dots, L\}$ with L the number of feasible associations). For example, $\pi_{1,l} = 2$ means that the target 1 is associated to the measurement 2. $\Pi_l(k)$ is also a vector of length M which contains all the associated measurement indices. In the case of a non-detection, a negative value is assigned. The set of all feasible associations is written $\Pi(k) = [\Pi_1(k), \dots, \Pi_L(k)]$. The associations are constrained to the following assumptions:

- The use of IPPF approach for the resampling step imposes that each measurement $z(k)$ can only be associated to one target t. This is the **group constraint** $C^g_{\pi_{t,l}}(k)$ for one target r ($\forall t \in \{1, \dots, M\}$) considering one target-measurement association l. This constraint is defined as $C^g_{\pi_{t,l}}(k) = \bigcap_{\forall t' < t} C^g_{\pi_{t',l}}(k)$, where $C^g_{\pi_{t',l}}(k)$ are the constraints imposed by each previous data association for target t'.
- Each partition-measurement association is limited by the validation gate. This is the **self constraint** $C^s_{\pi_{t,l}}(k)$.
- All convoy targets have the same velocity. This is the **velocity constraint** $C^v_{\pi_{t,l}}(k)$.

Finally, we can define, for each combination of target-measure association, $\pi_{t,l}(k)$ the set of constraints as:

$$C_{\pi_{t,l}}(k) = C^g_{\pi_{t,l}}(k) \bigcap C^s_{\pi_{t,l}}(k) \bigcap C^v_{\pi_{t,l}}(k) \tag{22}$$

4.3 Target-Measurement association

At each time k, the combination of associations which gives the strictest of all constraints is chosen. This is similar to finding the combination which gives the smallest sum of distances between the predicted position $\mathrm{X}_t(k+1|k)$ of the target t ($\forall t \in \{1, \ldots, M\}$) and the considered measurement $Z^{\pi_{t,l}}(k)$ for the l^{th} combination:

$$\Pi_{\hat{l}}(k) = \underset{\Pi_l(k) \in \Pi(k), \forall l \in \{1,\ldots,L\}}{\mathrm{argmin}} \sum_{t=1}^{M} \|\mathrm{X}_t(k|k-1) - Z^{\pi_{t,l}}(k)\|^2, \forall \pi_{t,l} > 0 \tag{23}$$

4.4 Resampling

Given all the constraints, we make the assumption that all targets belonging to the convoy have the same velocity. The state vector $X^c(k)$ and the particle state vector $X^c_p(k)$ can be written as in equations (15) and (16). Given the combination $\Pi_{\hat{l}}(k)$, the resampling step can be done as in an IPPF, but only for position. Finally the velocity is calculated as the normalized combination of velocity associated to all surviving partitions. This can be written as:

$$\dot{\mathrm{X}}^c_p = \sum_{t=1}^{M} \frac{\dot{\mathrm{X}}^c_p . b_{p,t}}{\sum_{p'=1}^{N_{part}} b_{p',t}} \tag{24}$$

where $\dot{\mathrm{X}}^c_p$ represent the velocity vector associated to particle p after resampling and $b_{p,t}$ is the bias imposed by the partition t of the particle p.

5. CONVOY TRACKING IN THE MIDST OF CIVILIAN TRAFFIC

One GMTI challenge is to track convoys in civilian traffic. Due to the sample generation and resampling step, particle filtering is very time-consuming and cannot be used for all traffic targets but only as a local algorithm when a convoy is detected. In this section, we propose to mix the IMM-MHT in order to track well discriminated targets and the particle filter for convoy tracking. When another target is detected crossing or overtaking the convoy, the particle filter takes it into account is then modified.

5.1 IMM-MHT Principle

Before describing the adapted particle filter, we explain briefly the multitarget tracker developped in[2] and made of the combination of an Interacting Multiple Model[3] (IMM) and a Multiple Hypothesis Tracker (MHT)[19].

5.1.1 IMM

The Kalman filter optimally describes the dynamics of one target motion model, but in reality a ground target is constantly manoeuvring and only one model is not enough to describe its dynamics. That is why the Interacting Multiple Model[20,21] (IMM) is an interesting alternative. This is a hybrid estimation method because it estimates state system and system occurrence probability. The principle is to use a finite number r of models, describing the target behavior globally and to integrate them in the filter. Finally, the estimated state is a combination of the different estimations using each model.

Here we define $r = 3$ with:

- M^0 the STOP model for tracking unmoving targets or targets moving at a very low velocity,
- M^1 the constant velocity model using state matrix 3 and the covariance matrix 4 using a very low model noise q,
- M^2 for manoeuvring targets using the same model as for M^1 but with a very high model noise q.

5.1.2 MHT

The Multiple Hypothesis Tracker[19] (MHT) is track oriented then decomposed in the following tasks:

- **Prediction** of all existing tracks.
- **Gating** around each predicted state in order to limit the complexity. The predicted covariance of each track forms an expectation area and only measurements inside this gate can be associated to the track.
- **Track confirmation** of the updated tracks. A sequential probability ratio test[19] is used to set up the track status either as deleted, tentative or confirmed. The tracks that fail the test are deleted and the surviving tracks are kept for the next stage.
- **Track extraction** to consider all hypotheses for each measurement. Thereby, we consider that a measurement can (a) be a false alarm, (b) belong to an existing track augmented by the gating step, (c) be the beginning of a new track.
- **Filtering** or estimation of all hypotheses.
- **Pruning** to remove of all hypotheses with track scores less than an appropriate threshold.
- **Merging** hypotheses with very similar state vectors and covariances into only one hypothesis.

5.2 Particle convoy tracking in the MHT

5.2.1 Basic principle

Let $X^T(k) = [X_1^T(k), \ldots, X_{m_T(k)}^T(k)]$ the set of confirmed tracks given by the MHT, with $m_t(k)$ the number of confirmed tracks at time k. The original idea is to manage the isolated targets and the convoy targets differently. When no convoy is detected, the complete set $Z(k)$ of m_k measurements is processed by the MHT. At time k, if a convoy is detected, we look for the best data association combination and the measurement set is split in two subsets. First, the subset $Z^c(k)$ of $m_c(k) \leq M$ measurements is associated to the targets of the convoy. This subset is managed by the particle filter as presented section 4. Second, the subset $Z^{MHT} = \{Z(k)\} \setminus \{Z^c(k)\}$ of measurements not associated to the convoy is processed by the MHT. We can summarize our approach as follows:

- Targets that are well discriminated from the convoy correspond to targets which surely do not belong to the convoy: processed by the MHT
- Convoy targets corresponding to targets which surely belong to the convoy: processed by the particle filter
- Targets badly discriminated from the convoy correspond to the rest of the targets: specifically processed.

This last type of target corresponds to *non-cooperative targets* whose dynamics are independent from the convoy dynamics but become close to the convoy such as target crossing or overtaking a convoy. In this case, the data association is difficult, so we propose to process these targets by the particle filter of the convoy which must be adapted. The different steps are the following:

- Detection: see section 5.2.2
- Tracking with the adapted particle filter: see section 5.2.4
- Exit detection: see section 5.2.3

5.2.2 Non-cooperative targets detection

Before convoy and MHT filtering, we have to check if any confirmed track is not well discriminated for any convoy targets. A gating validation is used based on track predicted state $\hat{X}^T_{t'}(k+1|k)$ ($\forall t' \in \{1,\ldots,m_T\}$ and m_T the number of confirmed tracks), convoy predicted state $\hat{\mathrm{X}}^c_t(k+1|k)$ and predicted state covariance matrix $P^c_t(k+1|k)$ ($\forall t \in \{1,\ldots,M\}$) and M the number of targets in the convoy. Finally, the set of non-cooperative targets badly discriminated with convoy at time k, $X^{nc}(k)$ are near the convoy and verify:

$$X^{nc}(k) = \left\{\hat{X}^T_{t'}(k)/[\hat{\mathrm{X}}^c_t(k+1|k) - \hat{X}^T_{t'}(k+1|k)]^T(P^c_t(k+1|k))^{-1}[\hat{\mathrm{X}}^c_t(k+1|k) - \hat{X}^T_{t'}(k+1|k)] < \gamma\right\} \tag{25}$$

where γ is the threshold obtained by the χ^2 test. For further information, see[7]. Tracks detected as close are processed in a special way described in section 5.2.4.

5.2.3 Non-cooperative target exit

Because it is non-cooperative, there is a time when the target leaves the convoy and must be reintegrated in the MHT process. In order to detect this time, a validation test T_{exit} is used as follows:

$$T_{exit} = \begin{cases} \text{true} & \text{if} \quad X_{test} = \{\phi\} \\ \text{false} & \text{if} \quad X_{test} \neq \{\phi\} \end{cases} \tag{26}$$

where X_{test} is defined by:

$$X_{test}(k) = \left\{ \begin{array}{l} \hat{X}^{nc}(k)/[\hat{\mathrm{X}}^c_t(k|k) - \hat{X}^{nc}(k|k)]^T((P^c_t(k|k))^{-1} + (P^{nc}(k|k))^{-1})[\hat{\mathrm{X}}^c_t(k|k) - \hat{X}^{nc}(k|k)] < \gamma, \\ \forall t \in \{1,\ldots,M\} \end{array} \right\} \tag{27}$$

meaning that the target moves away from the convoy.

If a non-cooperative target has finished crossing or overtaking a convoy, its track is *a posteriori* updated and returned to the MHT process.

5.2.4 Particle estimation with non-cooperative targets

When a non-cooperative target is poorly discriminated from a convoy target, it is integrated in the particle filter as other convoy tracks. But, because its dynamics are different from the convoy's, the particle filter must be adapted. At first, the state vector is modified:

$$X^{c\star}(k) = [\mathrm{X}^c_1(k),\ldots,\mathrm{X}^c_M(k), \dot{\mathrm{X}}^c_M(k), X^{nc}(k)]^T \tag{28}$$

with $X^{nc}(k)$ the non-cooperative target state vector given by (25) containing position and velocity information as in the state vector (1).

Concerning the data association, the constraint area is modified. Obviously, the velocity constraint cannot be applied. Also, $\forall t' > M$, the constraint $C_{\pi_{t',l}}(k)$ is similar than in the equation (22) without velocity constraint:

$$C_{\pi_{t',l}}(k) = C^g_{\pi_{t',l}}(k) \bigcap C^s_{\pi_{t',l}}(k) \tag{29}$$

In a similar way as in (19), the prediction equation for a convoy and poorly discriminated target can be written:

$$p(X^{c\star}_p(k)|X^{c\star}_p(k-1)) = \mathcal{N}(F^\star_c.X^{c\star}_p(k-1), Q^\star_c) \tag{30}$$

$$F^\star_c = \begin{pmatrix} F_c & 0 \\ 0 & F \end{pmatrix} \tag{31}$$

$$Q^\star_c = \begin{pmatrix} Q_c & 0 \\ 0 & Q \end{pmatrix} \tag{32}$$

where Q and F are the matrices given in (3) and (4).

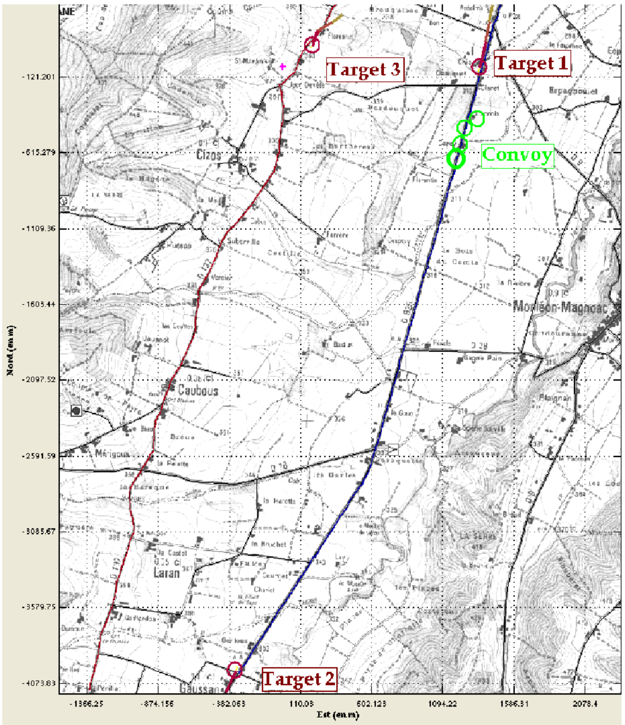


Figure 1. Scenario: cumulated MTI reports

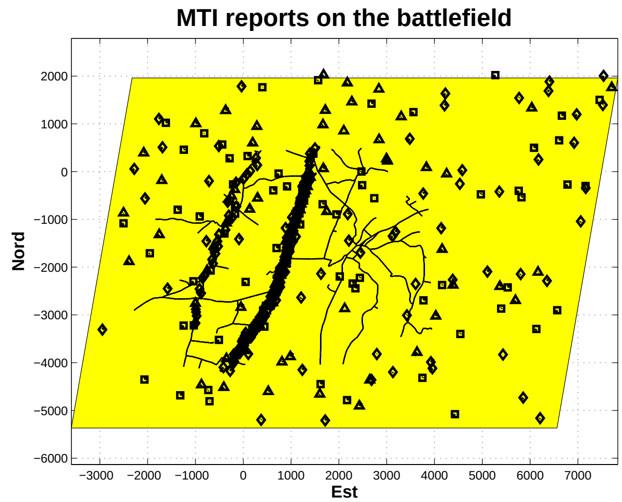


Figure 2. Snapshot of the cumulated MTI reports

5.3 Remark

Paragraphs 5.2.2, 5.2.3 and 5.2.4 describe principles and equations for only one poorly discriminated non-cooperative target. But all the equations can be adaptated for a finite number of non-cooperative targets as well as for several convoys.

6. SIMULATIONS AND RESULTS

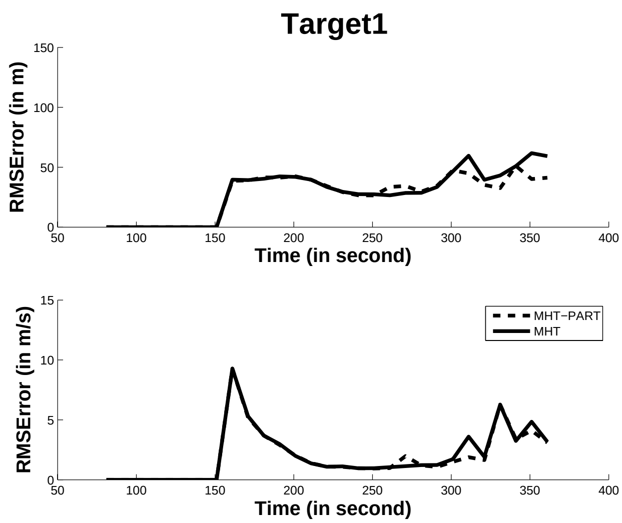
In the following, we present some simulation results that evaluate the performances of the proposed particle filtering approach and a classical IMM-MHT. The GMTI sensor has a linear trajectory and its altitude is 4000m. The typical measurement error is 20 meters in range and 0.008 in azimuth. The sensor scan time is 10s. The number of particles is fixed to $N_{part} = 500$.

Scenario time is limited to 430s. Trajectories are illustrated in Figure (1):

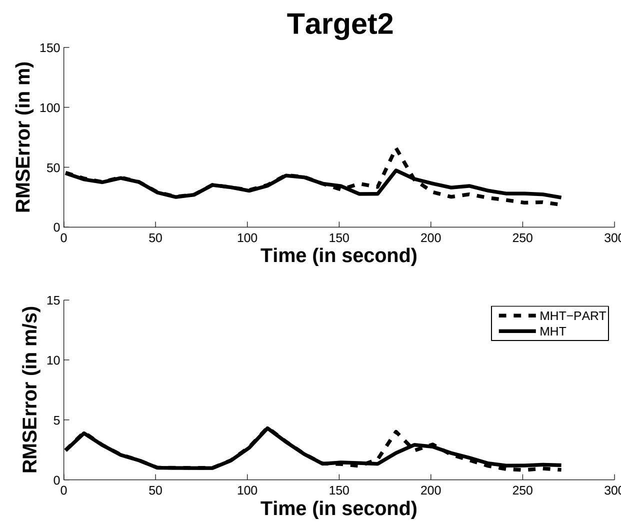
- Target 1 is moving on the blue road (to the East) with a constant velocity of 18m.s^{-1} from North to South.
- Target 2 is moving on the same road with a constant velocity of 18m.s^{-1} but from South to North.
- Target 3 is moving on the red road (to the West) with a constant velocity of 10m.s^{-1} from North to South.
- Targets 4-7 form a convoy moving on the blue road with a constant velocity of 10m.s^{-1} from North to South. Target 4 is the lead convoy target, Target 5-6 are the middle targets, Target 7 is the tail.

In the scenario, target 1 overtakes the convoy between times 200 and 300 and target 2 crosses the convoy between times 170 and 190 approximately. The cumulated MTI reports are shown in Figure 2.

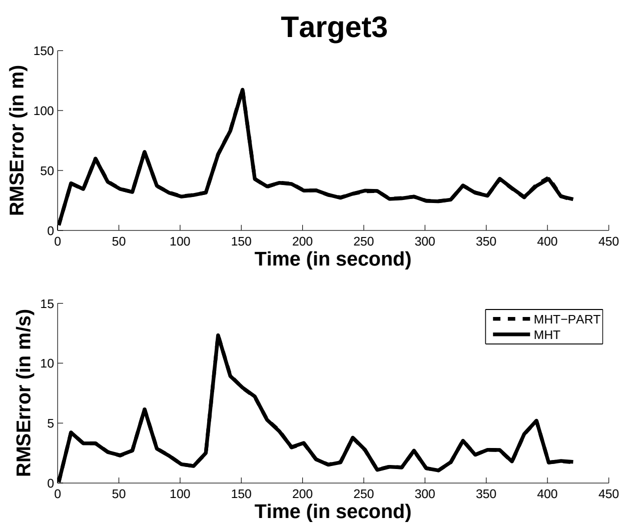
The performances of tracking algorithms have been compared, in Figure 3, based on the Root Mean Square Error (RMSE) in position (top) and velocity (bottom) for 100 independent Monte Carlo runs (a-g) and also on the track length ratio(h). The track length ratio is the ratio of the estimated track length over the actual track length. The performances of the proposed approach (dashed) are compared to those of a classical IMM-MTH (in black).



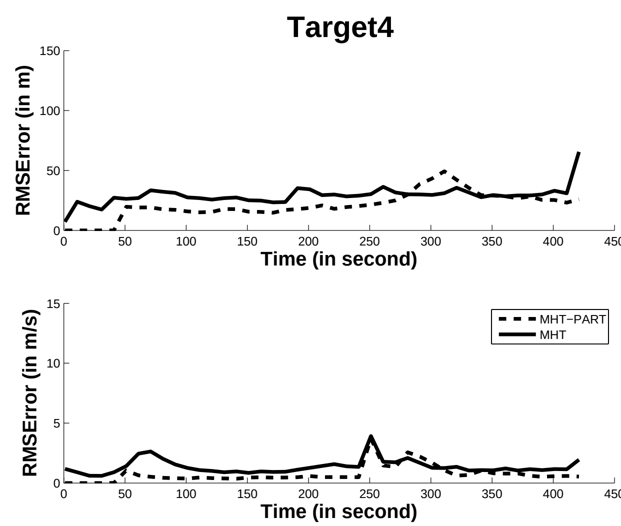
(a)



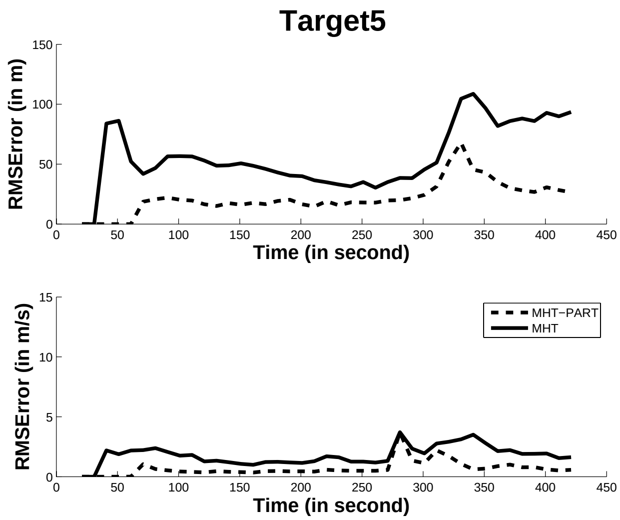
(b)



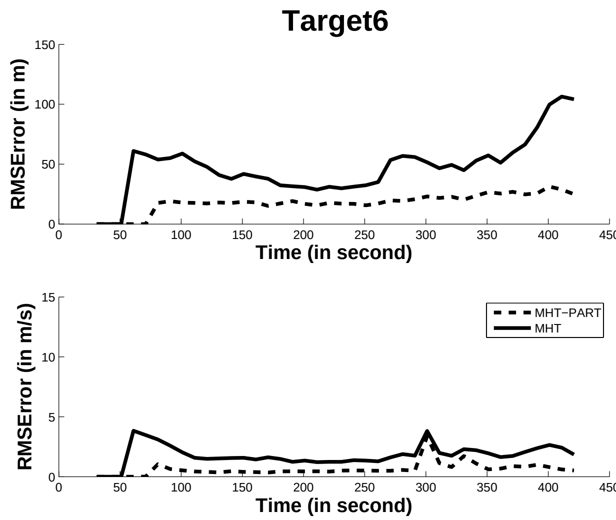
(c)



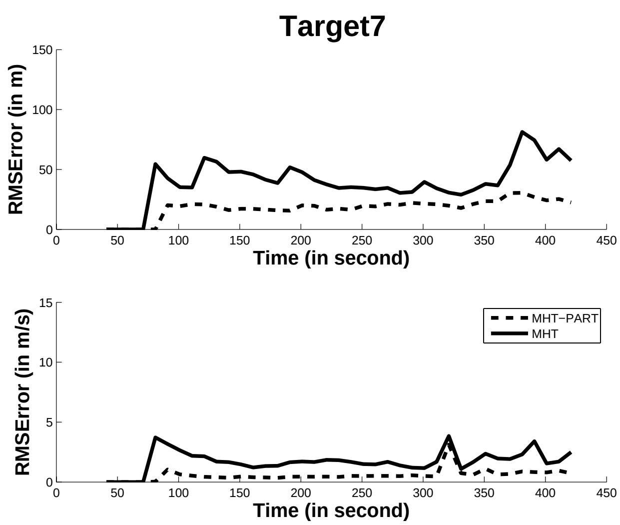
(d)



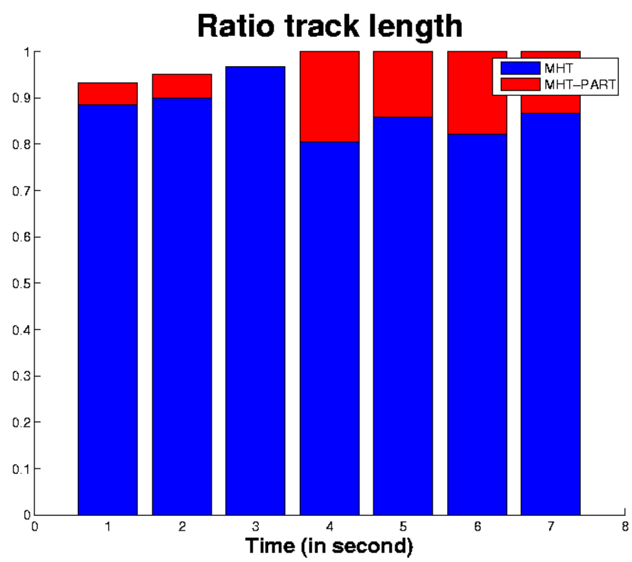
(e)



(f)



(g)



(h)

Figure 3. Measures of performances

First of all, the filters converge, and the RMSE for all targets are globally lower for our proposed approach than the RMSE for the IMM-MHT. As expected, the RMSE and track length ratio for target 3 are exactly the same because it is tracked with the same algorithm. In fact, target 3 does not cross the convoy during the simulation. For targets 4-7, RMSE are largely lower with our approach. For target 1 and 2, RMSE are very similar, differences beginning just at the crossing or overtaking time and finally RMSE are a little lower with our approach than with the MHT. Particle filtering, as a specific convoy tracking, is also more efficient than the IMM-MHT.

The problem with convoy tracking with a MHT is very obvious by regarding track length ratio of Figure 3-h. For convoy targets, it is from 0.85 to 0.7, although it is always 1 with particle MHT. Concerning the crossing target, as well as the overtaking target, track length ratio is only 0.85 for MHT and 1 for particle MHT, which allows to keep track of this type of targets.

7. CONCLUSION

In this paper, we proposed an algorithm to track convoys in the midst of civilian traffic because ground target tracking is a very complex task in battlefield surveillance. Very efficient algorithms to track multiple ground targets exist today, but now the next step in this field is to be able to detect objects which are interesting for military intelligence, called objects of interest, and to develop specific algorithms to track them. The proposed algorithm tracks convoy making the assumption that it has already been detected. Its specificity is to combine a particle approach, as a local tracking algorithm, with an IMM-MHT, very efficient in tracking independent targets. This meaningfully improves performances, especially when the tracked convoy is overtaken or crossed. We also proved, in this paper, that the convoy and the civilian targets are properly trackable. The challenge is now to be able to detect these convoys, considered as objects of interest.

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