BERNOULLI FILTER BASED ALGORITHM FOR JOINT TARGET TRACKING AND CLASSIFICATION IN A CLUTTERED ENVIRONMENT

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ABSTRACT

In this paper, single-target tracking using radar measurements is addressed. Recently, algorithms based on Bernoulli random finite sets have proved efficient in a cluttered environment. However, in Bayesian approaches, the choice of the motion model impacts the trajectory estimation accuracy. To select an appropriate set of motion models, a joint tracking and classification (JTC) algorithm can be used. The principle is to consider different target classes depending on their maneuvrability, each of them being associated to a set of motion models. In this context, additional information such as a target length extent measurement can improve both classification and trajectory estimation. Therefore, we propose a multiple-model Bernoulli filter to perform JTC. To jointly estimate the trajectory and the target length which is constant, a Rao-Blackwellized approach is considered. Another contribution is that a bank of probabilistic data association filters is run instead of Kalman filters to account for false detections.

Index Terms— Bernoulli filter, joint target tracking and classification, Rao-Blackwellized particle filter, multiple-model approach, random finite sets.

1. INTRODUCTION

In surveillance radar, point target measurements are generally composed of the radar-to-target distance and the bearing angle. These measurements are expected to arise from a target. When they come from the environment, they are referred as false detections. Given the set of available measurements, the goal is to on-line estimate the trajectory of the mobile object. However, several issues have still to be addressed. For instance, how to deal with false detections induced by the clutter or how to anticipate the type of trajectories that could be followed by the target?

On the one hand, algorithms based on a Bayesian formalism have been derived around the finite-set statistics (FISST). They consist in modelling both the false and true measurements as a single multi-object. In this way, no explicit target-to-measurement association is required when the trajectory is estimated. When dealing with a single-target scenario, the Bernoulli filter has been shown to be relevant in a cluttered environment [1].

On the other hand, estimation algorithms are based on a motion model describing the target kinematic. However, for targets with a high maneuvering capability, a single model is not enough to describe all the phases of the trajectory, leading to poor estimations. To address this issue, multiple-model (MM) algorithms can be considered but should not combine more than two or three [2] models to avoid a loss of accuracy. For this reason, joint tracking and classifications (JTC) algorithms have been proposed. In JTC, the targets are classified in different categories. For instance, target classes can be linked to the target maneuvering capabilities, ranging from the large targets such as a tanker, which are used to be non-maneuvering, to the smallest ones such as a rubber boat or a fishing vessel, which can be fastly accelerating. A class then indicates the most likely motion models to be used. The classification can be deduced from kinematic characteristics only [3, 4] or can use complementary information provided by electronic support measures (ESM) [5] for instance. A JTC method based on heterogeneous sensors is presented in [6]. Measurements of the target extent have also been of interest in tracking [7, 8] and in particular in JTC approaches [9, 10, 11, 12]. In absence of clutter, we have proposed various ways to estimate the target kinematic parameters in [13] for which the target length extent has proved useful through a JTC approach.

In this paper, we propose a multiple-motion-model Bernoulli filter to perform JTC using the target length extent. It is based on the random finite set (RFS) theory which provides a flexible framework to represent both the target and the measurements [14]. As the choice of the motion model is still of interest, we propose to derive a multiple-model Bernoulli filter. By using the target extent as complementary information in the algorithm, it simultaneously improves the trajectory estimation and the target classification. The Bernoulli filter can be implemented by particle filtering. Here, to improve state space exploration, we have propagated the particles according to the optimal proposal distribution. However, the particle filter is bound to degenerate while estimating the target length which is a constant. To overcome this problem, a Rao-Blackwellized approach is considered. As a consequence, only the trajectory is estimated by particle filtering whereas conditionnally upon the particles, the target length is estimated by a bank of probabilistic data association (PDA) filters. The latter is used instead of the classical bank of Kalman filters to directly take into account the false detections without re-introducing any hard decision through an association algorithm.

Our paper is organized as follows: in section 2, we derive the system model and the theoretical equations of the Bernoulli filter using both point target and target extent measurements. In section 3, the algorithm has been tested on simulated data and we study the relevance of the importance distribution and the use of the target length information.

In the following, $\delta_x(y)$ is the Kronecker symbol which is equal to 1 if $x = y$ and 0 otherwise. In addition, $\sim$ means *is distributed according to* and $\mathcal{N}(x, \mu, \Sigma)$ denotes the multivariate Gaussian distribution with mean μ and covariance matrix Σ. $|X|$ is the cardinal of X. $x_{k_1:k_2}$ denotes the collection of x from the instant k_1 to the instant k_2. $diag(a_1, ..., a_n)$ is the $n \times n$ diagonal matrix whose diagonal elements are $a_1, ..., a_n$.

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2. ALGORITHM PRESENTATION

2.1. RFS modelling

The goal is to estimate the target state by using the radar measurements. In order to describe a single-target scenario with potential false detections due to the clutter, two RFSs are considered: one for the state representation and one for the measurements. In this paper, the classical Bernoulli filter is extended to allow for multiple motion models. C classes of targets are considered and each class can be represented by a set of motion models. For a given class c, M_k^c denotes the number of candidate motion models. It should be noted that the sequence of the models over time is a Markov chain and the probability to switch from the i^{th} model to the j^{th} is denoted p_{ij} with $\sum_{j=1}^{M_k^c} p_{ij} = 1$.

State model: this RFS is denoted X_k for each instant k and describes the target dynamics. Two configurations can be considered:

$$X_k = \begin{cases} \{\emptyset\} & \text{when there is no target,} \\ \{\mathbf{x}_k\} & \text{when the target is present,} \end{cases} \tag{1}$$

with the state vector $\mathbf{x}_k = [x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k]^T$ in which (x_k, y_k), $(\dot{x}_k, \dot{y}_k)$ and $(\ddot{x}_k, \ddot{y}_k)$ are respectively the current target 2D-coordinates of position, velocity and acceleration.

A Bernoulli RFS is particularly suitable to represent the state behavior. Let p_b refer to the probability of "birth" - the object was not here at the previous instant and appears - and let p_s be the probability of "survival" - the object was here at the previous instant and is still here. In case of "birth", the corresponding birth probability density function (PDF) is denoted by $b_{k|k-1}(\mathbf{x}_k|c)$ which is assumed to be known. Conversely, when the target "survives", the transition PDF depends on the current motion model m_k^c and is denoted $\pi_{k|k-1}^{m_k^c}(\mathbf{x}_k|\mathbf{x}_{k-1})$. Unlike in the classical derivation of the Bernoulli transition FISST PDF [1] where only one model is used [14], the multiple-model transition FISST PDF $\phi_{k|k-1}(X_k|X_{k-1}, c)$ is given by:

$$\phi_{k|k-1}(X_k|\emptyset, c) = \begin{cases} 1 - p_b & \text{if } X = \emptyset, \\ p_b b_{k|k-1}(\mathbf{x}_k|c) & \text{if } X_k = \{\mathbf{x}_k\}, \end{cases} \tag{2}$$

$$\phi_{k|k-1}(X_k|\{\mathbf{x}_{k-1}\}, c) = \begin{cases} 1 - p_s \text{ if } X = \emptyset, \\ p_s \sum_{m_k^c=1}^{M_k^c} p_{m_{k-1}^c m_k^c} \pi_{k|k-1}^{m_k^c}(\mathbf{x}_k|\mathbf{x}_{k-1}) \\ \text{if } X_k = \{\mathbf{x}_k\}. \end{cases} \tag{3}$$

with $p_{m_{k-1}^c m_k^c}$ the probability to switch from the model used at $k-1$ to the one used at k in the class c.

Measurement model: by considering that J_k measurements are available at the instant k, the measurement RFS is denoted Ψ_k and is defined as:

$$\Psi_k = \{\psi_{k,1}, ..., \psi_{k,J_k}\}, \tag{4}$$

where $\left\{\psi_{k,j} = [r_{k,j}, \theta_{k,j}, L_{k,j}]^T\right\}_{j=1,\dots,J_k}$. $r_{k,j}$ is the j^{th} measurement of the radar-to-target distance, $\theta_{k,j}$ the j^{th} measurement of the bearing angle (ba) and $L_{k,j}$ the target length extent measurement.

Depending on the characteristics of the ground and the radar settings, a mean number λ of false detections is expected on the observation area. Then, Ψ_k is modelled by a Poisson RFS. The cardinal satisfies:

$$J_k = P\{|\Psi_k| = a\} = \frac{e^{-\lambda}\lambda^a}{a!}, a = 0, 1, 2... \tag{5}$$

False detections are modelled as independent and identically distributed random vectors with a uniform PDF $u(\psi)$ as it is supposed there is no prior knowledge available on their location. The likelihood FISST PDF ξ_k of all the detections coming from the clutter is given by:

$$\xi_k(\Psi_k|\emptyset) \triangleq \kappa(\Psi_k) = e^{-\lambda} \prod_{\psi \in \Psi_k} \lambda u(\psi). \tag{6}$$

When a target is effectively present, the FISST PDF becomes:

$$\xi_k(\Psi_k|\{\mathbf{x}_k\}, l) = \tag{7}$$
$$\kappa(\Psi_k) \left[1 - p_d + p_d \sum_{\psi \in \Psi_k} \tilde{g}(\psi|\mathbf{x}_k, l) \frac{\kappa(\Psi_k \backslash \{\psi\})}{\kappa(\Psi_k)}\right],$$

with p_d the probability of detection considered here constant, l the constant target length and $\tilde{g}(.|.)$ the likelihood function defined in the following equation. To simplify the notations, we can omit the second index on the measurements, $\tilde{g}(.|.)$ is then expressed as follows:

$$\tilde{g}(\psi_k|\mathbf{x}_k, l) \propto g_k(r_k, \theta_k|\mathbf{x}_k) g'_k(L_k|\mathbf{x}_k, l) \tag{8}$$

In (8), the two terms $g_k(r_k, \theta_k|\mathbf{x}_k)$ and $g'_k(L_k|\mathbf{x}_k, l)$ depend on the measurement model.

Concerning $g_k(r_k, \theta_k|\mathbf{x}_k)$, one has:

$$g_k(r_k, \theta_k|\mathbf{x}_k) = \mathcal{N}(x, h_k(x), R_k)_{|x=\mathbf{x}_k}, \tag{9}$$

with $R_k = diag(\sigma_d^2, \sigma_{ba}^2)$ the covariance matrix of the measurement noise on r_k and θ_k. In addition, $h_k(\mathbf{x}_k)$ is defined as follows:

$$h_k(\mathbf{x}_k) = \begin{bmatrix} \sqrt{(x_k - x_k^r)^2 + (y_k - y_k^r)^2} \\ \tan^{-1}\left(\frac{y_k - y_k^r}{x_k - x_k^r}\right) \end{bmatrix}, \tag{10}$$

with (x_k^r, y_k^r) the radar coordinates.

Concerning $g'_k(L_k|\mathbf{x}_k, l)$, L_k is related to the target length l and depends on the target geometry, its orientation and its position relative to the radar. With an elliptic geometry for the target, the relation between L_k and the true target length l was defined in [7], leading to:

$$g'_k(L_k|\mathbf{x}_k, l) = \mathcal{N}(L, \alpha_k l, \sigma_{u_k}^2)_{|L=L_k}, \tag{11}$$

with:

$$\alpha_k = \frac{\sqrt{(\dot{y}_k\Delta_{y_k} + \dot{x}_k\Delta_{x_k})^2 + \left(\frac{b}{a}\right)^2 (\dot{y}_k\Delta_{x_k} - \dot{x}_k\Delta_{y_k})^2}}{\sqrt{\Delta_{x_k}^2 + \Delta_{y_k}^2}\sqrt{\dot{x}_k^2 + \dot{y}_k^2}}, \tag{12}$$

with $\Delta_{x_k} = x_k - x_k^r$, $\Delta_{y_k} = y_k - y_k^r$. b/a is the ratio between the minor and the major axis of the ellipse and is an *a priori* choice for the model [7]. It should be noted that the likelihood (11) has the advantage of being Gaussian regarding the target length.

[1]In the FISST theory developed by Mahler [15], considering a RFS $X = [\mathbf{x}_1, ..., \mathbf{x}_n]$ whose cardinal is random and equal to n the FISST PDF $\tilde{f}$ can be integrated in the FISST framework as follows:

$$\int \tilde{f}(X)\delta X = \tilde{f}(\emptyset) + \sum_{n=1}^{+\infty} \frac{1}{n!} \int \tilde{f}(\{\mathbf{x}_1, ..., \mathbf{x}_n\}) d\mathbf{x}_1...d\mathbf{x}_n,$$

with:

$$\tilde{f}(\{\mathbf{x}_1, ..., \mathbf{x}_n\}) = n!\rho(n)p_n(\mathbf{x}_1, ..., \mathbf{x}_n),$$

$\rho(n) = P\{|X| = n\}$ and $p_n(\mathbf{x}_1, ..., \mathbf{x}_n)$ are symmetric joint distributions characterizing their element distributions over the state space.

In the next subsection, we present the estimation of the state vector by using a multiple-model Bernoulli filter based on the proposed RFS modelling. Since the computation cannot be carried out analytically, a particle filter (PF) implementation is used. However, to exploit the measurement L_k, the target length has to be jointly estimated with the kinematic parameters. Since it is constant, we select a Rao-Blackwellized approach to avoid PF degeneracy. One of the novelty is also that a bank of probabilistic data association filters (PDA) is run instead of classical Kalman filters in order to take into account the false alarms.

2.2. Prediction and update equations

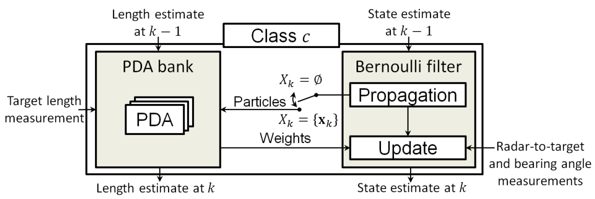

Fig. 1: Proposed multi-class Bernoulli filter

The Bernoulli filter enforces the posterior RFS to be Bernoulli. The Rao-Blackwellized approach consists in decomposing the posterior FISST PDF as follows:

$$\begin{aligned}&\tilde{f}_{k|k}(X_{1:k}, l|\Psi_{1:k}, c) \\ &\quad= f'_{k|k}(l|X_{1:k}, \Psi_{1:k}, c) f_{k|k}(X_{1:k}|\Psi_{1:k}, c),\end{aligned} \tag{13}$$

where $f_{k|k}(X_{1:k}|\Psi_{1:k}, c)$ is also a Bernoulli FISST PDF. The marginal of this FISST PDF at the current time takes the following form:

$$f_{k|k}(X_k|\Psi_{1:k}, c) = \begin{cases} 1 - q_{k|k}, \text{ if } X_k = \emptyset, \\ q_{k|k} s_{k|k}(\mathbf{x}_k|\Psi_{1:k}, c), \\ \text{if } X_k = \{\mathbf{x}_k\}, \end{cases} \tag{14}$$

with $q_{k|k}$ the probability of presence of the target and $1 - q_{k|k}$, the complementary one, *i.e.* the probability of absence. As we consider a single-target scenario, $q_{k|k} = P\{|X_k| = 1|\Psi_{1:k}\}$. For its part, $s_{k|k}(\mathbf{x}_k|\Psi_{1:k}, c)$ is the posterior spatial PDF.
Concerning $f'_{k|k}(l|X_{1:k}, \Psi_{1:k}, c)$, since there is no ambiguity on the cardinal conditionally upon X_k, this FISST PDF reduces to a PDF. The two terms appearing in (13) are then used to implement a Rao-Blackwellized approach.
In a first step, let us detail the calculation of $f_{k|k}(X_k|\Psi_{1:k}, c)$.
Prediction equation: once the transition FISST PDF (2) is defined, the prediction equations are derived from (14) and from the following relation:

$$\begin{aligned}&f_{k|k-1}(X_k|\Psi_{1:k-1}, c) = \\ &\int \phi_{k|k-1}(X_k|X', c) f_{k-1|k-1}(X'|\Psi_{1:k-1}, c)\delta X', \\ &= \phi_{k|k-1}(X_k|\emptyset, c) f_{k-1|k-1}(\emptyset|\Psi_{1:k-1}, c) \\ &+ \int \phi_{k|k-1}(X_k|X', c) f_{k-1|k-1}(X'|\Psi_{1:k-1}, c)\delta X',\end{aligned} \tag{15}$$

Considering the case when there is no target and combining (2), (14) and (15) leads to the prediction of the existence probability:

$$q_{k|k-1} = p_b(1 - q_{k-1|k-1}) + p_s q_{k-1|k-1}, \tag{16}$$

and the spatial PDF prediction can be expressed as the following sum of two terms:

$$\begin{aligned}&s_{k|k-1}(\mathbf{x}_k|\Psi_{1:k}, c) = \frac{p_b(1 - q_{k-1|k-1}) b_{k|k-1}(\mathbf{x}_k|c)}{q_{k|k-1}} \\ &+ \frac{p_s q_{k-1|k-1}}{q_{k|k-1}} \\ &\times \int \sum_{m_k^c=1}^{M_k^c} p_{m_{k-1}^c m_k^c} \pi_{k|k-1}^{m_k^c}(\mathbf{x}_k|x') s_{k-1|k-1}(x'|\Psi_{1:k}, c) dx'.\end{aligned} \tag{17}$$

Update equation: by using (6), (7) and the Bayes rule as derived in the FISST theory in [15], the updated FISST PDF is given by:

$$f_{k|k}(X_k|\Psi_{1:k}, c) = \frac{\xi_k(\Psi_k|X_k) f_{k|k-1}(X_k|\Psi_{1:k-1}, c)}{f_k(\Psi_k|\Psi_{1:k-1})}. \tag{18}$$

By considering the case when there is no target and combining (6), (7), (14) and (18), the update equation of the probability of existence is given by:

$$q_{k|k} = \frac{1 - \Delta_k}{1 - q_{k|k-1}\Delta_k} q_{k|k-1}, \tag{19}$$

where

$$\begin{aligned}&\Delta_k = p_d. \\ &\left(1 - \sum_{\psi \in \Psi_k} \frac{\int \tilde{g}_k(\psi|x, l) s_{k|k-1}(x|\Psi_{1:k-1}, c) f_l(l|\Psi_{1:k-1}, c) dl dx}{\lambda u(\psi)}\right),\end{aligned} \tag{20}$$

with $f_l(l|\Psi_{1:k-1}, c)$ the predictive distribution on the target length. By considering the case when the target is present and by combining (7), (14) and (18), the update equation of the spatial PDF is derived as:

$$\begin{aligned}&s_{k|k}(\mathbf{x}_k|\Psi_{1:k}, c) = \\ &\frac{1 - p_d + p_d \sum_{\psi \in \Psi_k} \frac{\int \tilde{g}_k(\psi|\mathbf{x}_k, l) f_l(l|\Psi_{1:k-1}, c) dl}{\lambda u(\psi)}}{1 - \Delta_k} s_{k|k-1}(\mathbf{x}_k|\Psi_{1:k}, c).\end{aligned} \tag{21}$$

Since the above equations are analytically intractable, a PF implementation is considered and the FISST PDF of interest is approximated as:

$$f_{k|k}(X_{1:k}|\Psi_{1:k}, c) \simeq \sum_{i=1}^{N} w_k^{(i,c)} \delta(X_{1:k} - X_{1:k}^{(i,c)}), \tag{22}$$

where the $X_{1:k}^{(i,c)}$ are the particles and the $w_k^{(i,c)}$ the weights. For the sake of brevity, we omit the PF derivation in this paper. However, it should be noted that the particles are simulated with the optimal law of propagation.
The term $f'_{k|k}(l|X_{1:k}^{(i,c)}, \Psi_{1:k}, c)$ can then be independently updated conditionally upon each particle. It should be noted that knowing the current i^{th} particle, the dependency on the bearing angles and distance measurements disappears.

Let us decompose the measurement RFS Ψ_k into two RFS $Z_k = \{\mathbf{z}_{k,1}, ..., \mathbf{z}_{k,J_k}\}$ with $\left\{\mathbf{z}_{k,j} = [r_{k,j}, \theta_{k,j}]^T\right\}_{j=1,\dots,J_k}$ and

$\Lambda_k = \{L_{k,1}, ..., L_{k,J_k}\}$, then $f'_{k|k}(l|X_{1:k}^{(i,c)}, \Psi_{1:k}, c)$ reduces to $f'_{k|k}(l|X_{1:k}^{(i,c)}, \Lambda_{1:k}, c)$.

Since the $\{L_{k,j}\}_{j=1,...,J_k}$ depend linearly on l and the measurement noise is Gaussian, the target length can then be optimally estimated by a Kalman filter. However, at one instant, as more than one measurement can be available, a target-to-measurement association algorithm would be required. Algorithms perfoming hard decisions on the association suffer a performance decrease when the number of false detections increases. For this reason, we suggest estimating l by a probabilistic data association Kalman filter [16]. It assumes that the posterior PDF of l is given by the following sum:

$$f'_{k|k}(l|X_{1:k}^{(i,c)}, \Lambda_{1:k}, c) = \sum_{j=0}^{J_k} \tilde{\beta}_{k,j}^{(i,c)} p(l|L_{k,j}, \Lambda_{1:k-1}, X_{1:k}^{(i,c)}, c). \tag{23}$$

The weight $\tilde{\beta}_{k,j}^{(i,c)}$ represents the probability that the j^{th} measurement is the one that arises from the target. $j = 0$ corresponds to the missed detection hypothesis. Note that from now on, all the quantities are computed conditionally to the i^{th} particle, which is denoted by the upperscript (i, c). To calculate the weights $\{\tilde{\beta}_{k,j}^{(i,c)}\}_{j=0,...,J_k}$, the likelihood $\beta_{k,j}^{(i,c)}$ is first computed as follows:

$$\beta_{k,j}^{(i,c)} = \begin{cases} 1 - p_d & \text{for } j = 0 \\ \frac{\mathcal{N}(L;\alpha_k^{(i,c)}\hat{l}_{k-1|k-1}^{(i,c)}, S_k^{(i,c)})_{|L=L_{k,j}} p_d}{\lambda} & \text{otherwise,} \end{cases} \tag{24}$$

with $S_k^{(i,c)} = \left(\alpha_k^{(i,c)}\right)^2 P_{k-1|k-1}^{(i,c)} + \sigma_{u_k}^2$, $P_{k-1|k-1}^{(i,c)}$ the Kalman error variance on the estimation recursively obtained. $\hat{l}_{k-1|k-1}^{(i,c)}$ is the estimate of l at the instant $k-1$ knowing $\Lambda_{1:k-1}$. In addition, $\{\tilde{\beta}_{k,j}^{(i,c)}\}_{j=0,...,J_k}$ corresponds to the normalized $\{\beta_{k,j}^{(i,c)}\}_{j=0,...,J_k}$. In our PF implementation, a PDA is thus run for each particle.
In the next subsection, we present some simulation results.

3. COMPARATIVE STUDY

In this simulation part, the relevance of the proposed Bernoulli PDA Rao-Blackwellized particle filter using the target extent measurement is studied.

Simulation protocol:
A scenario with two targets is considered. The first one, denoted T1, represents a non-maneuvering target. Its length is $120\,m$, and its trajectory is generated through two constant velocity (CV) models with standard deviations on the acceleration $\sigma_{CV1} = 5 \times 10^{-2}\ m.s^{-2}$ and $\sigma_{CV2} = 0.2\,m.s^{-2}$, the latter model will be referred to CV2 in the following. The probability to switch from one model to the other is 0.02 and the starting probability is 0.5 for both models. The second target, denoted T2, represents a maneuvering light object whose length is $10\ m$. Its trajectory can be generated by 5 motion models. Two of them are CV motion models with standard deviations on the acceleration 0.1 and $0.2\ m.s^{-2}$. The 3 others are Singer models whose standard deviations on the acceleration are $1, 2$ or $5\ m.s^{-2}$ and their correlation constant is $\tau = 15\ s$. The probability to switch from one model to another one is 0.1.
For these two targets, the characteristics of the measurement noises are the same and the standard deviations are $\sigma_d = 10\ m$ for the radar-to-target distance, $\sigma_{ba} = 0.001\ rad$ for the bearing angle and $\sigma_u = 5\ m$ for the target extent measurement. The period T between two scans is constant and is equal to $1\ s$. The probability of detection is 0.95 and the false detection rate is 10^{-6} per m^2. 100 Monte Carlo simulations are carried out to compute average results and each trajectory has 100 scans.

Comparison:
Four estimation filters are compared. The first one, denoted EKF, is an extended Kalman filter run with the proper motion model. It can be seen as a reference. The three others are multiple-class Bernoulli filters and are denoted by BF1, BF2 and BF3. They are run with $C = 2$ and 1000 particles for each motion model. The first class uses CV2 as motion model. The second class uses a CV2 and a Singer model with $\sigma_{Singer} = 5\ m.s^{-2}$ and $\tau = 15\ s$. The correct measurement model is used for every filter. $BF1$ uses an *a priori* propagation law in the PF whereas BF2 and BF3 use the optimal law. In addition, the target extent measurements with the correct associated measurement model is used in BF3.

			Our methods:		
Config. & Target	Meas.	EKF	BF1	BF2	BF3
T1	7.68	5.62	3.87	3.79	3.40
T2	7.72	6.23	4.61	4.43	4.34

Table 1: Root mean square errors on positions (m)

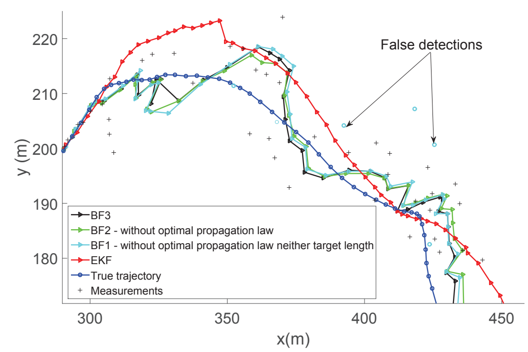

Fig. 2: T2 true trajectory and estimations

According to Table 1, the proposed multiple-class Bernoulli filter for JTC which uses the target extent measurement manages well false detections and the non-linearity introduced by the measurement-to-state relation. Optimal law for particle propagation improves the estimation accuracy. When using the target extent, the algorithm provides an even more accurate result by facilitating the classification. In Fig. 2, one simulation with T2 is presented.

4. CONCLUSIONS AND PERSPECTIVES

In this paper, we derive a multiple-class Bernoulli filter for JTC which uses the target extent measurement. It should be noted that when using the bank of PDA, the highly parallelisable structure inherited from the particle filter implementation is still preserved. As the estimated length is a scalar, no costly operations such as matrix inversions are needed. In further works, we plan to investigate a multi-target scenario by using a labeled multi-Bernoulli filter. It would have the advantage of allowing each target to be propagated with a different set of models which is not the case with current approaches based on probability hypothesis density (PHD) filters.

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