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Joint target tracking and classification via RFS-based multiple model filtering

Wei Yang *, Yaowen Fu, Xiang Li

College of Electronic Science and Engineering, National University of Defense Technology, Changsha 410073, PR China

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ABSTRACT

Firstly, a multiple model extension of the random finite set (RFS)-based single-target Bayesian filtering (STBF), referred as MM-STBF, is presented to accommodate the possible target maneuvering behavior in a straightforward manner. This paper is concerned with joint target tracking and classification (JTC) which are closely coupled. In particular, we take into account extraneous target-originated measurements which were not modeled in the existing JTC algorithms. Therefore, the main contribution is that the paper derives a new JTC algorithm based on the MM-STBF, i.e., MM-STBF–JTC. The MM-STBF–JTC is an optimal Bayesian solution, which can simultaneously accommodate unknown data association, miss-detection, clutter and several measurements originated from a target. The MM-STBF–JTC can reduce to a traditional JTC algorithm under some assumptions. The simulation results are provided to demonstrate the tracking and classification performance of the MM-STBF–JTC algorithm.

1. Introduction

The essential problems of any surveillance systems are target tracking and classification that usually treated separately for simplicity. In fact, they are closely coupled as pointed out in [1–5]. By now, there exist several 'Joint Tracking and Classification (JTC)' methods which estimate the target kinematic state and class jointly. In the literature, there are two kinds of JTC algorithms as indicated in [4], i.e., point-target-motion-model based JTC (PTJTC) and rigid-target-motion-model based JTC (RTJTC). The RTJTC algorithms proposed in [2,6,7] are limited to some specific JTC systems and bear heavy computation, while the PTJTC algorithms discussed in [3,4,8–12] can adapt to all JTC systems. For a detailed description of these JTC algorithms, the readers can be referred to [13]. Note that an alternative solution to the PTJTC problem is presented in the transferable belief model (TBM) paradigm in one-dimensional measurement space [14,15]. For the tracking phase, the state estimation is obtained from the classical Kalman filter, although it provides another interpretation under the TBM paradigm. For the classification phase, in [14,15] the authors differentiate the target classes and behaviors. Since more flexible ways are provided in the TBM paradigm to represent the target class-behavior relations, more reasonable results can be got within it than the Bayesian paradigm. All those above PTJTC algorithms focus on unity detection probability and no clutter case.

This paper is concerned with joint target tracking and classification in a cluttered environment, where the target can generate several measurements. The random finite set (RFS) framework of Mahler has several advantages [16–19] for this aim. First, the RFS framework overcomes the combinatorial computations due to data association while accommodating Poisson false alarms and miss-detection. Second, there is a rigorous Bayesian solution (i.e., single-target Bayesian filtering, STBF) in the RFS formalism for target tracking, where several measurements may be originated from the same target, while traditional association-based tracking approaches cannot be easily adapted to it. As for the TBM paradigm, no explicit form of the state estimation is available to accommodate clutter, miss-detection and/or extraneous target-originated measurements. One possible approach to the JTC problem in the above complicated situation is that the classification phase is handled in the TBM paradigm, whereas the tracking phase is handled in another paradigm. This leads theoretical inconsistency as stated in [14,15]. Besides, how to derive the distribution function (i.e., basic belief assignment in the TBM paradigm) of the set of possible behaviors needs further investigation in multi-dimensional measurement space [20,21]. The Ref. [21] presents a formulation for the derivation of basic belief assignment, but it cannot perform in general except for linear and Gaussian case. Finally and most importantly, the feature measurement likelihood in the TBM paradigm cannot be easily incorporated into the construction of the distribution function in behavior space. In fact, more and more features (such as target length and radar cross section) can be obtained along with the enhancement of sensor resolution, which can be utilized to assist tracking [22,23] and apparently augment

* Corresponding author. Tel.: +86 1346 7535618; fax: +86 0731 84575714.
E-mail address: yw850716@sina.com (W. Yang).

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the classification ability. These reasons motivate our choice of the Bayesian paradigm for developing the JTC algorithm.

Firstly, a multiple model extension of the STBF (i.e., MM-STBF) is presented to simultaneously accommodate the possible target maneuvering behavior, unknown data association, extraneous target-originated measurements, miss-detection and clutter, although it is straightforward. The main contribution is to derive a new JTC algorithm (i.e., MM-STBF–JTC) based on the MM-STBF within the Bayesian paradigm. The MM-STBF–JTC is an optimal Bayesian solution, which can simultaneously accommodate unknown data association, miss-detection, clutter and several measurements originated from a target. Assuming single model, exactly one target-generated measurement, the unity detection probability, and no clutter, the MM-STBF–JTC reduces to a classical JTC algorithm [10]. The MM-STBF–JTC avoids that the target classes can be permanently lost if they are with temporarily low likelihoods [8].

Section 2 introduces the STBF and then presents a multiple model extension of it, referred as the MM-STBF. A novel JTC algorithm is derived based on the MM-STBF in Section 3 within the Bayesian paradigm, which is illustrated by means of a representative example in Section 4. Section 5 concludes the paper.

2. Multiple model extension of the STBF

2.1. The STBF

The classical Bayesian recursion is formulated for single-target systems under ideal conditions, i.e., no clutter and exactly one measurement. However, there may be multiple measurements originated from the target in reality due to electronic counter measures, multi-path reflections, etc. The sensor can also receive some spurious measurements. The appearance order of measurements at any time step has no physical significance [19]. Assume that $\mathcal{Z}$ is the single-target observation space. The sensor at time k can receive an unordered measurement set $Z_k \in \mathcal{F}(\mathcal{Z})$. $\mathcal{F}(\mathcal{Z})$ is a space that consists of finite subsets of $\mathcal{Z}$. Vo et al. derived a rigorous set-valued measurement likelihood that encapsulates the models of clutter and several measurements originated from the target and then proposed a Bayesian filter (i.e., the STBF) [19].

Suppose at time k, the sensor receives M_k measurements (i.e., $Z_k = \{z_{k,1},\ldots,z_{k,M(k)}\}$) and the state vector of target is $\boldsymbol{x} \in \mathcal{X}$. $\mathcal{X}$ denotes the state space. The measuring process can be modeled by the equation $Z_k = W_k \cup E_k(\boldsymbol{x}) \cup \Theta_k(\boldsymbol{x})$. Note that W_k denotes the random finite set (RFS) of false alarms, the RFS $E_k(\boldsymbol{x})$ consists of extraneous target-originated measurements, and the RFS $\Theta_k(\boldsymbol{x})$ consists of the primary measurement originated from the target. Assume that conditioned on $\boldsymbol{x}$, $\Theta_k(\boldsymbol{x})$, $E_k(\boldsymbol{x})$ and W_k are independent.

$\Theta_k(\boldsymbol{x})$ is modeled by

$$\Theta_k(\boldsymbol{x}) = \begin{cases} \{\boldsymbol{z}_k^*\} & \text{with probability density } P_D(\boldsymbol{x})h_{\boldsymbol{z}_k^*}(\boldsymbol{x}) \\ \varnothing & \text{with probability } 1 - P_D(\boldsymbol{x}) \end{cases} \tag{1}$$

where $P_D(\cdot)$ is the detection probability of primary measurement, and $h_{\boldsymbol{z}_k^*}(\boldsymbol{x}) = g(\boldsymbol{z}_k^*|\boldsymbol{x})$ denotes the likelihood for the primary measurement $\boldsymbol{z}_k^*$. W_k and $E_k(\boldsymbol{x})$ are two Poisson RFSs whose intensities are denoted by $\upsilon_{E,k}(\cdot\ |\boldsymbol{x})$ and $\upsilon_{W,k}(\cdot)$, respectively. These two RFSs can be grouped as $K_k(\boldsymbol{x}) = W_k \cup E_k(\boldsymbol{x})$ which is also a Poisson RFS. The intensity of $K_k(\boldsymbol{x})$ is $\upsilon_{K,k}(\cdot|\boldsymbol{x}) = \upsilon_{W,k}(\cdot) + \upsilon_{E,k}(\cdot|\boldsymbol{x})$ and its cardinality distribution is denoted by $\rho_{K,k}(\cdot|\boldsymbol{x})$. Each element $\boldsymbol{z} \in K_k(\boldsymbol{x})$ is distributed according to the probability density

$$c_k(\cdot|\boldsymbol{x}) = \upsilon_{K,k}(\cdot|\boldsymbol{x}) \Big/ \int \upsilon_{K,k}(\boldsymbol{z}'|\boldsymbol{x})d\boldsymbol{z}' \tag{2}$$

Under the above assumptions, the STBF estimates the posterior density recursively through

$$p_{k|k-1}(\boldsymbol{x}|Z_{1:k-1}) = \int p_{k-1}(\boldsymbol{x}'|Z_{1:k-1})f_{k|k-1}(\boldsymbol{x}|\boldsymbol{x}',Z_{1:k-1})d\boldsymbol{x}' \tag{3}$$

$$p_k(\boldsymbol{x}|Z_{1:k}) = \frac{p_{k|k-1}(\boldsymbol{x}|Z_{1:k-1})\eta(Z_k|\boldsymbol{x})}{\int p_{k|k-1}(\boldsymbol{x}'|Z_{1:k-1})\eta(Z_k|\boldsymbol{x}')d\boldsymbol{x}'} \tag{4}$$

where $Z_{1:k} = [Z_1,\ldots,Z_k]$, and the generalized set-valued likelihood $\eta(Z_k|x)$ is given by

$$\eta(Z_k|\boldsymbol{x}) = K_o^{|Z_k|}(|Z_k|!)(1-p_D)\rho_{K,k}(|Z_k||\boldsymbol{x})\prod_{\boldsymbol{z}_k\in Z_k} c_k(\boldsymbol{z}_k|\boldsymbol{x}) + [(|Z_k| - 1)!]p_D\rho_{K,k}(|Z_k|-1|\boldsymbol{x})\sum_{\boldsymbol{z}_k^*\in Z_k} h_{\boldsymbol{z}_k^*}(\boldsymbol{x})\prod_{\boldsymbol{z}_k\neq\boldsymbol{z}_k^*} c_k(\boldsymbol{z}_k|\boldsymbol{x}) \tag{5}$$

where K_o denotes the unit of volume on $\mathcal{Z}$ and $|\cdot|$ indicates the cardinality.

In addition, Vo et al. proposed a particle implementation and a Gaussian mixture implementation of the STBF, respectively for generic models and linear Gaussian models (see [19] for detailed description).

The tracking methods based a single model filter may fail because maneuvering target might switch between different operation modes [24]. However, the multiple model techniques are effective to this case [25]. Next, a multiple model extension of the STBF is provided to accommodate the possible target maneuvering behavior, although it is straightforward.

2.2. Multiple model extension of the STBF

The target state vector $\tilde{\boldsymbol{x}} = [\boldsymbol{x}^T \quad r]^T$ is augmented with a model variable $r \in \mathcal{M}, \mathcal{M} = \{1,2,\ldots,M\}$, i.e., in the hybrid state space $\mathcal{X}\times\mathcal{M}$. Therefore, the posterior density p_k must have the form $p_k(\boldsymbol{x},\boldsymbol{r}|Z_{1:k})$, $\boldsymbol{r}\in\mathcal{M}$. If a target with augmented state $\tilde{\boldsymbol{x}}' = [(\boldsymbol{x}')^T \quad s]^T$, $s \in \mathcal{M}$ is in the scene at time $k-1$, it is assumed that its dynamic model between time step $k-1$ and k is switched to $r \in \mathcal{M}$ with Markov transition probability $\pi_{sr} \geqslant 0$, $\sum_{r=1}^{M}\pi_{sr} = 1$. Assume the single-target Markov density function is given by $f_{k|k-1}^r(\cdot|\boldsymbol{x}')$ when the target dynamic model switches to r at time k. Then, the predicted density must have the form

$$p_{k|k-1}(\boldsymbol{x},r|Z_{1:k-1}) = \sum_{s\in\mathcal{M}}\int \pi_{sr}p_{k-1}(\boldsymbol{x}',s|Z_{1:k-1})f_{k|k-1}^r(\boldsymbol{x}|\boldsymbol{x}')d\boldsymbol{x}' \tag{6}$$

With the available measurement set Z_k, the updated posterior density is characterized by

$$p_k(\boldsymbol{x},r|Z_{1:k}) = \frac{p_{k|k-1}(\boldsymbol{x},r|Z_{1:k-1})\eta(Z_k|\boldsymbol{x},r)}{\sum_{s\in\mathcal{M}}\int p_{k|k-1}(\boldsymbol{x}',s|Z_{1:k-1})\eta(Z_k|\boldsymbol{x}',s)d\boldsymbol{x}'} \tag{7}$$

where

$$\eta(Z_k|\boldsymbol{x},r) = K_o^{|Z_k|}(|Z_k|!)(1-p_D)\rho_{K,k}(|Z_k||\boldsymbol{x},r)\prod_{\boldsymbol{z}_k\in Z_k} c_k(\boldsymbol{z}_k|\boldsymbol{x},r) + [(|Z_k|-1)!]p_D\rho_{K,k}(|Z_k| - 1|\boldsymbol{x},r)\sum_{\boldsymbol{z}_k^*\in Z_k} h_b\boldsymbol{z}_k^*(\boldsymbol{x},r)\prod_{\boldsymbol{z}_k\neq\boldsymbol{z}_k^*} c_k(\boldsymbol{z}_k|\boldsymbol{x},r) \tag{8}$$

The above MM-STBF is intractable in general for its high complexity. Following the approach in [19,24], a particle implementation can easily be obtained and an analytic solution can be established for generic models and linear Gaussian models, respectively. The readers are referred to [26] for these two approximation methods and they are omitted here.

3. A novel joint maneuvering target tracking and classification algorithm based on the MM-STBF

To cope with several measurements originated from the target, miss-detection, association uncertainty, and false alarms, this section derives an optimal Bayesian JTC algorithm using the MM-STBF, i.e., MM-STBF–JTC.

Suppose the target class c which can take any value in a discrete class set $\mathcal{C} = \{1, 2, \ldots, C\}$ is time-invariant. The joint state and class vector is time-variant with respect to the state and time-invariant with respect to the class, which can take any value in the joint space $\bigcup_{c\in\mathcal{C}}(\mathcal{X} \times \mathcal{M}_c \times c)$. $\mathcal{M}_c$ is the model set of the cth class target.

The predicted distribution is characterized by

$$\begin{aligned} p_{k|k-1}(\tilde{\boldsymbol{x}}, c|Z_{1:k-1}) &= \int p_{k-1}(\tilde{\boldsymbol{x}}', c|Z_{1:k-1}) f_{k|k-1,c}(\tilde{\boldsymbol{x}}|\tilde{\boldsymbol{x}}')d\tilde{\boldsymbol{x}}' \\ &= \sum_{s\in\mathcal{M}_c} \int \pi^c_{sr} p_{k-1}(\boldsymbol{x}', s, c|Z_{1:k-1}) f^r_{k|k-1,c}(\boldsymbol{x}|\boldsymbol{x}')d\boldsymbol{x}' \end{aligned} \tag{9}$$

where $f_{k|k-1,c}(\tilde{\boldsymbol{x}}|\tilde{\boldsymbol{x}}')$ denotes the transition density conditioned on class c and is characterized by

$$f_{k|k-1,c}(\tilde{\boldsymbol{x}}|\tilde{\boldsymbol{x}}') = \pi^c_{sr} f^r_{k|k-1,c}(\boldsymbol{x}|\boldsymbol{x}') \tag{10}$$

where $\tilde{\boldsymbol{x}} = [\boldsymbol{x}^T \quad r]^T$, $\tilde{x}' = [(\boldsymbol{x}')^T \quad s]^T$, $r, s \in \mathcal{M}_c$. The associated Markov transition probabilities of $\mathcal{M}_c$ are given as $\pi^c_{sr} \geqslant 0$, $\sum_{r\in\mathcal{M}_c} \pi^c_{sr} = 1$, $r, s \in \mathcal{M}_c$.

Using Bayesian rule, the recursion can be completed

$$p_k(\tilde{\boldsymbol{x}}, c|Z_{1:k}) = p_{k|k-1}(\tilde{\boldsymbol{x}}, c|Z_{1:k-1})\eta_c(Z_k|\tilde{\boldsymbol{x}})/\ell_k \tag{11}$$

where $\eta_c(Z_k|\tilde{\boldsymbol{x}}) \triangleq p(Z_k|\tilde{\boldsymbol{x}}, c)$ denotes the class-conditioned likelihood and ℓ_k is a normalizing factor, i.e.

$$\ell_k = \sum_{t\in\mathcal{C}} \int p_{k|k-1}(\tilde{\boldsymbol{x}}, t|Z_{1:k-1})\eta_t(Z_k|\tilde{\boldsymbol{x}})d\tilde{\boldsymbol{x}} \tag{12}$$

The above derived recursion (9)–(12) is an optimal Bayesian estimator for the JTC problem. According to this recursion, the following proposition provides an effective way to extract the target state and class probabilities.

Proposition 1. *Given the prior class probability $p_{k-1}(c|Z_{1:k-1})$ and class-conditioned kinematic state distribution $p_{k|k-1}(x, s|c, Z_{1:k-1})$ for each $c \in \mathcal{C}$, the updated target class probability $p_k(c|Z_{1:k})$ is proportional to $p_{k-1}(c|Z_{1:k-1})\eta_c(Z_k|Z_{k-1})$, where*

$$\begin{aligned} \eta_c(Z_k|Z_{k-1}) &\triangleq \int p_{k|k-1}(\tilde{x}|c, Z_{1:k-1})\eta_c(Z_k|\tilde{x})d\tilde{x} \\ &= \sum_{s\in\mathcal{M}_c} \int p_{k|k-1}(x, s|c, Z_{1:k-1})\eta_c(Z_k|x, s)dx \end{aligned} \tag{13}$$

and the estimated target kinematic state is

$$E[x|Z_{1:k}] = \sum_{c\in\mathcal{C}} p_k(c|Z_{1:k})E[x|c, Z_{1:k}] \tag{14}$$

where $E[\cdot|Z_{1:k}]$ is the minimum mean-squared error (MMSE) estimator conditioned on $Z_{1:k}$ and $E[\cdot \mid c, Z_{1:k}]$ is the MMSE estimator conditioned on the target class c and $Z_{1:k}$.

Proof. To deduce the class probabilities, it needs to integrate the joint state and class probability density over the state. Therefore,

$$p_k(c|Z_{1:k}) = \int p_k(\tilde{x}, c|Z_{1:k})d\tilde{x} \tag{15}$$

So, from (9), (11) and (15),

$$\begin{aligned} p_k(c|Z_{1:k}) &= \int p_{k|k-1}(\tilde{x}, c|Z_{1:k-1})\eta_c(Z_k|\tilde{x})d\tilde{x}/\ell_k \\ &= \int\int f_{k|k-1,c}(\tilde{x}|\tilde{x}')p_{k-1}(\tilde{x}'|c, Z_{1:k-1})p_{k-1}(c|Z_{1:k-1})d\tilde{x}'\eta_c(Z_k|\tilde{x})d\tilde{x}/\ell_k \\ &= p_{k-1}(c|Z_{1:k-1})\int p_{k|k-1}(\tilde{x}|c, Z_{1:k-1})\eta_c(Z_k|\tilde{x})d\tilde{x}/\ell_k \\ &= p_{k-1}(c|Z_{1:k-1})\eta_c(Z_k|Z_{k-1})/\ell_k \end{aligned} \tag{16}$$

Since ℓ_k denotes a normalizing factor, $p_k(c|Z_{1:k})$ is proportional to $p_{k-1}(c|Z_{1:k-1})\eta_c(Z_k|Z_{k-1})$.

The target kinematic state can be derived from the MMSE principle. So,

$$\begin{aligned} E[x|Z_{1:k}] &= \int xp_k(x|Z_{1:k})dx = \sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{M}_c} \int xp_k(x, s, c|Z_{1:k})dx \\ &= \sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{M}_c} \int xp_k(x, s|c, Z_{1:k})p_k(c|Z_{1:k})dx \\ &= \sum_{c\in\mathcal{C}} p_k(c|Z_{1:k}) \int x\left(\sum_{s\in\mathcal{M}_c} p_k(x, s|c, Z_{1:k})\right)dx \\ &= \sum_{c\in\mathcal{C}} p_k(c|Z_{1:k}) \int xp_k(x|c, Z_{1:k})dx \\ &= \sum_{c\in\mathcal{C}} p_k(c|Z_{1:k})E[x|c, Z_{1:k}] \end{aligned} \tag{17}$$

From (13) and (16), it can be seen that these target class probabilities can be derived by calculating the class-conditioned one-step-ahead prediction errors of measurement set $\eta_c(Z_k|Z_{k-1}), c \in \mathcal{C}$. Eq. (14) implies that the final estimation of target kinematic state is a weighted sum of class-conditioned estimations. That is to say that the MM-STBF–JTC algorithm is a mix of C state estimators, each of which is the MM-STBF in Section 2.2. These argumentations are in accord with that of the reference [10]. However, the reference [10] only focuses on unity detection probability and no clutter case. □

Remark 1. The MM-STBF–JTC derived within the Bayesian paradigm is a PTJTC algorithm. In contrast to the reviewed PTJTC approaches in Section 1, the novel algorithm can accommodate detection uncertainty, association uncertainty, and false alarms. Because of its similarity to the JTC algorithm in [10] on the structure, the MM-STBF–JTC algorithm avoids that the target class can be permanently lost if they are with temporarily low likelihoods [8]. Moreover, the MM-STBF–JTC algorithm can realize the Poisson extended target tracking and classification in a cluttered environment, when multiple measurements originated from the target can be modeled as a Poisson RFS.

Remark 2. As proved in [19], assuming the target generates only one measurement, no miss-detection, and no clutter, the STBF reduces to the classical Bayesian filter. Therefore, the novel JTC algorithm based on the MM-STBF reduces to the traditional JTC algorithm in [10] restricted to a single model and the above assumptions.

As in the reference [10], a feature likelihood can be incorporated into the above measurement likelihood $\eta_c(Z_k|\tilde{x})$ in (11). If there are no associating feature measurements, then the target types can differ in terms of $f_{k|k-1,c}(\tilde{x}|\tilde{x}')$. These differences could be the result of different maneuver models being applicable for the different target types or different constraints being imposed on the different target types.

4. Simulation results

A representative example is utilized to show the tracking and classification performance of the novel JTC algorithm based on the MM-STBF. Moreover, the proposed JTC algorithm is compared with an IMMPDAF-based JTC algorithm, whose methodology is identical with the proposed JTC algorithm except its element estimators are replaced by the classical IMMPDA filters [27]. Our reason for choosing this IMMPDAF-based JTC algorithm is that there is no existing JTC algorithm to handle multiple target-generated measurements and the IMMPDAF is the most popular traditional technique for maneuvering target tracking in clutter.

A linear Gaussian scenario, adapted from the simulation in [28], is considered. Note that the derived JTC algorithm does not restrict the measurement and dynamic model and therefore it can perform in nonlinear and non-Gaussian case. The class label of the target is assumed to belong to $\mathcal{C} = \{1, 2, 3\}$. The model sets for tracking class 1, 2 and 3 target are $\mathcal{M}_1 = \{M^1, M^2\}, \mathcal{M}_2 = \{M^2, M^4\}$, and $\mathcal{M}_3 = \{M^1, M^2, M^3\}$, respectively. The target kinematics can be characterized in Cartesian coordinates uniformly by

$$x_k = Fx_{k-1} + Gv_{k-1} \tag{18}$$

Note that the target state consists of acceleration, velocity, and position in each of the coordinates. Therefore, $\boldsymbol{x}_k$ is a 6-dimensional vector. The system matrices $\boldsymbol{G}$ and $\boldsymbol{F}$ can be defined as

$$G = \begin{bmatrix} G_b & 0 \\ 0 & G_b \end{bmatrix}, \quad F = \begin{bmatrix} F_b & 0 \\ 0 & F_b \end{bmatrix} \tag{19}$$

M^1. Nearly constant velocity model with no acceleration perturbation, $G_b^1 = \begin{bmatrix} T^2/2 \\ T \\ 0 \end{bmatrix}$ and $F_b^1 = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$. The sampling interval $T = 1$ s and the standard deviation (SD) is set to 0.5 m/s^2 for the process noise $\boldsymbol{v}_{k-1}$.

M^2. Wiener process acceleration model with $G_b^2 = \begin{bmatrix} T^2/2 \\ T \\ 1 \end{bmatrix}$ and $F_b^2 = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$. The SD of process noise is 0.75 m/s^2.

M^3 and M^4. They are the same as M^2 except their SDs of process noise are 4 m/s^2 and 1 m/s^2, respectively.

The simulation is run over 90 *s*. A highly maneuvering class three target is in the two-dimensional scenario $[-2500, 2500] \times [-1200, 1200]$ m^2. The maneuvering target performs a same dynamic behavior in its course like the example of [28], where it starts at location $[919.9, 485]$ m and the initial velocity is $[-0.83, -39.99]$ m/s. The readers are referred to [28] for a detailed description.

The model switching probability matrices of $\mathcal{M}_1$ and $\mathcal{M}_2$ are same and are given by

$$Tp_1 = Tp_2 = \begin{bmatrix} 0.995 & 0.005 \\ 0.05 & 0.95 \end{bmatrix}. \tag{20}$$

The model switching probability matrix of $\mathcal{M}_3$ is given by (as in [28])

$$Tp_3 = \begin{bmatrix} 0.8 & 0.0 & 0.2 \\ 0.0 & 0.8 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{bmatrix} \tag{21}$$

The likelihood of primary target-generated measurement is linear Gaussian $h_z(x, r) = g(z|x, r) = \mathcal{N}(z; H_k x, R_k)$ with

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \tag{22}$$

$$R_k = \sigma_\xi^2 I_2 \tag{23}$$

where $\sigma_\xi = 30$ m is the SD of measurement noise, and $\kappa(Z) = \lambda V u(\boldsymbol{z})$ is the intensity of Poisson clutter, where $u(\cdot)$ denotes the uniform probability density in observation space and $\lambda = 10^{-5} m^{-2}$. $\mathcal{N}(\cdot; m, P)$ is a Gaussian probability density with covariance $\boldsymbol{P}$ and mean $\boldsymbol{m}$. $p_D = 0.8$. As in [19], extraneous target-originated measurements are modeled by a RFS with Poisson intensity $v_{E,k}(\cdot|x) = \lambda_e \mathcal{N}(\cdot; B_k x, D_k)$. $B_k = [2I_2 \quad 0_2]$, $D_k = \sigma_\tau^2 I_2$ and $\sigma_\tau = 30$ m. $\lambda_e = 2$ is same for classes 1–3 target. The gating and pruning/merging procedures described in [19] are used.

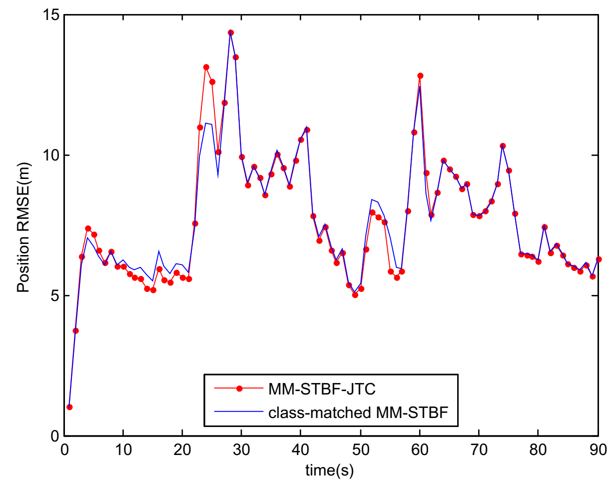

Fig. 1. Target position estimation RMSE.

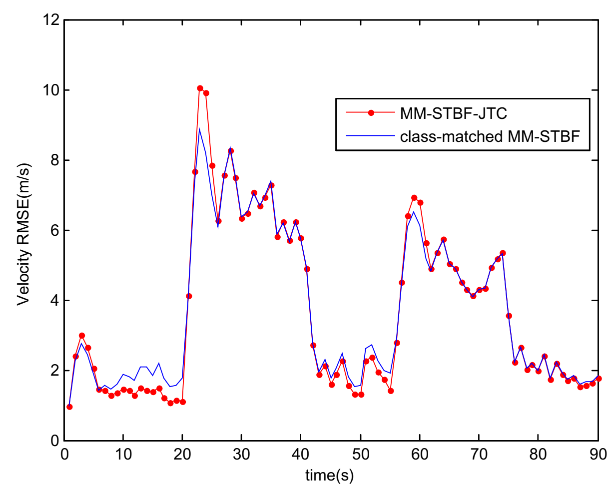

Fig. 2. Target velocity estimation RMSE.

Figs. 1–3 plot the root-mean-squared-errors (RMSEs) of acceleration, velocity, and position estimates of the proposed JTC algorithm and class-matched MM-STBF based on 100 Monte Carlo (MC) runs, which suggest that the proposed JTC algorithm performs similarly as the class-matched MM-STBF in kinematic state estimation. The RMSE of position estimates of the MM-STBF conditioned on classes 1 and 2 indicates that they suffer from a serious divergence, so they are not plotted here. These divergences can be attributed to their false kinematic model sets, which confirm the significance of treating target tracking and classification jointly. The RMSE of the position estimates of the IMMPDAF-based JTC algorithm are presented in Fig. 4, which also indicates that it diverges. In fact, the class-matched IMMPDA filter itself diverges as shown in Fig. 4. This divergence can be attributed to extraneous target-originated measurements, which cannot been accommodated by the IMMPDA filter.

In Fig. 5, the mean and SD of all class probabilities at each time step are shown for the proposed JTC algorithm. As $\mathcal{M}_1 \subseteq \mathcal{M}_3$ and between 0 and 20 s the real target moves with a constant velocity [28], the classifier tends to raise the probability of class 1. After the target performs the first highly maneuvering behavior (modeled by M^3), the probability of class 3 increases rapidly. The mean and SD of the probability of class 3 are shown in Fig. 6 for the IMMPDAF-based JTC algorithm. The results further demonstrate that

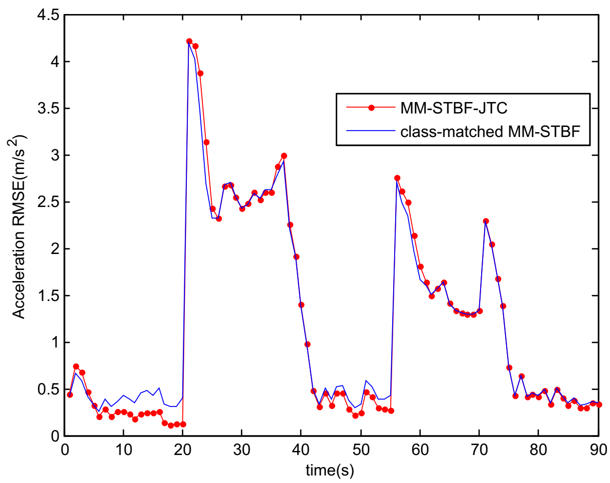

Fig. 3. Target acceleration estimation RMSE.

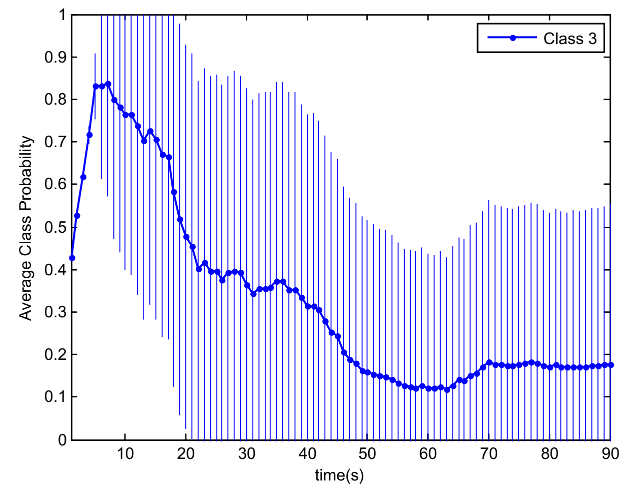

Fig. 6. Classification results of the IMMPDAF-based JTC algorithm.

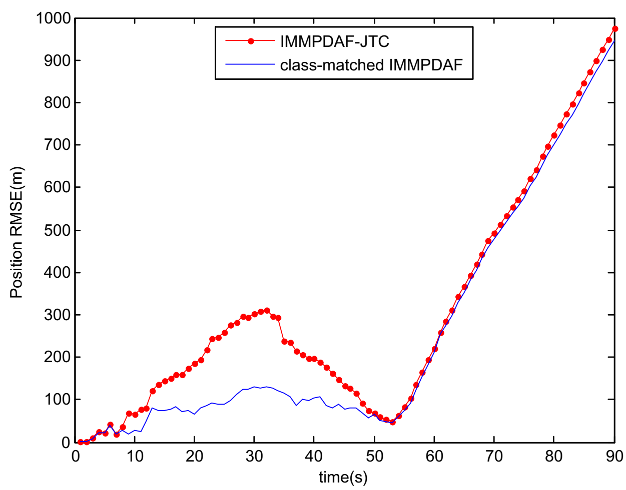

Fig. 4. Target position estimation RMSE of the IMMPDAF-based JTC algorithm and the class-matched IMMPDAF.

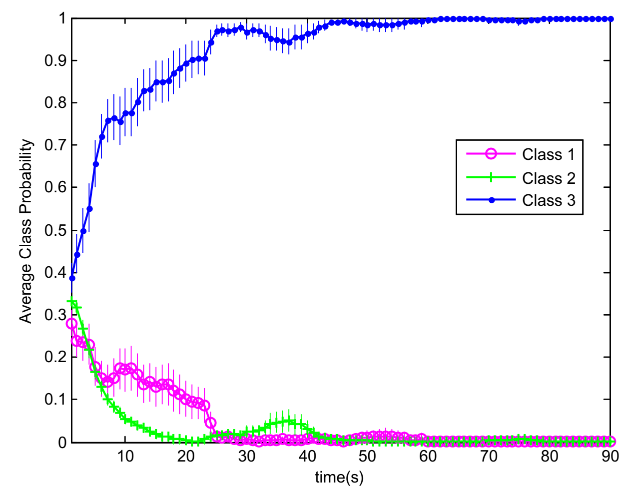

Fig. 7. Classification results with different extraneous target-originated measurement models.

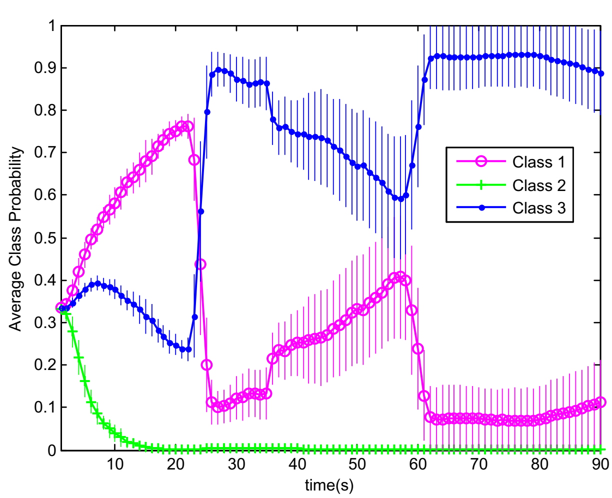

Fig. 5. Classification results with the same extraneous target-originated measurement models.

the IMMPDAF-based JTC algorithm diverges and the class estimates has a very high variance.

The classifier gives unreasonable classification results when the target does not perform any maneuvers as seen in Fig. 5. Ref. [29] proposed a second-order uncertainty model to avoid this phenomenon, in which an mapping from the feature to class space is constructed subjectively according to contextual information. In fact, the improvement in classification performance for JTC can be attributed to the inclusion of the feature measurement information in the filter, which has been studied previously in the target tracking literature [22,23]. The extraneous target-originated measurements may be a target feature. For example, λ_e for class 1, 2 and 3 target are 4, 3 and 2, respectively. The classification results of the proposed JTC algorithm are shown in Fig. 7. Comparing to Fig. 5, it indicates that the proposed JTC algorithm with different extraneous target-originated measurement models converges to the correct class quicker and has a much smaller variance.

5. Conclusions

A multiple model extension of the original STBF is presented in this paper straightforwardly, which can simultaneously accommodate the possible target maneuvering behavior, unknown data association, miss-detection, clutter and several measurements originated from a target. Based on this extension, a novel JTC algorithm in a cluttered environment is further developed. Under certain assumptions, the proposed JTC algorithm reduces to a traditional JTC algorithm. Simulation results validate the effectiveness of the novel JTC algorithm.

Note that the success of the novel JTC algorithm mainly depends on whether an appropriate model set can be found for each target class, like other JTC algorithms. The development of the methodology to JTC in the RFS framework can be extended to joint tracking and classifying multi-target [13].

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