Joint Multiple Target Tracking and Classification Using Controlled Based Cheap JPDA-Multiple Model Particle Filter in Cluttered Environment

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Abstract. In this paper, we address the problem of jointly tracking and classifying several targets in cluttered environment. It is assumed that the motion model of a given target belongs to one of several classes. We propose to use the multiple model particle filter (MMPF) to perform nonlinear filtering with switching dynamic models. Moreover, the principle of joint probabilistic data association (JPDA) is used to determine the measurements origin. Besides, the joint probabilities are calculated using Fitzgerald's had hoc formulation (Cheap JPDA) whose efficiency has been proven in the literature. On the other hand, a controller based on the quality of the innovation has been implemented in order to tune the number of particles. The feasibility and the performances of the proposal have been demonstrated using a set of Monte Carlo simulations dealing with two maneuvering targets.

1 Introduction

Tracking multiple targets arises in many engineering applications where a discrete uncertainty regarding measurement-target associations takes place. In radar tracking it is uncertain whether the radar echo stands for a friendly or an enemy aircraft or just a false alarm, whether it is a commercial or a military transport aircraft [1]. To solve the problem of data association, the joint probabilistic data association filter (JPDAF) has been successfully applied in many tracking examples [2,3]. The computational complexity for the joint probabilities increases exponentially as the number of targets increases. To reduce this computational complexity, Fitzgerald [8,9] developed the simplified version of the JPDAF, called the cheap JPDAF (CJPDAF) algorithm. However, the nonlinearities in the target/measurement, especially for highly manoeuvring targets, have limited the use of the JPDAF. These nonlinearities have often been addressed through the linearization around the state estimates. Unfortunately, the performance of the state estimation degrades as the non-linearities become more severe [4]. With, the particle filter (PF) [5-7] it is possible to overcome the effect of nonlinearity as well as the standard Gaussian assumption. Moreover, the multiple-model PF (MMFP)

can be used to perform nonlinear filtering with switching dynamic models using an augmented state vector which consists of both target kinematics variables and discrete-valued part (regime variable).

In this paper, we address the problem of jointly tracking and classifying several targets using CJPDA-MMPF in cluttered environment. The process of jointly tracking and classifying is based on the following ideas: i) The estimation process (target kinematics variables and regime variable) is carried out at each particle level, ii) The calculus of the joint probabilities is accomplished using JPDAF, iii) Similarly to [9], a controller is used to tune the number of controller at each iterations. Section 2 of this paper presents some aspects of the JPDAF and relates Fitzgerald's had hoc formulation. Section 3 presents the multiple switching dynamic model. In section 4, we propose the CJPDA-MMPF. In section 5, some simulation examples illustrate the feasibility and performances of the proposal.

2 Data Association Method

One of the most popular method for data association is probably the JPDAF. A detailed derivation of JPDAF can be found in [2,3]. The Kalman update equation is (one uses superscript t to refer to target t)

$$\hat{x}^t(k) = \hat{x}_p^t(k) + \mathbf{K}^t(k)v^t(k) \quad (1)$$

where $\hat{x}_p^t(k)$ is the predicted state vector, $\mathbf{K}^t(k)$ is the Kalman gain and $v^t(k)$ is the combined innovation given by

$$v^t(k) = \sum_{i=1}^{m^t(k)} \beta_i^t(k)v_i^t(k) \quad (2)$$

where $\beta_i^t(k)$ is the probability of associating track t with measurement i , $m^t(k)$ is the number of validated measurements for track t and $v_i^t(k)$ is the innovation of track t and measurement i .

In the standard JPDAF, the association probabilities $\beta_i^t(k)$ are calculated by considering every possible hypothesis as to the association of the new measurements with existing tracks. A had hoc JPDAF formulation to get very easily $\beta_j^t(k)$'s values was pointed out by Fitzgerald [8,9] as

$$\beta_i^t(k) = G_i^t(k)[S^t(k) + S_i(k) - G_i^t(k) + B]^{-1} \quad (3)$$

where $G_i^t(k)$ is the distribution of $v_i^t(k)$ usually assumed to be gaussian and

$$S^t(k) = \sum_{i=1}^{m^t(k)} G_i^t(k) \quad , \quad S_i(k) = \sum_{t=1}^M G_i^t(k)$$

with M is the number of targets and B is a constant which depends on clutter density (usually with $B = 0$, the algorithm works well).

3 Multiple Switching Dynamic Model

In many engineering applications one deals with nonlinear dynamic systems characterized by some modes of operation. For example, this is the case of maneuvering targets. These kinds of problems are referred to as hybrid state estimation problems involving both target state and mode variable. Generally, an hybrid system is described by the following equations [10]

$$x(k+1) = f(x(k), r(k), u(k)) \quad (4)$$

$$z(k) = h(x(k), r(k), w(k)) \quad (5)$$

where $r(k)$ is the mode variable commonly modeled by time-homogeneous s -state first-order Markov chain with transitional probabilities

$$\Pi_{i,j} = \text{Prob}(r(k) = j / r(k-1) = i) \quad (i, j \in \{1, 2, \dots, s\}) \quad (6)$$

In this work, two different motion models are considered for target t : the constant velocity and the coordinated turn rate models.

Constant velocity model: The target t is assumed to move with a constant velocity. For notational simplicity, $x^t(k)$ refers to the state (coordinates and velocities) of the target following this motion. We denote α^t and ζ^t the coordinates: $x^t(k) = [x_1^t(k), x_2^t(k), x_3^t(k), x_4^t(k)]^T = [\alpha^t, \dot{\alpha}^t, \zeta^t, \dot{\zeta}^t]^T$. In the following, Δ is assumed to be the sampling period.

$$x^t(k+1) = \mathbf{F}^t(r^t(k) = 1)x^t(k) + \mathbf{D}u(k) = \begin{bmatrix} 1 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta \\ 0 & 0 & 0 & 1 \end{bmatrix} x^t(k) + \mathbf{D}u(k) \quad (7)$$

where $\mathbf{D} = \begin{bmatrix} \frac{\Delta^2}{2} & \Delta & 0 & 0 \\ 0 & 0 & \frac{\Delta^2}{2} & \Delta \end{bmatrix}^T$ and $u(k)$ is white noise ($u(k) \sim \mathcal{N}(0, Q)$).

Coordinated turn rate model: In this model, the target t moves with a constant velocity and a constant known turn rate ω^t . Again $x^t(k)$ refers to the state (coordinates and velocities) of the target following this motion. To obtain this model, we only change the transition matrix $\mathbf{F}^t(r^t(k) = 1)$ in (7) by $\mathbf{F}^t(r^t(k) = 2)$ given by

$$\mathbf{F}^t(r^t(k) = 2) = \begin{bmatrix} 1 & \sin(\omega^t \Delta) & 0 & \frac{(1 - \cos(\omega^t \Delta))}{\omega^t} \\ 0 & \cos(\omega^t \Delta) & 0 & -\sin(\omega^t \Delta) \\ 0 & \frac{-(1 - \cos(\omega^t \Delta))}{\omega^t} & 1 & \frac{\sin(\omega^t \Delta)}{\omega^t} \\ 0 & \sin(\omega^t \Delta) & 0 & \cos(\omega^t \Delta) \end{bmatrix} \quad (8)$$

Measurement equation: The measurements are modeled by

$$z^t(k) = \phi(x^t(k)) + w(k) = \begin{bmatrix} \sqrt{(x_1^t(k))^2 + (x_3^t(k))^2} \\ \arctan\left(\frac{x_3^t(k)}{x_1^t(k)}\right) \end{bmatrix} + w(k) \quad (9)$$

where $w(k)$ is white noise ($w(k) \sim \mathcal{N}(0, R)$).

4 CJPDA-MMPF

The proposal developed in this paper is based on the following principle : i) The estimation process of the augmented state vector (target state and mode variable) is accomplished at each particle level, ii) The CJDAF is used in order to estimate the joint probability association target / measurement, iii) Similarly to [9], a classic controller is used to control the number of particles.

A pseudo code of a generic CJPDA-MMPF is mentionned below.

1. Initialization: Set $k = 0$
 - Generate N_p samples $\{\hat{x}_n^t(0)\}_{n=1}^{N_p}$ for all targets from $p(x^t(0))$
 - Generate N_p samples $\{r_n^t(1)\}_{n=1}^{N_p}$ for all targets from $p(r^t(1))$
2. Increase k
3. For each target t ($t = 1, \dots, M$) do
 - Generate a random set $\{r_n^t(k)\}_{n=1}^{N_p}$ based on $\{r_n^t(k-1)\}_{n=1}^{N_p}$ and the transition probabilities matrix $\mathbf{\Pi}$ (see table 3.9 [10]).
 - for each particle n ($n = 1, \dots, N_p$) do
 - Compute $\{\beta_i^t\}_{i=1}^{m^t(k)}$ according to (3) based on $r_n^t(k)$, $x_n^t(k-1)$ and validated measurements $\{z^i(k)\}_{i=1}^{m^t(k)}$
 - Evaluate

$$\hat{x}_{p,n}^t(k) = \mathbf{F}^t(r_n^t(k)) \hat{x}_n^t(k-1)$$

$$\hat{\mathbf{P}}_{p,n}^t(k) = \mathbf{F}^t(r_n^t(k)) \hat{\mathbf{P}}_n^t(k-1) [\mathbf{F}^t(r_n^t(k))]^T + \mathbf{D} \mathbf{Q} \mathbf{D}^T$$

$$\mathbf{H}(\hat{x}_{p,n}^t(k)) = \text{Jacobian, of } \phi \text{ given in (9), evaluated at } \hat{x}_{p,n}^t(k)$$

$$\mathbf{S}_n^t(k) = \mathbf{R} + \mathbf{H}(\hat{x}_{p,n}^t(k)) \hat{\mathbf{P}}_{p,n}^t(k) [\mathbf{H}(\hat{x}_{p,n}^t(k))]^T$$

$$\mathbf{K}_n^t(k) = \hat{\mathbf{P}}_{p,n}^t(k) [\mathbf{H}(\hat{x}_{p,n}^t(k))]^T [\mathbf{S}_n^t(k)]^{-1}$$

$$w_n^t(k) = \sum_{i=1}^{m^t(k)} \beta_i^t \mathcal{N}(z^i(k) - \phi(\hat{x}_{p,n}^t(k)), \mathbf{S}_n^t(k))$$

$$\hat{x}_n^t(k) = \hat{x}_{p,n}^t(k) + \mathbf{K}_n^t(k) \sum_{i=1}^{m^t(k)} \beta_i^t(k) (z^i(k) - \phi(\hat{x}_{p,n}^t(k)))$$

$$\hat{\mathbf{P}}_n^t(k) = \beta_0^t(k) \hat{\mathbf{P}}_{p,n}^t(k) + (1 - \beta_0^t(k)) [\mathbf{I} - \mathbf{K}_n^t(k) \mathbf{H}(\hat{x}_{p,n}^t(k))] \hat{\mathbf{P}}_{p,n}^t(k)$$

$$+ \mathbf{K}_n^t(k) \left[\sum_{j=1}^{m^t(k)} \beta_j^t(k) v_i^t(k) [v_i^t(k)]^T - v^t(k) [v^t(k)]^T \right] [\mathbf{K}_n^t(k)]^T$$

- Normalize the weights $\{w_n^t(k)\}_{n=1}^{N_p}$ (obtain $\{\hat{w}_n^t(k)\}_{n=1}^{N_p}$)
- Using the weights $\{\hat{w}_n^t(k)\}_{n=1}^{N_p}$, resample the set $\{r_n^t(k), \hat{x}_n^t(k), \hat{\mathbf{P}}_n^t(k)\}_{n=1}^{N_p}$
- Obtain : $\hat{r}^t(k) = \frac{1}{N_p} \sum_{n=1}^{N_p} r_n^t(k)$ and $\hat{x}^t(k) = \frac{1}{N_p} \sum_{n=1}^{N_p} \hat{x}_n^t(k)$

4. Let $\hat{z}^t(k) = \phi(\hat{x}^t(k))$

If $(z^t(k) - \hat{z}^t(k)) > \text{Threshold}$, $N_p = N_p + S_p$ else $N_p = N_p - S_p$

5. Go to step 2

$\beta_0^t(k)$ is the probability that all measurements in the validation gate of track t are false.

5 Simulations

Herein, the above mentioned algorithm is applied to jointly tracking and classifying two crossing targets. The targets trajectories are assumed as follows (the sampling period $\Delta = 10s$):

- Target 1: (1) The target starting from $[3000m - 10m/s \ 10000m - 10m/s]$ at time $k = 0s$, the target runs for 25Δ with constant velocity model. (2) Executing a coordinated turn rate model with $0.15^\circ/s$ coordinated for 75Δ .
- Target 2: (1) The target starting from $[1958m - 10m/s \ 10044m - 10m/s]$ at time $k = 0s$, the target runs for 50Δ with constant velocity model. (2) Executing a coordinated turn rate model with $-0.15^\circ/s$ coordinated for 50Δ .
- The crossing time is $t_0 = 25\Delta$.

The number of Monte Carlo runs is 50. The initial state vectors, of the MMPF, are 0.95 of the trues initial state vectors with covariance matrix $\text{diag}(100 \ 1 \ 100 \ 1)$. The initial number of particles is $N_p = 1000$ and the value of S_p in the previous algorithm is 20.

The measurement and the state covariance matrices are

$$R = \text{diag}(150^2 \ 0.005^2), \quad Q = \text{diag}(0.01^2 \ 0.01^2)$$

The mode switching probability matrix is:

$$\Pi = \begin{bmatrix} 0.98 & 0.02 \\ 0.02 & 0.98 \end{bmatrix}$$

Moreover, one simulates both the true measurements and a set false alarm measurements. The latter are generated randomly within the probabilistic ellipsoid of gate $g = \sqrt{\gamma} = 4$ and centered in the predicted measurement for each target. The total number of false measurements is Poisson distributed with parameter λV with $\lambda = 4$.

Figure 1 illustrates an example of tracking of the targets in presence of clutter. The obtained results show that the proposed algorithm presents good performances of tracking.

The figure 2 illustrates the mode probability of the two models for each target using the CJPDA-MMPF. According to these obtained results (with only 50 independent runs), one can see in figure 2 that the models are tracked successfully for the two targets. More precisely, the changes of the mode probabilities in figure 2 are approximatively the same as the changes of the state vectors of the system. It is obvious that the algorithm works well and the classification is right and can be made easily.

The behavior of the number of particles controller is illustrates in figure 3. We note that the number of particles chosen is not enough to get the quality chosen (innovation quality) for this reason it was increased.

Fig. 1. Trajectories of the two targets

Fig. 2. The mode probability using the CJPDA-MMPF

Fig. 3. Number of particles

6 Conclusion

In this paper, the problem, of jointly tracking and classifying several targets in cluttered environment, is addressed using the cheap joint probabilistic data association (CJPDA) associated with the multiple model particle filter (MMPF). It is assumed that the motion model of any target belongs to one of several classes. The MMPF is used to perform nonlinear filtering with switching dynamic models and the CJDAF is used to estimate the joint probability association target / measurement. Furthermore, a controller that tunes the number of particles used by the filter using the quality of the innovation is implemented. The estimation process is therefore carried out at each particle level. The numerical simulations show interesting performances of the CJPDA-MMPF for both classification and tracking multiple targets in cluttered environment.

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