Defence Science Journal, Vol. 59, No. 3, May 2009, pp. 197-204
© 2009, DESIDOC

Multiple Model Rao-Blackwellized Particle Filter for Manoeuvring Target Tracking

Li Liang-qun, Xie Wei-xin, Huang Jing-xiong, Huang Jian-jun

School of Information Engineering, Shenzhen University, Guangdong 518 060, China

ABSTRACT

Particle filters can become quite inefficient when applied to a high-dimensional state space since a prohibitively large number of samples may be required to approximate the underlying density functions with desired accuracy. In this paper, a novel multiple model Rao-Blackwellized particle filter (MMRBPF)-based algorithm has been proposed for manoeuvring target tracking in a cluttered environment. The advantage of the proposed approach is that the Rao-Blackwellization allows the algorithm to be partitioned into target tracking and model selection sub-problems, where the target tracking can be solved by the probabilistic data association filter, and the model selection by sequential importance sampling. The analytical relationship between target state and model is exploited to improve the efficiency and accuracy of the proposed algorithm. Moreover, to reduce the particle-degeneracy problem, the resampling approach is selectively carried out. Finally, experiment results, show that the proposed algorithm, has advantages over the conventional IMM-PDAF algorithm in terms of robust and efficiency.

Keywords: Miltiple model, Rao-Blackwellized particle filter, probabilistic data association filter, sequential importance sampling, MMRBPF, target tracking, clutter

1. INTRODUCTION

Recently, particle filters have been introduced and widely applied in manoeuvring target tracking field[1-10]. The first working particle filter has been reported by Gordon[1], *et al*. The key idea is to represent the required posterior density function by a set of random samples with associated weights and to compute estimates based on these samples and weights. So, particle filtering methods can deal with nonlinearities in the dynamics and measurements using the Monte Carlo (MC) method[2,3]. Particle filter approaches for markovian switching systems have also been proposed by Doucet[4] and Sarkka[5]. These methods propose augmentation of the state with the mode variable and straightforwardly apply a particle filter to this augmented state. However, these methods have two major drawbacks. Firstly, there is no control over the number of particles in a mode. In these methods, the number of particles in a specific mode is proportional to the mode probability, so that if the mode probability is very low, only a fraction of the total number of particles resides in that mode. This phenomenon is known to cause numerical problems. Secondly, particle filters can become quite inefficient when being applied to a high-dimensional state space, since a prohibitively large number of samples may be required to approximate the underlying density functions with desired accuracy. To solve this problem, Arnaud Doucet[3] proposed a new Rao-Blackwellized particle filtering. The idea of Rao-Blackwellized particle filtering is that, sometimes it is possible to evaluate a part of the filtering equations analytically and the other part by Monte Carlo sampling instead of computing everything by pure sampling. According to the Rao-Blackwell theorem, this leads to estimators with less variance than what could be obtained by pure Monte Carlo sampling. Simo Sarkka[6] proposed a new Rao-Blackwellized particle-filtering based algorithm for tracking an unknown number of targets. In Xu Xinyu[7] proposed an adaptive RBPF for surveillance tracking. In their method, the problem of target tracking has been partitioned into two separate groups, with the linear parts being computed by Kalman filter and nonlinear part being estimated by particle filter.

In this paper, a novel multiple model Rao-Blackwellized particle filtering (MMRBPF) is proposed for maneuvering target tracking in a cluttered environment.

2. PROPOSED MULTIPLE MODEL RAO-BLACKWELLIZED PARTICLE FILTER

Given the following jump Markov Gaussian system

$$x_k = f\left(x_{k-1}, M_k\right) + g\left(M_k\right) w_k \tag{1}$$

$$z_k = h\left(x_k, M_k\right) + v_k \tag{2}$$

$$M_k \sim p\left(M_k \mid M_{k-1}\right) \tag{3}$$

where $x_k \in \Re^{n_x}$ denotes the dynamical state of the system in mode M_k, $z_k \in \Re^{n_z}$ denotes the measurements in mode M_k, and M_k being the model state of the system and can be modelled as a first-order Markov process. The process noise and the measurement noise are possibly mode-dependent:

Received 2 April 2008

$w_k \sim \mathrm{N}(0, Q)$ and $v_k \sim \mathrm{N}(0, R)$.

Generally, suppose that one has an estimator $\eta(x,m)$ depending upon two variables *x* and *m*, the Rao–Blackwellization theorem reveals that its variance satisfies[4,8]

$$Var\left[\eta(x,m)\right] = Var\left[E\left(\eta(x,m)|x\right)\right] + Var\left[E\left(\eta(x,m)|m\right)\right] \quad (4)$$

Since $Var\left[E\left(\eta(x,m)|x\right)\right]$ is non-negative, the variance of the estimator $\eta' = E(\eta(x,m)|m)$ is less than that of the original estimator $\eta(x,m)$. The formal justification can be found in [8]. One can interpret the Rao–Blackwellization theorem by saying that the estimator obtained by the calculation of conditional expectation $E(\eta(x,m)|m)$ is superior to the original one $\eta(x,m)$, and the superiority manifests in the reduction in the variance of the estimates.

For the manoeuvring target tracking in a cluttered environment, let X_k denote the state to be estimated and the observation z_k, with subscript the time index *k*. The key idea of RBPF is to partition the original state-space into two parts x_k (state variables) and M_k (model variables), such that $p(x_k \mid x_{1:k-1}, M_{1:k}, z_{1:k})$ is a distribution that can be computed exactly conditional on the model variables, and the distribution $p(M_k \mid M_{1:k-1}, z_{1:k})$ will be estimated using Monte Carlo methods such as particle filtering. The justification for this decomposition follows from the factorisation of the posterior probability[8]

$$\begin{aligned} & p(x_k, M_k \mid x_{1:k-1}, M_{1:k-1}, z_{1:k}) \\ &= p(x_k \mid x_{1:k-1}, M_k, M_{1:k-1}, z_{1:k}) \\ & p(M_k \mid x_{1:k-1}, M_{1:k-1}, z_{1:k}) \end{aligned} \quad (5)$$

If the same number of particles is used in a regular particle filter and a RBPF, intuitively, the latter will provide better estimates for two reasons: first, the dimension of $p(M_k \mid x_{1:k-1}, M_{1:k-1}, z_{1:k})$ is smaller than $p(x_k, M_k \mid x_{1:k-1}, M_{1:k-1}, z_{1:k})$; second, optimal algorithms may be used to estimate the tractable substructure, such as PDA filter.The study shows how PDA filter is combined with particle filtering to facilitate maneuvering target tracking in a cluttered environment. Figure 1 illustrates one cycle of the proposed MMRBPF algorithm.

Like regular particle filter, in order to implement the multiple model Rao-Blackwellized particle filter for target tracking, one needs to evaluate the likelihood of measurements $p\left(z_k \mid M_k, z_{1:k-1}, M_{k-1}^i\right)$ and the optimal importance distribution $p\left(M_k \mid z_{1:k}, M_{k-1}^i\right)$. Once the distributions above is achieved, one can implement the multiple model Rao-Blackwellized particle filter as in Fig.1. Details of the derivation of the algorithmare given below.

2.1 Likelihood Function of Measurement

When there are m_k measurements in the k^{th} scan, the following mutually exclusive and exhaustive hypotheses is obtained:

$$\theta_j = \begin{cases} z_{kj} \text{ is the target originated measurement} & j = 1, 2, \ldots, m_k \\ \text{none of the measurments is target originated,} & j = 0 \end{cases} \quad (6)$$

Using the total probability theorem [11, 12]

$$\begin{aligned} & p\left(z_k \mid M_k, m_k, z_{1:k-1}, M_{k-1}^i\right) \\ &= \sum_{j=0}^{m_k} p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) p\left(\theta_j \mid M_k, m_k, z_{1:k-1}, M_{k-1}^i\right) \\ &= \sum_{j=0}^{m_k} p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) p\left(\theta_j \mid m_k\right) \end{aligned} \quad (7)$$

where $p(\theta_j \mid m_k)$ is the probability of the association event θ_j conditioned only on the number of validated measurements, $p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right)$ is the joint likelihood of the measurements. Since the measurements are conditionally independent,

1. Sequence importance sampling step
   - For $i = 1, \cdots, N$, Sample:
     $M_k^i \sim p\left(M_k \mid z_{1:k}, M_{k-1}^i\right)$
   - For $i = 1, \cdots, N$, evaluate the importance weight
     $$w_k^i \propto w_{k-1}^i \times \frac{p\left(z_k \mid M_k^i, z_{1:k-1}, M_{k-1}^i\right) p\left(M_k \mid M_{k-1}^i\right)}{p\left(M_k \mid z_{1:k}, M_{k-1}^i\right)}$$
   - For $i = 1, \cdots, N$, normalize the importance weight
     $$w_k^i = w_k^i \left[\sum_{j=1}^{N} w_k^j\right]^{-1}$$
2. Selection step
   - Multiple/suppress samples M_k^i with high/low importance weight w_k^i,respectively, to obtain *N* random samples M_k^i approximately distributed according to $p\left(M_k \mid z_{1:k}, M_{k-1}^i\right)$.
3. Updating step
   - For $i = 1, \cdots, N$, use one step of the PDA filter to update the state x_k.

Figure 1. Proposed multiple model Rao-Blackwellized particle filter.

$$p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) = \prod_{i=0}^{m_k} p\left(z_{ki} \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) = \begin{cases} V^{-m_k+1} P_G^{-1} p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right), & j=1,2,\ldots,m_k \\ V^{-m_k} & j=0 \end{cases} \quad (8)$$

where $p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right)$ is the likelihood of the measurement z_{kj}, upon conditioned on the target model M_k, the previous measurements $z_{1:k-1}$ and the previous state model $M_{1:k-1}$.

The probabilities of the association events conditioned only on the number of validated measurements[11] are

$$p\left(\theta_j \mid m_k\right) = \begin{cases} \frac{1}{m_k} P_D P_G \cdot \left[P_D P_G + \left(1 - P_D P_G\right) \frac{\mu_F\left[m_k\right]}{\mu_F\left[m_k - 1\right]} \right]^{-1}, & j=1,\ldots,m_k \\ \left(1 - P_D P_G\right) \frac{\mu_F\left[m_k\right]}{\mu_F\left[m_k - 1\right]} \cdot \left[P_D P_G + \left(1 - P_D P_G\right) \frac{\mu_F\left[m_k\right]}{\mu_F\left[m_k - 1\right]} \right]^{-1}, & j=0 \end{cases} \quad (9)$$

where $\mu_F\left[m_k\right]$ is the probability mass function (pmf) of the number of false measurements (FAs or clutter) in the validation region. P_D is the probability of detection.

Two models can be used for the pmf $\mu_F\left[m_k\right]$

Model 1. A Poisson model with a certain spatial density λ

$$\mu_F\left[m_k\right] = e^{-\lambda V} \frac{\left(\lambda V\right)^{m_k}}{m_k!} \quad (10)$$

Model 2. A diffuse prior model[11]

$$\mu_F\left[m_k\right] = \mu_F\left[m_k\right] = \delta \quad (11)$$

Using the (parametric) Poisson model[12] yields

$$p\left(\theta_j \mid m_k\right) = \begin{cases} P_D P_G \cdot \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1}, & j=1,\ldots,m_k \\ \left(1 - P_D P_G\right) \lambda V \cdot \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1}, & j=0 \end{cases} \quad (12)$$

Define

$$\Pi_{kj} = p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) p\left(\theta_j \mid m_k\right) \quad (13)$$

Using (8) and (12) in (13), one gets

$$\Pi_{kj} = p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) p\left(\theta_j \mid m_k\right) = \begin{cases} P_D \cdot \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1} V^{-m_k+1} p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right) \\ \left(1 - P_D P_G\right) \lambda \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1} V^{-m_k+1} \end{cases} = \xi \cdot \begin{cases} p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right), & j=1,2,\ldots,m \\ b, & j=0 \end{cases} \quad (14)$$

Where

$$\xi = P_D \cdot \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1} V^{-m_k+1},$$

$$b = \frac{\left(1 - P_D P_G\right) \lambda}{P_D}$$

Using (14) in (7), one gets

$$p\left(z_k \mid M_k, m_k, z_{1:k-1}, M_{k-1}^i\right) = \sum_{j=0}^{m_k} p\left(z_k \mid M_k, m_k, \theta_j, z_{1:k-1}, M_{k-1}^i\right) p\left(\theta_j \mid m_k\right) = \xi \left[b + \sum_{j=1}^{m_k} p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right) \right] \quad (15)$$

Now, the key issue remains unanswered that how to choose the likelihood $p_{lik}\left(z_{kj} \mid M_k, z_{1:k-1}, M_{k-1}^i\right)$ of the measurement z_{kj}. In order to evaluate the likelihood of measurement z_{kj}, suppose M target motion models are used in this algorithm. It is defined as

$M_k = 1 \Leftrightarrow$ *Denote the* Constant Velocity Motion at time step k

$M_k = 2 \Leftrightarrow$ *Denote the* Constant Turn Motion at time step k

$\vdots$

$M_k = M \Leftrightarrow$ *Denote the* Constant Acceleration Motion at time step k

If the measurement z_{kj} related to the target motion m, the measurement likelihood can be written as follows

$$p_{lik}\left(z_{kj} \mid M_k = m, z_{1:k-1}, M_{k-1}^i\right) = \int p\left(z_{kj} \mid M_k = m, x_{k,m}\right) p\left(x_{k,m} \mid z_{1:k-1}, M_{k-1}^i\right) dx_{k,m} = \int N\left(z_{kj} \mid h\left(x_k, M_k = m\right), R\right) N\left(x_{k,m} \mid f\left(x_{k-1}, M_{k-1}^i\right), Q\right) dx_{k,m} \quad (16)$$

From the Eqn (16), one sees that the measurement likelihood is the filter likelihood for target. One gets

$$p_{lik}\left(z_{kj} \mid M_k = m, z_{1:k-1}, M_{k-1}^i\right) = N\left(z_{kj} \mid h\left(f\left(x_{k-1}, M_{k-1}^i\right), M_k = m\right), S_{k,t}\right) \; m = 1,2,\ldots,M \quad (17)$$

where $S_{k,t}$ denotes the measurement covariance upon conditioned on the target model.

Using Eqn (17) in Eqn (15), the joint likelihood of the measurements can be denoted as

$$p\left(z_k \mid M_k, m_k, z_{1:k-1}, M_{k-1}^i\right) = \begin{cases} \xi \left[b + \sum_{j=1}^{m_k} N\left(z_{kj} \mid h\left(f\left(x_{k-1}, M_{k-1}^i\right), M_k = 1\right), S_{k,1}\right) \right] & \text{if } M_k = 1 \\ \xi \left[b + \sum_{j=1}^{m_k} N\left(z_{kj} \mid h\left(f\left(x_{k-1}, M_{k-1}^i\right), M_k = 2\right), S_{k,2}\right) \right] & \text{if } M_k = 2 \\ \vdots \\ \xi \left[b + \sum_{j=1}^{m_k} N\left(z_{kj} \mid h\left(f\left(x_{k-1}, M_{k-1}^i\right), M_k = M\right), S_{k,M}\right) \right] & \text{if } M_k = M \end{cases} \quad (18)$$

where

$$\xi = P_D \cdot \left[P_D P_G m_k + \left(1 - P_D P_G\right) \lambda V \right]^{-1} V^{-m_k+1},$$

$$b = \frac{\left(1 - P_D P_G\right) \lambda}{P_D}$$

2.2 Optimal Importance Distribution

For each particle i, the optimal importance distribution is computed by

$$\begin{aligned} & p\left(M_k \mid z_{1:k}, M_{k-1}^i\right) \\ & \propto p\left(z_k \mid M_k, z_{1:k-1}, M_{k-1}^i\right) p\left(M_k \mid z_{1:k-1}, M_{k-1}^i\right) \\ & = p\left(z_k \mid M_k, z_{1:k-1}, M_{k-1}^i\right) p\left(M_k \mid M_{k-1}^i\right) \end{aligned} \quad (19)$$

where the fact that the model M_k does not depend on the previous measurements $z_{1:k-1}$, and depends only on the previous model M_{k-1}^i has been used.

One can sample from the optimal importance distribution as follows:

1. Compute the probabilities for each model m=1,2,…,M

$$\Pi_m^i = p\left(z_k \mid M_k^i = m, z_{1:k-1}, M_{k-1}^i\right) p\left(M_k^i = m \mid M_{k-1}^i\right)$$

m=1,2,…,M (20)

2. Normalise the importance distribution:

$$\hat{\Pi}_m^i = \frac{\Pi_m^i}{\sum_{m=1}^{M} \Pi_m^i}, \; m=1,2,...,M \quad (21)$$

Hence, one can sample the new model M_k^i with the following probabilities:

- Draw $M_k^i = 1$ with the probability $\hat{\Pi}_1^i$
- Draw $M_k^i = 2$ with the probability $\hat{\Pi}_2^i$
- Draw $M_k^i = M$ with the probability $\hat{\Pi}_M^i$

3. EXPERIMENTAL RESULTS

In this section, a simulation scenario and a real scenario is presented to illustrate the implementation of the proposed MMRBPF method. For comparison, a conventional IMM-PDAF algorithm is also simulated.

Consider the system

$$x_k = f\left(x_{k-1}, M_k\right) + g\left(M_k\right) w_k \quad (22)$$

$$z_k = h\left(x_k, M_k\right) + v_k \quad (23)$$

where the target state is $x_k = \left(x, y, z, \hat{x}, \hat{y}, \hat{z}\right)$, $M_k \in \{1,2,3\}$, $m=1$ corresponds to the constant velocity motion model m=2, corresponds to the constant turn model (clockwise), m=2 corresponds to the constant turn model (counterclockwise)[13].

Two passive sensors are located along the x axis with sensor 1 at x = 5 km and sensor 2 at x = –5 km . Using the detection fusion architecture[14], the azimuth and elevation angles, α_i and β_i, measured by sensor i, are transmitted to the fusion node where the measurement vector $(\alpha_1, \beta_1, \alpha_2, \beta_2)$ is formed at each time step. The measurement function is given by

$$h\left(x_k, M_k\right) = \begin{pmatrix} \alpha_1 \\ \beta_1 \\ \alpha_2 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} \arctan\left(\frac{y_1}{x_1}\right) \\ \arctan\left(\frac{z_1}{\sqrt{x_1^2 + y_1^2}}\right) \\ \arctan\left(\frac{y_2}{x_2}\right) \\ \arctan\left(\frac{z_2}{\sqrt{x_2^2 + y_2^2}}\right) \end{pmatrix} \quad (24)$$

The model transition matrix is given by

$$\Pi = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \quad (25)$$

The clutter model is assumed to be of uniform distribution and the number of false measurements (clutters) is assumed to be of Poisson distribution with known parameter λ=1 (number of false measurements per unit of volume (km^2)).The detection probability of the true measurement P_D equals 1 and the gate probability P_G equals. In order to compare the performances of two filters, 50 Monte Carlo runs have been performed.

3.1 Scenario 1: Simulation Trajectory

Trajectory of the target is shown in Fig. 2. In this scenario, $T : t(k) - t(k-1)$ is constant, the initial position of the target is $(2\,\text{km}, 8\,\text{km}, 1\,\text{km})$, and the initial velocity is $(150\,\text{m/s}, 259.8\,\text{m/s}, 0)$. The segments are defined as follows.

- *1st segment*: Rectilinear flight until the plane is at $(6.35\,\text{km}, 15.53\,\text{km}, 1\,\text{km})$ space (from t=0s to t=30s).
- *2nd segment*: Circular turn with turn rate 6°/s (from t=31s to t=50s).
- *3rd segment*: Rectilinear flight until the plane is at

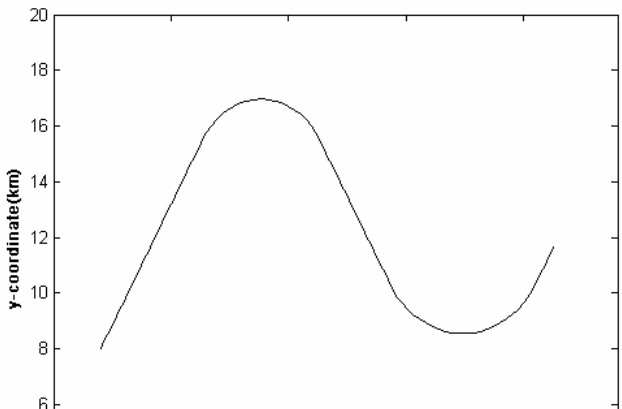


Figure 2. Target trajectory.

$(14.31\text{km}, 10.33\text{km}, 1\text{km})$ space (from t=51s to t=70s).

- 4^{th} *segment*: Circular turn with turn rate 4.8°/s (from t=71s to t=95s).
- 5^{th}*segment*: Rectilinear flight until the plane is at $(21.26\text{km}, 11.63\text{km}, 1\text{km})$ space (from t=96s to t=100s).

Figure 3 shows the RMS position errors of the IMM-PDAF and the MMRBPF. While Figure 4 shows the mode probabilities of the IMM-PDAF and the MMRBPF. It is apparent from Fig.3 that the result of the MMRBPF is better than that of the IMM-PDAF. Also, if one looks at Fig. 4, observed that the mode probabilities of the MMRBPF method are in accordance with the trajectory, and the correct model has the largest probability during each segment and the turns are quickly detected. During the second segment, it is seen that the probability of the model 3 rises at the start of the turn, and has a dominant probability. Once the turn is completed, the model 1 takes over again. One also sees the probability of model 1 for the IMM-PDAF method has dominated during all segments, so the mode probabilities cannot be completely trusted after.

3.2 Scenario 2: Real Trajectory Experiment

In this scenario, the real data experiment has been carried out to evaluate the performance of the proposed

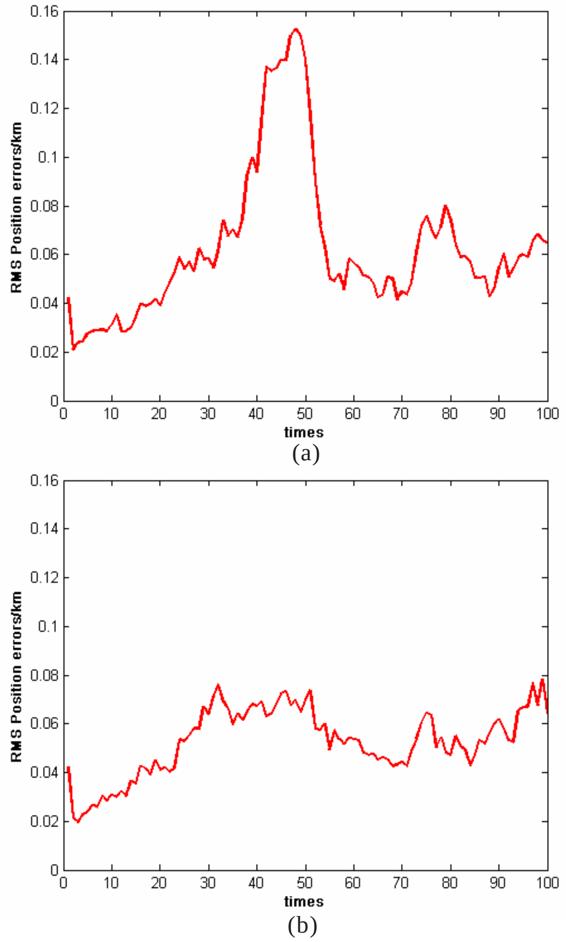


Figure 3. RMS error statistics. (a) IMM-PDAF, (b) MMRBPF.

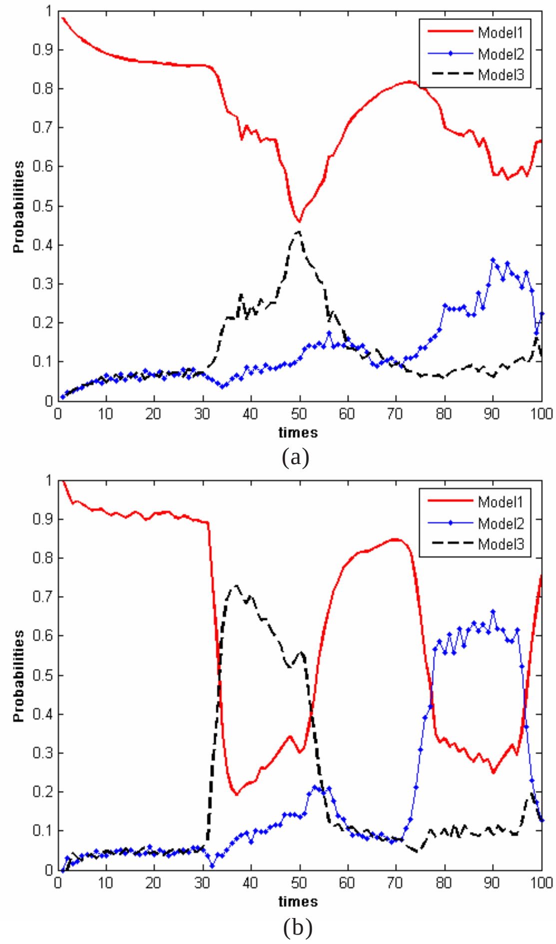


Figure 4. Mode probabilities. (a) IMM-PDAF, (b) MMRBPF.

MMRBPF algorithm. The real data includes 40 nonperiodic sampling points, and the target flight time is 107s. As such, the sampling interval $T : t(k) - t(k-1)$ is not constant. Others are the same as in the scenario one. Trajectory of the target is shown in Fig.5.

Figure 6 shows the estimated target trajectory of the IMM-PDAF and the MMRBPF. Figure 7 shows the RMS position errors of the IMM-PDAF and the MMRBPF. Figure

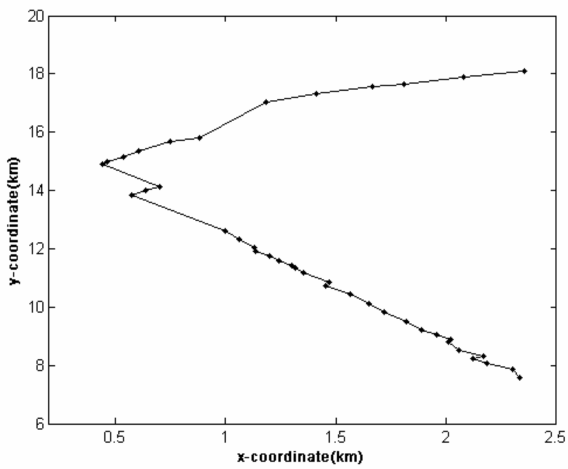


Figure 5. Target trajectory.

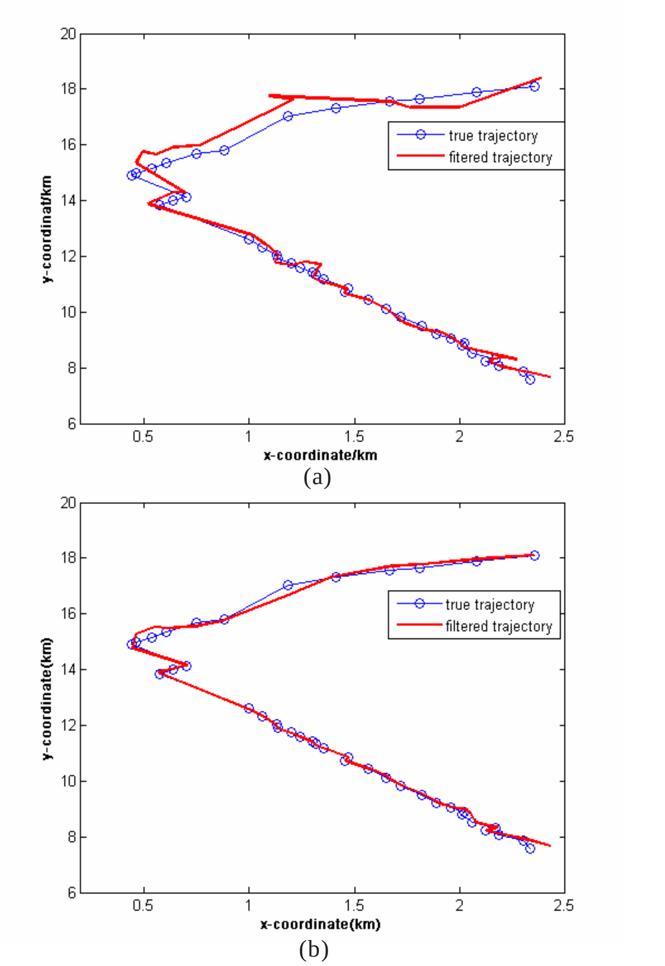


Figure 6. Estimated Target Trajectory. (a) IMM-PDAF, (b) MMRBPF.

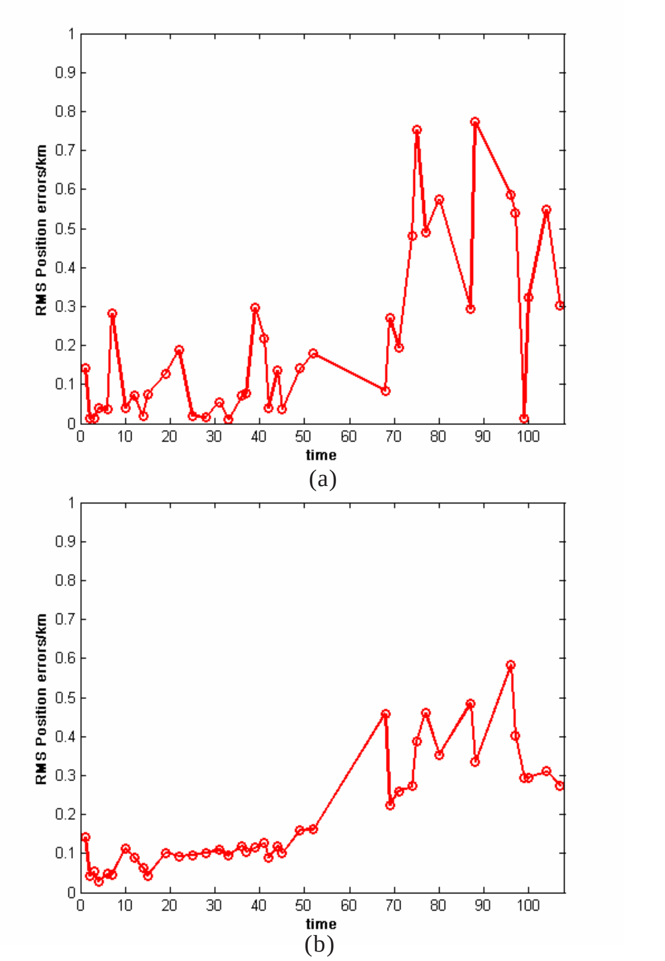


Figure 7. RMS error statistics. (a) IMM-PDAF, (b) MMRBPF.

8 shows the mode probabilities of the IMM-PDAF and the MMRBPF. It is apparent from Figs.6 and 7 that the result of the MMRBPF is better than that of the IMM-PDAF. Table 1 also displays the performance comparison between the IMM-PDA and the MMRBPF methods in terms of RMS position error for two different clutter densities. The percentage improvement obtained by using MMRBPF is calculated as the ratio of the difference between the RMS position errors of the MMRBPF method and the IMM-PDAF method to the RMS position error of the IMM-PDAF method. It is clear from Table 1 that in all cases the results of the MMRBPF are better than that of the IMM-PDA method.

The RMS Position error values apparently show that a significant improvement is obtained on the results of the IMM-PDAF. When the MMRBPF is used, the average

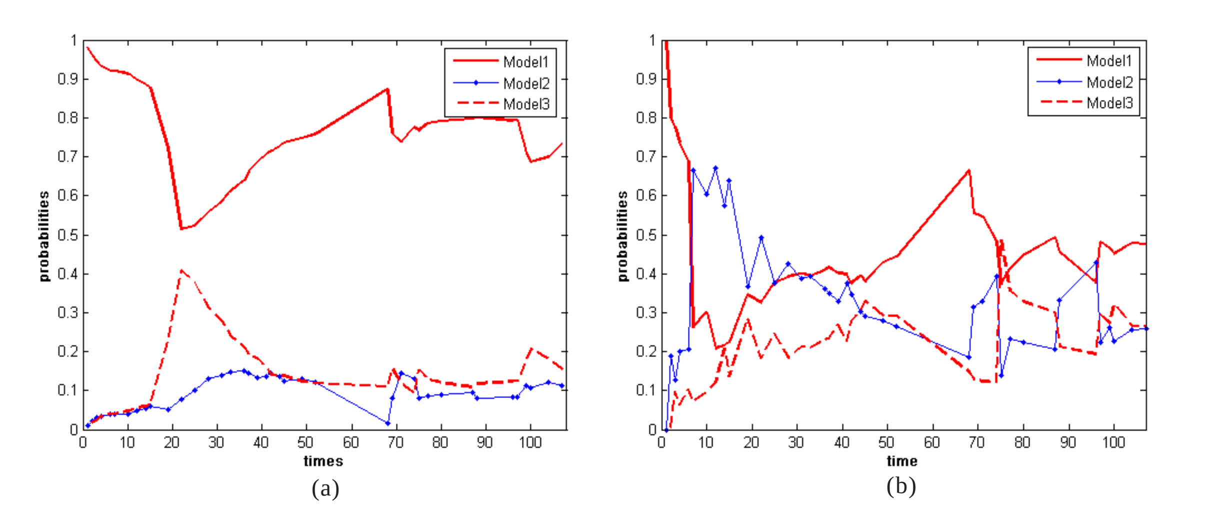


Figure 8. Mode probabilities. (a) IMM-PDAF, (b) MMRBPF.

Table 1. Performance comparison between the IMM-PDAF and the MMRBPF

Clutter density (λ)	Scenarios	RMS position errors(km) IMM-PDAF	MMRBPF	Percentage improvement wrt IMM-PDAF (%)
1.0	1	0.054	0.044	17.7
	2	0.090	0.079	12.1
2.0	1	0.065	0.052	19.7
	2	0.096	0.087	8.9

Table 2. Comparison the probabilities of track loss

Clutter density (λ)	Scenarios	Probabilities of track loss (%) IMM-PDAF	MMRBPF
1.0	1	0	0
	2	36	0
2.0	1	28	0
	2	38	2

percentage improvement with respect to the IMM-PDAF is 14.9 % for 1.0 clutter density and is 14.3 % for 2.0 clutter density, respectively.

Finally, Table 2 shows the probabilities of track loss of the IMM-PDAF method and the MMRBPF method. We have done 100 runs of the same trajectory with different clutter density for scenario 1 and scenario 2 have been performed. In scenario 1, it is seen from Table 2 that the IMM-PDAF method did not diverge and performed almost equally well as the MMRBPF method for 1.0 clutter density, but in 28 runs out of those 100 runs the IMM-PDAF method diverges for 2.0 clutter density. In scenario 2, it is clear from Table 2 that the results of the MMRBPF are better than that of the IMM-PDA method for two different clutter densities (λ=1 or λ=2). The reason for these phenomena is that in the PDAF method the target model is wrongly estimated. This is due to the model interaction stage in the PDAF method is not utilised for target measurement, and results in a bad estimate of the target model. The MMRBPF method, however, can deal with this situation and it is seen that the method has a low probability (2 per cent) of track loss for 2.0 clutter density in the scenario 2, and in other cases the probabilities of track loss is 0 per cent.

4. CONCLUSIONS

In this paper, a novel multiple model Rao-Blackwellized particle filter (MMRBPF)-based algorithm has been proposed for manoeuvring target tracking in a cluttered environment. Rao-Blackwellization allows the algorithm to be partitioned into target tracking and model selection sub-problems, where the target tracking can be solved by the probabilistic data association filter, and the model selection by sequential importance sampling. The analytical relationship between target state and model is exploited to improve the efficiency and accuracy of the proposed algorithm. Extensive comparative studies using both simulated and real data have demonstrated the improved performance of the proposed MMRBPF over the conventional IMM-PDAF.

ACKNOWLEDGEMENTS

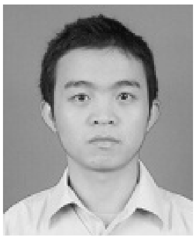
This work was supported by the China Postdoctoral Science Foundation (200804165), and the Natural Science Foundation of the GuangDong Province of China (8451806001001836).

REFERENCES

1. Gordon, N.J.; Salmond, D.J.& Smith, A.F.M. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *J. IEE F Proc. Radar Signal Proc.*, 1993, **140**(2), 107-13.
2. Arulampalam, M.S.; Maskell, S.& Gordon N. etc. A tutorial on particle filters for on-line nonlinear non-Gaussian Bayesian tracking. *J. IEEE Trans. Signal Processing*, 2002, **50**(2), 174-88.
3. McGinnity, S.& Irwin, G.W. Multiple model bootstrap filter for maneuvering target tracking, *IEEE Trans. Aerosp. Electron. Syst.*, 2000, **36**(3),1006–012
4. Doucet, A.;de Freitas, N., & Gordon, N. Sequential Monte Carlo methods in practice, Springer, New York, 2001.
5. Simo Sarkka, Aki Vehtari,& Jouko Lampinen. Rao-Blackwellized particle filter for multiple target tracking, *Information Fusion*, 2007, **8**(8), 2–15.
6. Xinyu Xu, & Baoxin Li. Adaptive Rao-Blackwellized Particle Filter and Its Evaluation for Tracking in Surveillance, *IEEE Trans. Image Proc.*, 2007, **16**(3), 838-49.
7. Casella, G.& Robet, C.P. Rao Blackwellisation of sampling schemes. *Biometrika*, 1996, **83**(1),81-94.
8. Boers, Y.& Driessen, J.N. Interacting multiple model

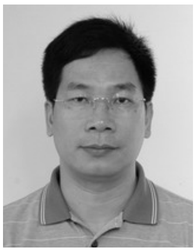
particle filter. *J. IEE Proc Radar Sonar Navig.*, 2003, **150**(5): 344-49
9. Jaco, Vermaak.; Simon J.Godsill,& Patrick, Perez. Monte Carlo filtering for multi-target tracking and data association. *IEEE Trans. Aero. Elect. Syst.*, 2005, **41**(1), 309-32
10. Mark, R. Morelande; Christopher, M.; Kreucher, Keith Kastella. A Bayesian approach to multiple target detection and tracking, *IEEE Trans. Signal Proc.*, 2007, **55**(5),1589-603.
11. Kirubarajan, T. & Bar-Shalom, Y. Probabilistic data association techniques for target tracking in clutter, *Proceedings IEEE*,2004, **92**(3), 536-57.
12. Liang-qun Li, Hong-bing Ji. A Novel Maneuvering Target Tracking Algorithm with Two Passive Sensors. *In* the International Conference on Signal processing, (ICSP'06), Guilin, 2006, **11**, 3047-050.
13. Mallick, Mahendra. & Kirubarajan, T. Multi-sensor single target bearing-only tracking in clutter. *AD Report*, Oct 2001.
14. Francois, Dufour & Michel, Mariton. Tracking a 3-D manoeuvring target with passive sensors. *IEEE Trans. Aeros. Electro. Syst.*, 1991, **27**(4), 725-39.

Contributors



Mr Li Liang-qun received the BS, MS and PhD degrees from the School of Electronic Engineering from Xidian University. His research interests include: Multi-sensor information fusion, target tracking, etc.

Mr Xie Wei-xin is a Professor at the School of Information Engineering, Shenzhen University. His research interests include: Radar target recognition, multi-sensor information fusion, fuzzy information processing, and image processing, etc.



Mr Huang Jing-xiong is a Professor of School of Information Engineering, Shenzhen University. His research interests include: Intelligent information processing, radar signal processing, etc.

Mr Huang Jian-jun is a Professor of School of Electronic Engineering, Shenzhen University. His research interests include: Pattern recognition, fuzzy information processing, image processing, etc.