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Improved Rao-Blackwellized particle filtering algorithms for multi-target tracking in clutter

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Abstract: We consider the problem of multiple target tracking in the presence of clutter (false alarm) measurements. To improve the performance of the Rao-Blackwellized particle filter (RBPF) data association algorithms, some simple but effective strategies are implemented. We first present a sequential likelihood method, i.e., all measurements are used to update the particles more than one time in each time step. It is observed that the tracking performance of the algorithm is not severely loss with fewer particles. We then present a simple gating technique to reduce the validated measurements to a feasible level. It is worth mentioning that the association probabilities are not calculated by grouping targets into clusters as the joint probabilistic data association (JPDA), but only reserve the validated measurements in the joint validation region (gate) and ignore the measurements outside. Simulations are also presented to compare the performance of the proposed algorithms.

Keywords: Multiple target tracking, data association, Rao-Blackwellized particle filter, sequential likelihood

1 INTRODUCTION

In multi-target tracking, data association remains a challenge in cluttered environment [1]-[3]. As an important enhancement of the particle filter, Rao-blackwellized particle filter (RBPF) has also been used to solve this problem in recent years [4]-[6]. The idea of this approach is that the joint data association and target tracking problem can be solved by partly sequential Monte Carlo method instead of pure particle filter sampling [7], [8], so that the needed number of particles may be reduced to a low order of magnitude.

However, in the application of the RBPF multi-target tracking algorithms, we found that the success rate of data association could not be improved only by increasing the number of particles. To improve the ability of the algorithms but not increase the time cost, we present in this paper some simple but effective methods. The main contribution of this paper has two folders, one is the development of a sequential likelihood method in RBPF multi-target tracking algorithms, the other is the application of the simple gating technique, which restrict data association into validation regions.

The rest of this paper is organized as follows. In Section 2, we give a brief introduction of the RBPF data association algorithms. The sequential likelihood and simple gating methods are presented in Section 3. Finally, simulation results and conclusions are given in Section 4 and Section 5, respectively.

2 RAO-BLACKWELLIZED PARTICLE FILTER FOR MULTIPLE TARGET TRACKING

In this section we will give a brief introduction of the RBPF algorithms for multi-target tracking. The basic RBPF model is assumed to be time-varying system as follows:

$$x_k^2 = F_{k-1}x_{k-1}^2 + w_{k-1} \tag{1}$$

$$z_k = H_k x_k^2 + v_k \tag{2}$$

where, w_{k-1} and v_k are zero mean Gaussian random vectors, F_{k-1} and H_k are matrices with compatible dimensions. This type of system can be termed conditionally linear-Gaussian for the set of variables x_k^1, a RBPF algorithm can be applied to estimate the state $x_k = \{x_k^1; x_k^2\}$. The RBPF can be seen as a form of constrained PF (Particle Filter) applicable to a subclass of state-space models. By choosing N_p particles at time step k, a generic RBPF algorithm, applicable to problems of the form (1) and (2) is presented as follows [9].

Step 1. For every $i \in \{1, 2, ..., N_p\}$:

- Draw $x_k^{1(i)} \sim q(x_k^1 | x_{1:k-1}^{1(i)}, z_{1:k})$
- Set $x_{1:k}^{1(i)} = \{x_k^{1(i)}; x_{1:k-1}^{1(i)}\}$
- Compute the normalized weights: $\tilde{w}_k^{(i)} \propto w_{k-1}^{(i)} \frac{p(z_k|x_{1:k}^{1(i)}, z_{1:k-1}) p(x_k^{1(i)}|x_{1:k-1}^{1(i)}, z_{1:k-1})}{q(x_k^{1(i)}|x_{1:k-1}^{1(i)}, z_{1:k})}$,

Step 2. For every $i \in \{1, 2, ..., N_p\}$:

- Update $p(x_k^2|x_{1:k}^{1(i)}, z_{1:k})$ using $p(x_{k-1}^2|x_{1:k-1}^{1(i)}, z_{1:k-1})$, $x_k^{1(i)}$, $x_{k-1}^{1(i)}$, and z_k.

Step 3. Resample the particles if needed.

In [5] it has been shown that the RBPF based data association algorithm can be obtained directly from the RBPF framework when the latent values x_k^1 are defined to contain the data association event indicators c_k,

$$x_k^1 = c_k \tag{3}$$

The advantage of RBPF is that only the index of data association needs to be sampled from the importance distribution so that the required number of particles can be greatly reduced. Nevertheless, it seems that the number of particles should still be large enough in dense clutter environment, because as data association becomes more difficult the importance distribution will be more complex. In experiments, it is found that only a few particles had unnegligible weights after a certain number of recursive steps, that is to say most of the particles are degenerated prematurely and we cannot improve the performance only by increasing the number of particles. Of course, the resampling strategy can be implemented when a significant degeneracy is observed, but the resampling threshold cannot be calculated analytically. Typically, the values of the threshold are selected ad hoc and degeneracy may possibly happen.

3 PROPOSED ALGORITHMS

In the following discussions, we will show two simple but effective methods to improve the performance of the RBPF algorithm in the application of multi-target tracking.

3.1 Sequential likelihood function based algorithms

we first present a sequential likelihood function based method to resolve the particle degeneracy problems, i.e., all validated measurements are used to update the state of particles more than one time in each time step. The proposed algorithm is derived based on an existing RBPF data association algorithm termed Rao-Blackwellized Monte Carlo data association (RBMCDA), in which the optimal importance distribution is used as the association sampling function. The main procedure of the proposed sequential likelihood technique based RBMCDA data association algorithm (S-RBMCDA) is presented as follows:

i. Calculation of the predicted measurement $\hat{z}_{j,k}$ and the related innovation $S_{j,k}$

$$\hat{z}_{j,k} = H_{j,k}\hat{x}_{j,k|k-1},\ S_{j,k} = H_{j,k}P_{j,k|k-1}H_{j,k}^T + R_{j,k} \tag{4}$$

where

$$\begin{cases} \hat{x}_{j,k|k-1} = \sum_{i=1}^{N_p} w^{(i)}\hat{x}_{j,k|k-1}^{(i)}, \\ P_{j,k|k-1} = \sum_{i=1}^{N_p} w^{(i)}P_{j,k|k-1}^{(i)}. \end{cases} \tag{5}$$

ii. Calculation of the association priors $p(c_k^{(i)}|c_{k-m:k-1}^{(i)})$ according to the Markov chain method introduced in [5].

iii. Calculation of the measurement likelihood for each data association hypothesis, $j = 1, \cdots, T$.

$$p(z_k|c_k = j, c_{1:k-1}^{(i)}, z_{1:k-1}) = \mathcal{N}(z_k|\hat{Z}_{j,k}^{(i)}, S_{j,k}^{(i)}) \tag{6}$$

and

$$p(z_k|c_k = 0, c_{1:k-1}^{(i)}, z_{1:k-1}) = V^{-1}, \tag{7}$$

where V is volume of the detection region.

iv. Calculation of the posterior distribution of $c_k^{(i)}$

$$\begin{aligned} & p(c_k^{(i)}|c_{1:k-1}^{(i)}, z_{1:k}) \\ & = p(z_k|c_k^{(i)}, c_{1:k-1}^{(i)}, z_{1:k-1})p(c_k^{(i)}|c_{k-m:k-1}^{(i)}), \end{aligned} \tag{8}$$

v. Sampling a new association $c_k^{(i)} = j$

vi. Calculation of the new weights for each particle

$$w_k^{(i)} \propto w_{k-1}^{(i)} \frac{p(z_k|c_k^{(i)}, c_{1:k-1}^{(i)}, z_{1:k-1})p(c_k^{(i)}|c_{k-m:k-1}^{(i)})}{p(c_k^{(i)}|c_{1:k-1}^{(i)}, z_{1:k})} \tag{9}$$

vii. Resampling the particles if needed.

In this procedure the target state priors can be represented as a weighted importance samples set

$$p(x_{j,0}) = \sum_{i=1}^{N_p} w_0^{(i)}\mathcal{N}(x_{j,0}|x_{j,0}^{(i)}, P_{j,0}^{(i)}) \tag{10}$$

where N_p is the number of particles. The dynamics and measurements for target j (j=1, $\cdots$, T) are assumed to be linear Gaussian

$$p(x_{j,k}|x_{j,k-1}) = \mathcal{N}(x_{j,k}|F_{j,k-1}\ x_{j,k-1}, Q_{j,k-1}) \tag{11}$$

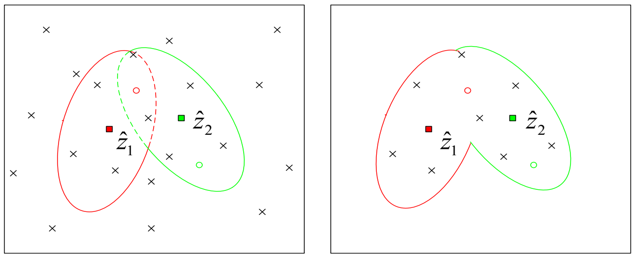
$$p(z_k|x_{j,k}, c_k = j) = \mathcal{N}(z_k|H_{j,k}x_{j,k}, R_{j,k}). \tag{12}$$

Note that this algorithm is generally the same as the generic RBMCDA [4], [5] except the sequential likelihood procedure which is used to improve the ability of the data association. It just need to repeat from the procedure ii. to v. several times.

3.2 Simple gating

In the RBMCDA algorithms, gating techniques for selecting validated measurements are not introduced. For the known number of target version of the RBMCDA algorithm, it always deals with all measurements in the entire detection region, which is the same as the unknown number of target version. Obviously, too many clutter originated measurements are considered in data association and high computational complexity arises.

To overcome this difficulty, we then present a simple gating technique which can be incorporated into the known



(a) (b)

Fig. 1: Example of the measurement validation. (a):Two targets tracking situation. (b): The equivalence simple gate.

number of target version of the RBMCDA algorithm for reducing the validated measurements to a feasible level. It is worth mentioning that the association probabilities are not calculated by grouping targets into clusters as the joint probabilistic data association (JPDA), but only reserve the validated measurements in the joint validation region (gate) and ignore the measurements outside. Following [10], the validation region is the elliptical region

$$\Gamma(k,\gamma) = \{z : [z - \hat{z}(k|k-1)]' S(k)^{-1} [z - \hat{z}(k|k-1)] \le \gamma\} \quad (13)$$

where γ is the gate threshold corresponding to the gate probability P_g, which is the probability that the gate contains the true measurement if detected, and $S(k)$ is the covariance of the innovation corresponding to the predicted measurement.

In Fig. 1, the target originated measurements "o" and clutter originated measurements "$\times$" are shown. A measurement is validated for target j if it falls inside the elliptical region centered at $\hat{Z}_j$ (the predicted measurement of target j), and only the validated measurements for a particular target are candidates to be association with that target. The simple gating technique can be easily incorporated into the framework of the algorithm in Section 3.1. In this gating based algorithm (G-RBMCDA), only the validated measurements are used to enumerate the data associations.

It should be noted that, the introduce simple gating technique can not be directly used in the sequential likelihood based algorithms. In fact, we found that the combinational algorithm may possibly be failed in experiments. An intuitive explanation of this problem is that the fixed validation regions should be changed even in one time step.

4 SIMULATIONS

The performance of S-RBMCDA and G-RBMCDA algorithms are compared with generic RBMCDA in this section. We model the two targets with near constant velocity model in 2-dimensional Cartesian coordinates and the discrete-time dynamic and measurement model of target j has the following form:

$$x_{j,k} = F x_{j,k-1} + w_{k-1} \quad (14)$$

$$z_{j,k} = H x_{j,k} + v_k \quad (15)$$

where

$$F = \begin{pmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \quad (16)$$

w_{k-1} and v_k are zero mean Gaussian process noise. The Process noise variance and the variance in the measurements are selected as 0.1. The sample interval $T = 0.1$ and the correct measurements returns with a know detection probability $P_d = 0.99$. The clutter are modeled as independent and identically distributed with uniform spatial distribution in a detection region of the coordinate plane $[0,\ 25] \times [0,\ 25]$, and the number of clutter measurements obeys a Poisson distribution with the Poisson random number λ. The gating region used is $P_g = 0.9997$ with $\gamma = 16$. The number of particles used in the three algorithms: 50 (RBMCDA), 20 (S-RBMCDA, repeat 2 times), 50 (G-RBMCDA). in All simulations are run on a PC with a 2.8-GHz Intel processor.

Fig. 2 and Fig. 3 show the position RMSE for tracking two crossing targets. The clutter rate $\lambda = 10$ and the experiments are repeated 100 times. It is observed that the RMSE of the S-RBMCDA algorithm is lower than the generic RBMCDA even with fewer particles. In fact, G-RBMCDA can further improve the ability of none-validation-region algorithms (RBMCDA and S-RBMCDA) mainly because only the validated measurements are considered in data association and the clutter measurements outside the validation regions are abandoned reasonably.

Fig. 4 gives the running time as a function of N_p, we can see that the S-RBMCDA and G-RBMCDA algorithms are computationally efficient than the generic RBMCDA as expected. The G-RBMCDA is the most efficient algorithms, but it can only be implemented in the known number version of target tracking. For each method we run the algorithms with the increasing number of particles and repeat each experiment 50 times to get an average results.

5 CONCLUSION

In this paper, the improved RBPF algorithms have been presented for multi-target tracking in clutter. The proposed sequential likelihood method can be used to improve the performance of the generic algorithm with less particles. If the number of targets is fixed, the simple gating based algorithm only consider validation regions where the true measurements are concentrated with high probability. The computational time is greatly decreased for less clutter needs to be considered. Moreover, the gating based algorithms can

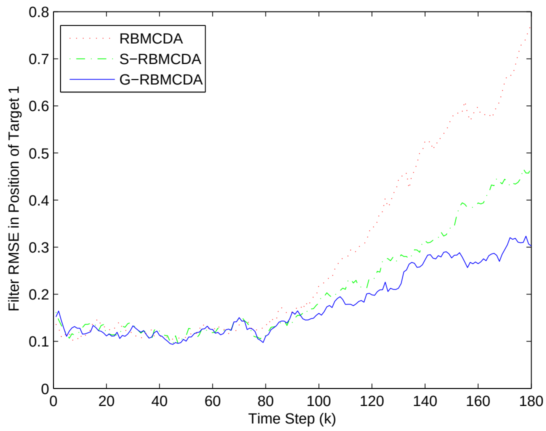


Fig. 2: Comparison of the average position estimation errors (RMSE) of target 1.

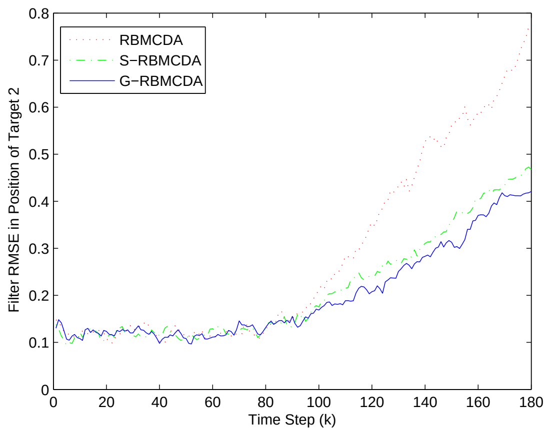


Fig. 3: Comparison of the average position estimation errors (RMSE) of target 2.

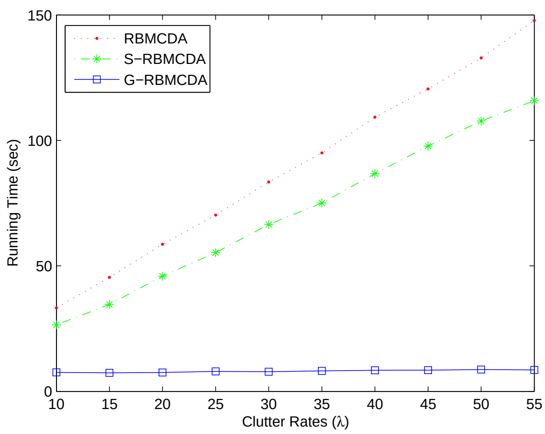


Fig. 4: Comparison of the average running time of the three algorithms.

improve the tracking ability of the algorithm without the disturbance of clutter outside the validation region. Future work should be done to intensively study the sequential likelihood method for the general particle filtering algorithms.

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