14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006, copyright by EURASIP

EFFICIENT VARIABLE RATE PARTICLE FILTERS FOR TRACKING MANOEUVRING TARGETS USING AN MRF-BASED MOTION MODEL

William Ng, Sze Kim Pang, Jack Li, and Simon Godsill

Department of Engineering
University of Cambridge
Trumpington Road, Cambridge,
U.K.
phone: + (44) 1223 3 32767, fax: + (44) 1223 3 32662, email: {kfn20, skp31, jfl28, sjg}@eng.cam.ac.uk
web: http://www-sigproc.eng.cam.ac.uk

ABSTRACT

In this paper we describe an efficient real-time tracking algorithm for multiple manoeuvring targets using particle filters. We combine independent partition filters with a Markov Random Field motion model to enable efficient and accurate tracking for interacting targets. A Poisson model is also used to model both targets and clutter measurements, avoiding the data association difficulties associated with traditional tracking approaches. Moreover, we present a variable rate dynamical model in which the states change at different and unknown rates compared with the observation process, thereby being able to model parsimoniously the manoeuvring behaviour of an object even though only a single dynamical model is employed. Computer simulations demonstrate the potential of the proposed method for tracking multiple highly manoeuvrable targets in a hostile environment with high clutter density and low detection probability.

1. INTRODUCTION

Existing multitarget tracking algorithms under the standard state-space modelling approach in [1, 2, 3] commonly assume that the hidden target states and the observations are processed at an identical rate. In the case where targets exhibit long periods of little activity (smooth or constant-velocity movement), followed by periods of more elaborate manoeuvring, multiple-model approaches [2, 3, 4, 5, 6] are usually adopted to track these targets where a bank of filters in parallel to match several possibilities for the actual target dynamics throughout the tracking time frame is used.

Here we propose a departure from the standard state-space modelling approach to the multitarget tracking problem using sequential Monte Carlo methods [7, 8, 9]. Based on variable rate particle filters (VRPF) for single target tracking [10, 11, 12], we assume that the states, which are modelled here by a dynamic model expressed in intrinsic coordinates, are modelled at a different rate from the observations, such that it is not necessary to estimate new target states every time we receive an observation. More importantly this new model enables us also to track and adapt to rapid manoeuvres without the extensive computations required by multiple filters. Related models that involve a random time of arrival process similar to ours can be found in the independent work of [13] for target classification. In order to model very high clutter and multiple targets a Poisson data model is adopted to model both the observations and the targets, as in [14, 15, 16]. These give rise to a reasonable representation of real target-sensor processes and also to a simpler observation likelihood function which is exempt from explicit computation of any data association variables.

We also propose to integrate the independent partition particle filter (IPPF) [17] and the Markov Random Field (MRF) motion model [18] with the VRPF framework in order to model the interactions between the targets, reduce the rejection rate of sampled particles, and suffer less from the curse of dimensionality.

The paper is organised as follows. Section 2 presents the state-space model, and Section 3 describes the MRF motion model to represent the target interactions. Section 4 formulates the intrinsic coordinate system, followed by a description of the proposed method where the VRPF, the MRF, and the IPPF are integrated in Section 5. Simulation results are shown in Section 6, followed by conclusions in Section 7.

2. DYNAMIC AND OBSERVATION MODELS

Assuming that the number of independent targets to be tracked K is fixed and known, we denote the state of target k by $\theta_{k,l_k} = \{\varphi_{k,l_k}, \tau_{k,l_k}\}$, where $l_k \in \mathbb{I}$ is a discrete state index of target k, τ_{k,l_k} is the continuous-valued time at which target k changes its state, and φ_{k,l_k} is comprised of the state parameters (e.g. positions, heading, speed, acceleration, etc.). Details of φ_{k,l_k} will be given later. Denote the combined state of all K targets by $\theta_{\mathbf{l}} = \{\theta_{1,l_1}, ..., \theta_{K,l_K}\}$. It is assumed that the state $\theta_{\mathbf{l}}$ evolves according to Markovian dynamic model as

$$p(\theta_{\mathbf{l}}|\theta_{\mathbf{l}-1}) \propto p_{\varphi}(\varphi_{\mathbf{l}}|\varphi_{\mathbf{l}-1})p_{\tau}(\tau_{\mathbf{l}}|\tau_{\mathbf{l}-1}), \tag{1}$$

where $p_{\varphi}(\cdot)$ and $p_{\tau}(\cdot)$ are the prior functions of $\varphi_{\mathbf{l}}$ and $\tau_{\mathbf{l}}$, respectively.

We will denote by $\mathfrak{Y}_n = \{\mathbf{y}_n^p\}$ a set of independent observations received at the discrete measurement index $n \in \mathbb{I}$ from N_o sensors independently scanning within the observation space $\mathfrak{R}_y$, where $\mathbf{y}_n^p$ is an observation vector received at sensor $p \in \{1, ..., N_o\}$. Note that the state process rate τ_{k,l_k} may be different from and/or slower than measurement process rate n. Let $\mathbf{y}_{m,n}^p$ be the mth element of $\mathbf{y}_n^p$ for $m \in \{1, ..., M_n^p\}$, where M_n^p is the number of measurements (both target and clutter) returned by sensor p. Since any element of $\mathbf{y}_n^p$ may originate from a true target or from clutter, we adopt a Poisson process to model the observations in which the number of the kth target measurements is randomly drawn from a Poisson distribution having mean Λ_θ^k whereas the number of clutter measurements have a mean number Λ_C [14, 15, 16].

Accordingly, the likelihood function of the observations can be expressed as

$$p(\mathfrak{Y}_n|\theta_1) \propto \prod_{p=1}^{N_o} \prod_{m=1}^{M_n^p} \Lambda(\mathbf{y}_{m,n}^p), \quad (2)$$

where $\Lambda(\mathbf{y}_{m,n}^p) = \sum_{k=1}^{K} \Lambda_\theta^k p_\theta(\mathbf{y}_{m,n}^p|\theta_{k,l_k},n) + \Lambda_C p_c(\mathbf{y}_{m,n}^p)$ with $p_\theta(\cdot)$ and $p_c(\cdot)$ being the likelihood functions of target and clutter measurements, respectively, given by

$$p_\theta(\mathbf{y}_{m,n}^p|\theta_{k,l_k},n) = \mathcal{N}\left(\mathbf{y}_{m,n}^p|\mathbf{g}(\widetilde{\theta}_{k,n},\vartheta_n^p),\mathbf{\Sigma}_w^p\right), \quad (3)$$

$$p_c(\mathbf{y}_{m,n}^p) = \mathcal{U}_{\mathfrak{R}_y}(\mathbf{y}_{m,n}^p), \quad (4)$$

where ϑ_n^p represents the state of the pth sensor, $\mathbf{\Sigma}_w^p$ is the observation noise covariance for sensor p, and $\mathcal{U}_{\mathfrak{R}_y}(\cdot)$ is the uniform distribution over the surveillance region $\mathfrak{R}_y$. The observation function $\mathbf{g}(\cdot)$ may be linear or nonlinear in $\widetilde{\theta}_{k,n}$, which is an interpolated state value obtained from a function $\mathbf{h}(\cdot)$ between the state values θ_{k,l_k-1} and θ_{k,l_k} as follows

$$\widetilde{\theta}_{k,n} \triangleq \mathbf{h}(\{\varphi_{k,l_k},\tau_{k,l_k}\},n),\ \tau_{k,l_k-1} < n \leq \tau_{k,l_k}, \quad (5)$$

where details on the function $\mathbf{h}(\cdot)$ will be given in the next section. Note that the model in (2) avoids any explicit treatment of the data association problem inherent in many tracking scenarios.

3. MARKOV RANDOM FIELD MOTION MODEL

Here we model the interaction between targets by a Markov random field (MRF) [18] constructed on the fly that penalises those states that are closely spaced with each other to avoid any track coalescence. We use a pairwise MRF to obtain a more realistic dynamical model that models the interactions between nearby targets as follows

$$\psi_n(\theta_{i,l_i},\theta_{j,l_j}) \propto \exp(-d_n^{i,j}), \quad (6)$$

where $\psi_n(\theta_{i,l_i},\theta_{j,l_j})$ is the pairwise interaction potential between targets i and j and $d_n^{i,j}$ is a penalty function that penalises the states of two targets that are closely spaced at time n. That is, $d_n^{i,j}$ is maximal when two targets coincide and gradually falls off as they move apart. The dynamic prior in (1) becomes

$$\begin{aligned} p(\theta_1|\theta_{1-1}) &\propto \widetilde{\psi}_n \prod_{k=1}^{K} p(\theta_{k,l_k}|\theta_{k,l_k-1}), \\ &= \widetilde{\psi}_n \prod_{k=1}^{K} p(\varphi_{k,l_k}|\varphi_{k,l_k-1})p(\tau_{k,l_k}|\tau_{k,l_k-1}), \end{aligned} \quad (7)$$

where

$$\widetilde{\psi}_n = \prod_{i,j\in\{1,..,K\}} \psi_n(\theta_{i,l_i},\theta_{j,l_j}). \quad (8)$$

4. VARIABLE RATE MODEL USING INTRINSIC COORDINATE SYSTEM

Since we consider targets are moving independently at this stage, the subscript target index k will be dropped to simplify our expression. To model the manoeuvring of an object we adopt an intrinsic coordinate system as in [11, 16] in which applied forces are related to the heading ϕ_t of the object as follows

$$\mathfrak{T} = \lambda\frac{ds_t}{dt} + \mathfrak{M}\frac{d^2 s_t}{dt^2}, \text{ and } \mathfrak{P} = \mathfrak{M}\frac{ds_t}{dt}\frac{d\phi_t}{dt}, \quad (9)$$

where $\mathfrak{T}$ and $\mathfrak{P}$ are the tangential and radial components of the applied force, $\mathfrak{M}$ is the mass of the object, and $\lambda\frac{ds}{dt}$ represents a resistance applied in the opposite direction to the heading with a known constant λ. Distance travelled along the path of motion is denoted by s_t, while angle relative to a fixed bearing is denoted by ϕ_t. In the variable rate model we assume that a piecewise constant thrust, relative to the direction of heading, is applied between τ_{l-1} and τ_l.

Integrating these differential equations [11] between τ_{l-1} and $\tau_l = \tau_{l-1} + \Delta\tau_l$ gives

$$v_l \triangleq v(\tau_l) = \lambda^{-1}\left(\mathfrak{T} - (\mathfrak{T} - \lambda v_{l-1})e^{-\frac{\Delta\tau_l}{\mathfrak{M}}\lambda}\right), \quad (10)$$

$$\begin{aligned} s_l \triangleq s(\tau_l) =& s_{l-1} + \frac{\Delta\tau_l}{\lambda}\mathfrak{T} + \\ & \frac{\mathfrak{M}}{\lambda}(\mathfrak{T} - \lambda v_{l-1})(e^{-\frac{\Delta\tau_l}{\mathfrak{M}}\lambda} - 1), \end{aligned} \quad (11)$$

$$\phi_l \triangleq \phi(\tau_l) = \phi_{l-1} + \frac{\mathfrak{P}}{\mathfrak{T}}\left(\frac{\Delta\tau_l\lambda}{\mathfrak{M}} - \log\left|\frac{v_{l-1}}{v_l}\right|\right), \quad (12)$$

where the Cartesian position can be obtained by $\mathbf{x}_l = \mathbf{x}_{l-1} + \int_{\tau_{l-1}}^{\tau_l} v_t e^{j\phi_t} dt$.

Accordingly, we define our variable rate state parameter of the kth target by $\varphi_{k,l_k} = \{\mathfrak{T}_{k,l_k},\mathfrak{P}_{k,l_k},\mathbf{x}_{k,l_k},v_{k,l_k},\phi_{k,l_k}\}$, where the target positions $\mathbf{x}_{k,t}$, speed $v_{k,t}$, and angle $\phi_{k,t}$ at any time t between τ_{k,l_k-1} and τ_{k,l_k} can be deterministically obtained. The functions in (10)–(12) collectively define the interpolation function $\mathbf{h}(\cdot)$ in (5). In other words, the parameters in θ_{k,l_k} that we need to stochastically sample are $\Delta\tau_{k,l_k}$, $\mathfrak{T}_{k,l_k}$, and $\mathfrak{P}_{k,l_k}$, whose prior functions are

$$p(\Delta\tau_{k,l_k}) = \mathcal{G}(\alpha_\tau,\beta_\tau), \quad (13)$$

$$p(\mathfrak{T}_{k,l_k}) = \mathcal{N}(\mu_{\mathfrak{T}_k},\sigma_{\mathfrak{T}_k}^2), \quad (14)$$

$$p(\mathfrak{P}_{k,l_k}) = \mathcal{N}(0,\sigma_{\mathfrak{P}_k}^2), \quad (15)$$

where $\mathcal{G}(\cdot)$ and $\mathcal{N}(\cdot)$ are the Gamma and Normal distributions, respectively. Accordingly we may rewrite (7) as

$$p(\theta_1|\theta_{1-1}) \propto \widetilde{\psi}_n \prod_{k=1}^{K} p(\mathfrak{T}_{k,l_k})p(\mathfrak{P}_{k,l_k})p(\Delta\tau_{k,l_k}). \quad (16)$$

5. SEQUENTIAL MONTE CARLO METHODS

In the VRPF framework we use N particles $\{\theta_1^{(i)}\}_{i=1}^N$, where $\theta_1^{(i)} = \{\theta_{k,l_k}^{(i)}\}_{k=1}^K$ is a particle of target states of θ_1, with their associated importance weights $\{w_n^{(i)}\}_{i=1}^N$ to approximate the posterior distribution function $\pi(\theta_1^{(i)}|\mathfrak{Y}_n)$, given $\{\theta_{1-1}^{(i)},w_{n-1}^{(i)}\}_{i=1}^N$, where for $i=1,...,N$,

$$\begin{aligned} \theta_1^{(i)} &\sim q_\theta(\theta_1^{(i)}|\theta_{1-1}^{(i)},\mathfrak{Y}_n), \\ &= q_\varphi(\varphi_1^{(i)}|\varphi_{1-1}^{(i)},\tau_1^{(i)},\tau_{1-1}^{(i)},\mathfrak{Y}_n)\,q_\tau(\tau_1^{(i)}|\tau_{1-1}^{(i)},\mathfrak{Y}_n), \end{aligned} \quad (17)$$

$$w_n^{(i)} \propto w_{n-1}^{(i)} \times \frac{p(\mathfrak{Y}_n|\theta_1^{(i)})\, p(\theta_1^{(i)}|\theta_{1-1}^{(i)})}{q_\theta(\theta_1^{(i)}|\theta_{1-1}^{(i)}, \mathfrak{Y}_n)}, \sum_{i=1}^{N} w_n^{(i)} = 1, \quad (18)$$

where $q_a(\cdot)$ is an importance sampling function for parameter a, which is not an efficient sampling method when the number of parameters becomes large. In traditional particle filters where all state parameters are jointly sampled and estimated in a particle, many good state estimates combined with the bad estimates with low probabilities in the particle will be rejected, leading to poor estimation. A solution is to adopt the Independent Partition Particle Filter [17] that allows particles to interact in such a way that a particle is assembled from "good" state estimates while the joint posterior distribution function is approximately correct under the assumption that the multitarget posterior factorises over individual targets.

5.1 Independent Partition Particle Filter (IPPF)

In the IPPF, we first *independently* estimate the state particles of the targets, and then strategically assemble these individual particles to form the joint state particles according to the corrected importance weights. Denote a set of *partition weights* for target k by $\{\rho_{k,n}^{(i)}\}$, where

$$\rho_{k,n}^{(i)} \propto \frac{p(\mathfrak{Y}_n|\theta_{k,l_k}^{(i)})p(\theta_{k,l_k}|\theta_{k,l_k-1}^{(i)})}{q_k(\theta_{k,l_k}|\theta_{k,l_k-1}^{(i)}, \mathfrak{Y}_n)}, \quad (19)$$

where $q_k(\theta_{k,l_k}|\theta_{k,l_k-1}^{(i)}, \mathfrak{Y}_n) \propto p(\mathfrak{T}_{k,l_k})p(\mathfrak{P}_{k,l_k})p(\Delta\tau_{k,l_k})$ is the importance sampling for target k. Once we have K sets of independent state particles with their associated partition weights, i.e., $\{\theta_{k,l_k}^{(i)}, \rho_{k,n}^{(i)}\}_{i=1}^{N}$ for $k = \{1,...,K\}$, a new joint particle $\theta_1^{(i)}$ can be constructed by sampling the individual target components from the pool of particles, according to the individual target partition weights. It follows that the associated joint importance weights can be computed as follows

$$w_n^{(i)} \propto w_{n-1}^{(i)} \times \frac{\widetilde{\psi}_n^{(i)}}{\widetilde{\rho}_n^{(i)}} \times p(\mathfrak{Y}_n|\theta_1^{(i)}), \quad (20)$$

where $\widetilde{\psi}_n^{(i)}$ is given in (8) and $\widetilde{\rho}_n^{(i)}$ is the composite partition weight [17] that will undo the bias introduced when the independent state particles are assembled. Details of this algorithm are summarised as follows.

Algorithm

1. For $k = 1,...,K$, $i = 1,...,N$, generate independent samples $\theta_{k,l_k}^{(i)} \sim q_k(\theta_{k,l_k}^{(i)}|\theta_{k,l_k-1}^{(i)}, \mathfrak{Y}_n)$ to obtain $\rho_{k,n}^{(i)}$ as follows
$$\rho_{k,n}^{(i)} \propto \frac{p(\mathfrak{Y}_n|\theta_{k,l_k}^{(i)})p(\theta_{k,l_k}|\theta_{k,l_k-1}^{(i)})}{q_k(\theta_{k,l_k}|\theta_{k,l_k-1}^{(i)}, \mathfrak{Y}_n)}, \ \sum_{i=1}^{N} \rho_{k,n}^{(i)} = 1.$$
2. For $k = 1,...,K$, $i = 1,...,N$ sample an index $j_k^{(i)} \sim \{\rho_{k,n}^{(i)}\}_{i=1}^{N}$ and replace $\{\theta_{k,l_k}^{(i)}, \rho_{k,n}^{(i)}\} \longleftarrow \{\theta_{k,l_k}^{(j_k)}, \rho_{k,n}^{(j_k)}\}$.
3. Form joint target particles for $i = 1,...,N$ as $\theta_1^{(i)} = \{\theta_{1,l_1}^{(j_1)}, ..., \theta_{K,l_K}^{(j_K)}\}$ for $j_k \in \{1,...,N\}$, and obtain the composite partition weight $\widetilde{\rho}_n^{(i)} = \prod_{k=1}^{K} \rho_{k,n}^{(j_k)}$.
4. Compute the interaction factor $\psi_n^{(i)}$ in (8) and the importance weights $w_n^{(i)}$ in (20) for $i = 1,...,N$, resample the joint particles $\theta_1^{(i)}$ according to $\{w_n^{(i)}\}$, and then set $w_n^{(i)} = 1/N \ \forall i$.

■

We note that the IPPF [17] implicitly makes an approximation at each time step that the joint posterior distribution factorises over individual targets. Alternative strategies are presented in [19].

6. COMPUTER SIMULATIONS

In this section we evaluate the performance of the proposed multitarget tracking algorithm on a challenging synthetic scenario with a high clutter rate and bearings-and-range measurements. The trajectories of all targets are generated by a nearly constant turn rate (NCT) model [1] given by

$$\mathbf{x}_{k,n} = \mathbf{A}_{k,n-1}\mathbf{x}_{k,n-1} + \mathbf{B}_{k,n-1}\mathbf{v}_{k,n}, \quad (21)$$

where $\mathbf{x}_{k,n} = [x_{k,n}, \dot{x}_{k,n}, y_{k,n}, \dot{y}_{k,n}]^T$ comprises the xy positions and velocities of target k, and

$$\mathbf{A}_{k,n-1} = \begin{bmatrix} 1 & \frac{\sin\omega_{k,n-1}\Delta T}{\omega_{k,n-1}} & 0 & -\frac{(1-\cos\omega_{k,n-1}\Delta T)}{\omega_{k,n-1}} \\ 0 & \cos\omega_{k,n-1}\Delta T & 0 & -\sin\omega_{k,n-1}\Delta T \\ 0 & \frac{1-\cos\omega_{k,n-1}\Delta T}{\omega_{k,n-1}} & 1 & \frac{\sin\omega_{k,n-1}\Delta T}{\omega_{k,n-1}} \\ 0 & \sin\omega_{k,n-1}\Delta T & 0 & \cos\omega_{k,n-1}\Delta T \end{bmatrix},$$

and

$$\mathbf{B}_{k,n-1} = \begin{bmatrix} \mathbf{G} & \mathbf{0}_{2\times1} \\ \mathbf{0}_{2\times1} & \mathbf{G} \end{bmatrix}, \quad \mathbf{G} = [\Delta T^2/2, \Delta T]^T, \quad (22)$$

where ΔT is the sampling rate. It is further assumed that the state noise $\mathbf{v}_{k,n}$ is a zero-mean Gaussian random variable with a known covariance $\mathbf{\Sigma}_v = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix}$. The turn rate $\omega_{k,n}$ is modelled as random walk, i.e., $\omega_{k,n} = \omega_{k,n-1} + \varpi_{k,n}$, where $\varpi_{k,n}$ is a zero-mean Gaussian random variable with a fixed and known variance σ_ω^2. Here we examine the performance of the proposed method in the robustness of target tracking as well as dynamic model mismatch.

We consider tracking a scenario with $K = 4$ targets, each synthesised independently from the same evolution model in (21). The turn rates are initialised as $\omega_{k,0} = 0 \ \forall k$. The state and turn rate noise standard deviations are given by $\sigma_x = \sigma_y = 0.1$ and $\sigma_\omega = 1°$, respectively. Bearings-and-range measurements are used in the experiment in which two stationary sensors whose positions $\vartheta_n^p = \{\vartheta_{x,n}^p, \vartheta_{y,n}^p\} \ \forall p$ are randomly located and known. Here we utilise a central-level data fusion and tracking strategy in which only a set of global tracks is maintained at the central unit [2, 3]. For each sensor, each target can be detected with probability $P_D = 0.5$. The measurement $\mathbf{y}_{m,n}^p$ originating from target k at sensor p is given as follows

$$\mathbf{y}_{m,n}^p = \begin{bmatrix} \tan^{-1}\left(\frac{x_{k,n}-\vartheta_{x,n}^p}{y_{k,n}-\vartheta_{y,n}^p}\right) \\ \sqrt{(x_{k,n}-\vartheta_{x,n}^p)^2 + (y_{k,n}-\vartheta_{y,n}^p)^2} \end{bmatrix} + \mathbf{w}_{m,n}^p, \quad (23)$$

Parameters	Values
Λ_C, Λ_θ	20 per sensor, 1
σ_x, σ_y	0.1
σ_ω, σ_θ, σ_r	1°, 3°, 10
ΔT (sampling interval)	1
T_n (no. of scans)	300
P_D	0.5
N	500
$(\mu_{\mathfrak{T}}, \sigma^2_{\mathfrak{T}})$	25, 25
$\sigma^2_{\mathfrak{P}}$	100
$\mathfrak{M}$	200
λ	3
$(\alpha_\tau, \beta_\tau)$	(0.5, 2)

Table 1: The parameters for computer simulations.

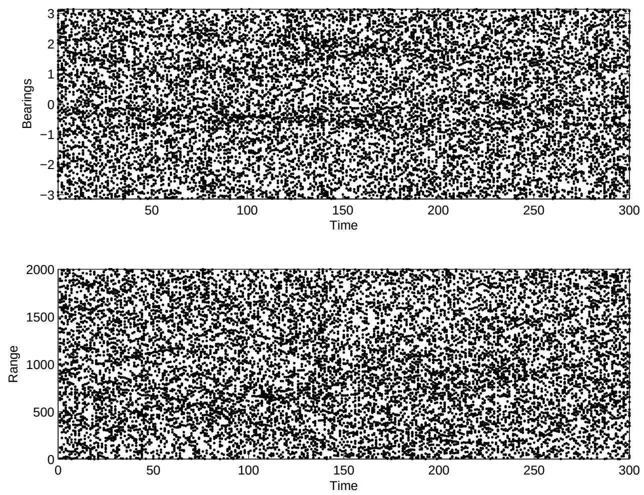

Figure 1: The synthesised measurements (bearings and range) collected from two stationary sensors.

where $\mathbf{w}^p_{m,n}$ is assumed to be a zero-mean Gaussian random variable with a known covariance (bearings and range) $\mathbf{\Sigma}^p_w = \begin{bmatrix} \sigma^2_\theta & 0 \\ 0 & \sigma^2_r \end{bmatrix}$ and common to all sensors. We generate $T_n = 300$ target states and observations according to (21) and (23) with the sampling rate $\Delta T = 1$. The number of clutter points is modelled as Poisson distributed with mean $\Lambda_C = 20$ for each sensor, and each clutter measurement is randomly drawn within the observation space. An example of the synthesised measurements with 2 sensors is plotted in Figure 1.

We run our algorithm with $N = 500$ particles which are initialised according to a Gaussian distribution around the true initial state values. All targets share the parameters in the intrinsic dynamic model that are summarised in Table 1. With the state particles, we may evaluate the *minimum mean square error* (MMSE) estimates of the combined target states

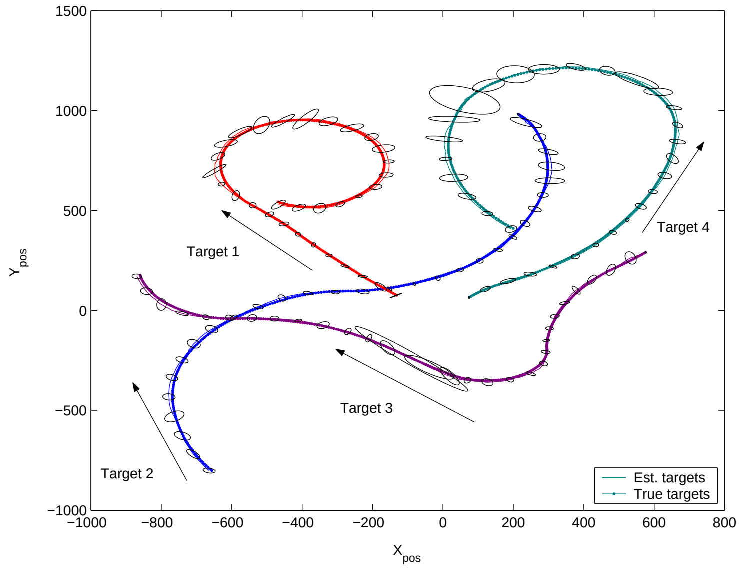

Figure 2: A comparison between the true target trajectories and their averaged estimates with estimation error ellipses for 20 independent trials.

N	$\mathbf{\Lambda_C = 5}$	$\mathbf{\Lambda_C = 15}$	$\mathbf{\Lambda_C = 20}$
100	23.7	32.6	44.0
500	15.5	20.2	25.2
1000	14.9	18.9	23.2

Table 2: Performance evaluation for the proposed method with different values of N and Λ_C.

by

$$\widehat{\mathbf{x}}_{k,n} = \sum_{i=1}^{N} w_n^{(i)} \widetilde{\mathbf{x}}^{(i)}_{k,n}, \quad (24)$$

where $\widetilde{\mathbf{x}}^{(i)}_{k,n}$ is the ith interpolated state particle of target k at time n according to the equations in (10), (11), and (12).

Figure 2 shows a comparison between the true target trajectories and their averaged estimates for 20 independent realisations. It can be seen that throughout the experiment the algorithm can successfully track the targets without using any multiple-model approaches and also resolve the interactions modelled by the MRF motion model. The excellent tracking performance can be justified by the estimation error ellipses in Figure 2, where almost all of them have enclosed the true targets.

Furthermore, the Poisson likelihood model in (2) does not need any data association between the targets and the observations and hence requires much fewer computational operations compared with many more classical data association approaches.

Table 2 presents a summary of performance evaluation of the proposed method with different values of N and Λ_C, where 20 independent run are conducted for each set of parameters. It can be seen that for a given Λ_C the MMSEs are improved when N is large, and that the MMSEs are degraded when Λ_C becomes large.

7. CONCLUSIONS

In this paper we presented an efficient method for online tracking of highly manoeuvrable objects with multiple observers using variable rate particle filters and an MRF motion model. We also adopted a more challenging Poisson point process to model the observations. The immediate benefits gained from the proposed approach included the more efficient estimation of the highly manoeuvrable objects and the avoidance of the requirement of data association inherent in most of the tracking applications. Finally, computer simulations demonstrated the performance of the proposed method for tracking highly manoeuvrable objects even the environment is highly cluttered with low detection probability.

REFERENCES

[1] X. R. Li and V. P. Jilkov, "A survey of maneuvering target tracking: dynamic models," *Proceedings of SPIE-Signal and Data Processing of Small Targets 2000*, pp. 212–236, Apr. 2000.

[2] Y. Bar-Shalom and W. D. Blair, *Multitarget-Multisensor Tracking: Applications and Advances*, vol. III. Norwood, MS: Archtech House, 2000.

[3] S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems*. Norwood, MA: Artech House, 1999.

[4] M. Chummum, T. Kirubarajan, K. Pattipati, and Y. Bar-Shalom, "Efficient multisensor-multitarget tracking using clustering algorithms," in *Proceedings of 2nd International Conference Information Fusion*, (Sunnyvale, CA), July 1999.

[5] B. L. Scala and G. W. Pulford, "Manoeuvring target tracking with the IMM–VDA algorithm," in *Proceedings 6th International Conference on Information Fusion*, (Philadelphia, PA, USA), July 2005.

[6] D. Mušicki, S. Suvorova, and S. Challa, "Multi target tracking of ground targets in clutter with LMIPDA-IMM," in *Proceedings of the Seventh International Conference on Information Fusion* (P. Svensson and J. Schubert, eds.), vol. II, (Mountain View, CA), pp. 1104–1110, International Society of Information Fusion, Jun 2004.

[7] N. Gordon, D. Salmond, and A. Smith, "Novel approach to non-linear/non-Gaussian Bayesian state estimation," *IEE Proceedings-F*, vol. 140, no. 2, pp. 107–113, 1993.

[8] A. Doucet, S. Godsill, and C. Andrieu, "On sequential Monte Carlo sampling methods for Bayesian filtering," *Statistics and Computing*, vol. 10, pp. 197–208, 2000.

[9] B. Ristic, S. Arulampalam, and N. Gordon, *Beyond the Kalman Filter: Particle Filters For Tracking Applications*. Boston, MA: Artech House Publishers, 2004.

[10] S. J. Godsill and J. Vermaak, "Models and algorithms for tracking using trans-dimensional sequential monte carlo," in *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2004.

[11] S. Godsill and J. Vermaak, "Variable rate particle filters for tracking applications," in *Proceedings of the IEEE/SP 13th workshop on Statistical Signal Processing*, (Bordeaux, France), 2005.

[12] S. Godsill, J. Li, and W. Ng, "Multiple and extended object tracking with Poisson spatial processes and variable rate filters," in *Proceedings of the IEEE Workshop on Computational Advances in Multi-Sensor Adaptive Processing*, (Puerto Vallarta, Jalisco State, Mexico), 2005.

[13] S. Maskell, "Tracking manoevring targets and classification of their maneovrability," *EURASIP J. App. Signal Proc.*, vol. 15, pp. 2339–2350, 2004. Special Issue on Particle Filtering in Signal Processing).

[14] K. Gilholm and D.Salmond, "Extended object and group tracking," in *RTO SET Symposium on Target tracking and sensor data fusion for military observation systems, RTO-MP-SET-059, NATO, Budapest, Hungary*, October 2003.

[15] K. Gilholm and D. Salmond, "A spatial distribution model for tracking extended objects," *IEE Proceedings on Radar, Sonar and Navigation*, vol. 152, no. 5, 2005.

[16] K. Gilholm, S. J. Godsill, S. Maskell, and D. J. Salmond, "Poisson models for extended target and group tracking," in *Proceedings of SPIE*, 2005.

[17] M. Orton and W. Fitzgerald, "A Bayesian apporach to tracking multiple targets using sensor arrays and particle filters," *IEEE Transactions on Signal Processing*, vol. 50, pp. 216–223, Feb. 2002.

[18] Z. Khan, T. Balch, and F. Dellaert, "MCMC-based particle filtering for tracking a variable number of interacting targets," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, Nov.

[19] J. Vermaak, S. Godsill, and P. Perez, "Monte Carlo filtering for multi-target tracking and data association," *IEEE Transactions Aerospace and Electronic Systems*, vol. 41, pp. 309–331, Jan. 2005.