MCMC PARTICLE FILTER FOR TRACKING IN A PARTIALLY KNOWN MULTIPATH ENVIRONMENT

B. Sachintha Karunaratne[⋆†] *Mark R. Morelande*[⋆] *Bill Moran*[⋆]

[⋆] Department of Electrical and Electronic Engineering, The University of Melbourne, Australia
[†] National ICT Australia, Victoria Research Laboratory, The University of Melbourne, Australia
Email: {bska,mrmore,wmoran}@unimelb.edu.au

ABSTRACT

The principal difficultly in tracking in an urban terrain is the presence of multipaths. However by using proper modelling and signal processing techniques these multipaths can be used favourably. In this paper we consider a more robust model of the urban terrain by not assuming exact wall locations but rather allowing for small deviations. This is achieved by introducing a random phase shift to the radar equation. A MCMC based particle filter which uses an adaptive kernel to improve the mobility of the Markov Chain is proposed with supporting simulation results.

Index Terms— MCMC, particle filter, multipath, kernel.

1. INTRODUCTION

The phenomenon of multipath in radar arises particularly in dense urban environments, where clutter causes the transmitted radar signal to travel through multiple routes. Once considered a nuisance [1, 2], multipath effects are actively investigated as a useful resource for tracking in urban environments.

Many researchers have studied the possibility of exploiting multipath favourably. In [3] the merits of using multipath is discussed by illustrating the increase in radar visibility and sweep width in the presence of multipath. Chakraborty *et al* [4] consider a 3-D terrain with parallel walls and propose a particle filter for this setup. An Orthogonal Frequency Division Multiplexing (OFDM) scheme is used by Sen *et al* [5] to improve the frequency diversity in a multipath environment. Almost all the existing work impose some restrictions on the geometry of the radar environment such as parallel walls etc [3, 4]. Furthermore the filters used for target state estimation use processed measurements (results of a detection stage using raw measurements) as input [4, 6]. Nevertheless work by Morelande *et al* in [7] suggest that using raw radar measurements directly results in a lower Posterior Cramer-Rao Bound (PCRB).

In this paper we relax the assumption that the wall locations are known exactly. Instead we assume that the location information is only accurate up to a few wavelengths. This uncertainty is modelled by introducing a uniformly distributed random phase shift to each of the multipath signals. Further no restrictions such as parallel/vertical/horizontal walls are imposed on the environment.

We use a particle filter to solve this non linear estimation problem. The principal challenge in particle filtering is choosing a good importance density. This was particularly critical for us because the uniformly distributed random phases increase the uncertainty of the measurements significantly rendering a challenging estimation problem. A desirable choice for an importance density would be the optimal importance density (OID)[8]. However it is often difficult to derive the OID in closed form. In our previous work we have proposed a particle filter with unscented transform (UT) approximation to the OID to track a target in a multipath environment where exact wall locations are known (i.e. the aforementioned phase variables are known) [9]. However that approach is not suitable to solve the estimation problem considered here. The structure of the new estimation problem suits the use of a particle filter where the particles are drawn from a Markov Chain as in [10]. In particular the Markov Chain is constructed by using a series of Gibbs and Metropolis-Hastings proposals [11].

A common problem in sequential Monte Carlo methods is *particle impoverishment* [8]. A kernel based regularisation method [12] is a widely used technique to reduce particle impoverishment. Use of this method requires a selection of a parameter known as kernel bandwidth and the common practice is to select this bandwidth to minimize the mean integrated square error (MISE) [13]. We propose an adaptive scheme to choose this bandwidth which seems to improve the robustness of the filter.

In summary the contributions of this paper extend and relate to the prior work found in literature by proposing a MCMC based particle filter consisting of Gibbs and Metropolis-Hastings steps to track a target in a partially known environment model. Secondly we propose an adaptive kernel bandwidth selection method to improve the robustness of the MCMC particle filter.

The rest of the paper is organised as follows. Section 2 formulates the estimation problem in the presence of multipath. Particle filtering in the context of urban radar tracking is presented in Section 3. The construction of the Markov Chain and the adaptive kernel bandwidth selection method are discussed in Section 4 followed by the results and conclusion to the paper.

2. MULTIPATH FILTERING PROBLEM

Consider a point target moving in a 2-D urban environment. Let $\mathbf{x}_k = [x_k \ \dot{x}_k \ y_k \ \dot{y}_k]$ denote the target state at time t_k, where $(x, y) \in \mathcal{R}^2$ and $(\dot{x}, \dot{y}) \in \mathcal{R}^2$ are position and velocities in the XY plane. The state evolves as

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{w}_k, \qquad k = 1, 2, \ldots, \tag{1}$$

where $\mathbf{F}_k$ is a transition matrix which dictates constant velocity motion. $\mathbf{w}_k$ is a Gaussian white noise process where $\text{cov}(\mathbf{w}_{k_1}, \mathbf{w}_{k_2}) = \delta_{k_1-k_2}\mathbf{Q}_k$ with $\mathbf{Q}_k$ being a positive semi-definite and symmetric matrix.

We use a MIMO setup with N radar transmitters placed at suitable locations and M uniform linear arrays are used to capture radar returns. The sensors sample the received signal with a period of T_2. All the reflections are assumed to be specular.

Let the total number of paths between the n^{th} transmitter and the m^{th} receiver be denoted by $P_{n,m}$. The signal vector received by the m^{th} sensor at time $t_k + uT_2$ can be written for $u = 0, \dots, U-1$ as

$$\mathbf{Y}_{k,m}(u) = \mathbf{H}_m(\mathbf{x}_k, \boldsymbol{\psi}_k; u) + \mathbf{e}(u), \quad (2)$$

where $\mathbf{e}(u)$ is a circular symmetric complex white Gaussian process with covariance matrix $2\sigma^2\mathbf{I}$ where the identity matrix with appropriate dimensions is denoted by $\mathbf{I}$ and

$$\mathbf{H}_m(\mathbf{x}_k, \boldsymbol{\psi}_k; u) = \sum_{n=1}^{N} \mu_{k,n,m}(\mathbf{x}_k, \boldsymbol{\psi}_k; uT_2),$$

with the measurement function $\mu_{k,n,m}$ given by

$$\mu_{k,n,m}(\mathbf{x}, \boldsymbol{\psi}_k; t) = \sum_{p=1}^{P_{n,m}} \exp(j\psi_{n,m}^p)\mathbf{g}_{n,m}^p(\mathbf{x}; t), \quad (3)$$

where $\mathbf{g}_{n,m}^p(\mathbf{x}; t)$ is the well known radar measurement function [14, 9] for a linear array receiver.

For multipaths the phase variable $\psi_{n,m}^p$ is unknown and is assumed to be uniformly distributed over the interval $[0, 2\pi)$. This models small uncertainties in the wall locations. The phase on the direct path is set to zero since the direct path does not hit any walls. The vector $\boldsymbol{\psi}_k$ denotes the collection of all random phases.

All the raw measurements could be separated into I-Q channels and stacked together in a vector form to result in a measurement equation as shown below:

$$\mathbf{y}_k = \mathbf{h}(\mathbf{x}_k, \boldsymbol{\psi}_k) + \mathbf{v}_k, \quad (4)$$

where $\mathbf{h}(\mathbf{x}_k, \boldsymbol{\psi}_k)$ is a known deterministic function of the target state $\mathbf{x}_k$ and $\boldsymbol{\psi}_k$. The the noise vector $\mathbf{v}_k$ is a white noise process with covariance matrix $\sigma^2\mathbf{I}$.

Let the superscript notation denote the trajectory of the variable in context over time (i.e. $\mathbf{y}^k = [\mathbf{y}_1', \dots, \mathbf{y}_k']'$). We define the multipath filtering problem as estimating the target state $\mathbf{x}_k$ after observing $\mathbf{y}^k$.

3. PARTICLE FILTERING FOR URBAN RADAR TRACKING

3.1. A Brief Review of Particle Filtering

A particle filter recursively approximates the posterior density using a set of weighted random samples. The review presented in this section follows the auxiliary variable implementation of [15]. Note that most popular techniques including the Bootstrap Filter (BF) [16] and the OID [8] are covered in the auxiliary variable framework.

Consider a first order Markov state sequence $\{\mathbf{z}_k, k \in \mathcal{N}\}$. Let $\mathbf{y}_k$ be the measurement vector at time k and satisfies $p(\mathbf{y}_k|\mathbf{z}^k) = p(\mathbf{y}_k|\mathbf{z}_k)$. Assume that at time $k-1$, the posterior is approximated using J samples $\mathbf{z}_{k-1}^{(1)}, \dots, \mathbf{z}_{k-1}^{(J)}$ and corresponding weights $w_{k-1}^1, \dots, w_{k-1}^J$ as follows:

$$p(\mathbf{z}_{k-1}|\mathbf{y}^{k-1}) \approx \sum_{j=1}^{J} w_{k-1}^j \delta(\mathbf{z}_{k-1} - \mathbf{z}_{k-1}^{(j)}). \quad (5)$$

Baye's rule leads to a posterior approximation at time k as shown below:

$$\begin{aligned} p(\mathbf{z}_k|\mathbf{y}^k) &\propto p(\mathbf{y}_k|\mathbf{z}_k)p(\mathbf{z}_k|\mathbf{y}^{k-1}), \\ &\approx \sum_{i=1}^{J} w_{k-1}^i p(\mathbf{y}_k|\mathbf{z}_k)p(\mathbf{z}_k|\mathbf{z}_{k-1}^{(i)}). \end{aligned} \quad (6)$$

Following [15], we reverse the marginalisation in (6) and introduce the particle index i as an auxiliary variable. This gives

$$p(\mathbf{z}_k, i|\mathbf{y}^k) \propto w_{k-1}^i p(\mathbf{y}_k|\mathbf{z}_k)p(\mathbf{z}_k|\mathbf{z}_{k-1}^{(i)}). \quad (7)$$

An approximation to the posterior at time k can be obtained by sampling from (7). The auxiliary variable which can be discarded after sampling, is intended to assist in the aim of drawing samples of the state vector. Often it is difficult to sample from $p(\mathbf{z}_k, i|\mathbf{y}^k)$ and instead a suitable candidate distribution known as *importance density* $q(\mathbf{z}_k, i|\mathbf{y}^k)$ is used to obtain samples which are then appropriately weighted. The choice of the importance density is crucial for a good particle filter design. The BF is obtained by choosing

$$q_{bs}(\mathbf{z}_k, i|\mathbf{y}^k) \propto w_{k-1}^i p(\mathbf{z}_k|\mathbf{z}_{k-1}^{(i)}). \quad (8)$$

The main drawback of $q_{bs}(\cdot)$ is that the current measurement $\mathbf{y}_k$ is not used to draw samples.

A desirable importance density is the OID which involves drawing directly from (7). Let $\phi_i = \int p(\mathbf{y}_k|\mathbf{z}_k)p(\mathbf{z}_k|\mathbf{z}_{k-1}^{(i)})d\mathbf{z}_k$. Then it can be shown that the OID is given by

$$q_{oid}(\mathbf{x}_z, i|\mathbf{y}^k) \propto \gamma_i p_i(\mathbf{z}_k|\mathbf{y}_k), \quad (9)$$

where $\gamma_i = w_{k-1}^i \phi_i$ and

$$p_i(\mathbf{z}_k|\mathbf{y}_k) = p(\mathbf{y}_k|\mathbf{z}_k)p(\mathbf{z}_k|\mathbf{z}_{k-1}^{(i)})/\phi_i.$$

Note that the importance weights of the samples obtained from the OID are constant irrespective of the value of the sample. It is this property which results in the use of the term OID for the density (9). Unlike the BF the OID has the desirable property of using the current measurement to influence the selection of the particle index and the state vector.

3.2. Developing a Particle Filter for a Partially Known Urban Environment

Applying (7) to our estimation problem results in the following.

$$p(\mathbf{x}_k, i|\mathbf{y}^k) \propto w_{k-1}^i \int p(\mathbf{y}_k|\boldsymbol{\psi}_k, \mathbf{x}_k)p(\boldsymbol{\psi}_k)d\boldsymbol{\psi}_k p(\mathbf{x}_k|\mathbf{x}_{k-1}^{(i)}). \quad (10)$$

The integral appearing in (10) is the normalising constant of a Generalised Von Mises ($\mathcal{GVM}$) distribution introduced in [17]. This quantity is not known in closed form but it is expressible as an infinite series summation involving products of modified Bessel functions of the first kind [17]. It is not clear how a term of this form could be combined with the prior to produce a sampling density for $\mathbf{x}_k$ and i.

Calculating the integral in (10) could be avoided by treating $\boldsymbol{\psi}_k$ as part of the state at time k and sampling from

$$p(\mathbf{x}_k, \boldsymbol{\psi}_k, i|\mathbf{y}^k) \propto w_{k-1}^i p(\mathbf{y}_k|\mathbf{x}_k, \boldsymbol{\psi}_k)p(\mathbf{x}_k|\mathbf{x}_{k-1}^{(i)})p(\boldsymbol{\psi}_k). \quad (11)$$

Note that if the phase variables are known, the filtering problem reduces to that of [9] and the UT approximation to the OID was shown to be a desirable importance density in this instance. However approximating (11) using the UT is not viable because of the large degree of uncertainty introduced by the random phases.

The challenges explained above lead us to explore alternative solutions. Note that we have an efficient importance density (i.e the UT approximation to the OID) if the random phases are known. On the other hand consider the situation where random phases are unknown but the target state is known. The distribution $p(\boldsymbol{\psi}_k|\mathbf{x}_k, \mathbf{y}^k)$ can be shown to be $\mathcal{GVM}$ and constructing a Gibbs chain for $\mathcal{GVM}$ is straightforward. In other words the relationship between $\boldsymbol{\psi}_k$ and $\mathbf{x}_k$ is such that each can be efficiently sampled given the knowledge of the other. This particular structure of the problem suggests the use of the Markov chain Monte Carlo (MCMC) method referred to as Gibbs sampling [11]. The Gibbs sampling procedure produces samples from a given distribution by constructing a Markov chain whose stationary distribution is that distribution. In the following section we show how this idea can be applied to drawing samples from (7).

4. MCMC PARTICLE FILTER

The MCMC particle filter was previously proposed in [10] where Metropolis-Hastings steps were used. Here we propose a procedure which combines Gibbs sampling with Metropolis-Hastings steps. We also propose an adaptive kernel technique to enhance the mobility of the Markov chain and increase filter robustness.

4.1. Construction of the Markov Chain

The Markov chain used here samples the phases, sample index and kinematic state in turn, as illustrated below:

$$(\mathbf{x}, \boldsymbol{\psi}, i) \overset{\text{step1}}{\dashrightarrow} (\mathbf{x}, \boldsymbol{\psi}', i) \xrightarrow{\text{step 2}} (\mathbf{x}, \boldsymbol{\psi}', i') \xrightarrow{\text{step 3}} (\mathbf{x}', \boldsymbol{\psi}', i').$$

Each step is described in detail below.

As mentioned previously, $p(\boldsymbol{\psi}_k|\mathbf{x}_k, i, \mathbf{y}^k)$ is a $\mathcal{GVM}$ distribution [17]. The conditional marginal distributions of the $\mathcal{GVM}$ distribution are the well known Von Mises ($\mathcal{VM}$) distributions. Thus, in the first step phases are drawn from a series of $\mathcal{VM}$ distributions as in

$$q_{\boldsymbol{\psi}}(\boldsymbol{\psi}_k^{(j)}|\boldsymbol{\psi}_k^{(j-1)}) = \prod_{i=1}^{q} \mathcal{VM}(\psi_{k,i}^{(j)}; \boldsymbol{\psi}_{k,1:i-1}^{(j)}, \boldsymbol{\psi}_{k,i+1:q}^{(j-1)}),$$

where $\boldsymbol{\psi}_{k,n:m}^{(j)} = [\psi_{k,n}^{j}, \psi_{k,n+1}^{j} \ldots, \psi_{k,m}^{j}]$ for $n < m$. More details on the form of the $\mathcal{VM}$ conditional marginal distributions can be found in [17].

In the second step the sample index is drawn from the conditional marginal distribution

$$p(i|\boldsymbol{\psi}_k, \mathbf{x}_k, \mathbf{y}^k) \propto \mathcal{N}(\mathbf{x}_k; \mathbf{F}_k \mathbf{x}_{k-1}^{(i)}, \mathbf{Q}_k). \quad (12)$$

where $\mathcal{N}(\cdot; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes the normal distribution with mean and covariance being $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ respectively.

In a Gibbs procedure the third step would require drawing a sample from $p(\mathbf{x}_k|\boldsymbol{\psi}_k, i, \mathbf{y}^k)$ but this distribution is not available in closed form. As a solution we fall back from a Gibbs step to a Metropolis-Hastings step [11]. This involves drawing a sample from a suitable proposal and accepting it with a certain probability such that the Markov Chain converges to the desired distribution. We use a proposal which approximates the Gibbs proposal. In particular, the UT approximation to $p(\mathbf{x}_k|\boldsymbol{\psi}_k, i, \mathbf{y}^k)$ is used. This was shown to be effective in [9] for the case of known phases. Let $q_{\mathbf{x}}$ denote this proposal.

The whole process of generating the Markov Chain is given in algorithmic form in algorithm 1.

Although in theory, a Markov Chain converges asymptotically to its stationary distribution irrespective of the initial starting point

Algorithm 1: Algorithm to generate a Markov Chain with $p(\mathbf{x}_k, i, \boldsymbol{\psi}_k|\mathbf{y}^k)$ as the stationary distribution.

Assign initial values to $(\mathbf{x}_k^{(0)}, \boldsymbol{\psi}_k^{(0)}, i^{(0)})$.

for $n = 1$ **to** S **do**

Draw $\boldsymbol{\psi}_k^{(n)} \sim q_{\boldsymbol{\psi}}(\cdot|\boldsymbol{\psi}_k^{(n-1)}, \mathbf{y}_k)$.

Draw $i^{(n)}$ with Probability$(i^{(n)} = j)$ $\propto \mathcal{N}(\mathbf{x}_k; \mathbf{F}_k \mathbf{x}_{k-1}^{(j)}, \mathbf{Q}_k)$.

Draw $\mathbf{v} \sim q_{\mathbf{x}}(\cdot|\boldsymbol{\psi}_k^{(n)}, i^{(n)}, \mathbf{y}^k)$.
Let

$$w_{new} = \frac{p(\mathbf{v}|\boldsymbol{\psi}_k^{(n)}, i^{(n)}, \mathbf{y}^k)}{q_{\mathbf{x}}(\mathbf{v}|\boldsymbol{\psi}_k^{(n)}, i^{(n)}, \mathbf{y}^k)},$$
$$w_{old} = \frac{p(\mathbf{x}_k^{(n-1)}|\boldsymbol{\psi}_k^{(n)}, i^{(n)}, \mathbf{y}^k)}{q_{\mathbf{x}}(\mathbf{x}_k^{(n-1)}|\boldsymbol{\psi}_k^{(n)}, i^{(n)}, \mathbf{y}^k)},$$
$$r = \min(1, w_{new}/w_{old}).$$

$$\mathbf{x}_k^{(n)} = \begin{cases} \mathbf{v} & \text{with probability } r, \\ \mathbf{x}_k^{(n-1)} & \text{with probability } 1 - r. \end{cases}$$

end

$(\mathbf{x}_k^{(0)}, \boldsymbol{\psi}_k^{(0)}, i^{(0)})$, in practice a good starting point is desirable as it will generally result in fast convergence of the chain. We choose an initial starting point by generating few samples from the prediction distribution and selecting the one with the highest likelihood. We then monitor the mobility of the chain and re-start if necessary using the sample with the next highest likelihood.

4.2. Adaptive Kernel Bandwidth Selection to Improve the Mobility of the Markov Chain

A potential drawback of the proposed MCMC particle filter is the issue of mobility where the Markov Chain gets stuck around a particular state. A good example of when this could happen is in step 2 of algorithm 1 where a particular index is heavily weighted.

In particle filtering two methods commonly used to improve diversity are *resample-move* [18] and particle regularisation using a kernel [12]. In this paper we have chosen to use the kernel method. We use a Gaussian kernel which results in replacing the process noise covariance matrix $\mathbf{Q}_k$ by $\mathbf{Q}_k + \mathbf{C}(h)$ where $\mathbf{C}(h) = h\boldsymbol{\Sigma}$ with $\boldsymbol{\Sigma}$ the sample covariance matrix and h the kernel bandwidth.

The kernel bandwidth plays an important role. The most common choices of the kernel bandwidth are the formulae given in [13] which aim to minimise the MISE between the target distribution and the regularised representation. While minimisation of the MISE may be a suitable aim in kernel density approximation, it is not necessarily appropriate for the purposes of particle filtering. Instead, we propose choosing h adaptively by solving

$$h = \arg\max_{b} \sum_{j=1}^{J} \int l_k(\mathbf{x}_k, \boldsymbol{\psi}_k^j) \mathcal{N}(\mathbf{x}_k; \hat{\mathbf{x}}_k^j, \mathbf{Q}_k + \mathbf{C}(b)) d\mathbf{x}_k. \quad (13)$$

where $\hat{\mathbf{x}}_k^j = \mathbf{F}_k \mathbf{x}_{k-1}^{(j)}$, $l_k(\cdot)$ is the likelihood and $\boldsymbol{\psi}_k^j \sim p(\boldsymbol{\psi}_k|\mathbf{y}_k, \hat{\mathbf{x}}_k^j)$. Intuitively (13) selects the kernel bandwidth with the strongest overlap (in terms of probability density) between the likelihood and the prior. Simulation results suggest an increase in robustness by using this approach. We use a grid search to solve the optimisation problem (13) and the UT is used to approximate the integral.

5. SIMULATION EXAMPLE

We used the simulation setup depicted in Figure 1. The setup is such that the receiver only receives multipaths (i.e. a path that hits the target as well as a wall(s)) throughout most of the trajectory. A direct path is available only towards the end of the trajectory.

Initial target state was drawn from $\mathcal{N}(\mathbf{x}_0; \boldsymbol{\mu}_0, \mathbf{P}_0)$ where

$$\boldsymbol{\mu}_0 = \begin{bmatrix} 2062 \\ 0.55 \\ 1240 \\ 15.5 \end{bmatrix} \text{ and } \mathbf{P}_0 = \mathbf{I}_2 \otimes \begin{bmatrix} 0.004 & 0 \\ 0 & 0.0005 \end{bmatrix}. \qquad (14)$$

and the Kronecker product is denoted by the symbol $\otimes$.

The covariance of the prediction density $\mathbf{Q}_k$ was set at

$$\mathbf{Q}_k = \mathbf{I}_2 \otimes \begin{bmatrix} 0.0067 & 0.01 \\ 0.01 & 0.0067 \end{bmatrix}. \qquad (15)$$

The time series emitted by the radar transmitted at time k is denoted by $s_k(t)$ and is chosen as a chirp with energy E given by

$$s_k(t) = \frac{\sqrt{E}}{\sqrt{P}} \sum_{p=-(P-1)/2}^{(P-1)/2} \frac{\exp\{[j\upsilon - 1/(2\rho^2)](t - pT_1)^2\}}{(\pi\rho^2)^{1/4}}. \qquad (16)$$

The number of pulses P is 3. The chirp parameter υ is chosen to result in an effective bandwidth of 40MHz and width parameter ρ is chosen such that the effective duration of the pulse is $D = 250ns$. The pulse repetition interval T_1 is set to $100\mu s$. The signal energy E is chosen to result in an average SNR of $20dB$ at the output of the matched filter over the nominal trajectory. The state sampling period $t_k - t_{k-1}$ is set to $1s$.

The radar receiver consists of 3 collinear elements separated from each other by 4λ, where the wavelength λ of the carrier is set at $0.1m$. The receiver samples the incoming signal with a sampling period of $T_2 = 10$ns. The measurement noise covariance is set using $\sigma^2 = 0.4$.

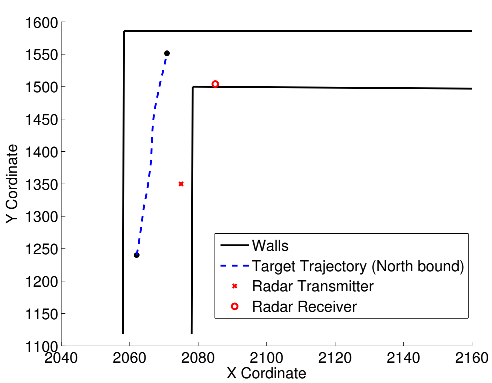
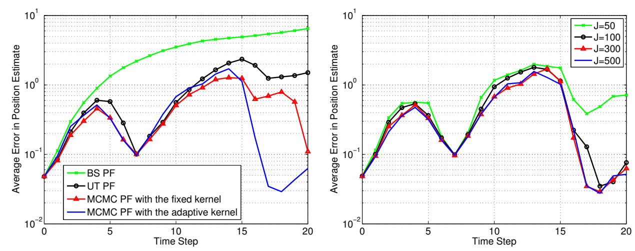


Fig. 1. Simulation setup

Algorithm performance is measured by averaging over 100 measurement realisations. Figure 2(a) shows a comparison of the proposed filter with alternative filters for $J = 300$ particles. One particular design is the UT approximated particle filter (UT PF) where the importance density consists of the UT approximation to the OID [9] in conjunction with drawing phase samples from $p(\boldsymbol{\psi}_k|\mathbf{y}_k, \hat{\mathbf{x}}^i)$ where $\hat{\mathbf{x}}^i$ is the predicted mean of the i^{th} particle. Lack of space restricts us from explaining the filter in more detail. Unsurprisingly the bootstrap filter fails to keep up with tracking. The UT PF design has a comparable performance to the proposed MCMC particle filter but seems unable to take advantage of the more informative measurements available during the latter stage of the trajectory.

The effect of choosing the kernel bandwidth adaptively for the proposed MCMC particle filter is also illustrated in figure 2(a). The bandwidth for the case of fixed kernel was chosen according to [13]. The results suggest that the adaptive kernel is more robust as evidenced by the much lower average error during the latter stage in the presence of sudden informative measurements. However the fixed kernel demonstrated marginally better performance when only multipath is present in the measurements. This suggests the adaptive kernel choice presents a trade off between accuracy and robustness.

Figure 2(b) illustrates the results of simulating the MCMC particle filter with the adaptive kernel with a varying number of particles. As expected an increase in the number of particles yields better results. However, the improvements in performance between 100, 300, and 500 particles are marginal. This indicates that the proposed filter can produce acceptable performance with comparatively few particles.



(a) (b)

Fig. 2. Simulation results: (a) Comparison with alternative filter designs (b) Effect of number J of particles.

6. CONCLUSION

We have considered a partially known urban radar environment where the uncertainty in the precise locations of the walls is modelled by introducing uniformly distributed random phase shifts to the measurement model. This makes the filtering problem very challenging. We have proposed a MCMC particle filter where the Markov Chain is constructed from Gibbs steps and Metropolis-Hastings steps. The suggested MCMC particle filter can be adapted to generic filtering problems where the state space could be partitioned to blocks where sampling from a block is complemented when all the other blocks are known. An adaptive method to choose the kernel bandwidth to improve the mobility of the Markov Chain is proposed. A challenging tracking setup is used to demonstrate the effectiveness of the proposed filter.

7. REFERENCES

[1] B.D. Rigling, "Urban RF multipath mitigation," *IET Radar, Sonar & Navigation*, vol. 2, no. 6, pp. 419–425, 2008.

[2] V.F. Mecca, D. Ramakrishnan, and J.L. Krolik, “MIMO Radar Space-Time Adaptive Processing for Multipath Clutter Mitigation,” *IEEE Workshop on Sensor Array and Multichannel Processing*, pp. 249–253, 2006.

[3] J.L. Krolik, J. Farrell, and A. Steinhardt, “Exploiting Multipath Propagation for GMTI in Urban Environments,” in *IEEE Conference on Radar*, 2006, pp. 65–68.

[4] B. Chakraborty, Y. Li, J.J. Zhang, T. Trueblood, A. Papandreou-Suppappola, and D. Morrell, “Multipath exploitation with adaptive waveform design for tracking in urban terrain,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2010, pp. 3894–3897.

[5] S. Sen and A. Nehorai, “Adaptive OFDM Radar for Target Detection in Multipath Scenarios,” *IEEE Transactions on Signal Processing*, vol. 59, no. 1, pp. 78–90, 2011.

[6] P. R. Barbosa, E. K. P. Chong, S. Suvorova, and B. Moran, “Multitarget-multisensor tracking in an urban environment: a closed-loop approach,” in *Proceedings of SPIE*, 2008.

[7] M. R. Morelande, S. Suvarova, and B. Moran, “Performance Bounds and Algorithms for Tracking with a Radar Array,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2007, pp. 1105–1108.

[8] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,” *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.

[9] B. S. Karunaratne, M. Morelande, and B. Moran, “Target tracking in a multipath environment,” in *IET International Conference on Radar Systems (IET Radar)*, 2012.

[10] 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 Learning*, vol. 27, 2005.

[11] C.P. Robert and G. Casella, *Monte Carlo Statistical Methods*, Springer, 2004.

[12] C. Musso, N. Oudjane, and C. Legland, “Improving regularized particle filters,” in *Sequential Monte Carlo Methods in Practice. New York*, A. Doucet, N. de Freitas, and N. Gordon, Eds. 2001, pp. 247–271, Springer.

[13] B. W. Silverman, *Density Estimation for Statistics and Data Analysis*, Chapman and Hall/CRC, 1986.

[14] B. S. Karunaratne, M. Morelande, B. Moran, and S. Howard, “Performance bounds for tracking in a multipath environment,” in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2011, pp. 3652–3655.

[15] M. K. Pitt and N. Shephard, “Filtering via simulation: auxiliary particle filters,” *Journal of the American Statistical Association*, vol. 94, no. 446, pp. 590–599, 1999.

[16] N.J. Gordon, D.J. Salmond, and A.F.M. Smith, “Novel approach to nonlinear/non-Gaussian Bayesian state estimation,” *IEE Proceedings F, Radar and Signal Processing,*, vol. 140, no. 2, pp. 107–113, 1993.

[17] B. S. Karunaratne, M.R. Morelande, and B. Moran, “Bayesian conjugate analysis for multiple phase estimation,” *IEEE International Conference on Information Fusion*, pp. 1927–1934, 2012.

[18] W.R. Gilks and C. Berzuini, “Following a moving target-Monte Carlo inference for dynamic Bayesian models,” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, vol. 63, no. 1, pp. 127–146, 2001.