Wireless Pers Commun (2007) 43:645–654
DOI 10.1007/s11277-007-9269-0

Particle filtering to combat inter-carrier interference in mobile communications

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Received: 21 June 2006 / Accepted: 16 January 2007 / Published online: 12 April 2007

Abstract This paper deals with the effect of the Doppler spread in a mobile communication system. The Doppler effect in a moving mobile is computed by predicting the mobile velocity via particle filtering, an instance of Sequential Monte Carlo (SMC) filtering. By calculating the Doppler spread in the receiver and adjusting the transmitter in the appropriate frequency, the performance of communication systems, such as Orthogonal frequency division multiplexing (OFDM) which suffer from loss of orthogonality due to frequency offset, can be improved. Moreover, it is shown that, via performance comparison of OFDM between the compensated and un-compensated for Doppler shift cases, a substantial improvement ($O(10^{-1})$) can be achieved in terms of Bit-Error-Rate (BER) for expectedly large values of Signal to Noise Ratio (SNR).

Keywords Doppler spread · Frequency offset · OFDM · Sequential Monte Carlo · Particle filtering · Target tracking

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1 Introduction

Orthogonal frequency division multiplexing (OFDM) is emerging as the preferred modulation scheme in modern high data rate wireless communication systems. OFDM has been adopted in the European digital audio and video broadcast radio system and is being investigated for broadband indoor wireless communications. Standards such as HIPERLAN2 (High-Performance Local Area Network), IEEE 802.11 a and IEEE 802.11g have emerged to support Internet Protocol (IP)-based services. Such systems are based on OFDM and are designed to operate in the 5 GHz band.

The OFDM is a special case of multi-carrier modulation. Multi-carrier modulation is the concept of splitting a signal into a number of signals, modulating each of these new signals to several frequency channels, and combining the data received on the multiple channels at the receiver. In OFDM, the multiple frequency channels, known as sub-carriers, are orthogonal to each other.

A well known problem of OFDM, however, is its sensitivity to frequency offset between the transmitted and received signals, which may be caused by Doppler shift in the channel, or by the difference between the transmitter and receiver local oscillator frequencies. This carrier frequency offset causes loss of orthogonality between sub-carriers and the signals transmitted on each carrier are not independent of each other, thus leading to inter-carrier

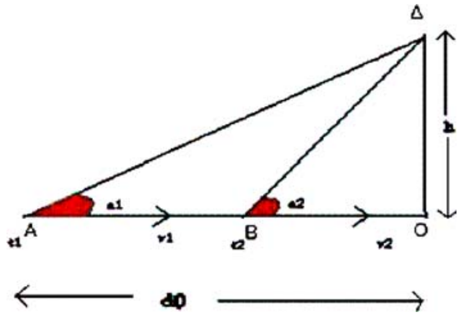

Fig. 1 Mobile moving in one dimension

interference (ICI). In this paper, we investigate the frequency offset induced by the movement of the mobile and propose a combat method based on a sequential Monte Carlo methodology named particle filtering [3]. It should be noted that the proposed Sequential Monte Carlo (SMC) algorithm combats the ICI caused by the mobile movement only and not by the frequency offset due to other reasons (e.g., oscillator drifts). The rest of the paper is organized as follows. In Sect. 2, a model of the Doppler shift due to a moving mobile is derived. In Sect. 3, the ICI level is deduced and in Sect. 4 the proposed SMC algorithm which is used to estimate the frequency offset is explicitly described. Section 5 presents the simulation model, while Sect. 6 gives the results obtained from simulation. Moreover, in order to clearly demonstrate the improvement of a mobile OFDM system when offset correction is implemented, Bit-Error Rate (BER) curves are also given. Finally, in Sect. 7 the main results of the paper are briefly discussed.

2 The model

First we examine the simplest form, that is, the case of LOS (line of sight), which consists of one propagation path and one mobile moving in one dimension as shown in Fig. 1.

The Doppler frequency offset f_d is, at time t, given by

$$f_d(t) = v(t)\left(\frac{f_c}{c}\right)\cos a(t), \tag{1}$$

where f_c is the frequency of the transmitted signal, c the speed of light, v the actual speed of the mobile, and a is the angle of the signal arrival.

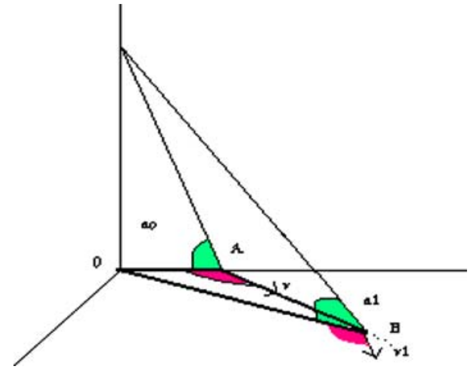

Fig. 2 Mobile moving in two dimensions

If h is the height of the antenna and d_0 the distance of the mobile from the antenna at time t_0, then at time t_1 the angle of arrival will be

$$a(t_1) = \arctan\frac{h}{d_0 - v(t_0)(t_1 - t_0)}. \tag{2}$$

We let $t_1 - t_2 = \Delta t$ become small enough so that the velocity will be considered constant at $t = \Delta t$. Then, at time $t = t_i$, the Doppler frequency offset is given by:

$$f_d(i) = v(i)\left(\frac{f_c}{c}\right)\cos\left(\arctan\left(\frac{h}{d(i-1) - v(i-1)(\Delta t)}\right)\right). \tag{3}$$

In the case of a two-dimensional movement, which is shown in Fig. 2, the velocity at time t that affects the Doppler shift is the projection of the mobile's velocity on the axis drawn between the antenna and the mobile, i.e.,

$$v(t) = v(t)\cos(\phi(t)). \tag{4}$$

The angle of arrival a at time t_1 is then given by

$$a_1 = \arctan\frac{h}{OB}. \tag{5}$$

Working in the triangle OAB, from the cosine law we get

$$OB = \sqrt{d_0^2 + v_0^2\Delta t^2 - 2d_0v_0\Delta t\cos(\phi_0)}. \tag{6}$$

At time t_i the Doppler offset is given by

$$f_d(i) = v(i)\cos(\phi(i))\left(\frac{f_c}{c}\right)\cos(a(i)), \tag{7}$$

where

$$a(i) = \arctan\left(\frac{h}{\sqrt{d^2(i-1) + v^2(i-1)\Delta t^2 - 2d(i-1)v(i-1)\Delta t \cos(\phi(i-1))}}\right). \quad (8)$$

We therefore have achieved to express the Doppler frequency offset at time t_i in terms of the mobile velocity and its position in the two-dimensional space. At time t the maximum Doppler offset will be

$$f_{d\_\max}(t) = v(t)\frac{f_c}{c}. \quad (9)$$

Thus, the Doppler offset will lie within the following upper and lower bounds:

$$f_c - f_{d\_\max} < f_d < f_c + f_{d\_\max} \quad . \quad (10)$$

3 Derivation of the inter-carrier interference (ICI) level

We will assume a two path model, where the two paths have different amplitudes and Doppler frequencies. Moreover, in such channels each path has a different time delay, but we need not be concerned with this effect as long as all the signals arrive within the guard interval employed in OFDM.

In the case of infinite sub-carriers [9], we get the ICI component for one path k onto the central sub-carrier to be

$$L_t(k) = (a^{(k)})^2[1 - \sin c^2(\pi f_d^{(k)})]. \quad (11)$$

The total ICI energy N_t in the central carrier is given by the sum

$$N_t = \sum_k L_t(k). \quad (12)$$

If we are given a statistical distribution for the Doppler frequency $p(f_d)$ and note that $L_t(k)$ is proportional to $(a^{(k)})^2$, then N_t can be written as follows:

$$N_t = a^2 \int_{-\infty}^{\infty} L_t(f_d)p(f_d)\mathrm{d}f_d. \quad (13)$$

The useful signal energy N_u^k contributed by one path with Doppler frequency f_d is then given by

$$N_u^{(k)} = (a^{(k)})^2 \sin c((\pi f_d^k)T). \quad (14)$$

Thus, the signal energies from each path are uncorrelated so the total useful energy P_u is easily shown to be given by

$$P_u = \sum_k N_u^{(k)}. \quad (15)$$

3.1 The two-path discrete model

For a two-path discrete model the pdf of the Doppler frequency is modeled as

$$p(f_d) = (1 - p2)\,\delta(f_d - f_1) + p2\,\delta(f_d - (f_1 + \Delta f)). \quad (16)$$

As it is shown in ref. [8], the useful signal energy for a two-path discrete model is

$$P_u = (1 - p2)\sin c^2(f_1\pi) + p2\ \sin c^2(\Delta f + f_1\pi), \quad (17)$$

where f_1 is the Doppler frequency of the path with energy $1 - p2$, Δf is the difference between the frequencies of the two paths and $p2$ is the second path's energy. For an infinite number of sub-carriers the ICI energy is

$$N_t = (1 - p2)\,[1 - \sin c^2(f_1\pi)] + p2\ [1 - \sin c^2(\Delta f + f_1\pi)]. \quad (18)$$

3.2 Uniform spectrum

The uniform distribution of the Doppler spread applies to a number of physically interesting cases. It has been shown in ref. [9] that for scattering environments the pdf of the Doppler frequency follows the uniform distribution. In this case the ICI level is given by

$$N_t = \frac{\cos(2\pi f_{d\_\max}) + 2\pi f_{d\_\max} Si(2\pi f_{d\_\max})}{2(\pi f_{d\_\max})^2} + \frac{(-1 - 2((\pi f_{d\_\max})^2)}{2(\pi f_{d\_\max})^2}, \quad (19)$$

where $Si(.)$ is the sine integral function.

Moreover, the signal energy takes the following form:

$$P_u = \frac{\cos(2\pi f_{d\_\max}) + 2\pi f_{d\_\max}\, Si(2\pi f_{d\_\max}) - 1}{2(\pi f_{d\_\max})^2}. \quad (20)$$

3.3 Classical spectrum

The classical Doppler spectrum is a long-term average. It results from uniformly distributed angles of arrival at the receiver antenna. From [7] we get that the first-order pdf in this case is

$$p(f_d) = \frac{1}{\pi f_{d\_\max}\sqrt{1-(\frac{f_d}{f_{\max}})^2}}. \tag{21}$$

In practice we can approximate the Doppler spread through the discrete two-path model with $p2 \neq 0.5$.

Using the generalized hyper-geometric function with $p = 1$ and $q = 2$, the ICI level is

$$N_t = 1 - {}_1F_2\left(\frac{1}{2};\frac{3}{2};2;-(f_{d\_\max}\pi)^2\right) \tag{22}$$

and the useful energy is

$$P_u = {}_1F_2\left(\frac{1}{2};\frac{3}{2};2;-(f_{d\_\max}\pi)^2\right). \tag{23}$$

In any case, the carrier-to-interference ratio (C/I) ratio is computed by dividing the useful signal energy by the ICI energy. So far we have expressed the ICI energy and the signal energy as functions of the maximum Doppler frequency offset. In the first part, we have derived the equation for evaluating the Doppler shift in terms of the mobile velocity. If we are able to estimate at time t the mobile's velocity, then we will be able to calculate at any given time the ICI energy and thus be able to optimally align the receiver's oscillator.

4 Particle filtering for target tracking

To define the problem of tracking, the evolution of the state sequence $\{\theta_k, k \in \mathbb{N}^{n_\theta}\}$ of a target is firstly given by

$$\theta_k = f_k(\theta_{k-1}, W_k), \tag{24}$$

where f_k is a possibly non-linear function of the state θ_{k-1} and W_k is an i.i.d. process known as noise sequence. The goal of tracking is to recursively estimate θ_k from the measurements

$$z_k = h_k(\theta_k, v_k), \tag{25}$$

where h_k is a possibly non-linear function of the state θ_k and v_k is an i.i.d. measurement noise sequence. From the Bayesian perspective, the problem is to determine at time k the state θ_k given the observation $z_{1:k}$ up to time k. Thus, it is required to construct the pdf $p(\theta_k/z_{1:k})$.

We assume that the prior pdf of the state vector is given by

$$p\,(\theta_o/z_o) = p(\theta_0), \tag{26}$$

where z_o is the set of no measurements. Then $p(\theta_k/z_{1:k})$ is obtained in two steps: first, prediction and then update. Suppose at time k–1 that $p(\theta_{k-1}/z_{1:k-1})$ is available.

In the prediction step, at time k, we obtain, via the Chapman–Kolmogorov equation,

$$p(\theta_k/z_{1:k-1}) = \int p(\theta_k/\theta_{k-1})p(\theta_{k-1}/z_{1:k-1})\,\mathrm{d}\theta_{k-1}. \tag{27}$$

During the update step, a new measurement z_k becomes available and by applying Bayes' rule we update (27) via:

$$p(\theta_k/z_{1:k}) = \frac{p(z_k/\theta_k)p(\theta_k/z_{1:k-1})}{\int p(z_k/\theta_k)p(\theta_k/z_{1:k-1})\mathrm{d}\theta_k}. \tag{28}$$

This recursive propagation of the posterior density forms the basis for the optimal Bayesian solution, but is only a conceptual solution and generally cannot be determined analytically.

It should be noted that many schemes have been proposed over the past years for solving the problem of estimating the unknown parameters of a moving target (i.e., position and velocity). Kalman (1960) was the first who proposed an optimal solution through his well-known Kalman filter. Moreover, another grid-based method was proposed. These two methods proved to be optimal only when some strict conditions hold, that is, when the state space is linear and the noise measurement is Gaussian. In a non-linear, non-Gaussian environment the Kalman filter does not seem to work because it diverges. Alternate schemes were then proposed such as the extended Kalman filter, which performs a local linearization over the non-linear equations that describe the state space, the Gaussian sum filter or the mixture Kalman filters. Moreover, over the past few years some new techniques have been reinvented known as Monte Carlo methods.

Most Monte Carlo techniques fall into one of the following categories: (a) Markov Chain Monte Carlo (MCMC) methods for batch data processing and (b) SMC methods for adaptive data processing. The basic idea behind the MCMC algorithms is that one can sample from the target distribution $p(.)$ by running a Markov chain whose equilibrium distribution is $p(\theta)$. The two basic MCMC algorithms are the Gibbs Sampler and the Metropolis–Hasting algorithm. The SMC methodology can be loosely defined as a family of methods that use Monte Carlo simulation to solve on-line estimation problems in dynamic systems. By recursively generating Monte Carlo samples of the state variables or some latent variables, these methods can easily adapt to the dynamics of the underlying stochastic systems. The SMC methodology is often named particle filtering.

There are many particle-filtering algorithms that can be used to solve the problem of on-line estimation of a moving target. These include the Sequential importance sampling algorithm (SIS), the Sampling importance resampling filter (SIR), the Auxiliary sampling importance-resampling filter (ASIR) or the Regularized particle filter (RPF). Our choice will be the SIR filter because the importance weights used in this filter are easily evaluated and moreover, due to the fact that the importance density can be easily sampled.

4.1 The sampling importance resampling (SIR) algorithm

The SIR filter proposed in ref. [6] is a Monte Carlo method that can be applied to recursive Bayesian filtering problems. The assumptions required to use the SIR filter are very weak. The state dynamics and measurement functions must be known. Moreover, it is only required to be able to sample realizations from the noise distribution and from the prior. Finally, the likelihood function must be available for pointwise evaluation (at least up to proportionality).

In order to develop the details of the algorithm, let $\{\theta_{0:k}^{i}, w_{k}^{i}\}_{i=1}^{N_s}$ denote a random measure that characterizes the posterior pdf $p(\theta_{0:k}/z_{1:k}), N_s$ is the number of samples, $\{\theta_{0:k}^{i}\}_{i=1}^{N_s}$ is a set of support points with associated weights $\{w_{k}^{i}\}_{i=1}^{N_s}$ and $\theta_{0:k} = \{\theta_j\}_{j=1}^{k}$ is the set of all states up to time k. Moreover, the weights are normalized such that

$$\sum\nolimits_{\iota} w_{i}^{k} = 1. \tag{29}$$

It can then be shown that the posterior density at time k can be approximated as follows:

$$p(\theta_{0:k}/z_{1:k}) = \sum_{\iota}^{N_s} w_{i}^{k} \delta(\theta_{0:k} - \theta_{0:k}^{i}). \tag{30}$$

The weights are chosen using the principle of importance sampling [1,3]. The first goal to achieve is the proper choice of the importance density $q(\theta_{0:k}/z_{1:k})$.We should note that the importance density $q(\theta_{0:k}/z_{1:k})$is used because it is difficult to sample directly from the generally unknown posterior $p(\theta_{0:k}/z_{1:k})$. The only assumption required for the choice of the importance density is that it must be constructed with its support proportional to the posterior $p(\theta_{0:k}/z_{1:k})$,i.e.,

$$q(\theta_{0:k}/z_{1:k}) \propto p(\theta_{0:k}/z_{1:k}). \tag{31}$$

The choice we make is to use the prior density $p(\theta_k/\theta_{k-1}^{i})$ as the importance density. The above choice of the importance density implies that we need samples from $p(\theta_k/\theta_{k-1}^{i})$. A sample from the importance density

$$\theta_k^i \sim p(\theta_k/\theta_{k-1}^{i}), \tag{32}$$

can be easily generated by first generating a noise sample

$$w_k^i \sim p_w(w_k), \tag{33}$$

where p_w is the pdf of w_k, and then set

$$\theta_i^k = f_k(\theta_{k-1}^{i}, w_i^k). \tag{34}$$

Finally, at every time step we resample with replacement the existing particles. The logic behind this step is that for the N_s particles, which we have obtained from the importance sampling step, we multiply or discard particles according to their normalized weights in order that, at the end of this step, to get new particles distributed according to a non-weighted approximate empirical distribution. Thus, during the selection step we discard "weak" particles with small importance weights and multiply "strong" particles with larger weights (i.e., survival of the fittest) [2].

5 The state space (bearings only tracking) model

The system model that will be considered is the one used in most of tracking models used in the literature (see, [4] and references therein). The state

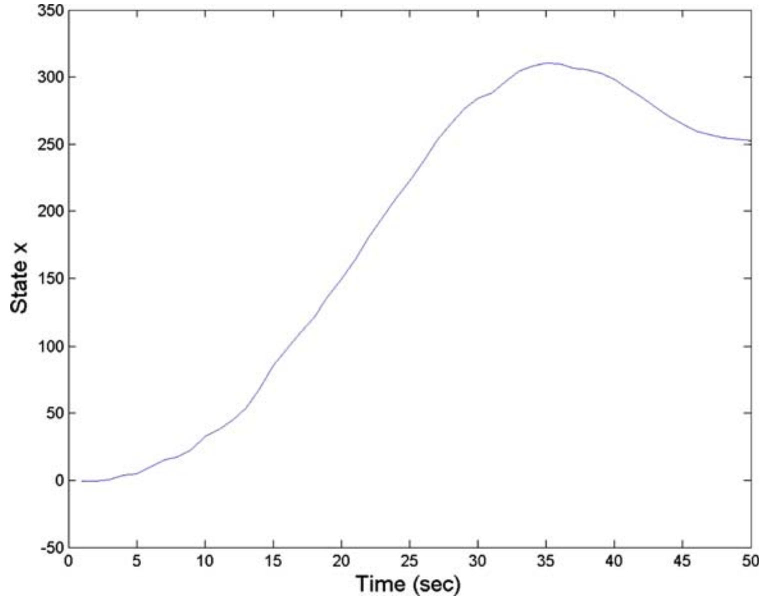

Fig. 3 The actual state of the mobile moving in the x-axis

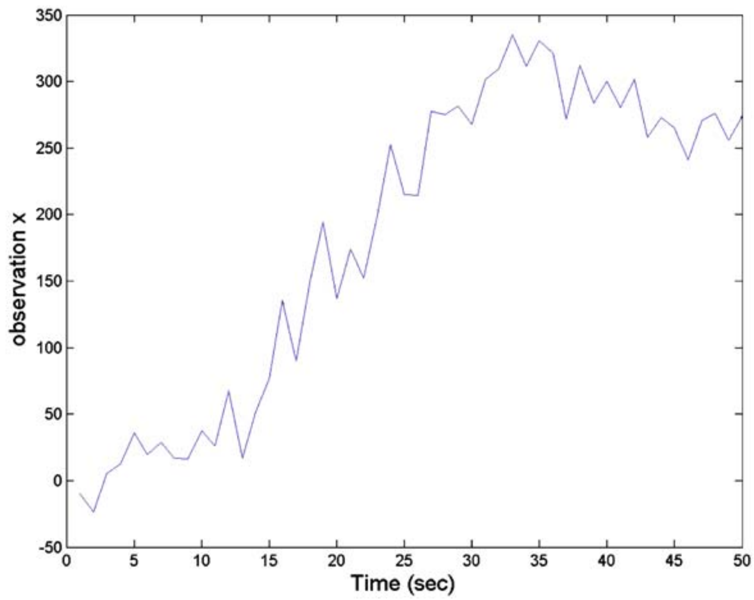

Fig. 4 The state observations of the mobile moving in the x-axis

vector at time t_k is $\theta_k = (x_k,\ u_{x_k},\ y_k,\ u_{y_k})^T$ and represents the target position and velocity in Cartesian co-ordinates. The times t_1, t_2, etc., are assumed to be at unit intervals and the velocities u_{x_k}, u_{y_k} represent the average velocity in the unit interval $[t_{k-1}, t_k]$. Moreover, the acceleration is modeled as additive Gaussian noise. Therefore, the system equation is

$$\Theta_k = F\Theta_{k-1} + \Phi W_k \tag{35}$$

or

$$\theta_k = f_k(\theta_{k-1}, W_k), \tag{36}$$

where

$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

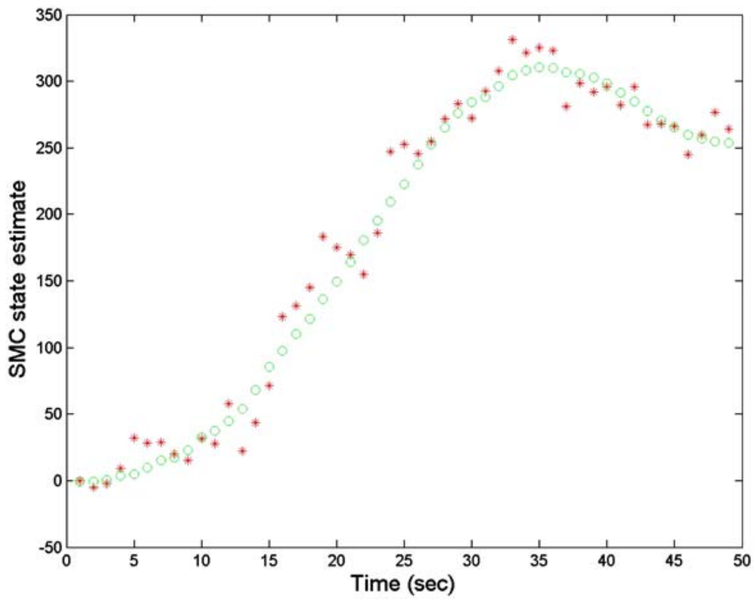

Fig. 5 The state estimate of the mobile (*with red stars*) compared to the actual state (*with green circles*) moving in the *x*-axis

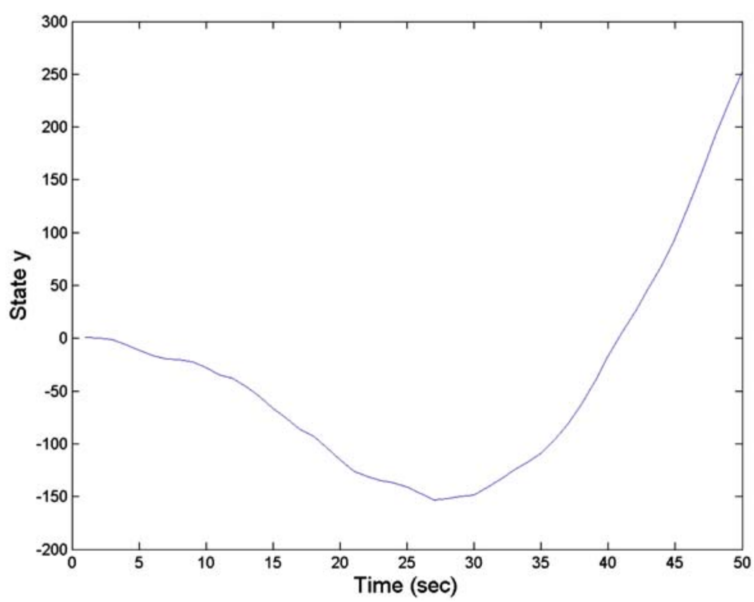

Fig. 6 The actual state of the mobile moving in the *y*-axis

and

$$\Phi = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}.$$

The system noise W_k is a two-dimensional Gaussian white noise process with covariance matrix $v^2\mathbf{I}_2$, where $\mathbf{I}_2$ is a 2x2 identity matrix. The prior for Θ_1 is a multivariate normal density, with mean $(\mu_1, \mu_2, \mu_3, \mu_4)^{\mathrm{T}}$ and covariance matrix $\mathrm{diag}(\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2)$. On the other hand the measurement process is given by the following equation:

$$\mathrm{Z}_k = S_k + V_k \tag{37}$$

or

$$z_k = h_k(\theta_k, v_k), \tag{38}$$

where $S_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix}$ and V_k is the 2x1 Gaussian white measurement noise vector. The velocities u_x

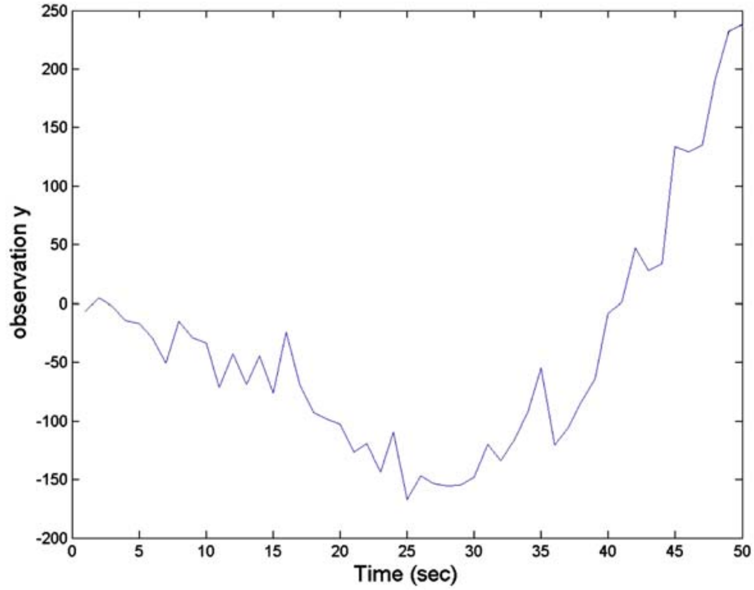

Fig. 7 The state observations of the mobile moving in the *y*-axis.

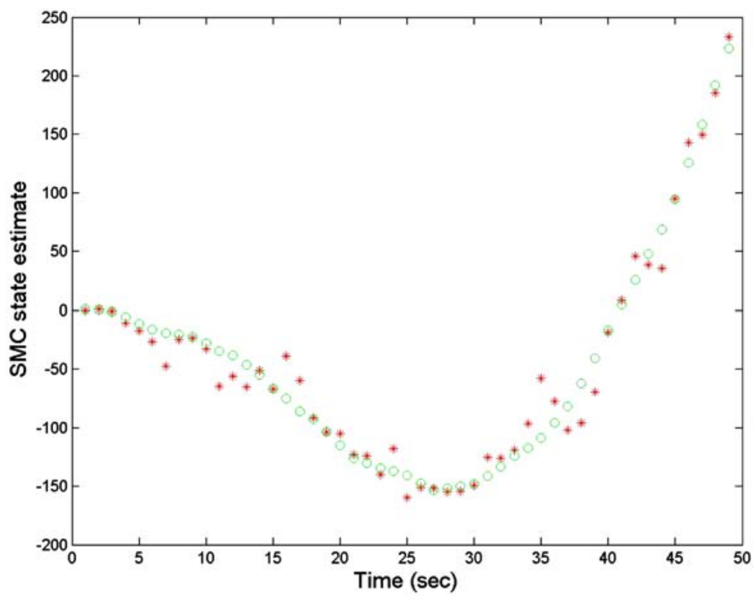

Fig. 8 The state estimate of the mobile (*with red stars*) compared to the actual state (*with green circles*) moving in the *y*-axis

and u_y in the $(x$–$y)$ plane are easily derived if we consider the unit time interval.

Here we should mention the existence of slightly different models proposed in refs. [5,6] where the authors choose Φ to be

$$\Phi = \begin{bmatrix} 0.5 & 0 \\ 1 & 0 \\ 0 & 0.5 \\ 0 & 1 \end{bmatrix}$$

in which case the velocities u_{x_k}, u_{y_k} represent the average velocity in the unit interval $[t_{k-\frac{1}{2}}, t_{k+\frac{1}{2}}]$ or

$$\Phi = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}$$

in which case the velocities u_{x_k}, u_{y_k} represent the average velocity in the unit interval $[t_k, t_{k+1}]$.

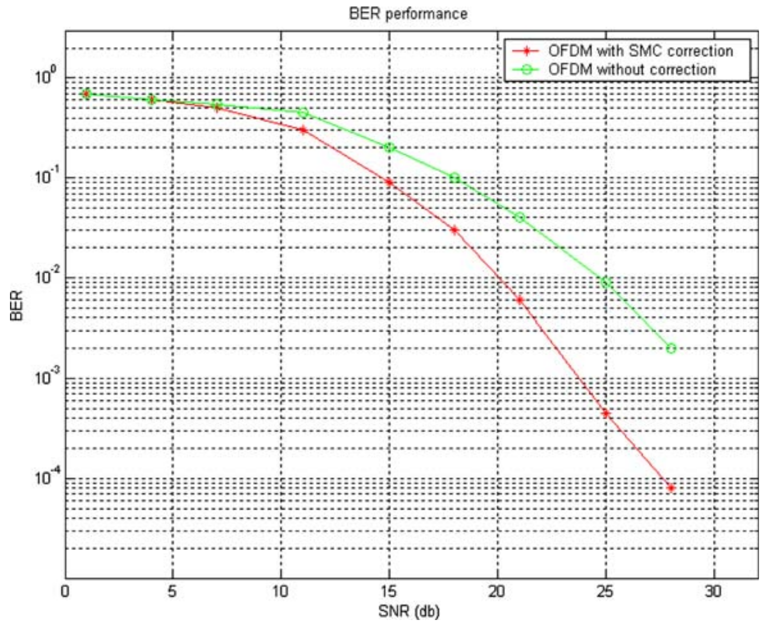

Fig. 9 BER curves for a mobile OFDM system with a SMC offset correction and without offset correction

6 Results

The results of the simulation of our SMC algorithm and moreover, a performance measure in terms of the Root Mean Squared Error (RMSE) are given in the first part of this section, while in the second part we present performance comparison via a BER versus SNR curve. The figures shown below were obtained via simulation with parameters $T = 50$ s (simulation time),$N_s = 500$ (number of particles), process noise variance $\sigma_w = \sqrt{10}$, and measurement noise variance $\sigma_v = 20$.

Figure 3 illustrates the evolution of the state space in the x-axis, i.e., the actual position on the x-axis of the moving mobile. The available observations for the x-axis position of the mobile are plotted in Figs. 4 and 5 the state estimation on the x-axis is, as obtained via the proposed SMC algorithm, shown. For comparison purposes, the actual state of the moving mobile is also plotted. Figures 6–8 give the corresponding diagrams for the actual state space, state observations, and state estimations on the y-axis, respectively.

In order to qualitatively evaluate the performance of the proposed algorithm, we use the well-known traditional measure of performance: the RMSE. We run the algorithm 50 times (50 simulations) and the RMSE between our estimate and the true state is found to be 6.49. The RMSE between the true state and the observations is found to be 20.25. The SMC algorithm seems to work satisfactorily, inducing a significant correction to the state space estimate with respect to the available observations.

Moreover, in order to present the performance improvement that can be achieved in a mobile OFDM communication system by predicting and correcting the frequency offset, BER curves are given for a system without offset correction and with offset correction, the latter obtained via an appropriate SMC algorithm. Figure 9 presents the simulation results for the two systems with SNR (the signal to noise ratio) ranging between 1 and 28 dB. It is observed that when the proposed SMC correction is used, there is a significant reduction of the BER (especially for relatively large SNR values) resulting in a substantial improvement of a mobile OFDM communication system.

7 Conclusions

In conclusion, we have analyzed the effect of the Doppler spread in a mobile communication system employing OFDM. We have provided analytical results for the evaluation of the ICI due to loss of orthogonality. We have calculated the Doppler effect in a moving mobile by predicting the mobile velocity through particle filtering. Particularly, an importance sampling—resampling algorithm was applied to the state space, which characterizes the target tracking problem. By calculating the Doppler effect in the receiver and adjusting the transmitter to the appropriate frequency (with a frequency synchronizer), it is shown that the performance of mobile OFDM communication systems, which suffer from loss of orthogonality by this kind of frequency shifts, can be significantly improved. In order to fully demonstrate the performance improvement, BER curves were also given for a system without correction and for a system with an SMC algorithm implemented. It is observed that when the proposed SMC offset correction is used, there is a significant reduction of the BER ($O(10^{-1})$ for a 20 dB SNR) resulting in a substantial improvement of a mobile OFDM communication system.

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