Multiuser Channel Estimation Using Robust Recursive Filters for CDMA System

Jang–Sub Kim, Ho–Jin Shin, and Dong–Ryeol Shin

Abstract: **In this paper, we present a novel blind adaptive multiuser detector structure and three robust recursive filters to improve the performance in CDMA environments: Sigma point kalman filter (SPKF), particle filter (PF), and Gaussian mixture sigma point particle filter (GMSPPF). Our proposed robust recursive filters have superior performance over a conventional extended Kalman filter (EKF). The proposed multiuser detector algorithms initially use Kalman prediction form to estimated channel parameters, and unknown data symbol be predicted. Second, based on this predicted data symbol, the robust recursive filters (e.g., GMSPPF) is a refined estimation of joint multipaths and time delays. With these estimated multipaths and time delays, data symbol detection is carried out (Kalman correction form). Computer simulations show that the proposed algorithms outperform the conventional blind multiuser detector with the EKF. Also we can see it provides a more viable means for tracking time-varying amplitudes and time delays in CDMA communication systems, compared to that of the EKF for near-far ratio of 20 dB. For this reason, it is believed that the proposed channel estimators can replace well-known filter such as the EKF.**

Index Terms: **Multiuser channel estimation, non-linear recursive filter, particle filter.**

I. INTRODUCTION

Code division multiple access (CDMA) has been adopted by many of the modern wireless communication systems as the physical layer technique. It is used already in IS-95 and cdma2000 networks developed by the Qualcomm Corp., and is the main radio interface for 3G proposals. Among the many advantages of the CDMA that can be highlighted is the increased network capacity, increased data rates and the possibility it offers in accommodating services with different data rates.

Multipath, multiple access interference (MAI), and near-far effects are the three main influences on the performance of CDMA-based wireless communication systems (e.g., cdma2000 and UMTS). Multiuser detection has the potential to reduce the MAI and solve the near-far problem in a CDMA channel [1]. The analysis of multi-user detectors for fading channels is often conducted under the ideal assumption of perfect channel estimation [2]–[5]. Imperfect channel estimation degrades the performance of multiuser detectors since many multiuser detectors require channel estimates to cancel the MAI and/or to perform coherent reception. To improve the performance of multiuser detectors for rapidly varying fading channels, we introduce the robust recursive filters that provide an improvement in the accuracy and stability over the extended Kalman filter (EKF). We focus on the channel estimators and propose a novel multiuser detector based on the adaptive channel estimators such as sigma point kalman filter (SPKF), particle filter (PF), and gaussian mixture sigma point particle filter (GMSPPF). This structure is shown Fig. 1, similarly configured with 2 stages PIC (parallel interference cancellation) multiuser detector.

The problem of channel parameter (channel coefficients and code delays) estimation has been addressed in the literature before (see [6]), and has proved to be difficult due to its inherited nonlinearity. The previously proposed approaches are mainly based on the use of the EKF. In a number of cases, when EKF methods are applied, the estimators are divergent [7], [8] since the measurement model has the highly nonlinear nature of time delay and it uses a first-order Taylor series expansion of the nonlinear terms around the mean values. A new filtering method, called SPKF has been employed to tackle the nonlinearity, showing its effectiveness in terms of divergence reduction and error propagation [9]. The SPKF addresses this problem by using a deterministic sampling approach. The SPKF guarantees the same performance as the truncated second order filter, with the same order of calculations as a conventional EKF but without the need to calculate any approximation or derivatives. The EKF, in contrast, only achieves first-order accuracy. Caffery [10] adapted a new way of parameterization (unscented filter: UF) for Gaussian variables and instead, applied extended Kalman filtering for channel estimation in CDMA environments. This UF has some problem that the calculated covariance can be non-positive semi-definite. As a result, this filter can diverge. SPKF developed to address this problem [9], [11], [12]. Thus, we apply the SPKF for multiuser detection in CDMA system.

The PF has already been successfully applied to the problems arising in the field of controls, statistics and digital communications, in particular, demodulation in fading channels [13], [14] and detection in synchronous CDMA [15]. Tanya [16] and Iltis [17] has recently developed a particle filtering method to estimation of only channel coefficients and code delays. In his approach, the unknown symbol sequence is obtained through a standard algorithm. Punskaya [18] has developed estimation of the channel coefficients, code delays, and symbols jointly using particle filtering techniques in flat Rayleigh fading. However, we extend the development of multiuser parameter estimators to joint estimation of the channel coefficients and code delays in frequency selective Rayleigh fading, and we added to propose a new unknown symbol detection mechanism (similar to Kalman predict correction forms). Thus, this paper proposes a

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novel receiver structure, since unknown symbols are discrete-value and channel parameters (channel coefficient and code delay) are (complex or real) continuous-values. In general, the PF rely on importance sampling and, as a result, require the design of proposal distributions that would approximate the posterior distribution reasonably well [19], [20]. The most common PF strategy is to sample from transition prior distribution. Since the prior proposal distribution employs no information from observations in proposing new samples, its use is often ineffective and leads to poor filtering performance. In order to overcome these problems, we additionally propose new method such as the GM-SPPF [21].

The GMSPPF combines importance sampling (IS) based measurement update step with a SPKF based Gaussian sum filter for the time-update and proposal density generation. The GMSPPF approximates prior, proposal, and posterior density function as GMM (Gaussian mixture model) using banks of parallel SPKF. The updated mean and covariance of each mixand follow from the SPKF updates. The GMSPPF has better estimation performance when compared to standard PF and SPPF, and we can reduce computational cost. The proposed GMSPPF results in better performance in the parameter (including other channel coefficients) estimation. The GMSPPF can apply for filtering with any nonlinearity and any distributions. In this paper, we propose three robust recursive filters as multiuser detector channel estimator and a novel multiuser detector structure. Three robust recursive filters as channel estimators are SPKF, PF, and GMSPPF. And we simply explain a novel multiuser detector structure. The unknown symbol sequence is obtained through a novel multiuser detection algorithm, and channel coefficients and time delays are estimated using three robust estimators, in order to overcome the EKF's weak points. Kalman filtering, in its prediction form, is employed to track the channel and time delays, and make an estimate of the current symbol data instead of decision directed (DD) mode. After the unknown symbol data is estimated, the proposed receiver will conduct a refined estimation of the channel and time delay using the robust recursive filters. And finally the proposed receiver will make a refined estimation of the unknown symbol data. Thus, the proposed receiver structure is similar with Kalman filtering form (prediction and correction). The tracking error analysis for the multiusers' channel coefficients and delays may show better performance over the EKF.

This paper is organized as follows. The signal, channel model, and estimation/detection objectives, used throughout the paper are introduced, with a description of problem formulation in Section II. Section III is devoted to the issues of channel estimation using a conventional EKF and our proposed robust recursive filtering methods (SPKF, PF, and GMSPPF). The computer simulation performance results are given in Section IV. Finally, we conclude our study in Section V.

II. IMPLEMENTATION OF A MANAGEMENT APPLICATION

A. System and Channel Model

Assuming that each of K users transmits over an M-path fading channel, the received signal is given by

$$r(l) = \sum_{k=1}^{K}\sum_{i=1}^{M} c_{k,i}(l) d_{k,m_l} a_k(l - m_l T_b - \tau_{k,i}(l)) + n(l) \quad (1)$$

where $c_{k,i}(l)$ represents complex channel coefficients, d_{k,m_l} is the mth symbol transmitted by the kth user, $m_l = \lfloor (l-\tau_k(l))/T_b \rfloor$, T_b is the symbol interval, $a_k(l)$ is the PN spreading waveform used by the kth user, $\tau_{k,i}(l)$ is the time delay introduced by the ith path of the kth user, and $n(l)$, AWGN (additive white Gaussian noise) is assumed to have a mean of zero and variance of $\sigma_n^2 = N_0/2$.

B. State-Space Model

Let the unknown parameters be represented by the following $2KM \times 1$ vector.

$$\mathbf{x} = [\mathbf{c} \quad \boldsymbol{\tau}]^T \quad (2)$$

where $\mathbf{c} = [c_{11}, c_{12}, \cdots, c_{1M}, \cdots, c_{2M}, \cdots, c_{K1}, \cdots, c_{KM}]$ and $\boldsymbol{\tau} = [\tau_{11}, \tau_{12}, \cdots, \tau_{1M}, \cdots, \tau_{2M}, \cdots, \tau_{K1}, \cdots, \tau_{KM}]$. From [6], we can write the state model as

$$\mathbf{x}(l+1) = \mathbf{F}(l)\mathbf{x}(l) + \mathbf{v}(l) \quad (3)$$

where $\mathbf{F}(l) = diag\{\mathbf{F_c}, \mathbf{F_\tau}\}$ is $2KM \times 2KM$ augmented by the state transition matrix, $\mathbf{v} = [\mathbf{v_c}^T \quad \mathbf{v_\tau}^T]$ is $2KM \times 1$ process noise vector with mean of zero and covariance matrix $\mathbf{Q} = diag\{\mathbf{Q_c}, \mathbf{Q_\tau}\}$, and $diag\{\cdot\}$ is the diagonal matrix. The scalar measurement model follows from the received signal of (1) by

$$z(l) = h(\mathbf{x}(l)) + n(l) \quad (4)$$

where the measurement $z(l) = r(l)$, and

$$h(\mathbf{x}(l)) = \sum_{k=1}^{K}\sum_{i=1}^{M} c_{k,i}(l) d_{k,m_l} a_k(l - m(l)T_b - \tau_{k,i}(l))).$$

The scalar measurement $z(l)$ is a nonlinear function of the state $\mathbf{x}(l)$. If it is assumed that the noise vectors $\mathbf{v}(l)$ and $n(l)$ are individually and mutually uncorrelated with correlation matrices

$$\begin{aligned} E[\mathbf{v}(i)\mathbf{v}(j)^T] &= \mathbf{Q}_i\delta_{ij} \\ E[n(i)n(j)^T] &= R_i\delta_{ij} \\ E[\mathbf{v}(i)n(j)^T] &= 0 \end{aligned} \quad (5)$$

where δ_{ij} is the two-dimensional Kronecker delta function.

C. Detection / Estimation Objectives

Since unknown symbols are discrete-values and channel parameters (channel coefficient and code delay) are (complex or real) continuous-values, our novel receiver will be implemented two steps: Channel estimation and unknown symbol detection. The symbols $\mathbf{d}$ and the channel coefficient and time delay $\mathbf{x}$ are unknown. Our aim is to obtain an MAP (maximum a posterior) estimate of the symbols

$$\hat{\mathbf{d}}(z) = \arg\max_{\mathbf{d}} \; p(\mathbf{d}|z, \hat{\mathbf{x}}) \quad (6)$$

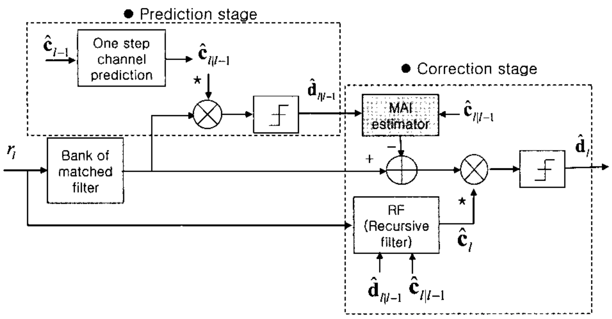


Fig. 1. Proposed multiuser detection structure.

and the MMSE (minimum mean square error) estimates of the channel coefficients and time delays $\hat{\mathbf{x}} = E\{\mathbf{x}|z^l, \hat{\mathbf{d}}\}$ with estimated error covariance

$$\mathbf{P} = E\{[\mathbf{x}(l) - \hat{\mathbf{x}}(l|l)][\mathbf{x}(l) - \hat{\mathbf{x}}(l|l)]^T|z^l, \hat{\mathbf{d}}\}. \quad (7)$$

This problem does not admit any analytical solution and, thus, we propose a novel receiver structure. In order to detect the symbol $\mathbf{d}$, assuming that channel and delay estimates $\mathbf{x}$ are available as depicted Fig. 1. The recursive algorithm based on this description is given in next section, we also discuss how the proposed structure may be used for simultaneous channel estimation.

III. NOVEL ADAPTIVE MULTIUSER RECEIVER AND CHANNEL ESTIMATORS

As we consider that channel parameters are (complex or real) continuous values and unknown symbols are discrete values, a novel multiuser detector based on the GMSPPF is shown in Fig. 1. To channel estimation and symbol detection, estimation of $\mathbf{x}$ and detection of $\mathbf{d}$ steps are recursively alternated. In [10], the receiver operated in decision-directed mode. We proposed a novel multiuser detector based on the recursive filters (RF) such as SPKF, PF, and GMSPPF, and it is shown Fig 1, similarly configure with 2 stages PIC multiuser detector. Our proposed channel estimators can employ all types multiuser detectors that need to estimate channel coefficient and time delay. To track the time varying channels and symbol detection, we exploit the recursive nature of the Kalman filtering. The prediction and correction steps at the lth iteration for the proposed receiver are:

1. Prediction
   - 1-Estimation step: Obtain a rough estimate, $\bar{\mathbf{x}}$, using state equation
   $$\bar{\mathbf{x}}_{l|l-1} = \mathbf{F}\bar{\mathbf{x}}_{l-1}.$$
   - 2-Detection step: Make an initial estimate of the current transmitted symbols, $\bar{\mathbf{d}}_{l|l-1}$,using the observation vector, z_l , and $\bar{\mathbf{x}}_{l|l-1}$
   $$\bar{\mathbf{d}}_{l|l-1}(z) = \arg\max_{\mathbf{d}}\ p(\mathbf{d}|z_l, \bar{\mathbf{x}}_{l|l-1}).$$
2. Correction
   - 3-Estimation step: Refine the channel estimate using RF and estimated symbols to yield $\bar{\mathbf{x}}_l$
   $$\bar{\mathbf{x}}_l = RF(\bar{\mathbf{d}}_{l|l-1}, z_l).$$
   - 4-Detection step: Re-estimate symbols, $\mathbf{d}_l$, from $\bar{\mathbf{x}}_l$
   $$\bar{\mathbf{d}}_l(z) = \arg\max_{\mathbf{d}}\ p(\mathbf{d}|z_l, \bar{\mathbf{x}}_l).$$

Since CDMA measurement model is nonlinear, we cannot use the KF. The EKF has probably had the most solution use the MMSE estimation in nonlinear estimation. The EKF takes the linear approximation by the Taylor series expansion of the nonlinear models. The EKF approximates the state distribution using a Gaussian random variable, which is then propagated analytically through the first-order linearization of the nonlinear system. The EKF does not take into account the second and higher order terms in mean and fourth and higher order terms in the covariance are negligible. These approximations can introduce large errors in the true posterior mean and covariance of the transformed random variable in many practical situations, leading to suboptimal performance and divergence of the filter. The EKF also need to analytical calculate Jacobians (or Hessian).

To improve the multiuser channel estimation accuracy over EKF, we propose the SPKF, PF, and GMSPPF. And to alleviate the implementation complexity more than sequential Monte Carlo filtering method such as PF, we propose the GMSPPF. We will study robust recursive filtering in this section.

A. Sigma Point Kalman Filter

In order to improve the accuracy, consistency and efficiency of EKF algorithms applied to CDMA channel estimation, we introduce the SPKF. This technique and its variations [9] have been used widely in engineering and the physical sciences to estimate parameters from noisy data.

The main idea of the SPKF is as follows: Instead of linearizing the nonlinear function through a truncated Taylor-series expansion at a single point (mean value of the random variable), we rather linearize the function through a linear regression between points drawn from the prior distribution of the random variable, and the true nonlinear functional evaluations of those points. Since this approach takes into account the statistical properties of the prior random variable, the resulting linearization error tends to be smaller than that of a truncated Taylor-series linearization. For in-depth, technically more rigorous treatment of the topic, the reader is directed to other sources [9].

The SPKF can be summarized briefly as follows. For each measurement time $l+1$, a set of deterministically selected points (sigma points) is used to approximate the distribution of the previous state estimates from time l using a normal distribution with a mean of $\bar{\mathbf{x}}_{l|l}$, and variance proportional to the state covariance matrix, $\mathbf{P}_{l|l}$. These points, termed sigma points, are specifically selected to capture the dispersion around $\bar{\mathbf{x}}_{l|l}$. These sigma points are then projected forward in time using the linear state function in (3) and weighted after the transformation to yield $\bar{\mathbf{x}}_{l+1|l}$ and $\mathbf{P}_{l+1|l}$. Then, the same sigma points are projected using the measurement function in (3), re-weighted, and used to update the estimates in conjunction with the new observation at time l to yield $\hat{\mathbf{x}}_{l+1|l+1}$ and $\mathbf{P}_{l+1|l+1}$. The abovementioned sigma point transformation algorithm, capitalized on repeated applications of a transformation technique known as the scaled unscented transformation, is computationally efficient. This is because the sigma points are selected according to a deterministic scheme (instead of a random sampling scheme as in the PF). A set of $2n+1$ weighted point where $\mathbf{S} = \{W_i, \mathbf{X}_i\}$ (such that $\sum_{i=0}^{p} W_i = 1$) are chosen to reflect certain properties of $\mathbf{x}$. From [9], the resulting set of sigma points and weights utilized by the SPKF are

$$\begin{aligned} \mathbf{X}_0(l|l) &= \bar{\mathbf{x}}(l|l) \\ \mathbf{X}_i(l|l) &= \bar{\mathbf{x}}(l|l) + (\sqrt{(n+\lambda)\mathbf{P}(l|l)})_i \quad i = 1,\cdots,n \\ \mathbf{X}_{i+n}(l|l) &= \bar{\mathbf{x}}(l|l) - (\sqrt{(n+\lambda)\mathbf{P}(l|l)})_i \quad i = 1,\cdots,n \\ W_0^{(m)} &= \lambda/(n+\lambda) \\ W_0^{(c)} &= \lambda/(n+\lambda) + (1-\alpha^2+\beta) \\ W_i^{(m)} &= W_i^{(c)} = 1/\{2(n+\lambda)\} \end{aligned} \tag{8}$$

where $\kappa \in \Re$, $\sqrt{(n+\lambda)\mathbf{P}(l|l)}_i$ is the ith row or column of the matrix square root of $(n+\lambda)$ **P** $(l|l)$ and W_i is the weight that associated with the ith point. $\lambda = \alpha^2(n+\kappa) - n$ is a scaling parameter and $\eta = \sqrt{(n+\lambda)}$. α is a positive scaling parameter which can be made arbitrarily small to minimize higher order effects(e.g., $1\mathrm{e}-2 \le \alpha \le 1$). κ is a secondary scaling parameter which is usually set to either 0 or $3-n$. β is an extra degree of freedom, and is a scalar parameter used to incorporate any extra prior knowledge of the distribution of $\mathbf{x}$ (for Guassian distributions, β is optimal). Further details pertaining to the SPKF are summarized below in three major steps [9].

Algorithm 1: Channel estimator based on SPKF

1. The sigma point is calculated as
$$\mathbf{X}(l) = \left[\bar{\mathbf{x}}(l|l) \quad \bar{\mathbf{x}}(l|l) + \eta\sqrt{\mathbf{P}(l|l)+\mathbf{Q}} \quad \bar{\mathbf{x}}(l|l) - \eta\sqrt{\mathbf{P}(l|l)+\mathbf{Q}}\right].$$
2. The SPKF time updates as follows
   - The transformed set is given by instantiating each point through the process model
   $$\mathbf{X}_i(l|l) = \mathbf{F}\mathbf{X}_i(l|l).$$
   - The predicted mean is computed as
   $$\bar{\mathbf{x}}(l+1|l) = \textstyle\sum_{i=0}^{2n} W_i^{(m)} \mathbf{X}_i(l+1|l).$$
   - The predicted covariance is computed as
   $$\mathbf{P}(l+1|l) = \textstyle\sum_{i=0}^{2n} W_i^{(c)} [\mathbf{X}_i(l+1|l) - \bar{\mathbf{x}}(l+1|l)] \cdot [\mathbf{X}_i(l+1|l) - \bar{\mathbf{x}}(l+1|l)]^T.$$
   - Instantiate each of the prediction points through the observation model
   $$Z(l+1|l) = h(\mathbf{X}(l+1|l)).$$
   - The predicted observation is calculated by
   $$\bar{\mathbf{z}}(l+1|l) = \textstyle\sum_{i=0}^{2n} W_i^{(m)} Z_i(l+1|l).$$
3. The SPKF measurement updates as follows
   - The innovation covariance is given by
   $$P_{zz}(l+1) = \textstyle\sum_{i=0}^{2n} W_i^{(c)} [Z_i(l+1|l) - \bar{z}(l+1|l)][Z_i(l+1|l) - \bar{z}(l+1|l)]^T.$$
   - Since the observation noise is additive and independent, the innovation covariance is
   $$P_{vv}(l+1) = P_{zz}(l+1) + \sigma_n^2.$$
   - The cross-covariance matrix of $\mathbf{x}$ and z, is determined by
   $$\mathbf{P}_{\mathbf{x}z}(l+1) = \textstyle\sum_{i=0}^{2n} W_i^{(c)} [\mathbf{X}_i(l+1|l) - \bar{\mathbf{x}}(l+1|l)][Z_i(l+1|l) - \bar{z}(l+1|l)]^T.$$
   - The Kalman gain matrix is found according to
   $$\mathbf{K}(l+1) = \mathbf{P}_{\mathbf{x}z}/P_{vv}.$$
   - The update mean (parameter estimated) is calculated
   $$\begin{aligned} \bar{\mathbf{x}}(l+1) &= \bar{\mathbf{x}}(l+1|l) + \mathbf{K}(l+1)v(l+1) \\ v(l+1) &= z(l+1) - \bar{z}(l+1|l). \end{aligned}$$
   - The update covariance (error covariance matrix are updated) is also provided by
   $$\mathbf{P}(l+1) = \mathbf{P}(l+1|l) - \mathbf{K}(l+1)P_{zz}\mathbf{K}^T(l+1).$$

In the SPKF where the SUT (scaled unscented transform) is employed in the prediction stages follows the given nonlinear function, no harmful loss in the above is expected. It is not necessary to calculate the Jacobian (and Hessian if 2nd order approximation in the Taylor series) and the prediction stage only consists of standard linear algebra operations (matrix square root, etc.).

B. Particle Filter

The PF uses the sequential Monte Carlo based method. These methods allow for a complete representation of the posterior distribution of the states using sequential importance sampling and resampling [19], [20]. Whereas the standard EKF and SPKF have the limitation that they do not apply to general non-Gaussian distributions, PF makes no assumptions on the form of the probability densities in question, i.e., nonlinear, non-Gaussian.

The key idea is to represent the required posterior density functions using a set of random samples (particles) with associated weights and computing estimates based on these samples and weights. As the number of samples becomes very large, this Monte Carlo characterization becomes an equivalent representation to the usual functional description of the posterior probability density function (pdf), and the PF approaches the optimal Bayesian estimate. If we know the posterior density function, we can easily derive various estimates of the system's states including means, modes, medians and confidence intervals.

The posterior density $p(\mathbf{x}_{0:l}|z_{1:l})$, where $\mathbf{x}_{0:l} = \{\mathbf{x}_0, \mathbf{x}_1, \cdots, \mathbf{x}_l\}$ and $z_{1:l} = \{z_1, z_2, \cdots, z_l\}$, constitutes the complete solution to the sequential estimation problem. In many applications, such as tracking, it is of interest to estimate one of its marginals, namely the filtering density $p(\mathbf{x}_l|z_{1:l})$. By computing the filtering density recursively, we do not need to keep track of the complete history of the states. Thus, from a storage point of view, the filtering density is more parsimonious than the full posterior density function. If we know the filtering density, we can easily derive various estimates of the system's states including means, modes, medians and confidence intervals. We show how the filtering density may be approximated using sequential importance sampling techniques.

In the PF, the posterior density at l can be approximated as:

$$p(\mathbf{x}_{0:l}|z_{1:l}) \approx \sum_{i=1}^{N} w_l^{(i)} \delta(\mathbf{x}_{0:l} - \mathbf{x}_{0:l}^{(i)}) \tag{9}$$

where $\{\mathbf{x}_{0:l}^{(i)}\}_{i=1}^{N}$ are a set of particles drawn from the posterior distribution and $\delta(\cdot)$ is the Dirac delta function. The weights ($w_l^{(i)}$) themselves can be shown to be updated as [19]:

$$w_l^{(i)} = w_{l-1}^{(i)} \frac{p(z_l|\mathbf{x}_l^{(i)}) p(\mathbf{x}_l^{(i)}|\mathbf{x}_{l-1}^{(i)})}{q(\mathbf{x}_l^{(i)}|\mathbf{x}_{l-1}^{(i)}, z_l)} \tag{10}$$

where the proposal distribution $q(\mathbf{x}_l^{(i)}|\mathbf{x}_{l-1}^{(i)}, z_l)$ represents all the a priori knowledge. It is, however, usually difficult to sample directly from a given posterior distribution. Thus, we choose what can be called a proposal distribution that is of probability distribution from which we can easily sample [19]. The selection of the proposal function is one of the most critical design issues in importance sampling algorithms and is the source of the main concern. The more accurate the proposal is to the true posterior, the better the performance of the particle filter. It is often convenient to choose the proposal distribution to be the prior [19]

$$q(\mathbf{x}_l^{(i)}|\mathbf{x}_{l-1}^{(i)}, z_l) = p(\mathbf{x}_l|\mathbf{x}_{l-1}^{(i)}). \tag{11}$$

Again, we choose the stochastic model given by (3) as our model for the proposal distribution. As a result of not incorporating the most recent observations, this would seem to be the most common choice of proposal distribution since it is intuitive and can be implemented easily. This has the effect of simplifying (10) to

$$w_l^{(i)} = w_{l-1}^{(i)} p(z_l|\mathbf{x}_l^{(i)}) \tag{12}$$

The update weights are based on the likelihood. New estimates of the posterior are then computed based on the previous samples. A common problem with the SIS particle filter is the degeneracy phenomenon [19], where after a few iterations, all but one particle will have negligible weight. To avoid this degeneracy, a resampling stage may be used to eliminate samples with low importance weights and multiply samples with high importance weights. A common heuristic used to maintain an appropriate number of particles is to first calculate the effective sample size N_{eff} introduced in [20], and defined as:

$$\hat{N}_{eff} = 1 \Bigg/ \left(\sum_{i=1}^{N} (w_l^{(i)})^2 \right). \tag{13}$$

A threshold number of particles N_{th} is then defined such that $N_{th} \leq N$. Multiple resampling of particles then becomes necessary whenever $N_{eff} \leq N_{th}$. To CDMA channel estimation, the PF are summarized below in two major steps

Algorithm 2: Channel estimator based on PF

1. Initialize weights ($l = 0$)
   - For $i = 1 : N$
     - Draw $\mathbf{x}_l^{(i)} - p(\mathbf{x}_0)$
     - Evaluate the importance weights $w_0^{(i)} = p(z_0|\mathbf{x}_0^{(i)})$, according to (12)
     - Normalize the weights $\hat{w}_0^{(i)} = w_0^{(i)}/\sum_{j=1}^{N} w_0^{(j)}$
2. For $l = 1, 2, \cdots$
   - Sampling Stage
     - Predict via the process model (3) : $\hat{\mathbf{x}}_{l+1}^{(i)} = \mathbf{F}\mathbf{x}_l^{(i)} + \mathbf{v}_l^{(i)}$.
     - Evaluate the weights : $w_{l+1}^{(i)} = w_l^{(i)} p(z_{l+1}|\hat{\mathbf{x}}_{l+1}^{(i)})$.
     - Normalize the weights : $\hat{w}_{l+1}^{(i)} = w_{l+1}^{(i)}/\sum_{j=1}^{N} w_{l+1}^{(j)}$.
   - Resampling Stage
     - For $i = 1 : N$
       If $N_{eff} \leq N_{th}$, Resampling
       Else, No Resampling
   - Inference : MMSE - $\hat{\mathbf{x}}_l = E[\mathbf{x}_l|z_l] \approx \frac{1}{N}\sum_{i=1}^{N} \mathbf{x}_l^{(i)}$

C. Gaussian Mixture Sigma Point Particle Filter

We present a further refinement of the PF called the GMSPPF [21]. This filter has equal or better estimation performance when compared to the PF and SPPF. The GMSPPF combines importance sampling based measurement update step with a SPKF based Gaussian sum filter for the time-update and proposal density generation. The GMSPPF also is a recursive process consisting of two stages. The time update state, where the previous observations and state were used to predict the current state, and the measurement update state, where current observation is used to increase the accuracy of the predicted state.

In the time update stage, the GMSPPF approximates prior, proposal and posterior density function as GMM using banks of parallel SPKF. The updated mean and covariance of each mixand follow from the SPKF updates. The predictive state density is now approximated by the GMM

$$p(\mathbf{x}_l|z_{l-1}) \approx p_g(\mathbf{x}_l|z_{l-1}) = \sum_{g'=1}^{G'} \alpha_l^{(g')} N(\mathbf{x}_l; \tilde{\mathbf{u}}_l^{(g')}, \tilde{\mathbf{P}}_l^{(g')}) \tag{14}$$

where N is the number of particles.

In the measurement update stage, the GMSPPF uses a finite GMM representation of the posterior filtering density

$$p(\mathbf{x}_l|z_l) \approx p_g(\mathbf{x}_l|z_l) = \sum_{g=1}^{G} \alpha_l^{(g)} N(\mathbf{x}_l; \mathbf{u}_l^{(g)}, \mathbf{P}_l^{(g)}). \tag{15}$$

This is recovered from the weighted posterior particle set of the IS based measurement update stage, by means of a expectation-maximization (EM) [22] step. The EM algorithm can be used to obtain Gaussian Mixture approximations from these particles and weights. In particular, EM is applicable to problems, where the observable data provide only partial information or where some data are "missing". With this mechanism, the EM recovered from the GMM posterior further mitigates the "sample depletion" problem through its inherent "kernel smoothing" nature. The EM algorithm provides an iterative method to solve for the which satisfies

$$\bar{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \; p(\mathbf{x}|\boldsymbol{\theta}) \tag{16}$$

where the Gaussian mixture is specified by the set of parameters $\boldsymbol{\theta} = \{\alpha_l^{(1)}, \cdots, \alpha_l^{(G)}, \mathbf{u}_l^{(1)}, \cdots, \mathbf{u}_l^{(G)}, \mathbf{P}_l^{(1)}, \cdots, \mathbf{P}_l^{(G)}\}$. Specifically, the EM algorithm is a two-step iterative algorithm which works as follows: Given a $\boldsymbol{\theta}^{(p)}$, find the next value $\boldsymbol{\theta}^{(p+1)}$ via

$$\begin{aligned} \mathrm{E-step}: \mathrm{Q}(\boldsymbol{\theta}|\boldsymbol{\theta}^{(\mathrm{p})}) &= E[\log \; p(\mathbf{x}|\boldsymbol{\theta})|z, \boldsymbol{\theta}^{(p)}] \\ \mathrm{M-step}: \quad \boldsymbol{\theta}^{(\mathrm{p}+1)} &= \arg\max_{\boldsymbol{\theta}} \; Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(p)}). \end{aligned}$$

See [22] for more detailed explanation of the EM Algorithm for GMMs. Finally, The Gaussian mixture approximation lends an advantage that MMSE estimates of the state and its error covariance can be obtained straightforwardly. The conditional mean state estimate and the corresponding error covariance can be calculated through the sampling and resampling stage as described above

$$\hat{\mathbf{x}}_l = \sum_{i=1}^{N} w_l^{(i)} \mathbf{x}_l^{(i)}$$
$$\hat{\mathbf{P}}_l = \sum_{i=1}^{N} w_l^{(i)} (\mathbf{x}_l^{(i)} - \hat{\mathbf{x}}_l)(\mathbf{x}_l^{(i)} - \hat{\mathbf{x}}_l)^T. \quad (17)$$

Alternatively, it can be directly fitted from the EM stage

$$\bar{\mathbf{x}}_l = \sum_{g=1}^{G} \alpha_l^{(g)} \mathbf{u}_l^{(g)}$$
$$\hat{\mathbf{P}}_l = \sum_{g=1}^{G} \alpha_l^{(g)} [\mathbf{P}_l^{(g)} + (\mathbf{u}_l^{(g)} - \bar{\mathbf{x}}_l)(\mathbf{u}_l^{(g)} - \bar{\mathbf{x}}_l)^T]. \quad (18)$$

The time update and measurement update algorithm of GM-SPPF for CDMA channel estimation is summarized in the following sections.

Algorithm 3: Channel estimator based on the GMSPPF

1. Initialization
   - At time l, assume the posterior state density, the process and measurement noise densities are approximated by the following G, I and J component GMMs, respectively

$$p_g(\mathbf{x}_{l-1}|z_{l-1}) = \sum_{g=1}^{G} \alpha_{l-1}^{(g)} N(\mathbf{x}_{l-1}; \mathbf{u}_{l-1}^{(g)}, \mathbf{P}_{l-1}^{(g)})$$
$$p_g(\mathbf{v}_{l-1}) = \sum_{i=1}^{I} \beta_{l-1}^{(i)} N(\mathbf{v}_{l-1}; \mathbf{u}_{\mathbf{v}_{l-1}}^{(i)}, \mathbf{Q}_{l-1}^{(i)})$$
$$p_g(n_l) = \sum_{j=1}^{J} \gamma_l^{(j)} N(n_l; u_{n_{l-1}}^{(j)}, R_l^{(j)})$$

   where α,β, and γ are the mixing weights, G, I, and J are the number of mixing component and $N(\mathbf{x}; \mathbf{u}, \mathbf{P})$ is a normal distribution with mean vector $\mathbf{u}$ and positive definite covariance matrix $\mathbf{P}$. For clarity of notation, define $g' = g + (i-1)G$ and note that references to g' implies references to the respective g and i, since they are uniquely mapped. Similarly define $g'' = g' + (j-1)GI$ with the same implied unique index mapping.
   - For $j = 1, 2, \cdots, J$, set $\tilde{p_j}(n_l) = N(n_l; u_{n_l}^{(j)}, R_l^{(j)})$, for $i = 1, 2, \cdots, I$, set $\tilde{p_i}(\mathbf{v}_{l-1}) = N(\mathbf{v}_{l-1}; \mathbf{u}_{\mathbf{v}_{l-1}}^{(i)}, \mathbf{Q}_l^{(i)})$, for $g = 1, 2, \cdots, G$, set $\tilde{p_g}(\mathbf{x}_{l-1}) = N(\mathbf{x}_{l-1}; \mathbf{u}_{l-1}^{(g)}, \mathbf{P}_{l-1}^{(g)})$.
2. The GMSPPF time updates as follows
   - For $g' = 1, \cdots, G'$,
     - The time update step of a SPKF employing the state (3)

$$\tilde{p}_{g'}(\mathbf{x}_{l-1}|z_l - 1) = \alpha_l^{(g')} N(\mathbf{x}_{l-1}; \tilde{\mathbf{u}}_{l-1}^{(g')}, \tilde{\mathbf{P}}_{l-1}^{(g')})$$
$$\alpha_l^{(g')} = \alpha_{l-1}^{(g)} \beta_{l-1}^{(i)} / \sum_{g=1}^{G} \sum_{i=1}^{I} \alpha_{l-1}^{(g)} \beta_{l-1}^{(i)}.$$

     - For $g'' = 1, \cdots, G''$,
       * The measurement update step of each SPKF employing the measurement (4)

$$\tilde{p}_{g''}(\mathbf{x}_l|z_l) = N(\mathbf{x}_{l-1}; \tilde{\mathbf{u}}_l^{(g'')}, \tilde{\mathbf{P}}_l^{(g'')})$$
$$\alpha_l^{(g'')} = \alpha_l^{(g')} \gamma_l^{(j)} \mathbf{S}_l^{(j)} / \sum_{g'=1}^{G'} \sum_{j=1}^{J} \alpha_l^{(g')} \gamma_l^{(j)} \mathbf{S}_l^{(j)}$$

       where $\mathbf{S}_l(j) = p_j(z_l|\mathbf{x}_l)$.
   - The predictive state density is now approximated by the GMM
     $p_g(\mathbf{x}_l|z_{l-1}) = \sum_{g'=1}^{G'} \alpha_l^{(g')} N(\mathbf{x}_l; \tilde{\mathbf{u}}_l^{(g')}, \tilde{\mathbf{P}}_l^{(g')})$.
   - The posterior state density (which will only be used as the proposal distribution in the IS-based measurement update step) is approximated by the GMM
     $\tilde{p}_g(\mathbf{x}_l|z_l) = \sum_{g''=1}^{G''} \alpha_l^{(g'')} N(\mathbf{x}_l; \mathbf{u}_l^{(g'')}, \mathbf{P}_l^{(g'')})$.
3. Measurement update
   - Draw N samples $\{\mathbf{x}_l^{(i)} : i = 1, 2, \cdots, N\}$ from the proposal distribution $p_g(\mathbf{x}_l|z_l)$ and calculate their corresponding importance weights
     $$\tilde{w}_l^{(i)} = \frac{p(z_l|\mathbf{x}_l^{(i)}) p_g(\mathbf{x}_l^{(i)}|z_{l-1}^{(i)})}{p_g(\mathbf{x}_l^{(i)}|z_l)}.$$
   - Normalize the weights: $w_l^{(i)} = \tilde{w}_l^{(i)} / \sum_{j=1}^{N} \tilde{w}_l^{(j)}$.
   - Resampling stage (optional): If $N_{eff} \le N_{th}$, take N samples with replacement from the set $\{\mathbf{x}_l^{(i)} : i = 1, 2, \cdots, N\}$, where the probability to take sample i is $w_l^{(i)}$. Let $w_l^{(i)} = 1/N$. Where N_{eff} and N_{th} are the effective sample size and threshold value, respectively.
   - Use a EM or WEM algorithm to fit a G-component GMM to the set of weighted particles $\{w_l(i), \mathbf{x}_l^{(i)} : i = 1, 2, \cdots, N\}$ representing the updated GMM approximate state posterior distribution at time l, i.e.,
     $p_g(\mathbf{x}_l|z_l) = \sum_{g=1}^{G} \alpha_l^{(g)} N(\mathbf{x}_l; \mathbf{u}_l^{(g)}, \mathbf{P}_l^{(g)})$.
   - Inference : MMSE
     - a direct weighted sum of the particle set: (17)
     - or after the posterior GMM has been fitted: (18)

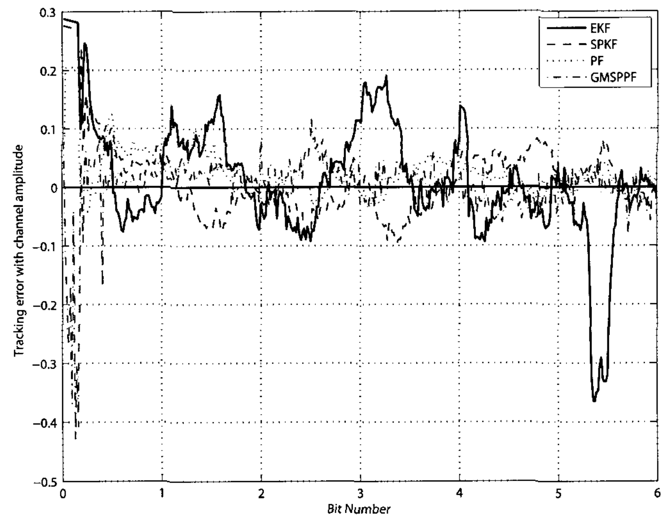
IV. NUMERICAL ANALYSIS

We examine the performance of the EKF, SPKF, PF, and GM-SPPF to make parameter estimates for a multiuser detector. We compare the four robust estimators with an estimator based on EKF [6]–[8]. Note that the form of channel amplitude corresponds to a Rayleigh uncorrelated scattering model for the channel [23]. The multipath profile structures are chosen as the 3-tap delay line model of JTC (Joint Technical Committee) Model [24]. The model is deviated slightly by assuming a classical Doppler spectrum for all taps. The multipath complex coefficients of the channel can be generated using the Jakes Fading Model [25], which provides taps into the appropriate distributions and near the correct tap autocorrelations, although the taps are somewhat correlated. For the state model, the augmented state transition matrix of (3) be chosen to $\mathbf{F} = 0.9999\mathbf{I}$. Also the process noise covariance matrix is $\mathbf{Q} = 0.001\mathbf{I}$. We simulate a two-user scenario (the weaker user and the stronger user) where the users' PN spreading codes are chosen from the set of Gold codes of length 31 and generated by the polynomials x^5+x^2+1 and $x^5+x^4+x^3+x^2+1$, in order to show that our proposed multiuser receiver has more near-far resistance than the EKF-based multiuser receiver. The SNR (signal-to-noise ratio)at the receiver of the weaker user is 5 dB. The near-far ratio (P_1/P_2) is 20 dB. The oversampling factor (sample/chip) is 2. Because AWGN is Gaussian, the three parameters (α, β, and κ) of the SPKF estimator are assumed $\alpha=1$, $\beta=2$, and $\kappa=0$. One aspect about using EKF, SPKF, PF, and GMSPPF-based estimator is the same initialization values. In the simulations, the data bits are detected from decision-directed adaptation, where the symbols $d_{k,m}$ are replaced by the decisions $\hat{d}_{k,m}$ shown in Fig. 1. The tracker for a two-user and three-multipath system is simulated in a fading channel where the channel coefficients are time varying, but the delay remains constant. Furthermore we assume that the weaker user (User 1) and the stronger user (User 2) are moving with normalized Doppler frequencies of $f_dT \approx 0.02$. The sampling time is taken to be $T_s = 1/(1.2288\text{Mbps}\times 2)$ and the bit rate is assumed to be $1/T_b = 9600\text{bps}$.

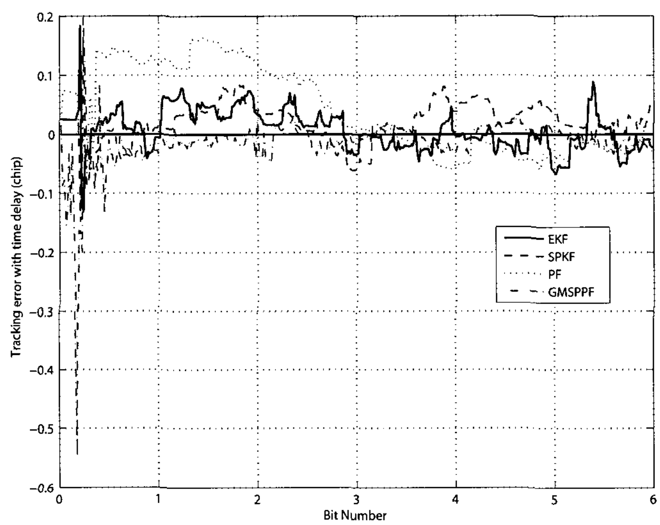
Figs. 2 (a) and (b) show the estimation error for the channel amplitude and time delays for the weaker user's firth multipath with imperfect power controlled using the EKF, SPKF, PF, and GMSPPF, respectively. As the figure indicates, the estimator/tracker is able to accurately track the time-varying channel amplitude of the weaker user, but expect for the EKF. It can be seen that the user is capable of accurately converging to the correct delays and channel amplitude. The GMSPPF has larger fluctuation before convergence, since it doesn't fit the GMM well and the GMM of variance increases. In near-far ratio of 20 dB and normalized Doppler frequency ($f_dT \approx 0.01$), proposed filters are able to accurately converge to the correct values of the parameters. The ability of the estimator to track time-varying parameters is shown in Figs. 3 and 4 where the time-delays are time-varying with 3333.33 m/s and the channel amplitudes are fast fading with normalized Doppler frequency ($f_dT = 0.1$). As the figure indicates, the proposed estimators are able to accurately track the time-varying channel amplitude of weaker and stronger user, even for fast fading rates of 1000 Hz (Doppler). Although the amount of change of time delays for each user doesn't appear to be significant in the Fig. 4, we note that the users's time delays change by $0.001T_c$ over 30 bits (1860 samples). Assuming the propagation speed is the speed of light in a vacuum (3×10^8 m/s) and $T_c = T_b/31 = 3.36\ \mu s$, then weaker and stronger users are moving ($v = f_d \times c/f = 10000\text{Hz}\times(3\times10^8\,\text{m/s})/900\text{MHz} = 3333.33\text{m/s}$) directly away from and home to base station, respectively. This means that each user moved a distance of 104.16m over a time span of 3.1msec(30 bits). The estimators were able to converge and track the parameters in such a great velocity.

Also, although the average near-far ratio is 20 dB, the instantaneous ratio varies drastically due to the fading of the channel since there is no power control. As shown in Fig. 5, the instantaneous near-far ratio with respect to the second user varies from -10 dB to + 50 dB. In spite of the varying powers, the proposed estimators are still able to display excellent performance except for the EKF.

To further quantify the performance of the estimator, the RMSE from simulation of the estimator is presented. In near-far



(a)



(b)

Fig. 2. Parameter estimation errors for channel amplitudes and time delay of firth path with weaker user.

situations, the first user is the weaker user. A root mean square error is computed for the estimates as follows:

$$RMSE_{\mathbf{x}}(n) = \frac{1}{N}\sum_{i=1}^{N_s}\sqrt{|\mathbf{X}-\hat{\mathbf{X}}^{(i)}|^2} \tag{19}$$

where $\mathbf{X}(\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), \cdots, \mathbf{x}(n)])$ denotes the RMSE of the channel parameters of the amplitude and time delay), at iteration n of the estimator. N_s is the number of ensemble samples used to form the RMSE and $\hat{\mathbf{X}}$ is the estimates of channel parameters at time n. Table 1 shows the RMSE of ensemble samples for the estimators (SPKF, PF, and GMSPPF) of the amplitudes and time delays of three multipath, respectively. The number of ensemble samples was chosen to be $N_s = 300$. The RMSE terms defined in (19) were computed for the parameter estimates formed during 300 iterations of the filter. In the case of a near-far ratio of 20 dB, the RMSE of the GMSPPF-based estimator is smaller than those of the SPKF and PF-based esti-

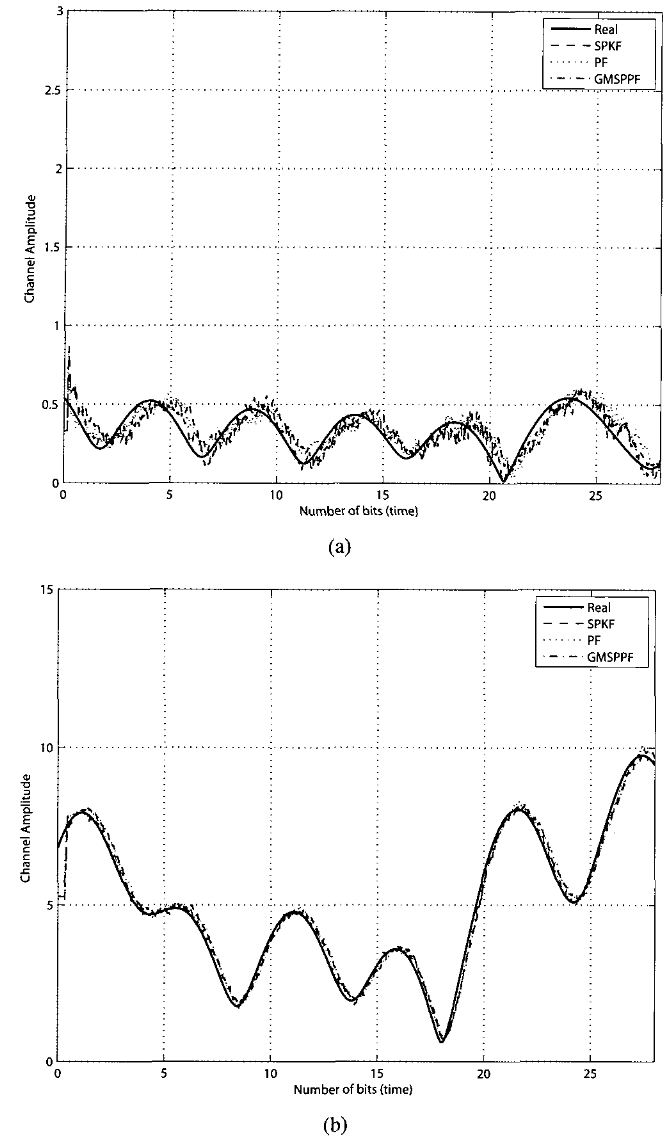


Fig. 3. Time-varying channel amplitude tracking of firth path with the weaker user: (a) The weaker user, (b)stronger user.

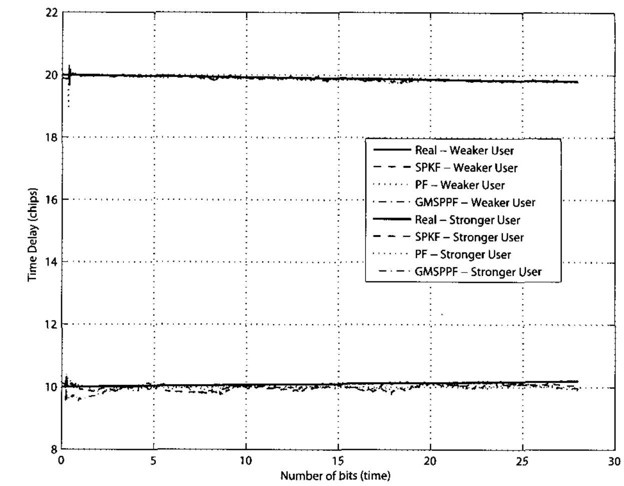


Fig. 4. Time-varing delay tracking of firth multipath with the weaker user (lower) and the stronger user (upper).

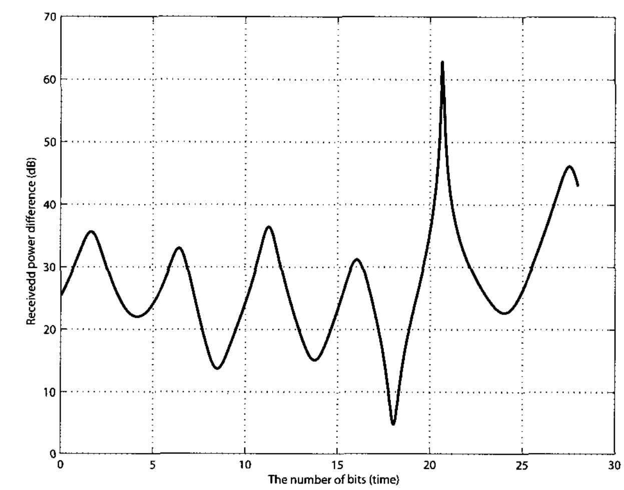


Fig. 5. Instantaneous near-far radio for the weaker user without power control.

mator. Thus, the GMSPPF-based estimator experiences a total lower RMSE than the SPKF and PF-based estimator, resulting in a drastic improvement in performance. In the case of a near-far ratio of 0 dB, the result is nearly the same. Specially, the GMSPPF-based estimator shows better performance irrespective of the near-far ratio.

Fig. 6 shows the BER (bit error rate) of the weaker user versus Near-far ratio considering normalized Doppler frequency $f_dT \approx 0.05$ and $E_b/N_0 = 5$ dB. In this simulation, we don't use multipath diversity since we are compared with channel estimators' performance. A lower bound for the performance of the tracking algorithm is given by using the ideal channel state information (CSI), i.e., perfectly known channel at the receiver side. The black solid line is a lower bound having ideal channel state information. The EKF-based estimator's BER performance is very poor compared to the other proposed algorithms. The GMSPPF-based estimator's BER performance is best but it doesn't large gap compared to the SPKF and PF. According to near-far ratio increase, BER performance is worse.

The complexity of the EKF, SPKF, PF, and GMSPPF approach are simply evaluated and compared. The EKF is approximately $O(L^3)$ from the matrix times matrix multiplication in the most time consuming step, the SPKF is approximately $O(L^2(2L+1)) \approx O(L^3)$ from the matrix times matrix multiplication $\mathbf{FX}_{i}{}_{i=0}^{2L}$, whereas the PF is approximately $O(NL^2)$ from the matrix times vector multiplication and sampling step, and the GMSPPF is approximately $O(GL^3)$ from SPKF step and $O(GL^2N)$ from EM step in case of the maximum complexity. If $N \gg L$, the GMSPPF is approximately $O(GL^2N)$. This indicates that the particle filter is approximately 250 times more complex than SPKF in an application with $L = 4$ and $N = 1000$. And the GMSPPF is at least about 3 times less complex than PF in an application with $L = 4$, $N = 100$, and $G = 3$, even though their MSEs are comparable.

A computation time is presented in Fig. 7, for simulations implemented on an Intel Pentium IV-2.4 GHz processor using

Table 1. RMSE and variance of ensenble samples for the SPKF, PF, and GMSPPF (firth path of three multipath).

Near-far ratio	Channel parameters	RMSE		
		SPKF	PF	GMSPPF
20 dB	c_1	0.21237	0.23450	0.19982
	c_2	0.24765	0.21989	0.21137
	τ_1	0.21225	0.22960	0.07452
	τ_2	0.21472	0.21284	0.05322
0 dB	c_1	0.22145	0.20937	0.20833
	c_2	0.24318	0.23146	0.22472
	τ_1	0.20256	0.21713	0.07823
	τ_2	0.20672	0.22154	0.01459

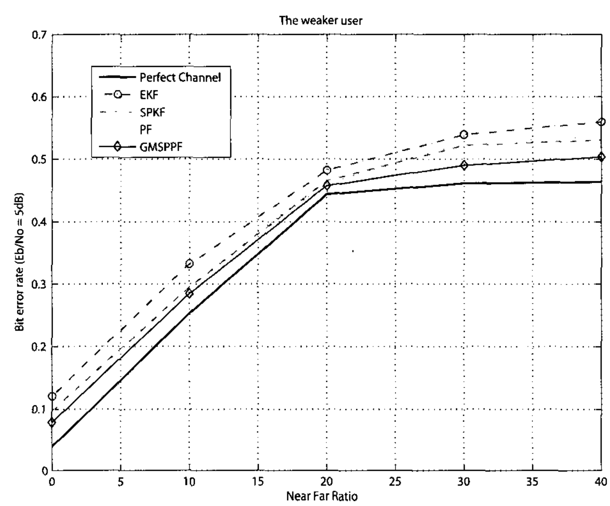


Fig. 6. BER of the weaker user with $SNR = 5$ dB.

MATLAB. The computation time for GMSPPF and PF is much greater than that of the SPKF (SUF) and EKF. More importantly, the GMSPPF has a considerably shorter computation time that the PF, even though their MSEs are comparable. This fact indicates that the GMSPPF has much more competition than the PF applying for CDMA system in case of computational complexity and accuracy. The difference in computation time increases proportional to the number of particles.

V. CONCLUSION

In this paper, we have applied the SPKF, PF, and GMSPPF-based algorithm to the estimation of multipath delays and related channel coefficients in CDMA environments. The SPKF, PF, and GMSPPF have been demonstrated better performance over the EKF. Our proposed three channel estimators can provide a better alternative to nonlinear filtering than the EKF, since it has superior performance over the other algorithm. Computer simulations also show that it provides a more viable means of tracking time-varying amplitudes and delays in CDMA communication systems than the EKF. Furthermore, proposed estimators are shown to have the ability to converge to the user's true coefficients and time delays for a near-far ratio of 20 dB. It was shown that the GMSPPF approach not only outperforms the standard PF, but has better performance when compared to the SPKF. Futhermore, the GMSPPF mitigates the effects of sample depletion by combining the improved SPKF based proposal distribution of the SPKF, with a novel WEM based posterior density recovery. This results in increased operational robustness. It consistently performs better than or equal to the well known EKF, with the added benefit of ease of implementation in that no analytical derivatives (Jacobians or Hessians) need to be calculated. The GMSPPF is of a less complexity when compared with the PF. Our future work is focused on non-Gaussian channel (fundamental middleton class A noise) model in CDMA systems.

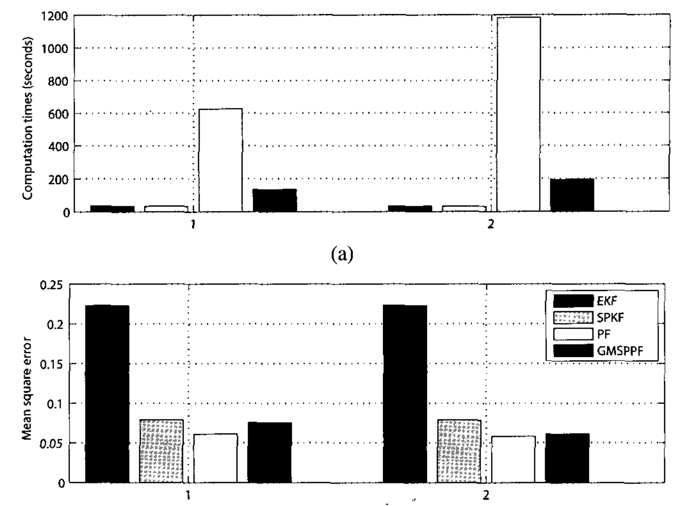


Fig. 7. The computation time and average RMSE of the EKF, SPKF, PF, and GMSPPF. (a) $N = 50$ (per mixands) for GMSPPF and $N = 500$ for PF. (b) $N = 100$ (per mixands) for GMSPPF and $N = 1000$ for PF.

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REFERENCES

[1] A. Duel-Hallen *et al.*, "Multiuser Detection for CDMA System," *IEEE Personal Commun. Mag.*, pp. 46–58, Apr. 1995.

[2] R. Lupas and S. Verdu, "Linear multiuser detectors for synchronous code-division multiple access channel," *IEEE Trans. Inf. Theory*, vol. IT-35, pp. 123–136, Jan. 1989.

[3] M. K. Varanasi and B. Aazhang, "Near-optimum detection in synchronous code-division multiple access channel," *IEEE Trans. Commun.*, vol. COM-39, pp. 725–736, May 1991.

[4] A. Duen-Hallen, "Decorrelating decision-feedback multiuser detector for synchronous code-division multiple access channel," *IEEE Trans. Commun.*, vol. COM-41, pp. 285–290, Feb. 1993.

[5] P. Patel and J. Holtzman, "Analysis of a simple successive interference cancellation scheme in DS/CDMA system," *IEEE J. Sel. Areas Commun. - Special issue on CDMA*, vol. 12, pp. 796–807, June 1994.

[6] R. A. ILitis, "Joint estimation of PN code delay and multipath using the extended Kalman filter," *IEEE Trans. Commun.*, vol. 38, Oct. 1990, pp. 1677–1685.

[7] R. A. Iltis and L. Mailaender, "An adaptive multiuser detector with joint amplitude and delay estimation," *IEEE J. Sel. Areas Commun.*, vol. 12, June 1994.

[8] R. A. Iltis, "A DS-CDMA tracking mode receiver with joint channel/delay

estimation and MMSE detection," *IEEE Trans. Commun.*, vol. 49, Oct. 2001.

[9] R. van der Merwe and E. Wan, "Efficient derivative-free Kalman filters for online learning," in *Proc. ESANN*, Apr. 2001.

[10] J. Jr. Caffery and G. L. Stuber, "Nonlinear multiuser parameter estimation and tracking in CDMA systems," *IEEE Trans. Commun.*, vol. 48, pp. 2053–2063, Dec. 2000.

[11] R. van der Merwe *et. al.*, "The unscented particle filter," *Oregon Graduate Institute Electrical and Computer Engineering*, vol. OR-97006, Aug. 2000.

[12] J. Kim and *et. al.*, "Nonlinear multiuser parameter estimation by the scaled unscented filter in CDMA systems," in *proc. The 2004 Int. Conf. on Wireless Networks*, June 2004.

[13] R. Chen, X. Wang, and J.S. Liu, "Adaptive joint detection and decoding in flat-fading channels via mixture Kalman filtering," *IEEE Trans. Inf. Theory*, vol. 46, pp. 2079–2094, Sept. 2000.

[14] E. Punskaya *et. al.*, "Particle filtering for demodulation in fading channels with non-Gaussian additive noise," *IEEE Trans. Commun.*, vol. 49, pp. 579–582, Apr. 2001.

[15] E. Punskaya *et. al.*, "Particle filtering for multiuser detection in fading CDMA channels," in *Proc. IEEE 11th Signal Processing Workshop on Statistical Signal Processing*, Aug. 2001.

[16] T.Bertozzi *et. al.*, "Channel tracking using particle filtering in unresolvable multipath enrironments," *EURASIP J. Applied Signal Process.*, pp. 2328–2338, 2004.

[17] R. A. Iltis, "A sequential monte carlo filter for joint linear/nonlinear state estimation with application to DS-CDMA," *IEEE Trans. Signal Process.*, vol. 51, pp. 417–426, Feb. 2003.

[18] E. Punskaya, A. Doucet, and W. J. Fitzgerald, "Particle filtering for joint symbol and code delay estimation in DS spread spectrum systems in multipath environment," *EURASIP Applied Signal Process.*, pp. 2306–2314, 2004.

[19] A. Doucet, "On sequential simulation-based methods for bayesian filtering," Tech. Report CUED/F-INFENG/TR 310, (Cambridge University), 1998.

[20] M. Arulampalam *et. al.*, "A tutorial on particle filters for on-line nonlinear/non-gaussian bayesian tracking," *IEEE Trans. Signal Process.*, pp. 174–188, Feb. 2002.

[21] R. van der Merwe and E. Wan."Gaussian mixture sigma-point particle filters for sequential probabilistic inference in dynamic state-space models," in *Proc. ICASSP*, Apr. 2003.

[22] F. Pernkopf and D. Bouchaffra, "Genetic-Based EM algorithm for learning gaussian mixture models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, Aug. 2005.

[23] T. S. Rappaport, *Wireless Communications*. New York : IEEE Press, 1996.

[24] Kaveh Pahlavan and Allen H. Levesque, *Wireless Information Networks*. John Wiley & Sons, 1995.

[25] Gordon L. Stuber, *Principles of Mobile Communication*. 2nd Ed. Kluwer Academic, 2001.

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