Application of Sequential Monte Carlo for Multiuser Detection of DS-CDMA Systems in Fading Channels

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Abstract—This paper presents the application of sequential Monte Carlo (SMC) methodology for blind detection in wireless DS-CDMA systems over fading channels. A novel blind Cholesky-SMC receiver based on the techniques of Cholesky factorization and sequential importance sampling is developed for differentially encoded DS-CDMA systems. With simulated results, the promising performance of the proposed receiver is demonstrated for the both the systems over the flat fading channels and frequency-selective fading channels.

I. Introduction

The Bayesian Monte Carlo (MC) methodologies have been recently reported as low cost signal processing techniques with performance approaching to the theoretical optimum for wireless communication systems [1]. Most MC techniques fall into one of the two categories - Markov chain Monte Carlo (MCMC) methods and sequential Monte Carlo (SMC) methods. The MCMC methods have been well developed and widely used to deal with optimal signal processing problems encountered in wireless communications [1] [2]. Compared to the MCMC methods, the SMC in the other category provides a better performance achieved by parallel processing and is well-suited to practical applications. The complete theoretical framework for SMC methods is described in [3]. The SMC has been successfully applied to a few problems in communications, such as blind equalization and detection in fading channels [4]-[7]. For applications to CDMA system, the SMC-KF reported in [8] combines the conventional Kalman filter and importance sampling technique to solve the problem of single-user detection by assuming the multi-access interference (MAI) to be circular Gaussian. Although the solution to the detection problem for general MIMO systems was presented in [7], the SMC method cannot be directly applied to multiuser detection of DS-CDMA system because the required computational complexity grows exponentially with the number of users.

In this paper, a new SMC-based formulation of blind multiuser detection is presented for DS-CDMA systems in both flat fading and frequency-selective fading channels. Unlike the existing SMC detectors, the Cholesky factorization algorithm is used to decompose the observed data according to the number of users. Under the decision feedback framework, the parameters of each user are then estimated by the SMC method sequentially. With the proposed novel blind Cholesky-SMC receiver, the computational complexity of the SMC detection is reduced substantially. Simulation results are presented to show that the proposed receiver performs well over both flat fading channels and frequency-selective fading channels.

II. Signal Model

A. Flat Fading Channels

Let us consider a DS-CDMA system that has $K$ active users whose signals are transmitted over flat fading channels with additive Gaussian noise. Let $T$ denote the symbol duration and $s_k(t)$ the normalized spreading waveform assigned to the $k$th user. The received signal $r(t)$ at the $n$th symbol interval is given by

$$r(t) = \sum_{k=1}^{K} g_k b_k(n) s_k(t) + \omega(t). \quad (1)$$

It is assumed that the transmitted symbols are independent, and for each user $k = 1, \cdots, K$, the transmitted symbols $\{b_k(n)\}_{n=0}^{N}$ are differentially modulated from the source information symbols $\{d_k(n)\}_{n=1}^{N}$ with $b_k(0) = 1$. Such a differential encoding scheme is necessary to resolve the phase ambiguity inherent to any blind receiver. In (1), $g_k$ is the coefficient of the fading channel for user $k$ and $\omega(t)$ is the received zero mean additive complex white Gaussian noise with variance $\sigma^2$.

The cross-correlation between the signature waveforms of the users is given by the cross-correlation matrix $R$, where the element $R_{i,j}$, defined as

$$R_{i,j} = \langle s_i, s_j \rangle = \int_{(n-1)T}^{nT} s_i(t)s_j(t)dt, \quad (2)$$

represents the cross-correlation between the signature waveforms of the $i$th user and $j$th user. The received signal is processed by a bank of matched filters to give outputs $y(n) = [y_1(n), \cdots, y_K(n)]^T$, where

$$y_k(n) = \langle r(t), s_k(t) \rangle = \int_{(n-1)T}^{nT} r(t)s_k(t)dt. \quad (3)$$

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It is convenient to express the $K \times 1$ vector $\mathbf{y}(n)$ in the form as:

$$\mathbf{y}(n) = \mathbf{R} \mathbf{H} \mathbf{b}(n) + \mathbf{w}(n)$$  \hspace{1cm} (4)

where $\mathbf{H} = \text{diag}\{g_1, \cdots, g_K\}$ is the $K \times K$ diagonal matrix of the channel state information, $\mathbf{b}(n) = [b_1(n), \cdots, b_K(n)]^T$ is the data vector and $\mathbf{w}(n)$ is the $K \times 1$ complex Gaussian noise vector with covariance matrix of $\sigma^2 \mathbf{R}$.

Let $\mathbf{Y} = \{\mathbf{y}(n)\}_{n=1}^N$ and $\mathbf{d}(n) = \{d_k(n)\}_{k=1}^K$. Our objective is to estimate the a posteriori probabilities of the information symbols

$$P(\mathbf{d}(n) = \mathbf{a}_i | \mathbf{Y}), \mathbf{a}_i \in \mathbb{A}^K, n = 1, \cdots, N$$  \hspace{1cm} (5)

based on the received signals $\mathbf{Y}$ without knowing the channel information $\mathbf{H}$.

B. Frequency-Selective Fading Channels

Let us now consider the DS-CDMA system with the same signals over frequency-selective fading channels. That is, the transmitted signal of the $k$th user at the $n$th symbol interval is

$$x_k(t) = b_k(n)s_k(t),$$  \hspace{1cm} (6)

and the multipath channel is modeled by

$$h_k(t) = \sum_{l=1}^L g_{k,l}\delta(t-\tau_{k,l})$$  \hspace{1cm} (7)

where $L$ is the number of paths in each user’s channel, $g_{k,l}$ and $\tau_{k,l}$ are, respectively, the complex gain and delay of $l$th path of the $k$th user’s signal. The total received signal at the receiver is the superposition of the signals from $K$ users plus the additive ambient noise

$$r(t) = \sum_{k=1}^K x_k(t) * h_k(t) + \omega(t)$$

$$= \sum_{k=1}^K b_k(n) \sum_{l=1}^L g_{k,l}s_k(t-\tau_{k,l}) + \omega(t)$$  \hspace{1cm} (8)

where $*$ denotes the convolution and $\omega(t)$ is zero mean additive complex white Gaussian noise with variance $\sigma^2$.

The received signals are processed by a bank of matched filters for each path of each user to generate the observation vector expressed as

$$y_{k,l}(n) = <r(t), s_k(t-\tau_{k,l})>$$

$$= \int_{(n-1)T}^{nT} r(t)s_k(t-\tau_{k,l})dt$$

$$= \sum_{k'=1}^K b_{k'}(n) \sum_{l'=1}^L g_{k',l'}\rho_{k,l}(k',l') + w_{k,l}(n)$$  \hspace{1cm} (9)

where $\rho_{k,l}(k',l')$ is defined as the correlation between the spreading waveforms of the $k$th user’s $l$th path and the $k'$th user’s $l'$th path.

$$\rho_{k,l}(k',l') = \int_{(n-1)T}^{nT} s_k(t-\tau_{k,l})s_{k'}(t-\tau_{k',l'})dt.$$  \hspace{1cm} (10)

The output set of the matched filters is represented by a vector $\mathbf{y}(n)$ of $KL$ elements, that is,

$$\mathbf{y}(n)=[y_{1,1}(n), \cdots, y_{1,L}(n), \cdots, y_{K,1}(n), \cdots, y_{K,L}(n)]^T$$  \hspace{1cm} (11)

and the correlation matrix as $KL \times KL$ matrix $\mathbf{R}$

$$\mathbf{R} = \begin{bmatrix}
\rho(1,1)(1,1) & \cdots & \rho(1,1)(1,L) & \cdots & \rho(1,1)(K,L) \\
\rho(2,1)(1,1) & \cdots & \rho(2,1)(1,L) & \cdots & \rho(2,1)(K,L) \\
\vdots & & \vdots & & \vdots \\
\rho(K,L)(1,1) & \cdots & \rho(K,L)(1,L) & \cdots & \rho(K,L)(K,L)
\end{bmatrix}.$$  \hspace{1cm} (12)

Then the expression for the observation vector is expressed as:

$$\mathbf{y}(n) = \mathbf{R} \mathbf{H} \mathbf{b}(n) + \mathbf{w}(n)$$  \hspace{1cm} (13)

where $\mathbf{b}(n) = [b_1(n), \cdots, b_K(n)]^T$ is the data vector, and the $KL \times K$ matrix $\mathbf{R} = \text{diag}\{g_1, \cdots, g_K\}$ is the channel response information with $g_k = [g_{k,1}, \cdots, g_{K,1}]$.

The noise term $\mathbf{w}(n) = [w_{1,1}(n), \cdots, w_{1,L}(n), \cdots, w_{K,1}(n), \cdots, w_{K,L}(n)]^T$ is the complex Gaussian vector of $KL$ elements with a zero-mean and a covariance matrix $\sigma^2 \mathbf{R}$. Again, without knowing the channel response $\mathbf{H}$, the a posteriori probabilities of the information symbols $\{d_k(n)\}_{n=1}^N$ are to be estimated based on the received signals $\{\mathbf{y}(n)\}_{n=1}^N$ and the a priori information symbol probabilities.

III. Cholesky-SMC Receiver

The main obstacle for applying the SMC to CDMA system is that the computational complexity grows exponentially with the number of system inputs. Cholesky factorization is one of the most efficient techniques for the solution of linear system equations. Cholesky factorization decomposes the positive-definite matrix $\mathbf{B}$ into a lower triangular matrix $\mathbf{L}$ and the conjugate transpose of the lower triangular matrix $\mathbf{L}^H$, i.e., $\mathbf{B} = \mathbf{L}^H \mathbf{L}$. For the SMC-based detection problem, let us start with the Cholesky factorization of the cross-correlation matrix $\mathbf{R}$ as

$$\mathbf{R} = \mathbf{L}^H \mathbf{L}.$$  \hspace{1cm} (14)

The matched filter outputs $\mathbf{y}(n)$ are then processed by multiplying the matrix $(\mathbf{L}^H)^{-1}$ to obtain the output of the whitened matched filter

$$\bar{\mathbf{y}}(n) = (\mathbf{L}^H)^{-1} \mathbf{y}(n)$$

$$= (\mathbf{L}^H)^{-1} \mathbf{R} \mathbf{H} \mathbf{b}(n) + (\mathbf{L}^H)^{-1} \mathbf{w}(n)$$

$$= \mathbf{F} \mathbf{H} \mathbf{b}(n) + \bar{\mathbf{w}}(n).$$  \hspace{1cm} (15)

The covariance matrix of $\bar{\mathbf{w}}(n)$ is

$$E(\bar{\mathbf{w}}(n)\bar{\mathbf{w}}(n)^H) = \sigma^2 (\mathbf{L}^H)^{-1} \mathbf{R} \mathbf{F}^{-1} = \sigma^2 \mathbf{I}.$$  \hspace{1cm} (16)

For flat fading channel systems defined in (4), $\mathbf{I}$ is a $K \times K$ identity matrix, and for frequency-selective fading channel systems described in (13), $\mathbf{I}$ is a $KL \times KL$ identity matrix.
For (15), let us decompose the system into the components of each user as follows:

(a) For flat fading channel

\[ x_1(n) = y_1(n) = F_{1,1}y_1(n) + w_1(n) \]  \hfill (17)

for \( k = 2 : K \)

\[ x_k(n) = y_k(n) - \sum_{i=1}^{k-1} F_{k,i}y_i(n) = F_{k,k}y_k(n) + w_k(n) \]  \hfill (18)

where \( F_{i,j} \) is the element of the \( i \)th row and \( j \)th column of matrix \( F \), \( \tilde{y}_i(n) \) and \( \tilde{w}_i(n) \) are the \( i \)th elements of the vector \( \tilde{y}(n) \) and the vector \( \tilde{w}(n) \), respectively.

(b) For frequency-selective fading channel

\[ x_1(n) = \tilde{y}_1(n) = F_{1,1}g_1b_1(n) + \tilde{w}_1(n) \]  \hfill (19)

for \( k = 2 : K \)

\[ x_k(n) = \tilde{y}_k(n) - \sum_{i=1}^{k-1} F_{k,i}g_i b_i(n) = F_{k,k}g_k b_k(n) + \tilde{w}_k(n) \]  \hfill (20)

where \( F_{i,j} \) is the \( L \times L \) submatrix of the matrix \( F \), i.e., \( F_{i,j} = F((i - 1)L + 1 : LL, (j - 1)L + 1 : jL) \). \( \tilde{y}_i(n) = \tilde{y}(n)((i - 1)L + 1 : iL) \) and \( \tilde{w}_i(n) = \tilde{w}(n)((i - 1)L + 1 : iL) \) are the \( L \times 1 \) subvectors of the vector \( \tilde{y}(n) \) and the vector \( \tilde{w}(n) \), respectively. Here we denote \( U(i : j, k : l) \) as the submatrix having rows from \( i \) to \( j \) and columns from \( k \) to \( l \) of \( U \) and similarly, the \( u(i : j) \) is denoted as the subvector having elements from \( i \) to \( j \) of \( u \).

According to the decomposed signal model, the SMC-based detection is derived with the decision feedback framework. It should be understood that in this framework, the symbols are detected sequentially from the first user to the last one. Since the decision for the \( k \)th user is available, the SMC inference for the next user can be made by using the inference results of all previous users. The complete framework is illustrated in Fig.1, where the parameters have different expressions for different fading channel systems.

Fig. 1. The receiver framework

Here, the SMC inference methods are used to achieve the optimum estimations for \( \{b_k(n), \gamma_k \}_{k=1}^{K} \) and \( \{b_k(n), g_k \}_{k=1}^{K} \) according to the models in (18) and (20). For convenience, only the model in (20) is taken for developing the following SMC inference procedure. The results for the model in (18) are similar and simpler. Denote \( \mathbf{X}_{k,n} \triangleq \{x_k(0), x_k(1), \ldots, x_k(n)\} \). Let \( \{b^{(j)}_\nu(n) \}_{\nu=1}^{m} \) be a sample drawn by the SMC at time \( n \) and denote \( \mathbf{B}^{(j)}_{k,n} = \{b^{(j)}_\nu(k), \ldots, b^{(j)}_\nu(n) \} \) for each value of \( n \), a set of Monte Carlo samples of transmitted symbols, \( \{\mathbf{B}^{(j)}_{k,n}, w^{(j)}_{k,n} \}_{j=1}^{m} \), which are properly weighted with respect to the distribution \( p(\mathbf{B}^{(j)}_{k,n}|\mathbf{X}_{k,n}) \), are to be obtained. For every symbol \( a_i \in A \), the \textit{a posteriori} probability of the information symbol \( d_k(n) \) can be estimated as

\[ P(d_k(n) = a_i|\mathbf{X}_{k,n}) = P(b_k(n) = b_i(n - 1) = a_i|\mathbf{X}_{k,n}) \]

\[ = E\{1(b_k(n) + b_i(n - 1) = a_i)|\mathbf{X}_{k,n}\} \]

\[ \geq \frac{1}{W_{k,n}} \sum_{j=1}^{m} 1(b^{(j)}_\nu(n) + b^{(j)}_\nu(n - 1) = a_i) w^{(j)}_{k,n} \]  \hfill (21)

where \( W_{k,n} \triangleq \sum_{j=1}^{m} w^{(j)}_{k,n} \) denotes the differential encoding and \( 1(\cdot) \) is an indicator function defined as

\[ 1(x = a) = \begin{cases} 1, & \text{if } x = a \\ 0, & \text{if } x \neq a \end{cases} \]  \hfill (22)

The samples \( \{b^{(j)}_\nu(n)\}_{\nu=1}^{m} \) are drawn from the trial sampling density

\[ q(b^{(j)}_\nu(n)|\mathbf{B}^{(j)}_{k,n-1}, \mathbf{X}_{k,n}) \triangleq p(b^{(j)}_\nu(n)|\mathbf{B}^{(j)}_{k,n-1}, \mathbf{X}_{k,n}) \]  \hfill (23)

and the importance weight can be updated according to

\[ w^{(j)}_{k,n} \propto w^{(j)}_{k,n-1} p(\mathbf{X}_{k,n}|\mathbf{B}^{(j)}_{k,n-1}, \mathbf{X}_{k,n-1}) \]

\[ = w^{(j)}_{k,n-1} \sum_{a_i \in A} p(\mathbf{X}_{k,n}|\mathbf{B}^{(j)}_{k,n-1}) p(\mathbf{B}^{(j)}_{k,n-1}) \]

\[ \times p(b_k(n) = a_i|\mathbf{B}^{(j)}_{k,n-1}, \mathbf{X}_{k,n-1}) \]

\[ = w^{(j)}_{k,n-1} \sum_{a_i \in A} \alpha^{(j)}_{k,n,a_i} \]  \hfill (24)

Assign a Gaussian distribution to the channel \( g_k \), i.e.,

\[ g_k \sim \mathcal{N}_c(g_k, \Sigma_k) \]  \hfill (25)

Then, the distribution of \( g_k \), conditioned on \( B^{(j)}_{k,n} \) and \( X_{k,n} \), can be computed as

\[ p(g_k|B^{(j)}_{k,n}, X_{k,n}) \propto p(X_{k,n}|B^{(j)}_{k,n}, g_k) p(g_k) \]

\[ \sim \mathcal{N}_c(g_k^{(j)}, \Sigma^{(j)}_{k,n}) \]  \hfill (26)

where

\[ g_k^{(j)} \triangleq \Sigma^{(j)}_{k,n} \left[ \Sigma^{-1}_{k,n} g_k + \frac{1}{\alpha^2} \sum_{i=0}^{n} \psi^{(j)H}_{k,i} x_k(i) \right] \]  \hfill (27)

\[ \Sigma^{(j)}_{k,n} \triangleq \left[ \Sigma^{-1}_{k,n} + \frac{1}{\alpha^2} \sum_{i=0}^{n} \psi^{(j)H}_{k,i} \psi^{(j)}_{k,i} \right]^{-1} \]  \hfill (28)
and
\[ \Psi_{k,i}^{(j)} = l_{k,i}^{(j)}(i)F_{k,k}. \] (29)

Hence, the conditional density \( p(x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}) \) is given by
\[ p(x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}) = \int p(x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}, g_k) \times p(g_k|B_{k,n-1}^{(j)}, X_{k,n-1})dg_k. \] (30)

Because (30) is an integral of a Gaussian probability density function (pdf) with respect to another Gaussian pdf, the resulting pdf is still Gaussian, i.e.,
\[ p(x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}) = \mathcal{N}_c(\mu_{k,n,i}, \Theta_{k,n,i}). \] (31)

with a mean
\[ \mu_{k,n,i}^{(j)} \triangleq E\{x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}\} = \Psi_{k,i}^{(j)}g_k^{(j)}, \] (32)

and a covariance
\[ \Theta_{k,n,i}^{(j)} \triangleq \text{Cov}\{x_k(n)|B_{k,n-1}^{(j)}, b_k(n) = a_i, X_{k,n-1}\} = \sigma^2I_L + \Phi_{k,i}^{(j)}\Sigma_{k,n-1}^{(j)}\Phi_{k,i}^{(j)}H \] (33)

where
\[ \Phi_{k,i} = a_i F_{k,k}. \] (34)

Then, \( \alpha_{k,n,i}^{(j)} \) in (24) can be computed by
\[ \alpha_{k,n,i}^{(j)} = \Theta_{k,n,i}^{(j)}\Sigma_{k,n-1}^{(j)}\Phi_{k,i}^{(j)}H \] \[ \times \exp\left\{- (x_k(n) - \mu_{k,n,i}^{(j)})^T (x_k(n) - \mu_{k,n,i}^{(j)}) \right\} \] \[ \times P(d_k(n) = a_i \pm l_{k,i}(n - 1)). \] (35)

It is noted that the \( a \) posteriori mean and covariance of the channel in (27) and (28) can be updated recursively as follows. At the \( n \)th step, the new sample of \( b_k^{(j)}(n) \) and the past samples \( B_{k,n-1}^{(j)} \) are combined to form \( B_{k,n}^{(j)} \). Let \( \mu_{k,n}^{(j)} \) and \( \Theta_{k,n}^{(j)} \) be the quantities computed by (32) and (33) for the imputed \( b_k^{(j)}(n) \). Based on a matrix inversion lemma, (27) and (28) become
\[ g_k^{(j)} = g_{k,n-1}^{(j)} + \Omega_{k,n}^{(j)}g_{k,n}^{(j)} \] \[ \Sigma_{k,n}^{(j)} = \Sigma_{k,n-1}^{(j)} - \Omega_{k,n}^{(j)}g_{k,n}^{(j)}H \] (36)

with
\[ \Omega_{k,n}^{(j)} = \Omega_{k,n-1}^{(j)} - \Psi_{k,n}^{(j)}H. \] (37)

The SMC blind detector for each decomposed signal component is summarized as follows.

**Initialization:**
Set the initial values of channel vector as \( g_k^{(j)} \sim \mathcal{N}_c(\mathbf{0}, 100I_L) \), for each \( j = 1, \cdots, m \), and all important weights are initialized as \( w_{k,-1}^{(j)} = 1, j = 1, \cdots, m \).

**Estimation:**
For \( j = 1, \cdots, m \), update each weighted sample at the \( n \)th recursion (\( n = 0, \cdots, N \)):

- For each \( a_i \in A \), compute \( \mu_{k,n,i}^{(j)}, \Theta_{k,n,i}^{(j)} \) and trial sampling distribution \( \alpha_{k,n,i}^{(j)} \) according to (32), (33), and (35), respectively.
- Draw a sample \( b_k^{(j)}(n) \) from the set \( A \) with the probability,
\[ P(b_k(n) = a_i|B_{k,n-1}^{(j)}, X_{k,n-1}) \propto \alpha_{k,n,i}^{(j)}, a_i \in A. \] (39)
- Compute the importance weight
\[ \hat{w}_{k,n}^{(j)} = w_{k,n-1}^{(j)} \sum_{i \in A} \alpha_{k,n,i}^{(j)} \] (40)

and normalized it as
\[ w_{k,n}^{(j)} = \frac{\hat{w}_{k,n}^{(j)}}{\sum_{j=1}^{m} \hat{w}_{k,n}^{(j)}}. \] (41)

- Update the \( a \) posteriori mean and covariance of the channel. If the imputed samples \( b_k^{(j)}(n) = a_i \), then set \( \mu_{k,n}^{(j)} = \mu_{k,n,i}^{(j)}, \Theta_{k,n}^{(j)} = \Theta_{k,n,i}^{(j)} \), and update \( g_{k,n}^{(j)} \) and \( \Sigma_{k,n}^{(j)} \) according to (36) and (37).
- Compute the \( a \) posteriori probability of the information symbol \( d_k(n) \) according to (21), and obtain \( b_k(n) \) according to \( b_k(n) = d_k(n) \oplus b_k(n-1) \).
- Perform resampling as described in [4], when \( n \) is a multiple of the resampling interval. Draw a new set of \( \{B_{k,n}^{(j)}, g_{k,n}^{(j)}, \Sigma_{k,n}^{(j)}\}_{j=1}^{m} \) from the original set with probability proportional to the importance weights \( \{\hat{w}_{k,n}^{(j)}\}_{j=1}^{m} \). Then assign equal weight for each new sample, i.e., \( \hat{w}_{k,n}^{(j)} = 1/m \).

It is observed that the \( m \) samples operate independently, therefore the proposed SMC estimation is well suited for parallel implementation. The computational complexity of the conventional SMC method is known to be in the order of \( O(|A|^K) \). However, the proposed new method samples one user at a time and therefore permits efficient implementation. The required computational complexity is reduced to be in the order of \( O(|A| \times K) \). Thus, the proposed Cholesky-SMC detection algorithm can be applied to the DS-CDMA system with a manageable computational complexity.

**IV. Simulation Results**

This section provides simulation results to illustrate the performance of the blind Cholesky-SMC multiuser receiver in both flat fading channels and frequency-selective fading channels for DS-CDMA systems. The fading coefficients of the channels are generated according to uncorrelated circular complex Gaussian distribution. The channels are assumed to be block fading, that is the fading coefficients remain constant over the entire block of \( N \) symbols. All the users’ spreading sequences with a processing gain \( P = 10 \) are generated randomly from binary codes with an equal probability and
then normalized to \( \{ \pm 1/\sqrt{P} \} \). The block size is \( N = 128 \) and the number of users is \( K = 8 \). The number of Monte Carlo samples is taken as \( m = 50 \). Two types of channels, i.e., flat fading channel and frequency-selective fading channel with \( L = 3 \), are considered.

The BER performance of the proposed receiver for both the flat fading and frequency-selective fading systems is studied. At the same time, the performance comparisons are made between the proposed receiver and other reported ones, i.e., MCMC receiver described in [1] and the conventional SMC receiver. For a fair comparison, the Gibbs sample of MCMC receiver is performed for 100 iterations with the first 50 iterations as the burning-in period. The number of Monte Carlo samples used for conventional SMC receiver is 50, which is the same as that used for the proposed receiver. The results for the flat fading system are shown in Fig. 2, while the results for the frequency-selective fading system are shown in Fig. 3. It is seen from these two figures that the performance of the blind Cholesky-SMC receiver is better than that of Gibbs MCMC receiver, and is comparable to that of the conventional SMC receiver. When the SNR is in small values, the proposed receiver is a little inferior to the conventional SMC receivers. When the value of the SNR becomes larger, the performance of the proposed receiver becomes superior to that of the conventional SMC receivers. This is because that the decision feedback framework attempts to cancel all multiuser interference provided that the feedback data are correct. With the MAI cancellation, the detection of each user is similar to that for single user system. It is also seen from the figures that the improvement made by the proposed receiver is more obvious with the increase of the SNR, which can be explained as follows. Without the MAI effects in (18) and (20), the detection performance can improve more significantly as the SNR increases. When the background noise is hypothetically absent, i.e. \( \sigma = 0 \), the detector should guarantee error-free demodulation approximately. As described previously, the computational complexity required by the proposed receiver is much lower than that for the conventional SMC method. It needs a computational complexity increasing linearly with the number of users compared with other reported methods requiring a computational complexity growing exponentially with the number of users.

V. Conclusions

In this paper, a blind multiuser receiver is developed for the DS-CDMA systems over both flat fading and frequency-selective fading channels based on the Bayesian SMC inference method. The Cholesky factorization is utilized before the implementation of the SMC detection to achieve significant reductions in computational complexity. As presented in the simulation results, the proposed receiver also achieves a comparable performance with the conventional SMC receiver. Due to the inherent parallel computational structure of the SMC, the proposed receiver is proved to be better suited to future DS-CDMA multiuser systems.

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