

# Blind Despreading of Short-Code DS-CDMA Signals with Bayesian Techniques

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**Abstract**—This paper introduces an algorithm for joint spreading codes and information sequences estimation based on reversible jump Markov chain Monte Carlo (RJ-MCMC) for direct-sequence code division multiple access (DS-CDMA) signals with low signal-to-noise ratio (SNR) in non-cooperative systems, by analyzing signal model. The proposed algorithm establishes a joint posterior distribution model of signal parameters and user number, and obtains the samples of distribution to be estimated through iterative sampling. The algorithm is able to construct a reversible Markov chain sampler that jumps between parameter subspaces of different dimensionality, so that the posterior distribution of parameters to be estimated is obtained. Simulation results indicate that the proposed algorithm can be applied to low SNR with equal or unequal power and to different user number. Moreover, the estimation performance of this algorithm is a significant improvement of the existing method.

**Index Terms**—Bayesian model, MCMC, Reversible jump, Spreading code, Information sequence

## I. INTRODUCTION

Direct-sequence code division multiple access (DS-CDMA) signal, due to its use of pseudo-random code modulation, has low interception probability, and good interference resistance and confidentiality properties. Therefore, it is widely used in satellite communications and navigation. In conventional cooperative applications, the DS-CDMA spreading codes are known to the receiver. However, in non-cooperative systems such as communication reconnaissance, the receiver usually does not know the number of user signals, spreading codes and information sequences. Hence, the demodulation and processing of the received signals are difficult. Blind estimation of spreading codes and information sequences of DS-CDMA signals with low signal-to-noise ratio (SNR) is important for its application in communication reconnaissance.

Multi-user DS-CDMA signal is divided into synchronous and asynchronous signals depending on the time delay at which the user signal arrives at the receiver. Or it can be divided into long-code and short-code depending on the period of spread-spectrum and symbol period. A DS-CDMA signal is superimposed by multiple user signals, which completely overlap in time domain and frequency domain. Thus, the estimation of spreading codes and information sequences of DS-CDMA signals is in essence

the separation of these two sequences from the mixed signals with overlapping time-frequency domain under single-channel condition. This process is very difficult.

At present, blind despreading and recovery of DS-CDMA signals have not gained very much attention within the research community. The various techniques for blind estimation of spreading codes and information sequences of DS-CDMA signals commonly estimate the spreading codes of each user first, before the obtaining of information sequences and power by demodulation. However, the joint estimation of the two sequences has been rarely reported. Also most of the work in open literature is dealing with single user scenarios. Joutsensalo proposed the estimation method for spreading codes of short-code DS-CDMA signals by subspace iteration in [1]. This method has fast convergence speed, though it can be hardly applied to low SNR. Building on Joutsensalo's work, Haghighat A and Soleymani proposed the blind estimation algorithm for spreading codes based on MUSIC in [2-3]. His method can better adapt to low SNR, but has the shortcoming of exponentially growing calculation load. As a modification of this technique, Qin P Y et al proposed OSMUSIC algorithm in [4-6], which reduces the calculation load. As the spreading code and information sequence for each user in DS-CDMA signal are mutually independent, Sidiropoulos N D et al modeled the observation signals as the mathematical form for blind signal separation, and suggested the estimation algorithm for spreading codes based on ICA in [7-10]. Their method can simultaneously estimate spreading code and information sequence for each user with the use of multiple receiving arrays. Also, literature [11-14] describe some novel methods, but the SNR can further be improved.

To address the shortcomings of the above methods, this paper first assumes that spread-spectrum period and chip period have already been estimated. Focusing on synchronous short-code DS-CDMA signals in downlink, this paper proposes an algorithm for joint estimation of spreading codes and information sequences based on RJ-MCMC under low SNR. After the joint posterior distribution model of signal parameters and the number of users is established by bayesian theory, direct sampling of joint posterior distribution is done by RJ-MCMC. The samples of distribution to be estimated are obtained by iterative sampling. Finally, the number of users  $K$ , spreading codes and information sequences are effectively

estimated. Simulation experiment confirms that the proposed algorithm can be applied to low SNR with equal or unequal power and to different number of users.

The paper is organized as follows. In Section II we describe the signal model that is used in this paper. Then in Section III we formalize the Bayesian model and specify the prior distributions. Section IV is devoted to Bayesian computation. The performance of this algorithm is illustrated by computer simulations and compared with classical method in Section V. Finally, some conclusions are drawn in Section VI.

## II. SIGNAL MODEL

An synchronous downlink DS-CDMA system with  $K$  users is considered. Employing down-conversion to received signal through carrier synchronization[15], the equivalent baseband signal within  $N$  spread-spectrum period may be modeled as

$$r(t) = \sum_{k=1}^K \sum_{i=0}^{N_0-1} A_k b_k(i) q(t - iT_s - \tau) \sum_{l=0}^{N-1} s_k(t - lT - \tau) + w(t) \quad (1)$$

where  $N_0$  denotes the length of the data frame within  $N$  spread-spectrum period,  $T_s$  is the symbol period,  $A_k$ ,  $\{b_k(i)\}$ , and  $\tau$  ( $0 < \tau < T_s$ ) denote, respectively, the amplitude, the symbol stream, and the delay of the  $k$ th user's signal.  $T$  is the spread-spectrum period.  $q(t)$  is a rectangular pulse of duration  $T_s$ , and  $w(t)$  is the received zero mean additive white Gaussian noise with variance  $\sigma^2$ . The spreading waveform  $s_k(t)$  can be expressed as

$$s_k(t) = \sum_{j=0}^{R-1} c_k(j) g(t - jT_c) \quad (0 \leq t < T) \quad (2)$$

where  $T_c$  is the chip period,  $R = T/T_c$  is the spreading factor,  $\{c_k(j), 0 \leq j < R\}$  is the spreading sequence of user  $k$ ,  $g(t)$  is a normalized chip waveform of duration  $T_c$ . The spreading gain  $P = T_s/T_c$ , which called long-code DS-CDMA system when  $P < R$  and short-code DS-CDMA system when  $P = R$ .

This paper focus on synchronous short-code DS-CDMA signals. At the receiver, the received signal  $r(t)$  is filtered by a chip matched filter  $g(T_c - t)$  and done chip synchronization[16], then sampled at the chip-rate. The discrete form of the received signal may be written as

$$r(n) = \sum_{k=1}^K A_k \sum_{i=0}^{N-1} b_k(i) c_k(n - iR) + w(n) \quad (1 \leq n \leq NR) \quad (3)$$

It is convenient to express the signal model (3) in a vector-matrix form as

$$\mathbf{r}(n) = \mathbf{c}(n) \mathbf{A}(\mathbf{a}, \mathbf{B}) + \mathbf{w}(n) \quad (1 \leq n \leq R) \quad (4)$$

where  $\mathbf{r}(n) = [r_1(n), \dots, r_N(n)]$ ,  $\mathbf{c}(n) = [c_1(n), \dots, c_K(n)]$  and  $\mathbf{w}(n) = [w_1(n), \dots, w_N(n)]$ , elements  $r_i(n) = r[(i-1)R + n]$  and  $w_i(n) = w[(i-1)R + n]$ . The Matrix  $\mathbf{A}(\mathbf{a}, \mathbf{B}) \in \mathbf{R}^{K \times N}$  can be expressed as

$$\mathbf{A}(\mathbf{a}, \mathbf{B}) = \begin{bmatrix} A_1 b_1(0), \dots, A_1 b_1(N-1) \\ \vdots \quad \ddots \quad \vdots \\ A_K b_K(0), \dots, A_K b_K(N-1) \end{bmatrix} \quad (5)$$

where  $\mathbf{a} \triangleq [A_1 \ A_2 \ \dots \ A_K]^T$ ,  $\mathbf{B} = \begin{bmatrix} b_1(0), \dots, b_1(N-1) \\ \vdots \quad \ddots \quad \vdots \\ b_K(0), \dots, b_K(N-1) \end{bmatrix}$ ,

and then the signal model in (3) can further be written in a matrix-matrix form as

$$\mathbf{R} = \mathbf{C} \mathbf{A}(\mathbf{a}, \mathbf{B}) + \mathbf{W} \quad (6)$$

Thus,  $\mathbf{R}$  is a  $R \times N$  matrix composed by  $NR$   $r(n)$ , similarly we can see  $\mathbf{C}$  and  $\mathbf{W}$ , and  $w_i(j) \sim N(0, \sigma^2)$ , ( $1 \leq i \leq N, 1 \leq j \leq R$ ).

## III. BAYESIAN MONTE CARLO INFERENCE

Focusing on the problem of ill-posed in blind estimation of spreading codes and information sequences of single-channel DS-CDMA signal, we convert the blind estimation of spreading codes and information sequences into joint estimation of signal parameters and the number of users, on the basis of mixed signal model constructed in the previous section. Then we reconstruct spreading codes and information sequences using the sampled value.

We assume here that the number  $K$  of users and their parameters  $\theta_k \triangleq (\mathbf{a}, \mathbf{C}, \mathbf{B}, \sigma^2)$  are unknown. Then the parameter space is  $\Theta_K \triangleq \{K, \theta_K\}$ . Given the observation data  $\mathbf{R}$ , our objective is to estimate  $\Theta_K$ . We follow a Bayesian approach where the unknowns  $K$  and  $\theta_k$  are regarded as being drawn from appropriate prior distributions. These priors reflect our degree of belief of the relevant values of these parameters. In order to implement a robust estimation of these parameters, we adopt a hierarchical prior structure that enables us to treat the hyper-parameters as random variables drawn from suitable distributions. We first exploit the analytical properties of the model to obtain an expression, up to a normalizing constant, of the joint posterior distribution  $p(K, \mathbf{a}, \mathbf{C}, \mathbf{B}, \Lambda | \mathbf{R})$ . Then the conditional posterior distributions of  $\mathbf{a}, \sigma^2, \Lambda$ ,  $\mathbf{B}$  and  $\mathbf{C}$  are given.

### A. Prior Distributions

In general considerations, the selection of the prior distributions is based on two principles. One is the prior distributions should be chosen such that they have a minimal impact on the posterior distribution. Such priors are termed noninformative. Another consideration in the selection of the prior distributions is to simplify computations. To that end, conjugate priors are usually used to obtain simple analytical forms for the resulting posterior distributions. The property guaranteed that the posterior distribution belongs to the same distribution family as the prior distribution. According to the hierarchical prior structure, the overall parameter space is

$\Theta_K \times \Psi$ . The hyper-parameter space  $\Psi$ , with element  $\{\Lambda\}$ . We formalize by modeling the joint posterior distribution of all variables as

$$p(K, \theta_K, \Psi | \mathbf{R}) = \frac{p(K, \theta_K, \Psi, \mathbf{R})}{p(\mathbf{R})} \propto p(\mathbf{R} | K, \theta_K, \Psi) p(K, \theta_K, \Psi) \quad (7)$$

where  $p(\mathbf{R} | K, \theta_K, \Psi)$  is the likelihood,  $p(K, \theta_K, \Psi)$  is the parameters' joint prior distribution. From the model given in (6), the likelihood is

$$p(\mathbf{R} | K, \theta_K, \Psi) = (2\pi\sigma^2)^{-NR/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2\right) \quad (8)$$

where  $\mathbf{R}_{1:R,i}$  and  $\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}$  denotes the  $i$ th column of matrix  $\mathbf{R}$  and  $\mathbf{A}(\mathbf{a}, \mathbf{B})$  respectively. For  $(K, \theta_K, \Psi)$ , we assume the following structure

$$p(K, \theta_K, \Psi) = p(K, \mathbf{a}, \mathbf{C}, \mathbf{B}, \sigma^2, \Lambda) = p(\mathbf{B} | K) p(\mathbf{C} | K) p(\mathbf{a}) p(K | \Lambda) p(\sigma^2) p(\Lambda) \quad (9)$$

where  $\sigma^2$  is a scale parameter that is assumed to be distributed according to a conjugate inverse-Gamma prior distribution  $Ig(\nu_0, \gamma_0)$

$$p(\sigma^2) = \frac{(\gamma_0)^{\nu_0}}{\Gamma(\nu_0)} (\sigma^2)^{-\nu_0-1} \exp\left(-\frac{\gamma_0}{\sigma^2}\right) \quad (10)$$

We have Chosen here  $\nu_0 = \gamma_0 = 0$ , then Jeffreys' uninformative prior  $p(\sigma^2) \propto 1/\sigma^2$  is obtained. Conditional upon  $\Lambda$ , the prior probability model distribution  $p(K|\Lambda)$  is a truncated Poisson distribution

$$p(K|\Lambda) = \frac{\Lambda^K}{K!} e^{-\Lambda} \quad (11)$$

where  $K \in [0, K_{\max}]$ . For the unknown amplitude vector  $\mathbf{a}$ , a truncated Gaussian prior distribution  $N(\mathbf{a}_0, \Sigma_0) I_{(\mathbf{a}>0)}$  is assumed

$$p(\mathbf{a}) = |2\pi\Sigma_0|^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{a} - \mathbf{a}_0)' \Sigma_0^{-1} (\mathbf{a} - \mathbf{a}_0)\right] \quad (12)$$

where  $I_{(\mathbf{a}>0)}$  is an indicator that is 1 if all elements of  $\mathbf{a}$  are positive and it is zero otherwise. Note that large value of  $\Sigma_0$  corresponds to the less-informative prior. For hyper-parameter  $\Lambda$ , an uninformative conjugate Gamma prior distribution  $ga(1/2 + \varepsilon_1, \varepsilon_2)$ , ( $\varepsilon_i \ll 1, i = 1, 2$ ) is assumed

$$p(\Lambda) = \frac{\varepsilon_2^{1/2+\varepsilon_1}}{\Gamma(1/2 + \varepsilon_1)} \Lambda^{\varepsilon_1-1/2} \exp(-\varepsilon_2\Lambda) \quad (13)$$

Since the spreading codes  $\{c_k(j), 1 \leq k \leq K, 0 \leq j < R\}$  are assumed to be independent of each other, the prior distribution  $p(\mathbf{C})$  is a discrete uniform distribution  $DU(\mathbb{S})$  with  $\mathbb{S} \triangleq \{-1, +1\}$

$$p(\mathbf{C}) = (1/2)^{KR} \quad (14)$$

Similarly the symbols  $\{b_k(i), 1 \leq k \leq K, 0 \leq i < N\}$  are assumed to be independent of each other, the prior distribution  $p(\mathbf{B})$  is a discrete uniform distribution  $DU(\mathbb{C})$ . If modulation type of BPSK is adopted, then  $\mathbb{C} \triangleq \{-1, +1\}$ . We assumed that the discrete alphabet number  $T$  has been estimated in previous work. The prior distribution  $p(\mathbf{B})$  can be expressed as

$$p(\mathbf{B}) = (1/T)^{KN} \quad (15)$$

Use the prior distribution mentioned above, (9) can be written as

$$p(K, \theta_K, \Psi) = p(\mathbf{B} | K) p(\mathbf{C} | K) p(\mathbf{a}) p(K | \Lambda) p(\sigma^2) p(\Lambda) \propto \left(\frac{1}{T}\right)^{KN} \left(\frac{1}{2}\right)^{KR} |2\pi\Sigma_0|^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{a} - \mathbf{a}_0)' \Sigma_0^{-1} (\mathbf{a} - \mathbf{a}_0)\right] \times \left[\frac{\Lambda^K}{K!} e^{-\Lambda}\right] \left[\frac{\varepsilon_2^{1/2+\varepsilon_1}}{\Gamma(1/2 + \varepsilon_1)} \Lambda^{\varepsilon_1-1/2} \exp(-\varepsilon_2\Lambda)\right] \times \left[\frac{(\gamma_0)^{\nu_0}}{\Gamma(\nu_0)} (\sigma^2)^{-\nu_0-1} \exp\left(-\frac{\gamma_0}{\sigma^2}\right)\right] \quad (16)$$

According to Bayesian theory

$$p(K, \theta_K, \Psi | \mathbf{R}) \propto p(\mathbf{R} | K, \theta_K, \Psi) p(K, \theta_K, \Psi) \propto (2\pi\sigma^2)^{-NR/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2\right) \left(\frac{1}{T}\right)^{KN} \left(\frac{1}{2}\right)^{KR} \times \left[\frac{\Lambda^K}{K!} e^{-\Lambda}\right] |2\pi\Sigma_0|^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{a} - \mathbf{a}_0)' \Sigma_0^{-1} (\mathbf{a} - \mathbf{a}_0)\right] \times \left[\frac{\varepsilon_2^{1/2+\varepsilon_1}}{\Gamma(1/2 + \varepsilon_1)} \Lambda^{\varepsilon_1-1/2} \exp(-\varepsilon_2\Lambda)\right] \left[\frac{(\gamma_0)^{\nu_0}}{\Gamma(\nu_0)} (\sigma^2)^{-\nu_0-1} \exp\left(-\frac{\gamma_0}{\sigma^2}\right)\right] \quad (17)$$

The integration of  $\sigma^2$  with inverse-Gamma distribution yields

$$p(K, \mathbf{a}, \mathbf{C}, \mathbf{B}, \Lambda | \mathbf{R}) \propto \left(\frac{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2}{2}\right)^{\left(\frac{-NR+2\nu_0}{2}\right)} \left(\frac{1}{T}\right)^{KN} \left(\frac{1}{2}\right)^{KR} \times \left[\frac{\Lambda^K}{K!} e^{-\Lambda}\right] |2\pi\Sigma_0|^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{a} - \mathbf{a}_0)' \Sigma_0^{-1} (\mathbf{a} - \mathbf{a}_0)\right] \times \left[\frac{\varepsilon_2^{1/2+\varepsilon_1}}{\Gamma(1/2 + \varepsilon_1)} \Lambda^{\varepsilon_1-1/2} \exp(-\varepsilon_2\Lambda)\right] \quad (18)$$

### B. Conditional Posterior Distributions

We propose to use Gibbs steps to sample  $\mathbf{a}, \sigma^2, \Lambda$ , Metropolis-Hastings(MH) steps to sample  $\mathbf{B}$  and  $\mathbf{C}$ . The following full conditional posterior distributions are required by the RJ-MCMC sampler. The derivations can reference [17].

1) Full Conditional Posterior Distributions of  $\mathbf{a}, \sigma^2, \Lambda$

The conditional posterior distribution of the amplitude vector  $\mathbf{a}$  given  $K, \mathbf{C}, \mathbf{B}, \sigma^2, \Lambda$  and  $\mathbf{R}$  is given by

$$p(\mathbf{a} | K, \mathbf{C}, \mathbf{B}, \sigma^2, \Lambda, \mathbf{R}) \sim N(\mathbf{a}_*, \Sigma_*) \quad (19)$$

with mean  $\mathbf{a}_* \triangleq \Sigma_* \left( \Sigma_0^{-1} \mathbf{a}_0 + \frac{1}{\sigma^2} \sum_{i=1}^N \mathbf{B}(i) \mathbf{C}' \mathbf{R}_{1:R,i} \right)$ ,

$$\Sigma_*^{-1} \triangleq \Sigma_0^{-1} + \frac{1}{\sigma^2} \sum_{i=1}^N \mathbf{B}(i) \mathbf{C}' \mathbf{C} \mathbf{B}(i), \mathbf{B}(i) = \text{diag} \{ \mathbf{B}(1,i), \dots, \mathbf{B}(K,i) \}$$

The conditional posterior distribution of the noise variance  $\sigma^2$  given  $\mathbf{a}, K, \mathbf{C}, \mathbf{B}, \Lambda$  and  $\mathbf{R}$  is given by

$$p(\sigma^2 | \mathbf{a}, K, \mathbf{C}, \mathbf{B}, \Lambda, \mathbf{R}) \sim \text{Ig} \left( \nu_0 + \frac{NR}{2}, \frac{1}{2} \sum_{i=1}^N \left\| \mathbf{R}_{1:R,i} - \mathbf{C} \mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i} \right\|^2 + \gamma_0 \right) \quad (20)$$

The full conditional distribution of the hyper-parameter  $\Lambda$  given  $\mathbf{a}, K, \mathbf{C}, \mathbf{B}, \sigma^2$  and  $\mathbf{R}$  is given by

$$p(\Lambda | \mathbf{a}, K, \mathbf{C}, \mathbf{B}, \sigma^2, \mathbf{R}) \sim \text{ga}(\varepsilon_1 + 1/2 + K, 1 + \varepsilon_2) \quad (21)$$

2) Full Conditional Posterior Distributions of  $\mathbf{B}$  and  $\mathbf{C}$

To simplify the calculations, using (18) to obtain the full conditional posterior distributions of  $\mathbf{B}$  and  $\mathbf{C}$ . The conditional posterior distributions of  $\mathbf{B}(k,i)$  given  $\mathbf{R}$  and  $\mathbf{a}, K, \mathbf{C}, \mathbf{B}_{ki}, \Lambda$  can be obtained from

$$p(\mathbf{B}(k,i) | \mathbf{a}, K, \mathbf{C}, \mathbf{B}_{ki}, \Lambda, \mathbf{R}) \propto \left( \frac{2\gamma_0 + \left\| \mathbf{R}_{1:R,i} - \mathbf{C} \mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i} \right\|^2 + \Sigma}{2} \right)^{\left( \frac{-NR + 2\nu_0}{2} \right)} \quad (22)$$

where  $\mathbf{B}(k,i)$  denotes the  $k$ th row and  $i$ th column element of the matrix  $\mathbf{B}$ ,  $\mathbf{B}_{ki} \triangleq \mathbf{B} \setminus \mathbf{B}(k,i)$  denotes the set containing all elements of  $\mathbf{B}$  except for  $\mathbf{B}(k,i)$ , with

$1 \leq k \leq K, 1 \leq i \leq N$  and  $\Sigma = \sum_{l=1, l \neq i}^N \left\| \mathbf{R}_{1:R,l} - \mathbf{C} \mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,l} \right\|^2$  is

a constant. The full conditional posterior distributions of  $\mathbf{C}(r,k)$  given  $\mathbf{R}$  and  $\mathbf{a}, K, \mathbf{C}_{rk}, \mathbf{B}, \Lambda$  is given by

$$p(\mathbf{C}(r,k) = +1 | \mathbf{a}, K, \mathbf{C}_{rk}, \mathbf{B}, \Lambda, \mathbf{R}) \propto \left( \frac{2\gamma_0 + \sum_{i=1}^N \left\| \mathbf{R}_{1:R,i} - \mathbf{C} \mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i} \right\|^2}{2} \right)^{\left( \frac{-NR + 2\nu_0}{2} \right)} \quad (23)$$

where  $\mathbf{C}(r,k)$  denotes the  $r$ th row and  $k$ th column element of the matrix  $\mathbf{C}$ ,  $\mathbf{C}_{rk} \triangleq \mathbf{C} \setminus \mathbf{C}(r,k)$  denotes the set containing all elements of  $\mathbf{C}$  except for  $\mathbf{C}(r,k)$ , with  $1 \leq r \leq R, 1 \leq k \leq K$ .

IV. BAYESIAN COMPUTATION WITH RJ-MCMC

See from (18), it is worth noticing that this posterior distribution is highly non-linear in the amplitude vector  $\mathbf{a}$  and that an expression of  $p(K | \mathbf{R})$  cannot be obtained in closed-form. For the case where  $K$  is unknown, the standard MCMC method suffers from severe drawbacks to estimate the required posterior distribution. Firstly, it is computationally very expensive since  $K_{\max}$  can be large. Secondly, the same computational effort is attributed to each value of  $K$ , but in fact, some of these values are of no interest in practice. So we employ RJ-MCMC sampler [18] for direct sampling of joint posterior distribution  $p(K, \mathbf{a}, \mathbf{C}, \mathbf{B}, \Lambda | \mathbf{R})$ . It can jump between subspaces of different dimensions, thus avoiding over-sampling of useless values and reducing the calculation load. Also, the number of users  $K$  is estimated.

RJ-MCMC basically resembles MCMC, both obtaining the samples of posterior distribution to be estimated by iterative sampling. For each iteration, the direct sampling of distribution to be estimated is impossible, therefore it is necessary to first determine the proposal distribution of the current model order. The sampling of the proposal distribution is the candidate sampling, which is either accepted or rejected according to acceptance ratio. If the candidate sampling is rejected, then the sampled value of the current iteration is identical to that of the previous iteration. This method ensures reversibility and thus invariance of the Markov chain with respect to the posterior distribution, which make the chain must move across subspaces of different dimensions. The acceptance probability is given by

$$A = \min \left\{ 1, \frac{p(K^*, \theta_K^*, \psi^* | \mathbf{R}) q(K, \theta_K, \psi | K^*, \theta_K^*, \psi^*)}{p(K, \theta_K, \psi | \mathbf{R}) q(K^*, \theta_K^*, \psi^* | K, \theta_K, \psi)} \right\} \quad (24)$$

where  $K^*, \theta_K^*, \psi^*$  denotes the candidate values and  $K, \theta_K, \psi$  denotes the current values. The selection principle for proposal distribution  $q(\bullet)$  is easy to sample. For our problem, the following moves have been selected:

- 1) birth of a new user (demand  $K < K_{\max}$ ), i.e., proposing a new user with prior distribution  $p(\mathbf{B})$  and  $p(\mathbf{C})$ , the parameter space changes from  $\{K, \theta_K, \psi\}$  to  $\{K+1, \theta_{K+1}, \psi\}$ ;
- 2) death of an existing user (demand  $K > 0$ ), i.e., removing an user chosen randomly, the parameter space changes from  $\{K, \theta_K, \psi\}$  to  $\{K-1, \theta_{K-1}, \psi\}$ ;
- 3) update of the parameters of all the users for fixed  $K$ .

The resulting transition kernel of the simulated Markov chain is then a mixture of the different transition kernels associated with the moves described above. This means that at each iteration, one of the candidate moves (birth, death or update) is randomly chosen. The probabilities for choosing these moves are  $b_K, d_K$  and  $u_K$ , respectively, such that  $b_K + d_K + u_K = 1$  for all  $0 \leq K \leq K_{\max}$ . For  $K = 0$ , the death move is impossible, therefore,  $d_0 \triangleq 0$ . For  $K = K_{\max}$ , the birth move is impossible, and thus,

$b_{K_{\max}} \triangleq 0$ . Except in the cases described above, we adopt the following probabilities

$$b_K \triangleq \varepsilon \cdot \min \{1, p(K+1)/p(K)\} \quad (25)$$

$$d_{K+1} \triangleq \varepsilon \cdot \min \{1, p(K)/p(K+1)\} \quad (26)$$

where  $p(K)$  is the prior probability of user number  $K$  and  $\varepsilon$  is a parameter that tunes the proportion of update move to jump move. We choose  $\varepsilon = 0.5$  and then  $b_K + d_K \in [0.5, 1]$  for all  $K$ . We can now describe the main steps of the algorithm as follows:

*Step 1.* Initialisation: set  $(K^{(0)}, \theta_K^{(0)}, \psi^{(0)}) \in \Theta_K \times \Psi$ ,  $i \leftarrow 1$  and choose the number of iterations  $m$ .

*Step 2.* Iteration  $i$ . Firstly, sample  $\mu \sim U_{[0,1]}$ , if  $\mu \leq b_K^{(i)}$ , then birth move; else if  $\mu \leq b_K^{(i)} + d_K^{(i)}$ , then death move; else update the parameters; End if. Secondly, sample the parameters  $\mathbf{a}, \sigma^2, \Lambda$  using (19) (20) and (21).

*Step 3.* Set  $i \leftarrow i + 1$ . If  $i \leq m$ , go back to step 2.

In the above steps, we drop the superscript  $\cdot^{(i)}$  from all variables at iteration  $i$ . To further understand the algorithm, we describe more precisely these different moves in the following subsections.

*A. Birth Move*

Suppose that the current state of the Markov chain is in parameter space  $\{K, \theta_K, \psi\}$ , and  $K < K_{\max}$ . According to the prior distribution of  $p(\mathbf{B})$  and  $p(\mathbf{C})$ , we can propose a new user randomly, the parameter space changes to  $\{K+1, \theta_{K+1}, \psi\}$ . Then proposal distribution is given by

$$q(K+1, \theta_{K+1}, \psi | K, \theta_K, \psi) = b_K \cdot (1/2)^R \cdot (1/T)^N \quad (27)$$

$$q(K, \theta_K, \psi | K+1, \theta_{K+1}, \psi) = d_{K+1}/K+1 \quad (28)$$

From (25) and (26) we obtain  $\frac{b_K}{d_{K+1}} = \frac{p(K+1)}{p(K)}$ , thus the proposal ratio can be written as

$$\frac{q(K, \theta_K, \psi | K+1, \theta_{K+1}, \psi)}{q(K+1, \theta_{K+1}, \psi | K, \theta_K, \psi)} = \frac{p(K) \cdot 2^R \cdot T^N}{p(K+1) \cdot (K+1)} \quad (29)$$

Also, the posterior distributions ratio can derived from (18)

$$\begin{aligned} & \frac{p(K+1, \theta_{K+1}, \psi | \mathbf{R})}{p(K, \theta_K, \psi | \mathbf{R})} \\ &= \left( \frac{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2}{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}_{1:R,1:K+1}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K+1,i}\|^2} \right)^{\left(\frac{NR+2\gamma_0}{2}\right)} \\ & \times \left(\frac{1}{T}\right)^N \cdot \left(\frac{1}{2}\right)^R \cdot \frac{\Lambda}{K+1} \end{aligned} \quad (30)$$

where  $\mathbf{C}_{1:R,1:K+1}$  and  $\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K+1,i}$  denote, respectively, the spreading codes matrix and the  $i$ th column of information sequences matrix after proposing a new user. According to (29) and (30), the acceptance ratio for the proposed birth move is given by

$$\begin{aligned} r_{birth} &= \frac{p(K+1, \theta_{K+1}, \psi | \mathbf{R})}{p(K, \theta_K, \psi | \mathbf{R})} \cdot \frac{q(K, \theta_K, \psi | K+1, \theta_{K+1}, \psi)}{q(K+1, \theta_{K+1}, \psi | K, \theta_K, \psi)} \\ &= \left( \frac{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2}{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}_{1:R,1:K+1}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K+1,i}\|^2} \right)^{\left(\frac{NR+2\gamma_0}{2}\right)} \cdot \frac{1}{K+1} \end{aligned} \quad (31)$$

Then the acceptance probability for the proposed birth move is

$$A_{birth} = \min \{1, r_{birth}\} \quad (32)$$

*B. Death Move*

Similarly, in the death move case, we assume the current state is in  $\{K, \theta_K, \psi\}$ , and  $K > 0$ , removing an user chosen randomly, the parameter space changes to  $\{K-1, \theta_{K-1}, \psi\}$ , the acceptance ratio for the proposed death move is then generated

$$\begin{aligned} r_{death} &= \frac{p(K-1, \theta_{K-1}, \psi | \mathbf{R})}{p(K, \theta_K, \psi | \mathbf{R})} \cdot \frac{q(K, \theta_K, \psi | K-1, \theta_{K-1}, \psi)}{q(K-1, \theta_{K-1}, \psi | K, \theta_K, \psi)} \\ &= \left( \frac{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2}{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}_{1:R,1:K-1}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K-1,i}\|^2} \right)^{\left(\frac{NR+2\gamma_0}{2}\right)} \cdot K \end{aligned} \quad (33)$$

Similarly, the acceptance probability for the proposed death move is

$$A_{death} = \min \{1, r_{death}\} \quad (34)$$

*C. Update Move*

Here, we assume the current state is in  $\{K, \theta_K, \psi\}$ . When the update move is selected, the algorithm samples only on the space of  $\theta_K$ , for  $K$  fixed. We propose to use Gibbs steps to update  $\mathbf{a}, \sigma^2, \Lambda$  and MH steps to update  $\mathbf{B}$  and  $\mathbf{C}$

*1) Update B and C*

For parameter  $\mathbf{B}$ , using (22) as the invariant distribution and  $q(\mathbf{B}^*(k, i) | \mathbf{B}(k, i)) \sim DU(\mathbf{C})$  as proposal distribution, which involves sampling a candidate value  $\mathbf{B}^*(k, i)$  given the current value  $\mathbf{B}(k, i)$  according to  $q(\mathbf{B}^*(k, i) | \mathbf{B}(k, i))$ . Similarly, for parameter  $\mathbf{C}$ , using (23) as the invariant distribution and  $q(\mathbf{C}^*(r, k) | \mathbf{C}(r, k)) \sim DU(\mathbf{S})$  as the proposal distribution. Respectively, the acceptance probabilities are given by

$$A(\mathbf{B}(k,i), \mathbf{B}^*(k,i)) = \min \left\{ 1, \frac{2\gamma_0 + \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2 + \Sigma}{2\gamma_0 + \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B}^*)_{1:K,i}\|^2 + \Sigma} \right\} \quad (35)$$

$$A(\mathbf{C}(r,k), \mathbf{C}^*(r,k)) = \min \left\{ 1, \frac{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2}{2\gamma_0 + \sum_{i=1}^N \|\mathbf{R}_{1:R,i} - \mathbf{C}^*\mathbf{A}(\mathbf{a}, \mathbf{B})_{1:K,i}\|^2} \right\} \quad (36)$$

where  $\mathbf{C}^*$  and  $\mathbf{B}^*$  are similar to  $\mathbf{C}$  and  $\mathbf{B}$  with  $\mathbf{C}(r,k)$  replaced by  $\mathbf{C}^*(r,k)$  and  $\mathbf{B}(k,i)$  replaced by  $\mathbf{B}^*(k,i)$ .

2) Update  $\mathbf{a}, \sigma^2, \Lambda$

Sample these parameters  $\mathbf{a}, \sigma^2, \Lambda$  using (19), (20) and (21), respectively.

V. SIMULATION EXPERIMENT AND ANALYSIS

In this section, the performance of the proposed algorithm is studied as a function of SNR and number of iterations used in the estimation.

A. Simulation Setup

To verify the performance of the proposed algorithm, we need to establish reasonable assessment indicators. In light of the contents of this study, the cosine of vector of estimated spreading sequence and that of true spreading sequence can be used to assess the performance (i.e. the similarity degree between the two vectors)[19]. Also the output SNR can be used in assessing the estimation performance. For the estimation of information sequence, bit error rate is more suitable. Below are the expressions for the first 2 assessment indicators

$$R(\hat{\mathbf{u}}, \mathbf{u}) = \frac{\hat{\mathbf{u}}^H \mathbf{u}}{\|\hat{\mathbf{u}}\| \|\mathbf{u}\|} \quad (37)$$

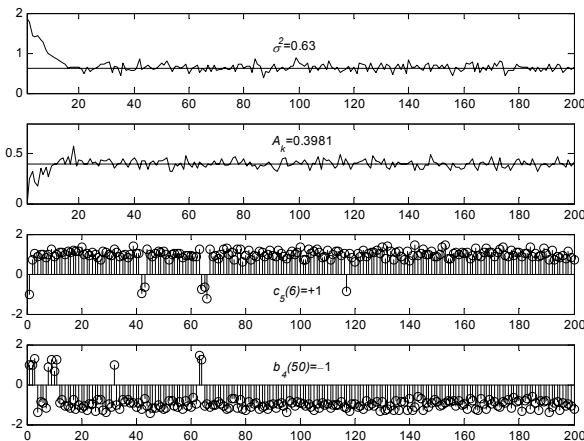


Figure 1. Convergence of each parameter for samples

$$\text{SNR}_0^k = 10 \lg \frac{E[c_k(n)^2]}{E[(c_k(n) - \hat{c}_k(n))^2]} \quad (38)$$

When the power is the same with all users, mean output SNR  $\text{SNR}_0 = \frac{1}{K} \sum_{k=1}^K \text{SNR}_0^k$  can be used to assess the estimation performance.

Parameter selection for the algorithm has no impact on posterior distribution, but only on the convergence speed of the algorithm. We choose  $\sigma^2 \sim \text{Ig}(v_0, \gamma_0) \rightarrow v_0 = \gamma_0 = 0$ ,  $\Lambda \sim \text{ga}(1/2 + \varepsilon_1, \varepsilon_2) \rightarrow \varepsilon_1 = \varepsilon_2 = 10^{-4}$ ,  $K_{\max} = 30$ ,  $\varepsilon = 0.5$ , and  $\mathbf{a} \sim \mathcal{N}(\mathbf{a}_0, \Sigma_\theta) \rightarrow \mathbf{a}_0 = \text{ones}(K, 1)$ ,  $\Sigma_\theta = 1000 \text{eye}(K)$

B. Simulation Experiments and Analysis

Five experiments are carried out to verify the estimation performance of the proposed algorithm. Experiment 1 tests the convergence of the algorithm; experiment 2 and 3 test the estimation performance of spreading codes and information sequences either at equal or unequal power; experiment 4 is a performance simulation of spreading sequence and information sequences at different number of users; experiment 5 is the comparison between the performance of OSMUSIC algorithm [5] and Fast-ICA algorithm [9]. In the five experiments, SNR of the  $k$ th user  $\text{SNR}_k$  is defined as  $10 \lg A_k^2 / \sigma^2$ , and at equal power for all users, the mean  $\text{SNR} = \text{SNR}_k$ . The algorithm is performed for 500 iterations, with the first 100 iterations as the ‘‘burn-in’’ period, and the iterated results of 100-500 iterations are used for estimation.

Experiment 1: convergence of the proposed algorithm

Simulation conditions: user number  $K = 5$ ; spreading code for each user is  $R = 127$  bit random sequence; chip rate 10MHz; symbol rate  $10\text{MHz}/127 = 78.74\text{KHz}$ ; spreading gain  $P = 127$ ; the length of data is  $N = 200$  spread-spectrum period, and the length of information sequence is 200 (randomly generated sequence, BPSK-modulated). The sampling is done at chip rate, with the number of sampling points within each spread-spectrum period of 127. If the power is equal for all users, i.e.  $A_k^2 = -8\text{dB} (1 \leq k \leq 5)$ ,  $\sigma^2 = -2\text{dB}$ , the output  $\text{SNR} = \text{SNR}_k = 10 \lg A_k^2 / \sigma^2 = -6\text{dB}$ .

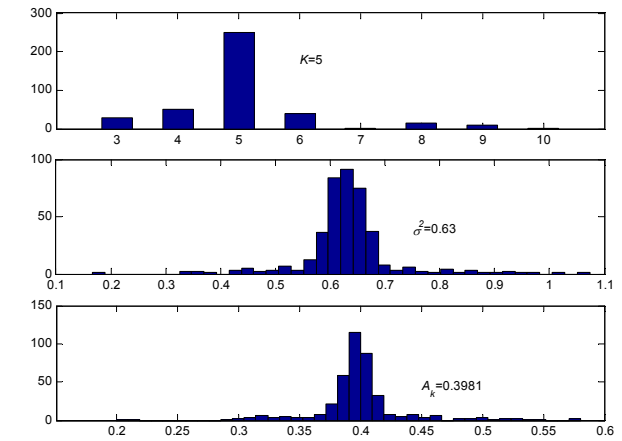


Figure 2. Histogram of  $K, \sigma^2, A_k$  for posterior distribution

Fig. 1 shows the sampled values of posterior distribution of parameters  $K$ ,  $\sigma^2$ ,  $A_k$ ,  $c_5(6)$  and  $b_4(50)$  in the first 200 iterations. The corresponding true values are also shown in the same figure as the straight lines, from which we can see that after a dozen of iteration, the posterior distribution nearly converges to the true values.

Fig. 2 shows the parameter estimation using the values of the last 400 iterations, presented in histogram. The top panel in Fig. 2 is the estimation of posterior distribution of user number. We can see that when the number of users amounts to 5, there is the maximum posterior probability, that is, the estimated number of users is 5, which is equal to the true value. The middle panel in Fig. 2 is the estimation of posterior distribution of noise variance, revealing that the maximum posterior probability is very close to 0.63, the true value of noise variance. The bottom panel in Fig. 2 indicates the estimation of posterior distribution of signal amplitude of users, the maximum posterior probability also very close to 0.3981, the true value. The estimated spreading codes and information sequences will be listed in the following experiments.

*Experiment 2: performance of spreading codes and information sequences at equal power*

Simulation conditions: the simulation conditions for experiment 2 are basically the same with those in experiment 1, except that SNR varies from -20dB to 20dB as  $A_k$  and  $\sigma^2$  change dynamically.

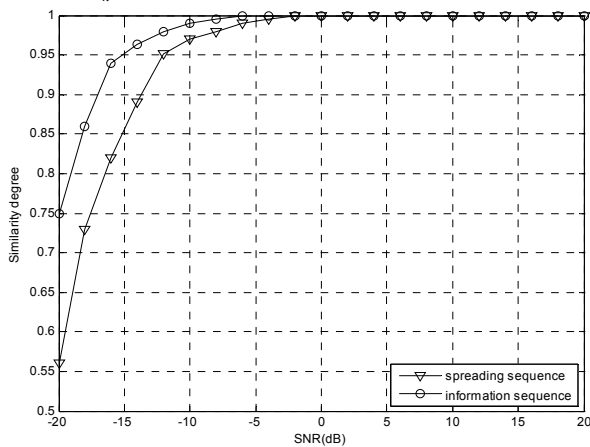


Figure 3. The curve of similarity degree against SNR for equal power

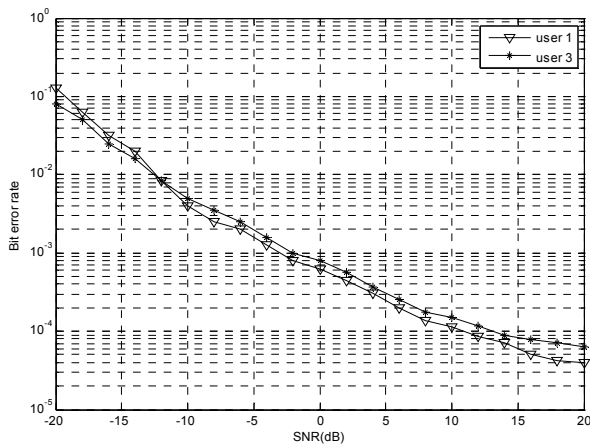


Figure 4. The curve of bit error rate against SNR for equal power

Fig. 3 shows the estimation performance of spreading code and information sequence at 5 users, SNR varying between -20dB and 20dB, and the similarity degree specified by (37). In this paper, only the results for user 1 is given. When SNR is greater than -12dB, the similarity degree between the estimated value and the true value for the two sequences exceed 0.95. Therefore, the proposed algorithm can effectively estimate spreading code and information sequence at low SNR.

Fig. 4 shows the estimation performance of information sequence, at 5 users and SNR varying between -20dB and 20dB, using bit error rate as the assessment indicator. The simulation results for user 1 and 3 are given. In simulation experiment 50100 iterations are done, and the values of the last 50000 iterations are averaged to obtain the bit error rate. When SNR is greater than -12dB, the bit error rate for the estimated information sequence is lower than  $10^{-2}$ .

*Experiment 3: performance of spreading codes and information sequences at unequal power*

Simulation conditions: the simulation conditions in experiment 3 are basically the same as in experiment 1, except that user number  $K = 4$ . The ratio of power among 4 users is 1:2:4:8. SNR<sub>1</sub> for user with the smallest power varies between -20dB and 20dB. The level of the smallest power is the same to that in experiment 1.

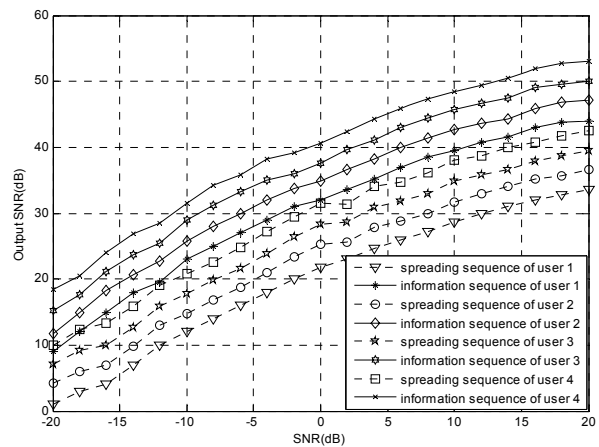


Figure 5. The curve of output SNR against SNR for unequal power

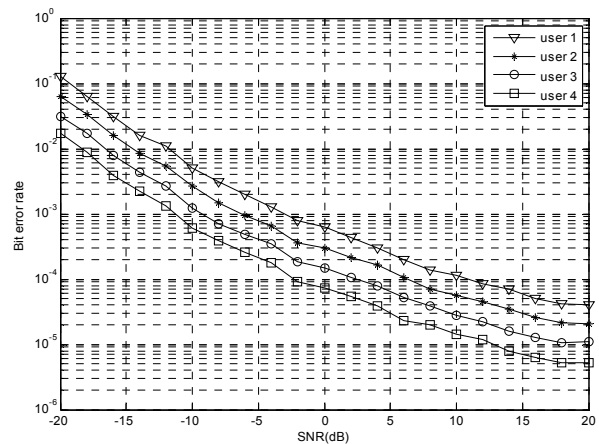


Figure 6. The curve of bit error rate against SNR for unequal power

Fig. 5 shows that when there are four users, the ratio of power among the users is 1:2:4:8. The curve of output SNR against SNR<sub>i</sub> for the smallest power is plotted using (38). We can see from the figure that when the power is unequal, the proposed algorithm can maintain its performance in estimating spreading code and information sequence for each user. As the ratio of power among all users is 2, the output SNR varies by about 3dB, which is consistent with SNR set by the user. Comparison of the results for user 1 and 4 reveals that the estimation performance for signals with greater power is significantly higher than signals with smaller power. This corresponds to the results of theoretical analysis.

Fig. 6 shows the curve of bit error rate plotted against SNR<sub>i</sub> for the smallest power. When SNR is greater than -11dB, bit error rate of estimated information sequence for all users is lower than 10<sup>-2</sup>, which is slightly lower than the situation where the power is equal.

*Experiment 4: performance of spreading sequence and information sequence at different number of users*

Simulation conditions: simulation conditions in experiment 4 are basically the same with those in experiment 1, except that SNR varies from -20dB to 20dB, and the number of users *K* is respectively 2, 4, 6, 8 and 10.

Fig. 7 shows the curve of similarity degree of spreading sequence plotted against SNR and Fig. 8 shows the curve of bit error rate of information sequence against SNR in the proposed algorithm at different number of users. The procedures of the experiment are the same as in all the

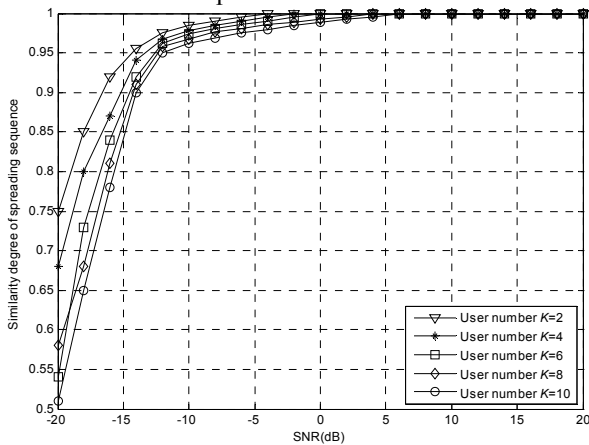


Figure 7. Curve of similarity degree against SNR for different users

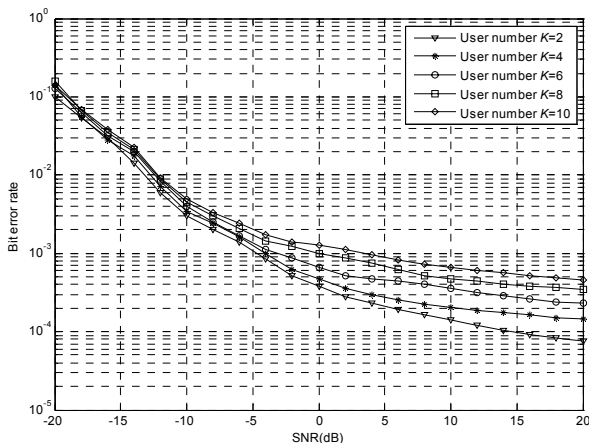


Figure 8. Curve of bit error rate against SNR for different users

experiments above. Under multi-user condition, the bit error rate are calculated based on the mean values of estimated information sequence for all users. The figure indicates that since short-code DS-CDMA signals for all users are not strictly orthogonal, with the increasing number of users, the estimation performance of information sequence will decrease somewhat. When SNR is greater than -12dB and the number of users is not over 10, the similarity degree between the estimated sequence and the true sequence exceeds 0.95. Bit error rate of estimated information sequence for all users is lower than 10<sup>-2</sup>.

*Experiment 5: comparison of the proposed algorithm with Fast-ICA and OSMUSIC algorithm*

The simulation conditions in experiment 5 are identical to those in experiment 2. Fig. 9 shows the performance comparison of the proposed algorithm, Fast-ICA algorithm and OSMUSIC algorithm in estimating output SNR. Fig. 10 shows the comparison in estimation performance among the three algorithms with respect to bit error rate. The proposed algorithm has the highest estimation performance, with SNR higher by an average of respectively about 3dB than Fast-ICA algorithm and OSMUSIC algorithm. When the input SNR is greater than -12dB with the proposed algorithm, output SNR of information sequence is greater than 20dB, and the corresponding bit error rate lower than 10<sup>-2</sup>. However, the calculation load required in the proposed algorithm is greater than in the other two algorithms.

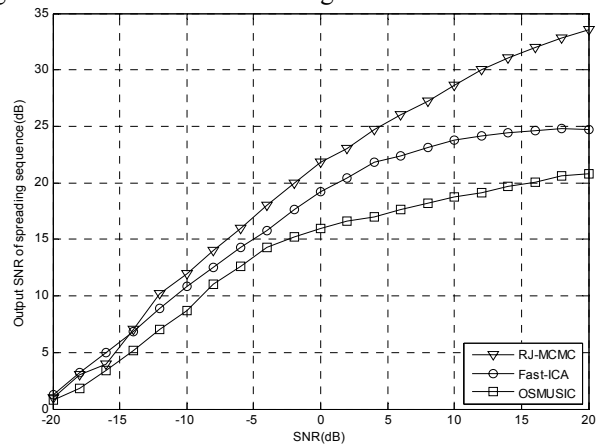


Figure 9. The output SNR comparison for different algorithms

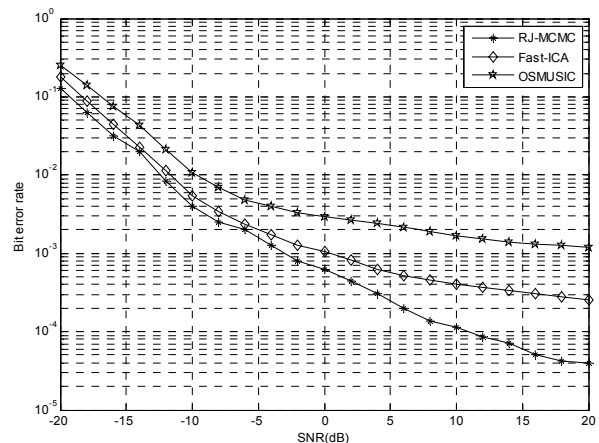


Figure 10. The bit error rate comparison for different algorithms



## VI. CONCLUSION

This paper deduces an algorithm for multi-user detection of DS-CDMA signals in non-cooperative system, built on Bayesian theory. Given unknown number of users, the proposed algorithm uses RJ-MCMC algorithm for direct sampling of joint posterior distribution. A reversible Markov chain sampler is constructed. It can jump between subspaces with different dimensionality. The iteration using the proposed algorithm finally converges to posterior distribution of parameter to be estimated. The simulation experiment confirms the estimation performance of the proposed algorithm.

The deduction process is based on the simplest synchronous short-code DS-CDMA signal model. Only the situation when the signal is the real value of analyzed. The extended application of the proposed technique is possible for multipath delay of signals which are complex values and asynchronous long-code DS-CDMA signals. In future work, theoretical analysis of the estimation performance can be performed, which further confirms the effectiveness of the proposed algorithm.

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