Improved Multi-Channel Blind De-Convolution Algorithm for Linear Convolved Mixture DS/CDMA Signals

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Abstract —In this paper, an improved multi-channel blind de-convolution algorithm for code division multiple access signals is proposed. Through minimizing the average squared cross-output-channel-correlation, the proposed scheme achieves a better source separation performance for the linear convolved mixture system. Unlike most of the existing linear convolved mixture separation algorithms in the literature, the improved algorithm can obtain the original users' signal even in low signal-to-noise ratio in a non-cooperation scenario. Simulation results show that the proposed optimal scheme not only achieves superior performance on the bit error rate to those of the existing ones, but also provides a convergent solution under different channel conditions.

Index Terms—CDMA signal, non-cooperation, blind de-convolution, gradient algorithms

I. INTRODUCTION

Spread spectrum signals have been used for the secure communications for several decades. Nowadays, they are also widely used outside the military domain, especially in Code Division Multiple Access (CDMA) system. They are mainly used to transmit at a low power without interference due to jamming to others users or to multi-path propagation. The CDMA techniques are useful for the secure communication while the receiver has to know the sequence used by the transmitter and recover the transmitted data using a correlator [1].

Direct sequence spread spectrum (DSSS) transmitters use a periodical pseudo-random sequence to modulate the base-band signal before transmission. In the context of spectrum surveillance, the pseudo-random sequence used by the transmitter is unknown as well as other transmitter parameters such as duration of the sequence, symbol frequency and carrier frequency. Hence, in this context, a DSSS signal is very difficult to detect and demodulate, because it is often below the noise level.

In this paper, our motivation is to determine the spreading sequence automatically in a multi-user CDMA system, whereas the receiver has no knowledge of the transmitter's pseudo-noise (PN) sequence. We also present the technique of DSSS and explain the difficulty to recover the data in an unfriendly context. The algorithm is particularly important in a non-cooperative condition of the military field. This algorithm can decode the local spread spectrum sequence, so as to monitor, interference, and decipher the enemy signal.

A more complex multi-channel blind de-convolution algorithm is required to achieve better source separation [2]. We propose a method to estimate the pseudo-random sequence without prior knowledge about the transmitter. Only the duration of the pseudorandom sequence is assumed to have been estimated. (This can be done by the method proposed in [3]). This method is based on minimizing the average squared cross output channel correlation criterion. There are many ways to construct a numerical algorithm based on the above criterion for blind source separation. We derive here a new stochastic gradient algorithm, which has these characteristics for the optimization of the de-mixing matrix $\mathbf{D}$. Experimental results are given to illustrate the performances of the method and show that a good estimation can be obtained.

This paper is organized as follows. In Section II, the fundamental models and assumptions of MIMO blind de-convolution is introduced. In Section III, we give the DS/CDMA data model and separation criterion. Then, the proposed approach is described in Section IV. Finally, experimental results are provided to illustrate the approach in Section V and a conclusion is drawn.

II. MODELS FOR MIMO BLIND DE-CONVOLUTION [4]

A. Models for MIMO Convolution

A multi-channel linear time invariant (LTI), discrete time dynamical system can be described in the most general form as:

$$\mathbf{x}(k) = \sum_{p=-\infty}^{\infty} \mathbf{H_p s}(k - p) \tag{1}$$

where $\mathbf{H}_p$ is an $n \times m$ dimensional matrix of mixing coefficients at time-lag p (called the impulse response at time-lag p), and $\mathbf{s}(k - p)$ is an n-dimensional vector of source signals with mutually independent components. It should be noted that the causality in time domain is satisfied only when $\mathbf{H}_p = 0$ for all $p < 0$. $\mathbf{x}(k)$ is the received signal (sensor signals) after convolution mixed, and $\mathbf{x}(k) = [x_1(k), x_2(k), L, x_n(k)]^T$ is an n dimensional vector of the outputs.

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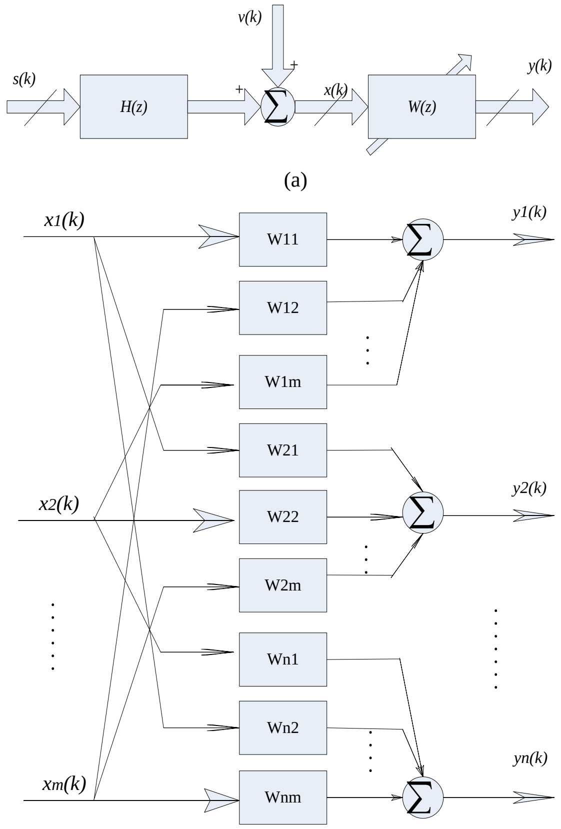

(a)

(b)

Fig. 1. Illustration of the multi-channel deconvolution models: (a) Functional block diagram of the feed-forward model and (b) Architecture of feed-forward neural network (each synaptic weight W is an FIR or stable IIR filter

The goal of the multi-channel blind de-convolution is to estimate source signals using the received sensor signals $\mathbf{x}(k)$ only and certain knowledge of the source signal distributions and statistics. In the most general case, we attempt to estimate the sources by employing another multi-channel, LTI, discrete-time, stable dynamical system (Fig. 1 (a) and (b)) described at time domain:

$$\mathbf{y}(k) = \sum_{p=-\infty}^{\infty} \mathbf{W}_p \mathbf{x}(k - p) \tag{2}$$

where $\mathbf{y}(k) = [y_1(k), y_2(k), \cdots, y_n(k)]^T$ is an n dimensional vector of the outputs after the novel separation algorithm, and $\mathbf{W}_p$ is an $n \times m$ dimensional coefficient matrix at time lag p. $\mathbf{W}_p$ can be called de-mixed matrix, too. $\mathbf{x}(k) = [x_1(k), x_2(k), \cdots, x_n(k)]^T$ acts as an n dimensional input signal vector while $\mathbf{x}(k)$ is an outputs in (1).

In the practical applications, we have to implement the blind de-convolution method with a finite impulse response (FIR) multi-channel filter with a matrix transfer function:

$$\mathbf{W}(z) = \sum_{p=0}^{L} \mathbf{W}_p \mathbf{x}^{-p} \tag{3}$$

where $\mathbf{W}(z)$ is the Z-transformation of $\mathbf{W}_p$. The Z-transformation means the time domain signal (i.e., discrete time series) transformation in the complex frequency domain. With the symbol $\mathbf{W}(z)$, we can better understand the convolution signal than $\mathbf{W}_p$. $\mathbf{x}^{-p}$ is another expression of $\mathbf{x}(k - p)$, there is no variable k in $\mathbf{W}(z)$, so we use the symbol $\mathbf{x}^{-p}$ instead of $\mathbf{x}(k - p)$.

In some other applications, a non-causal (doubly-finite) feed-forward multi-channel de-mixing matrix

$$\mathbf{W}(z) = \sum_{p=-K}^{L} \mathbf{W}_p \mathbf{x}^{-p} \tag{4}$$

where K and L are two variables of positive integers. The global transfer function $\mathbf{G}(z)$ is defined by

$$\mathbf{G}(z) = \mathbf{W}(z)\mathbf{H}(z) \tag{5}$$

where $\mathbf{H}(z)$ is the Z-transformation of $\mathbf{H}_p$, and $\mathbf{H}_p$ is the channel impulse response for time domain. We can obtain form (6), $\mathbf{H}(z)$ is the channel impulse response for frequency domain, can also be called channel filter.

$$\mathbf{H}(z) = \sum_{p=-\infty}^{\infty} \mathbf{H}_p z^{-p} \tag{6}$$

where z^{-p} is the expression of $\mathbf{H}_p$ at time lag p.

In order to ensure that the mixed signal is recoverable, we put the following constraints on the convolute and mixed signal.

The channel impulse response function $\mathbf{H}(z)$ is stable, i.e., its impulse response satisfies the absolute summability condition:

$$\sum_{p=-\infty}^{\infty} \| \mathbf{H}_p \|_2^2 < \infty \tag{7}$$

where $\| \cdot \|$ denotes the Euclidean norm.

The channel impulse response transfer function $\mathbf{H}_p$ is a full rank on the unit circle ($\left\| \mathbf{H}_p \right\| = 1$), that is, it has no zeros on the unit circle.

B. DS/CDMA Data Model's Notations and Hypotheses

Base on the model of Section II, the goal of this paper is to recover the PN sequence $\mathbf{s}_k$ when user's data symbol and user's fading coefficient are both unknown, and no training samples are available either. The following assumptions will be in effect throughout the rest of the paper.

We assume the parameters f_0, T_c and T_s are known in advance. The more detailed estimation algorithms are provided in the literature [3], [5], [6]. In the reference [5] and [6], the method based on cyclo-stationarity analysis can estimate the chip period T_c and carrier frequency f_0 even in a low SNR. If the estimation of T_c and f_0 are available, we can process the signals in the base band and the sampling period can be set to T_c. In the Section V, we will demonstrate that is available. In the reference [3], the symbol duration T_s can be estimated using fluctuations of correlation even in –10dB (that is enough low to our method in the paper). We can adapt the DS-CDMA data model as follow.

The received CDMA signal $\mathbf{r}(t)$ can be written in the reference [7], [8]:

$$\mathbf{r}(t)=\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{L}a_{klm}b_{km}\mathbf{s}_k(t-mT-d_{kl})+\mathbf{n}(t) \qquad (8)$$

where M symbols are sent to K users and received via L path. a_{klm} is the amplitude (fading) coefficient of lth path of the kth user during the mth symbol duration, b_{km} is the kth user's mth data symbol.

$\mathbf{s}_k$ is the user's chip sequence:

$$\mathbf{s}_k(t)\in\{-1,+1\},\ \ t\in[0,T];\ \ \mathbf{s}_k(t)=0,\ \ t\notin[0,T]$$

d_{kl} is the delay of kth user's lth path. The delays are different for different users, and each delay is assumed to change sufficiently slowly for most of the time. $\mathbf{n}(t)$ denotes noise.

The signal is then sampled by chip rate. After sampling the samples are collected into vectors of suitable dimension. This depends on the delay spread. We collect C-length column vectors from subsequent discrete data samples vector $\mathbf{r}_m$:

$$\mathbf{r}_m=[r(mC)\ r(mC+1)\cdots r(mC+C-1)]^T \qquad (9)$$

where $\mathbf{r}_m$ is the discrete time domain expression of the $\mathbf{r}(t)$ in (8), and C is the chip sequence length. Equation (9) can further be written with respect to the current symbol vector and the immediately preceding one:

$$\mathbf{r}_m(t)=\sum_{k=1}^{K}[b_{k,m-1}\sum_{l=1}^{L}a_{klm}\mathbf{g}_{kl'}]+\sum_{k=1}^{K}[b_{k,m}\sum_{l=1}^{L}a_{klm}\mathbf{g}_{kl''}]+\mathbf{n}_m \quad (10)$$

where $\mathbf{n}_m$ is a C-length column vectors and it is the expression of $\mathbf{n}(t)$ in discrete time domain, and denotes the noise vector. $\mathbf{g}_{kl'}$ is the 'early' parts of the code vectors and $\mathbf{g}_{kl''}$ is the 'late' parts of the code vectors.

$$\begin{aligned}\mathbf{g}_{kl'}&=\left[s_k[C-d_{kl}+1],s_k[C-d_{kl}+2],\cdots,s_k[C]\ \ 0,\cdots,0\right]^T\\ \mathbf{g}_{kl''}&=\left[0,\cdots,0,s_k[1],s_k[2],\cdots,s_k[C-d_{kl}-1],s_k[C-d_{kl}]\right]^T\end{aligned} \quad (11)$$

where contains d_{kl} "0" in the vectors $\mathbf{g}_{kl'}$ and $\mathbf{g}_{kl''}$.

In this paper, we assume that the codes vectors $\mathbf{g}_{kl'}+\mathbf{g}_{kl''}$ are unknown. The approach exploits directly the binary form of the sources. The proposed algorithms yield good results in test examples with CDMA data. Due to the neural structure of the algorithms, they can be used for tracking purposes when the parameters are slowly changing.

Hence (10) could be written as follows

$$\begin{aligned}\mathbf{r}_m&=\mathbf{G}_0b_{k,m}+\mathbf{G}_1b_{k,m-1}+\mathbf{n}_m\\ &=\sum_{i=0}^{1}\mathbf{G}_ib_{k,m-i}+\mathbf{n}_m\end{aligned} \qquad (12)$$

where $\mathbf{G}_0$ and $\mathbf{G}_1$ are $C\times K$ dimension mixing matrices corresponding to the original and the one time unit delayed symbols. The column vectors of $\mathbf{G}_0$ and $\mathbf{G}_1$ as follow:

$$\begin{aligned}\mathbf{G}_0&=\left[\sum_{l=1}^{L}a_{klm}\mathbf{g}_{1l'},\sum_{l=1}^{L}a_{klm}\mathbf{g}_{2l'},\cdots,\sum_{l=1}^{L}a_{klm}\mathbf{g}_{Kl'}\right]\\ \mathbf{G}_1&=\left[\sum_{l=1}^{L}a_{klm}\mathbf{g}_{1l''},\sum_{l=1}^{L}a_{klm}\mathbf{g}_{2l''},\cdots,\sum_{l=1}^{L}a_{klm}\mathbf{g}_{Kl''}\right]\end{aligned} \qquad (13)$$

We notice from (12) that our signal model can be regarded as a linear mixture of the delayed and convolved sources, in the particular case when the maximum delay is one time unit. If we have known neither the mixing matrices nor symbol sequences, then we are in the framework of blind sources separation. The equation (12) is the general form of the BSS problem.

III. Adaptive Algorithm

We use the same basic insight in this paper, but propose a new criterion to exploit it, which leads to a simple and convenient algorithm. The object function is defined to minimize the risk function J :

$$J=E\left[\sum_{i=1}^{M}\sum_{\substack{j=1\\ j\neq i}}^{M}r_{y_iy_j}^2+\sum_{i=1}^{M}v_i(r_{y_iy_i}-\delta_i^2)^2\right] \qquad (14)$$

where the variable v_i is the convergence coefficients, and variable δ_i is the power factor, y_i and y_j are the channel's output vectors. $r_{y_iy_j}(n)$ is the correlation function of y_i and y_j.

$$r_{y_iy_j}(n)=\frac{\mathbf{h}(n)*[y_i(n)y_j(n)]}{\sum_k\mathbf{h}(k)} \qquad (15)$$

where the operator "$*$" is the convolution representation. $\mathbf{h}(k)$ and $\mathbf{h}(n)$ are the low-pass averaging filter vectors to compute a short-term estimate of the cross-correlation of output channels y_i and y_j at time n .

There are a lot of numerical algorithms based on the above criterion for the non-stationary source separation problem for the equation (14). We use a new stochastic gradient algorithm here. For the optimization of the de-mixing matrix $\mathbf{D}(n)$, a stochastic gradient [9] update takes the form

$$\mathbf{D}(n+1)=\mathbf{D}(n)-\mu\nabla(n) \qquad (16)$$

where $\nabla(n)$ is the differential function of $J(n)$, and μ is the convergence coefficient $0<\mu<1$.

$$\begin{aligned}\nabla(n)&=\frac{\partial J(n)}{\partial D(n)}\\ \nabla_{pq}(n)&=\frac{\partial J(n)}{\partial d_{pq}(n)}\\ &=\frac{\partial}{\partial d_{pq}(n)}\left\{\sum_{i=1}^{M}\sum_{\substack{j=1\\ j\neq i}}^{M}r_{y_iy_j}^2(n)+\sum_{i=1}^{M}v_i[r_{y_iy_j}(n)-\delta_i^2]^2\right\}\end{aligned} \qquad (17)$$

where $\mathbf{D}(n)$ is the discrete time domain of the de-mixing matrix $\mathbf{D}$ and its dimension p and q are the row and column indices gradient matrix that is designed by the number of users, and $J(n)$ is the nth step criterion function J in (14). Note the use of the instantaneous value at time n of the error function in (15) gradient computation. The (p,q)th element of the instantaneous gradient matrix can easily be shown to be [10]

$$\begin{aligned}\nabla_{pq}(n,l) &= 4\sum_{\substack{i=1\\ i\neq p}}^{M} r_{y_p y_i}(n) r_{y_i x_q}(n,l) + \ldots \\ & 2\lambda[r_{y_p y_p}(n) - \delta_p^2] r_{y_p x_q}(n,l)\end{aligned} \tag{18}$$

The above matrix expression for the stochastic gradient update yields a straightforward computation method once the short-time correlations are available. We now derive efficient recursive updates form for the averaging filter. For the computational efficiency, we select a first-order IIR averaging filter with impulse response

$$\mathbf{h}(n) = a^n u(k) \quad 0 < a < 1 \tag{19}$$

where $u(k)$ is the unit step function, and a is a constant $0 < a < 1$. With this form, the elements of $(1-a) - r_{yy}$ can easily be updated recursively according to

$$\begin{aligned} r_{y_p y_i}(n) &= a r_{y_p y_i}(n-1) + (1-a) y_p(n) y_i(n) \\ & \qquad 1 \le p, i \le M \\ r_{y_p x_i}(n) &= a r_{y_p x_i}(n-1) + (1-a) y_p(n) x_i(n) \\ & \qquad 1 \le p, i \le M \end{aligned} \tag{20}$$

$r_{y_p y_i}(n)$ and $r_{y_p x_i}(n)$ are the correlation functions between y_p y_i and y_p x_i.

This completes the simple recursive algorithm for non stationary blind source separation as below.

Step 1: Compute output according to (14).
Step 2: Update short-time correlations using (20).
Step 3: Compute separation filter gradient using (18).
Step 4: Update separation matrix using (16).
Step 5: Go back to step 1.

IV. Perfomance Evaluation and Simulation

A. Simulation Parameter Setup

The minimizing average squared cross-output-channel-correlation algorithm is demonstrated here via computer simulation, for a DS/CDMA signal received in the presence of various levels of white Gaussian background noise. In the experiment, we considered a 2-users CDMA system. The source signal was generated by the computer and the signal parameters were set as follow: carrier frequency $f_0 = 5000$, chip period $T_c = 1/1000$, symbol period $T_s = 31/1000$ (PN code length $C = 31$), users number $K = 2$, path $L = 2$, $SNR = 2$ (the SNR is higher than assumption 1 and assumption 2).

In evaluating the algorithms, two parameter matrices, $\mathbf{G}_0$ and $\mathbf{G}_1$ are chosen (randomly) as the convoluted mixing matrices. Both sources are zero-mean and have unit variances. A Gaussian vector noise process is added to the observation with noise covariance $\sigma^2\mathbf{I}$. The Signal-to-Noise Ratio (SNR) is then defined as

$$SNR = 10\log_{10}\frac{1}{\sigma^2}(dB) \tag{21}$$

where σ^2 is a covariance factor, and $\mathbf{I}$ is a unit matrix

$$\mathbf{I} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{22}$$

In this section, we evaluate the performance of the adaptive algorithm by some heuristic arguments and simulation results.

B. Results Analysis

As the CDMA signal exhibit cyclo-stationary, we utilize the spectral correlation method in the reference [11] to get the carrier frequency f_0 and the chip period T_c. Fig. 2 shows the measured spectral correlation function magnitude for the 2-users' CDMA system.

Form Fig. 2, the first peak value coordinate appear at the frequency $\pm 1\times 10^4$ Hz, according the definition of cyclic-correlation, we can get the carrier frequency at $f_0 = \pm\frac{1}{2}\times 10^4\,\text{Hz}$, the carrier frequency f_0 has been estimated. The second peak value appear at the both sides of each main peak, and the coordinates is ± 9000 Hz (that is not distinct in Fig. 2) and ± 11000 Hz, so we can obtain the chip period $T_c = \frac{1}{1000}\,\text{s}$. We can process the aboriginal signals in the base-band and set the sampling period to T_c.

Using the fluctuations of correlation method, we obtain the $T_s = 0.0311\,\text{s}$ (aberrancy near upon 0.3%). So the PN code length can be known as $C = T_s / T_c = 31$.

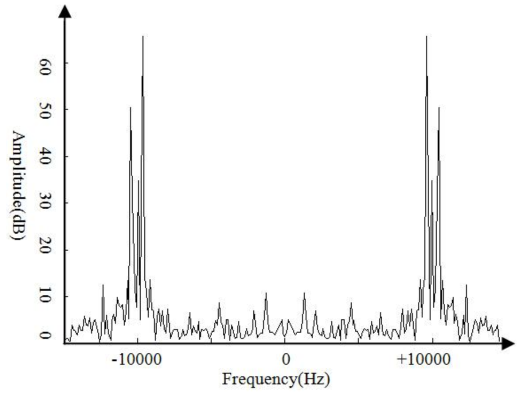

Fig. 2. Spectral correlation function magnitude for the 2 users' CDMA system.

For the aim of observation, we only display 800 points in Fig. 2.

Fig. 3 shows the 2-users' CDMA signal sources with AWGN channel (SNR=3).

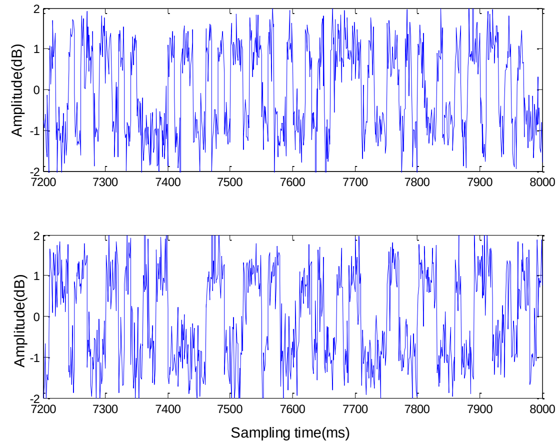

Fig. 3. 2-users' CDMA signal sources with AWGN channel

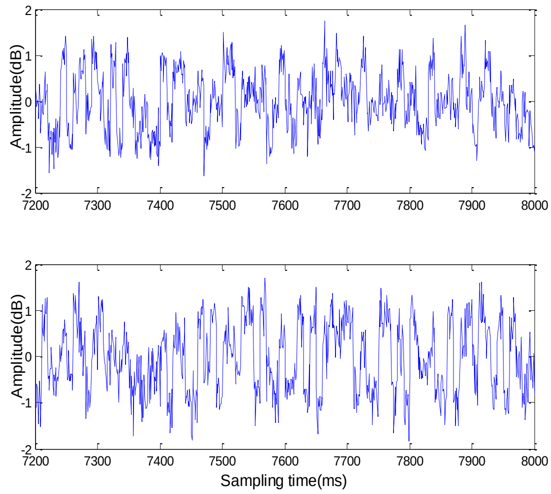

Fig. 4. The 2-users' data after convolute mixing

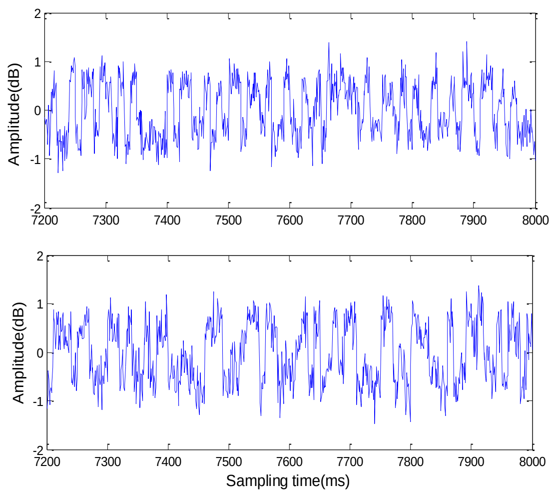

Fig. 5. The output data after separation

Fig. 4 shows the 2-users' data after convolute mixing. Two unknown GOLDEN sequences are used as the spreading codes. The output data after separation between 7200~8000 is shown in Fig. 4.

The unitary output binary estimated data after separation between 7200~8000 is shown in Fig. 5.

With the comparison of the results in the Fig. 3 and Fig. 5, the estimated data after separation is similar to the sources signal. In this experiment, the all symbols were correctly estimated, which shows the data are received correctly.

According the assumption before, we have estimated the PN code length that becomes very simple to seek the 2-users' PN code. We adopt traditional slippage correlation method or matrix Eigen analysis techniques to resolve the problem. In the paper, we use the slippage correlation method, and get the 2-users' PN code as Fig. 6.

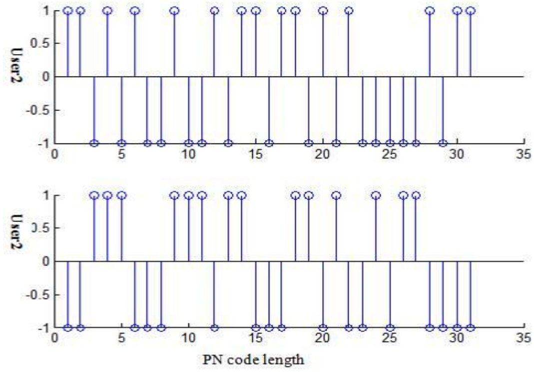

Fig. 6. The 2-users' PN codes

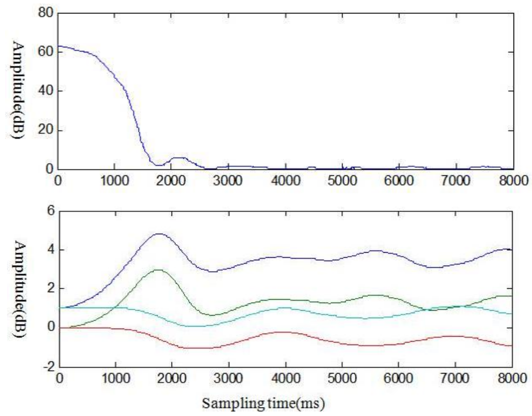

Fig. 7. Adaptation of the coefficient in the de-mixing matrix $\mathbf{D}$

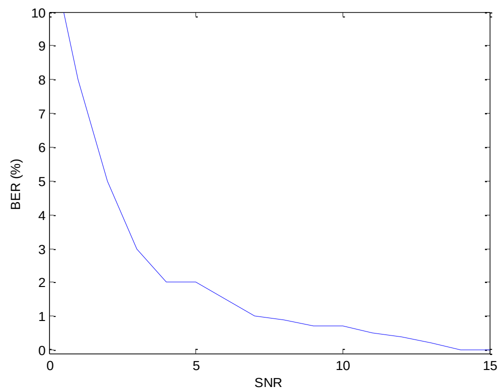

Fig. 8. BER for convoluted mixture CDMA signals separation

The self-adaptive coefficients in the de-mixing matrix $\mathbf{D}$ are shown in Fig. 7 when the $\alpha = 0.9$. The experiment result of the bit-error-rate (BER) to SNR is shown in Fig. 8.

C. The Influence of J, δ, v and α

The risk function J fluctuation with the sample serial n is shown in the Fig. 9. The recursion operation after about 3000 point, the risk function J is convergent. The recursion operation after about 6000 point, the risk function J is near to 0. The convergence rate is in accordance with the adaptation of the coefficient in the de-mixing matrix $\mathbf{D}$ as Fig. 7.

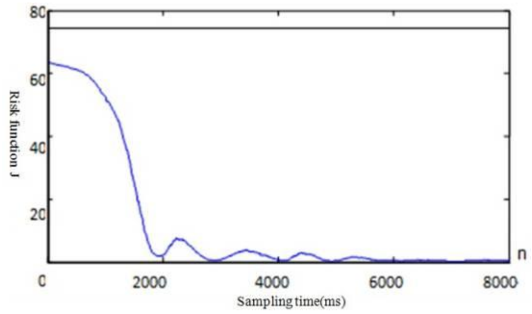

Fig. 9. Fluctuation of risk function J

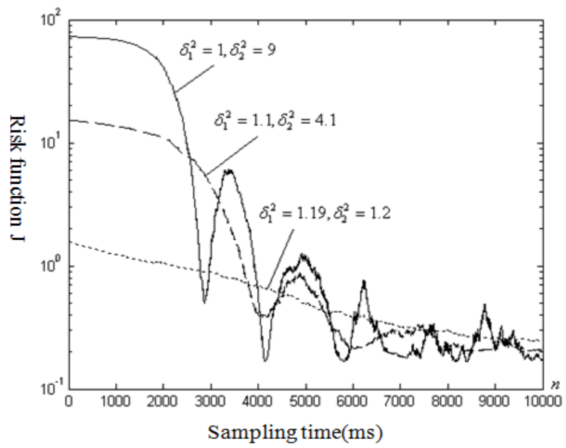

Fig. 10. Varity power factor δ influence on the J

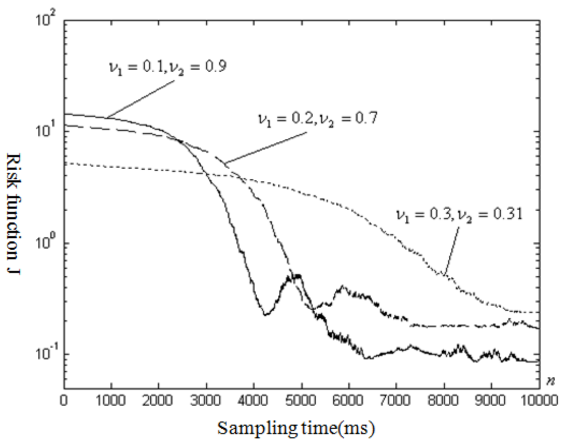

Fig. 11. Varity power factor v influence on the J

We also find the impacts on de-mixing matrices about convergence factor v and the power factor δ. The power factor δ exist dual effects on the de-mixing matrices. First, when the value of δ is lager, the convergence rate is faster but un-stabilization [12]. From a contrasting point of view, the convergence rate is slower but stable. Second, the least value of δ affects the convergence limit of risk function. The value of power factor δ is coherent with the risk function convergence limit.

We test 10000 samples for 3 times under the same condition, and get the risk function J over time, as Fig. 10. The shape and energy factor's value indicate the influence which energy factor has on the algorithm. Convergence factor v also exist the similar influence like energy factor as Fig. 11.

In the algorithm, we choose the low pass filter (19). The aim is to abbreviate the algorithm complexity and average the de-mixing output data. Under the same condition, we get the risk function J over α, as Fig. 12. The conclusion has been received that the value of α is ager, the convergence rate is slower but stabilization and α is smaller; the convergence rate is faster but unstable.

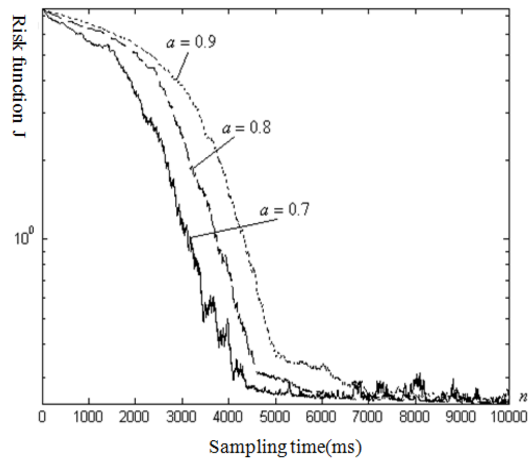

Fig. 12. Variety filter parameter α influence on the J

V. Conclusions

A blind source separation algorithm for the DS-CDMA signals is developed and demonstrated in this paper. By minimizing the average squared cross-output-channel-correlation, a criterion function J is proposed to estimate the spreading code. This technology not only can be used in military for CDMA signal interception, also can be used in a commercial anti-jamming for CDMA signal. The experiment results show that the proposed algorithm is a promising alternative to the existing BSS algorithms for DS/CDMA signals. This algorithm is also applicable to signals with long code, such as commercial communication signals, which allow it to be implemented with a reasonable computational complexity and over reasonably short reception intervals. This method is also a particular applicable estimation in downlink signal processing, because the codes of the interfering users are unknown. It is capable to separate the signals and remove the multi-path channel effect.

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