Blind Multi User Detection in DS-CDMA Systems using Natural Gradient based Symbol Recovery Structures

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ABSTRACT

Blind Multi User Detection (BMUD) is the process to simultaneously estimate multiple symbol sequences associated with multiple users in the downlink of a Code Division Multiple Access (CDMA) communication system using only the received data. In this paper, we propose BMUD algorithms based on the Natural Gradient Blind Source Recovery (BSR) techniques in feedback and feedforward structures developed for linear convolutive mixing environments. The quasi-orthogonality of the spreading codes and the inherent independence among the various transmitted user symbol sequences form the basis of the proposed BMUD methods. The application of these algorithms is justified since a slowly fading multipath CDMA environment is conveniently represented as a linear combination of convolved independent symbol sequences. The proposed structures and algorithms demonstrate promising results as compared to (i) the conventional techniques comprising matched filters and MMSE receivers, and (ii) previous BMUD structures and algorithms. This paper also extends the earlier proposed BMUD CDMA models by including effects of the channel symbol memory. Illustrative simulation results compare the BER performance of the various natural gradient algorithms, both in the instantaneous (i.e., on-line) and the batch modes, to the conventional detectors.

1. INTRODUCTION

Code Division Multiple Access (CDMA) uses the spread spectrum techniques in which all the users share the same temporal and spectral resources [6, 16]. In the downlink signal processing, each user is identified by a unique code, which is chosen to be "quasi-orthogonal" to the codes allotted to other users in the system. The Direct-Sequence Code-Division Multiple Access (DS-CDMA) is a promising data transmission technique capable of high data rates and immunity to channel noise. The signal energy is "spread" over a wide frequency range, which reduces the effects of fading channels. Other advantageous features include soft capacity limit, cell frequency reuse, soft handover of users etc. Wide bandwidth CDMA will be a dominant technology for the third generation (3G) wireless communication systems and forms an integral part of the UMTS/IMT-2000 and CDMA2000 standards [16].

Unlike the uplink communication channel, where all user codes are known and the base/controlling station possesses much higher signal processing capabilities, the downlink channel has a different set of constraints. The receiver (e.g., a mobile phone) has just the knowledge of a single self-identification code, and also has limited computational resources. In a CDMA system, the symbol train to a user may be detected using either a single-user or a multi-user detector. A single-user receiver basically estimates the desired signal for a desired user by modeling all the interfering users and disturbances as noise. In contrast, a multi-user detector (MUD) [6] includes all the users in the signal model. Significant improvement can be obtained with a multi-user receiver [11]. However the optimal MUD [12] is computationally intensive and requires several system parameters to be known. In typical downlink signal processing, where many of the system parameters are unknown including the codes for co-existing users at any instant of time, one can use the blind techniques for better estimate of the user signal [14].

In the conventional detection techniques for CDMA signals, only the second order statistics among the user codes are exploited but in most practical situations the user data symbols among themselves are independent. This is a powerful assumption, which enables one to apply the existing blind source recovery techniques to solve the detection problem in the multi user environment. Blind Source Recovery (BSR) in this context is the process of estimating the original independent user-specific symbol sequences independent of, and in the absence of precise system identification [8,9].

The received CDMA signal can be considered as a set of non-gaussian random variables generated by the linear convolutive transformation of statistically independent component variables [2,3,7]. This linear transformation accounts for the user codes, multiple channel paths and slowly fading channel symbol memory. Our goal is to estimate another linear transformation such that it counters, as best as possible, the effects of the first transformation resulting in the recovery of the original signal. A similar blind deconvolution approach has been earlier described in [2,3]. However, this prior algorithm does not represent the class of natural gradient algorithms and as such does not give desirable performance as the ratio between the number of users in the system and code length increases. Secondly, the prior algorithm gives good results in the batch mode of operation, which is computationally expensive. Our proposed natural gradient feedforward and feedback structure algorithms [8,9] can be implemented using both the batch as well as the instantaneous update approaches. These proposed algorithms provide robust performance when realized in the batch mode of operations. Further, the proposed algorithms have competitive performance and do outperform traditional detectors such as the matched filter (MF) and the minimum mean square (MMSE) detectors for the reasonable received SNR range of 5dB or higher even for a relatively large ratio of the number of users to the user-identification code length in the simulated AWGN channels [4,6,11,12].

2. DOWNLINK RECEIVER SIGNAL MODEL

We will consider a wide sense stationary slowly fading, multipath, downlink AWGN model with symbol memory. This symbol memory exists due to the presence of previous transmitted symbol in the receiver environment [6,14]. The received data in this case can be modeled as a multipath generalization of the model in [6] as

$$r(t) = s(t) + n(t) \tag{2.1}$$

where

$n(t)$: represents the channel additive white gaussian noise

$s(t)$: represents the channel corrupted transmitted signal

$$s(t) = \sum_{n=1}^{N}\sum_{k=1}^{K} b_k(n)\sqrt{\varepsilon_{kn}}\sum_{l=0}^{L-1} a_k(l)\, g_k(t - nT - \tau_l) \tag{2.2}$$

N : represents the total number of symbols during the observation interval

K : represents the total number of users during the observation interval

L : represents the total number of transmission paths per symbol

$b_k(n)$: represents the transmitted n^{th} symbol for the k^{th} user.

ε_{kn} : represents the signal energy of the n^{th} symbol for the k^{th} user

$a_k(l)$: represents the fading factor for l^{th} transmission path, and

τ_l : is the corresponding transmission delay for the l^{th} transmission path which satisfies the condition $0 \le \tau_l \le T$ for all users and constant during the observation time.

$g_k(t)$: represents the signature code for the k^{th} user, generated by

$$g_k(t) = \sum_{m=0}^{M-1} \alpha_k(m) p(t - mT_c) \tag{2.3}$$

$\alpha_k(m); 0 \le m \le M-1$: is a PN code sequence for the k^{th} user containing M chips, $\alpha_k(m) \in \{\pm 1\}$

$p(t)$: is a chipping pulse of duration T_c

T : is the total code time, given by $T = MT_c$

The model presented by (2.1) and (2.2) represents a case where the current symbol is corrupted by the multipath self-echoes only. However, considering a more realistic scenario for DS-CDMA systems, where at any instant of time the transmission medium comprises the currently transmitted symbol as well as weakened versions of prior symbols corrupting the reception of the current symbol. In this case the n^{th} received symbol will be corrupted by previous J transmitted symbols as

$$\begin{aligned} r_n = &\sum_{k=1}^{K} b_k(n)\sqrt{\varepsilon_{kn}}\sum_{l=0}^{L-1} a_k(l)\, g_k(t - nT - \tau_l) + n_n + \\ &\sum_{j=1}^{J}\sum_{k=1}^{K} b_k(n-j)\sqrt{\varepsilon_{k(n-j)}}\sum_{l=0}^{L-1} a_k(l)\, g_k(t - (n-j)T - \tau_l) \end{aligned} \tag{2.4}$$

where, for a fading channel $\sqrt{\varepsilon_{k(n-j)}} \ge \sqrt{\varepsilon_{k(n-j-1)}};\ \forall j \ge 0$.

For the clarity of presentation, restricting ourselves to the case where the existing symbol is corrupted by only one previously transmitted symbol, i.e., we assume that the effect of symbols transmitted prior to the previous symbol is negligible due to its temporal dispersion and absorption in the channel.

$$r_n = \sum_{k=1}^{K}\left[b_{kn}\sqrt{\varepsilon_{kn}}\sum_{l=0}^{L-1} a_{kl}\bar{z}_{kl} + b_{k,n-1}\sqrt{\varepsilon_{k,n-1}}\sum_{l=0}^{L-1} a_{kl}\underline{z}_{kl}\right] + n_n \tag{2.5}$$

where

$$\bar{z}_{kl} = \begin{bmatrix} 0 & \cdots & 0 & g_k[1] & \cdots & g_k[M-\tau_l] \end{bmatrix}^T \tag{2.6}$$

and

$$\underline{z}_{kl} = \begin{bmatrix} g_k[M-\tau_l+1] & \cdots & g_k[M] & g_k[1] & \cdots & g_k[M-\tau_l] \end{bmatrix}^T \tag{2.7}$$

Note that for the case of no channel symbol memory [2,3], we can rewrite $\underline{z}_{kl}$ as

$$\underline{z}_{kl} = \begin{bmatrix} g_k[M-\tau_l+1] & \cdots & g_k[M] & 0 & \cdots & 0 \end{bmatrix} \tag{2.8}$$

and τ_l is the discretized delay still satisfying the constraint $0 \le \tau_l \le T$.

Alternately we can represent the model in a more compact matrix-vector form as

$$r_n = H_0 b_n + H_1 b_{n-1} + n_n \tag{2.9}$$

where

b_n and b_{n-1} are the K-d vectors of current and previous symbol for all the K users.

H_0 and H_1 are $M \times K$ mixing matrices given by

$$H_0 = \begin{bmatrix} H_{0,0} & H_{0,1} & \cdots & H_{0,K} \end{bmatrix}$$

$$H_1 = \begin{bmatrix} H_{1,0} & H_{1,1} & \cdots & H_{1,K} \end{bmatrix}$$

such that

$$H_{0,k} = \sqrt{\varepsilon_0}\sum_{l=0}^{L-1} a_{kl}\bar{z}_{kl} \tag{2.10}$$

$$H_{1,k} = \sqrt{\varepsilon_1}\sum_{l=0}^{L-1} a_{kl}\underline{z}_{kl} \tag{2.11}$$

and $\varepsilon_0 \ge \varepsilon_1 > 0$ represent the energy of the current and the previous symbol respectively at the instant of observation.

3. NATURAL GRADIENT BLIND MULTI-USER DETECTION (BMUD) ALGORITHMS

As discussed in the previous section, the received signal comprises a noise-corrupted linear mixture of delayed and convolved user symbol sequences. It is reasonable to assume that the various transmitted symbol sequences are mutually independent as they are generated by independent sources. Assuming no preamble transmission to the receiver, both the transmitted sequence and the mixing matrices in the model (2.9) are unknown to the user. The only known quantity to the user is the self-identification code. Other available prior information is the nature of transmitted data, which is binary but can be assumed to take bimodal distribution due to noise corruption and colvolutive effects, i.e., it falls in the class of sub-gaussian distributions. We have enough information to apply the Blind Source Recovery (BSR) algorithms for BMUD in this case [8,9,13].

Further we assume that the DS-CDMA channel is not over-saturated and $K \le M$. The proposed BSR algorithms do not require any pre-whitening of received data. However, in most modern WCDMA, M is chosen to be very large and in general $K < M$. Therefore, it is computationally advantageous to pre-process the data for dimension reduction to K which is the actual number of principal independent symbol components in the received data. The process of pre-whitening will also remove the second order dependence among the received data samples and some of the additive noise [2,3,7]. The data pre-whitening can be achieved either online using adaptive principal component analysis (PCA) algorithms or it may be done using an algebraic PCA estimate over a large batch (say N samples) of received data, i.e.,

$$R = \begin{bmatrix} r_1 & r_2 & \cdots & r_{N-1} & r_N \end{bmatrix}$$

with the correlation matrix

$$\Lambda_C = \frac{1}{N-1} RR^T \qquad (3.1)$$

Then the whitening is achieved using the filtering matrix

$$W = D^{-1/2} V^T$$

where

D : represents the K-dim matrix of principle eigenvalues of the data correlation matrix Λ_C

V : represents the $K \times M$ matrix of principal eigen vectors of the data correlation matrix Λ_C .

The whitened version of (2.9) is given by

$$r_n^w = W\left(H_0 b_n + H_1 b_{n-1} + n_n\right) \cong \bar{H}_0 b_n + \bar{H}_1 b_{n-1} \qquad (3.2)$$

where

r_n^w : represents the K-d received data at the n^{th} sampling instant

$\bar{H}_0$, $\bar{H}_1$: represent the equivalent square K-d mixing matrices for the current and the delayed symbols.

3.1. Demixing Structures

The natural gradient BMUD network for such a problem can be either in the feedforward [1,8,9] or the feedback configuration [8]. We present the update laws for both cases; further the performance of the proposed algorithms is discussed and compared with conventional and another proposed BMUD algorithms [2].

3.1.1. Feedback BMUD Configuration

In the feedback configuration the output is estimated by

$$y_n = W_0^{-1}\left(r_n^w - \sum_{k=1}^{K} W_k y_{n-k}\right) \qquad (3.3)$$

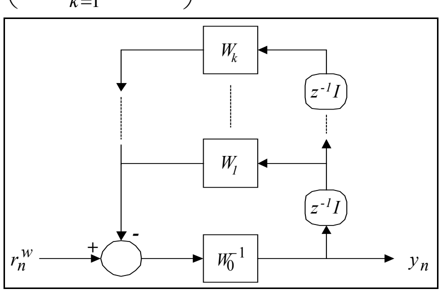

Figure 1. Feedback Demixing Structure

This is followed by a decision stage to best estimate the recovered symbol $\hat{b}_n$ from the demixing network output y_n .

$$\hat{b}_n = \psi(y_n) \qquad (3.4)$$

where $\psi(.)$: represents the (nonlinear) decision stage.

The update laws for this structure using the natural gradient have been derived in [9]. The update law for the feedforward matrix W_0 is given by

$$\Delta W_0 \propto -W_0\left(I - \varphi(y_n) y_n^T\right) \qquad (3.5)$$

While for the feedback matrices W_k , the update law is

$$\Delta W_k \propto W_0\left(\varphi(y_n) y_{n-k}^T\right) \qquad (3.6)$$

where

$\varphi(.)$: represents an element-wise acting nonlinearity (score function) [8,9,13]

I : represents a K-d identity matrix.

An alternate update law for a similar structure using the so-called collected temporal gradient was derived in [1] and has been proposed in [2] for BMUD. The update laws for the feedback matrices for this algorithm are different from (3.6) and are given by

$$\Delta W_k \propto -\left(I + W_k\right)\left(\varphi(y_n) y_{n-k}^T\right) \qquad (3.7)$$

This alternate algorithm using (3.7) is not as stable as the proposed algorithm using (3.6). This algorithm in [2] is amenable only in the batch mode, while the true natural gradient algorithm [8] give better results both in instantaneous and batch modes of operation.

For initialization of the algorithm, W_0 is chosen to be either identity or dominantly diagonal, while the feedback matrices W_k are initialized to be either small random or as a matrix of zeros.

3.1.2. Feedforward BMUD Configuration

For the feedforward configuration, the BMUD stage output is computed as

$$y_n = W_0 r_n^w + \sum_{k=1}^{K} W_k y_{n-k} \qquad (3.8)$$

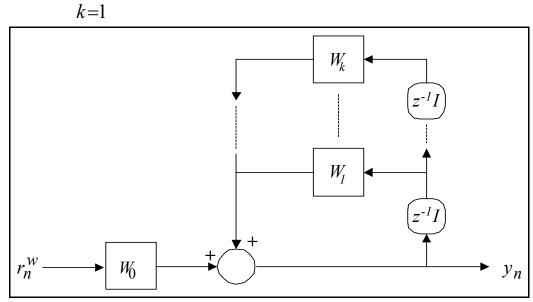

Figure 2. Feedforward Demixing Structure

This computation is followed by the estimator for symbol $\hat{b}_n$ recovery (3.4).

The update laws for this feedforward structure have been derived in [8,9] and are given by

$$\Delta W_0 \propto \left(I - \varphi(y_n) y_n^T\right) W_0 \qquad (3.9)$$

$$\Delta W_k \propto \left(I - \varphi(y_n)y_n^T\right)W_k - \varphi(y_n)y_{n-k}^T \tag{3.10}$$

The matrices in this case are also initialized in a fashion similar to the feedback case. Note that no matrix inversion is required for this algorithm.

3.1.3. Conventional MUD Configurations

For the purpose of comparison, we apply the conventional user detection schemes such as the Matched Filter (MF) and the Minimum Mean Squared Error (MMSE) estimators [2, and the references therein]. The conventional estimators are computed using the following relations, respectively.

$$\hat{b}_{kn,MF} = g_k^T r_n \tag{3.11}$$

and

$$\hat{b}_{kn,MMSE} = g_k^T V D^{-1} V^T r_n \tag{3.12}$$

where

$\hat{b}_{kn}$: represents the estimated symbol for the k^{th} user at the n^{th} instant

g_k : represents the self-identification code for the k^{th} user

D, *V*: represent the eigenvalues and the corresponding eigenvectors for the estimated data auto-correlation matrix Λ_C .

4. SIMULATIONS

Two simulation cases are presented, one with no symbol memory and the other with symbol memory. The BMUD performance of all the algorithms is compared using the Bit Error rate (BER) of the recovered symbol sequences. Both simulation models assume that both the mixing and demixing models use the current and one prior symbol. The algorithms are updated as per the update laws described in the previous section. The performance for the natural gradient BMUD algorithms is compared for both instantaneous and batch updates. The convergence criterion is set to be a threshold on the L_2 norm of the difference between consecutive updates of weight matrices. As the symbol sequence is directly estimated using the proposed technique, therefore, a data preamble is used for user identification.

An alternate performance comparison can be done for the synthetic simulation cases by computing diagonalization of the global transfer function. The global transfer function presents the combined effect of the mixing and demixing transfer functions. For the order 2 transfer functions simulated, the global transfer function for the natural gradient algorithms in the z-domain are given by:

$$G = G_0 + G_1 z^{-1} \tag{4.1}$$

where, for the *feedback* algorithm

$$G_0 = W_0^{-1}\bar{H}_0 = W_0^{-1}WH_0 \tag{4.2}$$

$$G_1 = W_0^{-1}\left(\bar{H}_1 - W_1\right) = W_0^{-1}\left(WH_1 - W_1\right) \tag{4.3}$$

and for the *feedforward* algorithm

$$G_0 = W_0\bar{H}_0 = W_0 WH_0 \tag{4.4}$$

$$G_1 = W_0\bar{H}_1 + W_1 = W_0 WH_1 + W_1 \tag{4.5}$$

4.1. Case I: No Symbol Memory

In this simulation, the previous symbol is convolved with the current symbol due to the multipath effects only. This case is similar to the simulation presented in [2] where z_{kl} is given by (2.8).

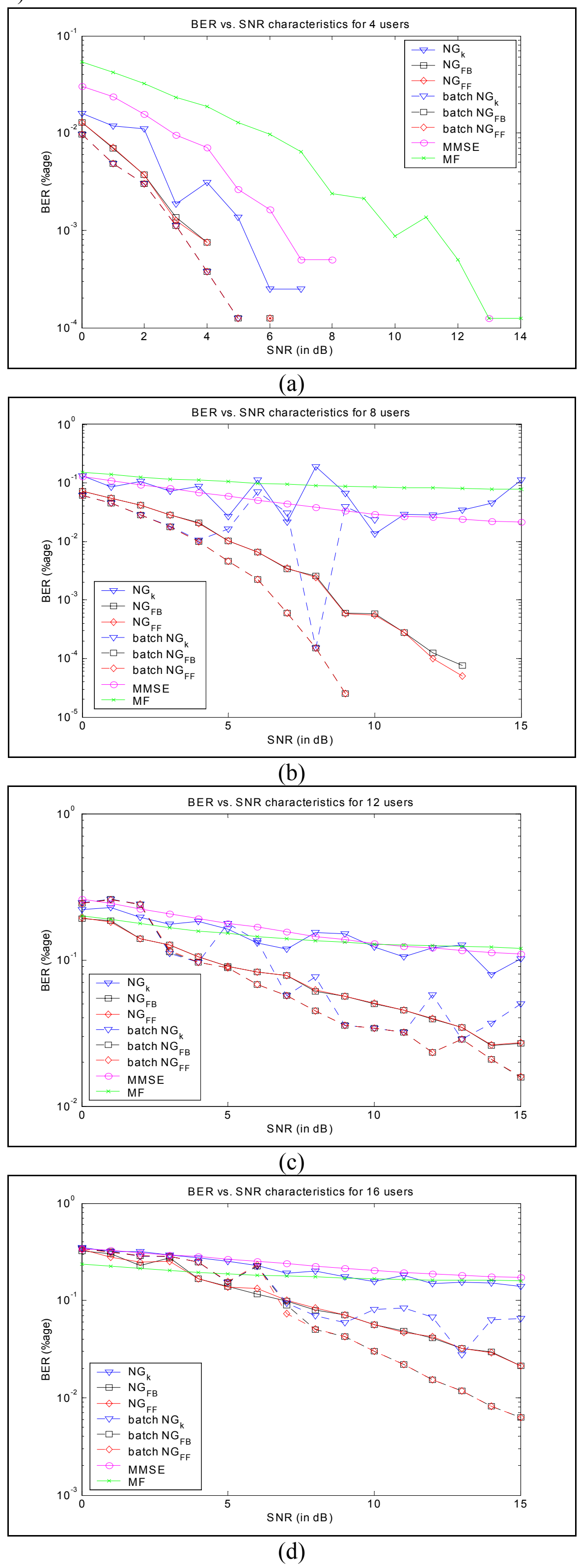

Figure 3. BER results with no symbol memory for (a) K=4, (b) K=8, (c) K=12, (d) K=16

Our simulation uses gold codes [5] of length 31. The modulation is assumed to be BPSK. The channel has L=3, the paths have a power of 0, -5 and –5 dB for the corresponding delays of 0, 1 and 2 chips respectively. The SNR for the user is varied from 0dB to 15dB. The number of users is chosen to be K=4, 8, 12, 16 for different simulation runs respectively. For the instantaneous and batch modes the observation intervals N were 1 and 500 respectively. The learning rate is initialized at 0.1 and then exponentially decayed.

As the transmitted signals are bipodal, the symbol decision is done using a sign function. The results are shown in Figure 3 and 4. All the simulated results show 8 cases that include both instantaneous and batch modes of the prior algorithm (NG_k), proposed feedback and feedforward algorithms (NG_{FB} and NG_{FF}), and the conventional configurations (MMSE and MF).

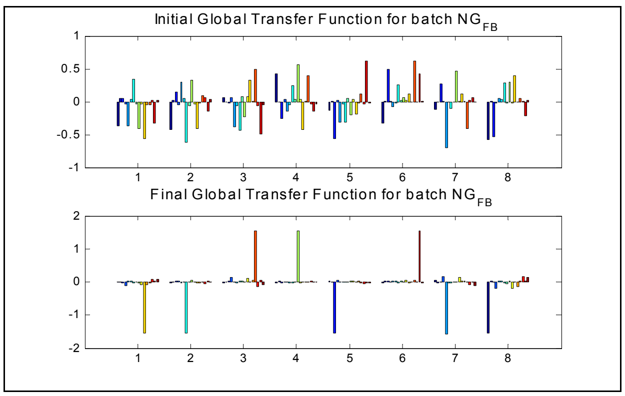

Figure 4. Typical Global Transfer Function for K=8

The batch versions of the proposed true natural gradient algorithms provide the best performance in all cases. The instantaneous versions of these algorithms also perform much better than the conventional techniques for a SNR of 4 dB or higher but their computational load is an order of magnitude smaller than the batch versions of the algorithms. The prior algorithm proposed in [2] does not match the performance of the proposed algorithms, even in the batch mode, as the number of users increases, and as such is not reliable for BMUD. Also note that MMSE is superior to MF for a lower number of users, but the MF supersedes MMSE performance for a larger number of users in the CDMA system.

Figure 4 presents the typical global transfer function, i.e., the mixing environment and the demixing network transfer functions combined for the case of 8 users. We observe that the natural gradient algorithms have identified all the users successfully. The global transfer function exhibits user permutations, scaling and sign ambiguities, which are inherent in BSR based solutions. In the case of DS-CDMA, this can be overcome using a preamble for user identification.

4.2. Case II: 1 Symbol Memory

In this simulation, the previous symbol is assumed to be present in the receiver's environment though with somewhat reduced power of –3dB (due to temporal diffusion and absorption losses in the transmission medium) and acts as an additional interferer in BMUD as compared to the previous case. z_{kl} in this case is given by (2.7). The remaining elements of the simulations are similar to the previous case.

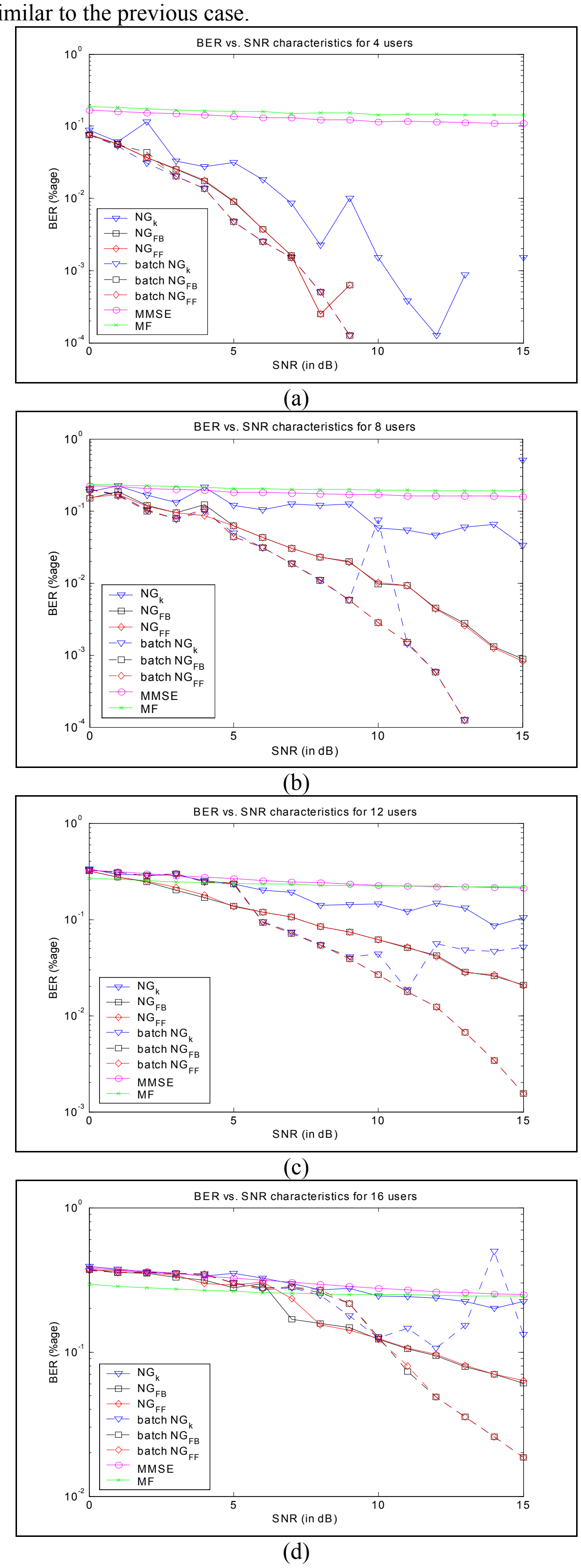

Figure 5. BER results with 1symbol memory for (a) K=4, (b) K=8, (c) K=12, (d) K=16

The comparative simulation results for the instantaneous and batch modes of the prior algorithm (NG_k), proposed natural gradient feedback and feedforward algorithms (NG_{FB} and NG_{FF}), and the conventional configurations (MMSE and MF) for the cases of 4, 8, 12 and 16 users in a DS-CDMA communication channel using gold codes of length 31[5] are summarized in Figure 5.

The performance trends of the various algorithms are similar to the previous simulation results in this case as well. The natural gradient algorithms outperform the conventional techniques for an SNR of 6 dB or higher even for a 50% ratio between the number of users and the code length. For lower SNRs and relatively higher number of users, the matched filter (or single user detection) is the most promising technique, but as the SNR improves, the proposed algorithms seem to be the most promising providing at least an order of magnitude BER improvement. The instantaneous version of the proposed natural gradient algorithms again appear as the compromise candidates of choice for achieving robust good performance at relatively lower computational cost compared to the batch mode implementations. Also note that the prior BMUD algorithm [2] overall provides a poor performance versus the proposed natural gradient algorithms. In some results this prior algorithm touches a BER rate of 0.5 in some cases, indicating that the algorithm did not converge for that particular trial, making it unreliable as a practical choice.

5. CONCLUSIONS

We have introduced effective blind natural gradient source recovery algorithms both in the feedforward and feedback configurations to the realm of DS-CDMA blind multi-user identification and recovery. For a moderate SNR of 5 dB or higher, the proposed algorithms outperform the conventional MUD techniques even in channels which exhibit symbol memory. The proposed natural gradient based batch mode algorithms give the best performance. The instantaneous versions of the algorithms have lesser computational complexity and smaller memory requirements, yet their performance far exceeds the performance of conventional MUD techniques even for a relatively higher ratio of the number of users to the length of quasi-orthogonal code used. The collective temporal gradient feedback algorithm[1] earlier proposed for BMUD in [2] performs poorly even in batch mode for a higher number of users and a given code length. The BMUD is a promising technique as there is no need of precise synchronization required similar to the conventional techniques. The problem formulated in this paper is directly applicable to the CDMA techniques used for GPS, Wireless LAN: ad-hoc and ATM networks to name a few.

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