2001 Conference on Information Sciences and Systems, Johns Hopkins University, March 21-23, 2001

Multistage Blind Interference Cancellation and Channel Estimation for DS-CDMA Systems [1]

Dragan Samardzija
Wireless Communications Research Department,
Bell Labs, Lucent Technologies,
791 Holmdel-Keyport Road,
Holmdel, NJ 07733, USA
dragan@lucent.com

Narayan Mandayam, Ivan Seskar
WINLAB, Rutgers University,
73 Brett Road,
Piscataway NJ 08854, USA
narayan,
seskar@winlab.rutgers.edu

Abstract — **In this paper we propose a blind interference cancellation and channel estimation receiver for direct-sequence code-division multiple-access (DS-CDMA) systems, which assumes knowledge of only the nominal desired user signature sequence. It is a multistage nonlinear blind interference cancellation and channel estimation receiver that uses higher order statistics (second and fourth moments) of the received baseband signal. Simulation results show that unlike linear receivers, the scheme is exceptionally efficient in systems with strong and highly correlated interferers, and is also able to jointly estimate channel response and perform interference cancellation.**

I. Introduction

Modern wireless DS-CDMA communications systems use variable spreading gain in order to accommodate different data rates, and in general, different quality of service, while maintaining the same chip rate [1]. To achieve higher data rates, channelization codes (signature sequences) with lower spreading gains are to be extensively used (e.g., in W-CDMA systems spreading gains of $4, 8, 16$ and 32 are of prime interest for higher data rates). Because of lower spreading gains, these cases are more affected by multiple-access interference (MAI), than in the cases of higher spreading gains. Even though it is possible to design good signature sequences, asynchronous transmissions, overloading (more users than signal dimensions) and dispersive environments make it very difficult to guarantee low signature crosscorrelations. Therefore, in order to provide required bit-error rates (BER), interference cancellation (IC) and/or multiuser detection (MUD) are to be applied in the cases of lower spreading gains. A number of different solutions, assuming knowledge of all users' parameters in the system, perform different centralized IC or MUD schemes (e.g., [2, 3, 4, 5]).

In this paper we consider a DS-CDMA system where the signature sequences are short (i.e., for a user, the same signature sequence is used for each symbol period). This assumption allows a receiver to adaptively learn the structure of MAI and the channel response and apply the results for IC and detection. Unlike adaptive receivers that use a predefined training sequence (e.g., see [4, 6, 7]), we present a fully decentralized (i.e. blind) solution that assumes only knowledge of the nominal (i.e., transmitted) signature sequence. This work represents an extension of the algorithm that is originally presented in [8]. In [8] the focus was on blind interference cancellation, but here we present a solution for joint blind channel estimation and interference cancellation. It is well known that linear receivers (centralized and decentralized) do not perform well in the case of systems with strong and highly correlated interferers (with respect to desired user signature sequence), as may be the case in overloaded DS-CDMA systems and/or dispersive environments where multipath components introduce significant interference.

In this paper we propose a blind interference cancellation and channel estimation receiver. It is a multistage nonlinear blind interference cancellation and channel estimation receiver (BICCE) that uses higher order statistics of the received baseband signal. Specifically, we use the second and fourth moments of the received signal to determine a component of the received vector that has significant mean energy and low variability of the energy which are favorable characteristics for application in an interference cancellation scheme that uses hard decisions. The structure of the receiver is multidimensional and can be viewed as a matrix of receivers. Each row in the matrix consists of receivers that perform (hard decisions) cancellation of successive components that have significant mean energy and low variability of the energy and, at the same time, estimates the channel response for the desired user. The columns of the matrix essentially resemble multistage receivers that iteratively refine performance from earlier stages. Simulation results show that unlike linear receivers, the BICCE is exceptionally efficient in systems with strong and highly correlated interferers, and is also able to jointly estimate channel response and perform interference cancellation.

II. System Model and MVE-MME Optimization Criterion

The received vector in a DS-CDMA antipodal system is

$$r(t) = \sum_{i=-J}^{J} \sum_{k=1}^{K} A_k \, b_k(i) \, s_k(t - iT - \tau_k) \; + \; \sigma n(t) \qquad (1)$$

where A_k is the received amplitude, $b_k(i) \in \{-1, +1\}$ is binary, independent and equiprobable data, τ_k is relative time offset, all for the k^{th} user. T is the symbol period and $n(t)$ is AWGN with unit power spectral density. $s_k(t)$ represents an effective signature sequence which is result of nominal (transmitted) signature sequence $c_k(t)$ being passed through the communication channel. In other words, $s_k(t) = c_k(t) * h_k(t)$, where $h_k(t)$ is channel response for the k^{th} user. Considering

[1]This work is supported in part by the New Jersey Commission on Science and Technology under the New Jersey Center for Wireless Communication Technologies

all users in the system, $2J+1$ corresponds to the maximum duration (in symbol periods) of all effective signature sequences. At the receiver, after sampling, we obtain the vector $\mathbf{r}$, which corresponds to (1). $\mathbf{r} \in \Re^{M+D}$, where M is the spreading factor, and D corresponds to the delay spread introduced by the channel. $M+D$ presents the duration (in number of samples, i.e., in number of chips) of the information bearing waveform $s_k(t)$. $D > 0$ is a consequence of the dispersive environment, which actually results in inter-symbol interference (ISI). In the following we assume knowledge of the parameter D.

We now present an optimization criterion which is used in deriving a nonlinear blind adaptive interference cancellation and channel estimation scheme. The goal of the optimization approach is to determine a component of the received vector $\mathbf{r}$ that has low variability in the energy and significant mean energy. We consider the squared output of the projection of $\mathbf{r}$ onto a vector $\mathbf{v} \in \Re^{M+D}$. The vector $\mathbf{v}$ is obtained from the following nonlinear procedure which is

$$\mathbf{v} = \arg\min_{\mathbf{u}} \{\alpha(\mathbf{u}) = (1-\mu)\,\alpha_1(\mathbf{u}) - \mu\,\alpha_2(\mathbf{u})\} \tag{2}$$

where $\mathbf{u} \in \Re^{M+D}$ is subject to $\mathbf{u}^\top \mathbf{u} = 1$ and $0 < \mu < 1$. The function $\alpha_1(\mathbf{u})$ denotes the variance of the squared output $\mathbf{r}^\top \mathbf{u}$ and is given as

$$\alpha_1(\mathbf{u}) = E\left[\left((\mathbf{r}^\top \mathbf{u})^2 - E\left[(\mathbf{r}^\top \mathbf{u})^2\right]\right)^2\right] \tag{3}$$

The function $\alpha_2(\mathbf{u})$ in (2) denotes the square mean energy given as

$$\alpha_2(\mathbf{u}) = \left(E\left[(\mathbf{r}^\top \mathbf{u})^2\right]\right)^2 \tag{4}$$

Consider the function $\alpha_1(\mathbf{u})$. Let us now compare $\alpha_1(\mathbf{u})$ with the following, well known, Godard's dispersion function [11]:

$$J_p = \frac{1}{2p} E\left[\left((\mathbf{r}^\top \mathbf{u})^p - \eta\right)^2\right] \tag{5}$$

where η is a real constant, and p is an integer. For $\eta = E\left[(\mathbf{r}^\top \mathbf{u})^2\right]$ and $p = 2$, the cost function in (5) is directly proportional to $\alpha_1(\mathbf{u})$. In other words, $\alpha_1(\mathbf{u})$ penalizes dispersions of the squared output $(\mathbf{r}^\top \mathbf{u})^2$ away from the constant $E\left[(\mathbf{r}^\top \mathbf{u})^2\right]$. Furthermore, the well studied constant modulus (CM) cost function is defined as a special form of the function in equation (5), where $\eta = E\left[(\mathbf{r}^\top \mathbf{u})^4\right]/\sigma^2$, and $p = 2$. The CM cost function is widely used for blind equalization (see [12] and references therein). Later in this work, $\alpha_1(\mathbf{u})$, which may be viewed as a slightly modified form of the CM cost function, is applied for blind interference cancellation in DS-CDMA systems.

Let us now consider the function $\alpha_2(\mathbf{u})$. It can be shown that the vector $\mathbf{v}_{max} = \arg\max_{\mathbf{u}}(\alpha_2(\mathbf{u}))$, constrained as $\mathbf{u}^\top \mathbf{u} = 1$, is equal to the vector that also maximizes the mean energy $E\left[(\mathbf{r}^\top \mathbf{u})^2\right]$. It is shown in [10, 9] that $\mathbf{v}_{max}$ is the eigenvector that corresponds to the largest eigenvalue of the input covariance matrix $\mathbf{R}_r = E[\mathbf{r}\,\mathbf{r}^\top]$. Instead of the mean energy $E\left[(\mathbf{r}^\top \mathbf{u})^2\right]$, $\left(E\left[(\mathbf{r}^\top \mathbf{u})^2\right]\right)^2$ is applied in (2) such that both terms ($\alpha_1()$ and $\alpha_2()$) are of the same order (i.e., fourth order). Based on the above, the vector $\mathbf{v}$, which is defined in equation (2), corresponds to that component of the received signal $\mathbf{r}$ that has low variability in the energy and significant mean energy. The parameter μ is used to control which of these two characteristics (low variability of the energy or significant mean energy) is dominant. For example, if $\mu = 0$, the optimization in (2) is equivalent to minimum variance of energy (MVE), and for $\mu = 1$ it is equivalent to maximum mean energy (MME) optimization criterion. Therefore, we refer to (2) as the minimum variance of energy and maximum mean energy (MVE-MME) optimization criterion. Later, we revisit issues related to the parameter μ and propose design choices for it.

We now present an adaptive algorithm that solves (2). We exploit some properties of the functions given in (3) and (4). Let us assume that the input process $\mathbf{r}$ is wide sense stationary (WSS) and also that

$$E[(\mathbf{r}^\top(n)\,\mathbf{u})^2(\mathbf{r}^\top(n+m)\,\mathbf{u})^2] =$$

$$= E[(\mathbf{r}^\top(n)\,\mathbf{u})^2]\,E[(\mathbf{r}^\top(n+m)\,\mathbf{u})^2] \tag{6}$$

where n and m are time indices, and $n \neq m$. In other words, we assume that the energy of $\mathbf{r}$ in direction of the vector $\mathbf{u}$ is uncorrelated in different symbol (bit) intervals. Using the properties of WSS processes and (6) we can show that (3) can be written as

$$\alpha_1(\mathbf{u}) = \frac{1}{2} E\left[\left((\mathbf{r}^\top(n)\,\mathbf{u})^2 - (\mathbf{r}^\top(n+m)\,\mathbf{u})^2\right)^2\right] \tag{7}$$

for all integer n and m, $n \neq m$. Similarly, the expression (4) can be written as

$$\alpha_2(\mathbf{u}) = E\left[(\mathbf{r}^\top(n)\,\mathbf{u})^2\right] E\left[(\mathbf{r}^\top(n+m)\,\mathbf{u})^2\right] \tag{8}$$

According to (7) and (8), and using sample statistics, the function $f(\mathbf{u})$ is defined as an approximation of $\alpha(\mathbf{u})$ as

$$f(\mathbf{u}, n) = \frac{1}{F}\sum_{m=1}^{F}\{\frac{1}{2}(1-\mu)((\mathbf{r}^\top(n)\mathbf{u})^2 -$$

$$-(\mathbf{r}^\top(n+m)\mathbf{u})^2)^2 \;-\; \mu\,(\mathbf{r}^\top(n)\mathbf{u})^2(\mathbf{r}^\top(n+m)\mathbf{u})^2\} \tag{9}$$

where F is a number of consecutive symbols used for the approximation. We can use a stochastic gradient algorithm that solves (2) as

$$\hat{\mathbf{v}}^{l+1} = \hat{\mathbf{v}}^{l} \;-\; \gamma\,\nabla(f(\hat{\mathbf{v}}^{l}, l)) \tag{10}$$

where l is the index of the iteration step, and $0 < \gamma < 1$ is a certain scalar which defines the length of adaptation step. The constraint $|\hat{\mathbf{v}}^{l+1}| = 1$ is forced after every iteration, where $\hat{\mathbf{v}}^{l}$ stands for estimate of $\mathbf{v}$ in l^{th} iteration step.

As mentioned earlier, the parameter μ is used to control which of the two characteristics of $\mathbf{v}$ (low variability of the energy or significant mean energy) is dominant. We choose μ as

$$\mu = \mu(\mathbf{u}) = \frac{\left(E\left[(\mathbf{r}^\top \mathbf{u})^2\right]\right)^2}{E\left[(\mathbf{r}^\top \mathbf{u})^4\right]} \tag{11}$$

Note that the above definition is similar to the inverse of the normalized kurtosis ($k_s = E\left[(\mathbf{r}^\top \mathbf{u})^4\right]/\sigma^4$), but further analysis of this relationship is beyond the scope of this work. Furthermore, as an approximation of the above definition, we set

$$\mu(\mathbf{u}, n) = \frac{\sum_{m=1}^{F}(\mathbf{r}^\top(n)\mathbf{u})^2(\mathbf{r}^\top(n+m)\mathbf{u})^2}{\sum_{m=1}^{F}\left[(\mathbf{r}^\top(n)\mathbf{u})^4 + (\mathbf{r}^\top(n+m)\mathbf{u})^4\right]/2} \tag{12}$$

Considering characteristics of the parameter μ that is defined by (11), it can be shown that

1. If $\mathbf{r}^\top \mathbf{u}$ is a real-valued Gaussian random process, μ is 1/3.

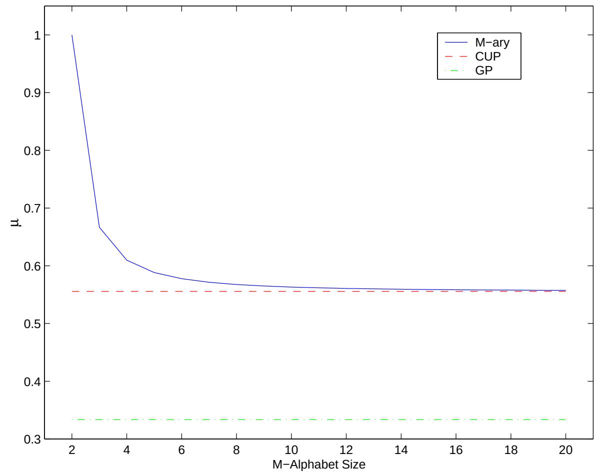

Figure 1: Parameter μ as a function of the alphabet size of uniform, real-valued M-ary random process.

2. Let μ_M denote μ corresponding to $\mathbf{r}^\top \mathbf{u}$, which is a uniform discrete real-valued M-ary random process, i.e., $\mathbf{r}^\top \mathbf{u} \in \{a_i \mid a_i = A(-1+2(i-1)/(M-1)), i = 1, \cdots, M\}$, where A is the maximum absolute value of $\mathbf{r}^\top \mathbf{u}$. Based on the above definition, it can be shown that

$$\mu_M = \frac{1}{M} \frac{\left(\sum_{i=1}^{M} a_i^2\right)^2}{\sum_{i=1}^{M} a_i^4} \tag{13}$$

Figure 1 depicts the parameter μ as a function of the alphabet size of a uniform, real-valued M-ary random process. As a reference, we present μ that corresponds to a continuous uniformly distributed random process (denoted as CU), and a Gaussian random process (denoted as GP). Note that the function is decreasing with alphabet size M, or in other words,

$$\mu_M > \mu_{M+1} \tag{14}$$

Furthermore, we may note that μ is maximum at $M = 2$ ($\mu_2 = 1$), i.e., for a real-valued bipolar random process. In addition, we note μ_M in equation (13) converges towards μ that corresponds to the continuous uniformly distributed random process (CU in Figure 1).

From the above properties of the parameter μ, we may draw the following conclusions. When the received signal of the output of the correlator, $\mathbf{r}^\top \mathbf{u}$, is a real-valued Gaussian random process (i.e., $\mathbf{u}$ lies in the noise subspace of the received vector $\mathbf{r}$), then μ takes a value close to its minimum thereby steering the MVE-MME criterion towards minimizing variance of energy (MVE). On the other hand, when the output $\mathbf{r}^\top \mathbf{u}$ is close to a discrete-valued random process (as in the case when MAI dominates), μ approaches its maximum value thus steering the MVE-MME criterion towards maximizing mean energy (MME). In the course of adaptation, the value of μ given in equation (12) changes according to the projection $\mathbf{r}^\top \mathbf{u}$, i.e. $\mathbf{u}$ being in the noise (Gaussian) part of the signal subspace or the interference (discrete-valued random process) subspace.

III. Application of the MVE-MME Criterion in the Multistage Nonlinear Blind Receiver

We now present a multistage nonlinear blind interference cancellation and channel estimation scheme, denoted as BICCE. The structure of the receiver is multidimensional and can be viewed as a matrix of receivers (i.e., matrix of IC stages). The BICCE receiver consists of P rows and Q columns, where each entry of the matrix corresponds to an interference cancellation stage denoted as $\mathbf{IC}_{ij}$ ($i = 1, \ldots, P, j = 1, \ldots, Q$). The following steps are executed in the $\mathbf{IC}_{ij}$ stage (where $\mathbf{r}_{ij}$ is the input vector to that stage):

1. Add back $\mathbf{x}_{(i-1)j}$ as

$$\mathbf{r}'_{ij} = \mathbf{r}_{ij} + \mathbf{x}_{(i-1)j} \tag{15}$$

where $\mathbf{x}_{(i-1)j}$ is a portion of the received signal that is cancelled in the $\mathbf{IC}_{i-1j}$ stage. Note that the $\mathbf{IC}_{i-1j}$ stage is the same column, but earlier row of the matrix. For the first row ($i = 1$), $\mathbf{x}_{0j} = 0$ ($j = 1, \cdots, Q$) and $\mathbf{r}_{11} = \mathbf{r}$, because no cancellation is performed prior to this row.

2. Use adaptation rule in (10) ($\mathbf{r}'_{ij}$ replaces $\mathbf{r}$) to estimate $\mathbf{v}_{ij}$ as $\hat{\mathbf{v}}_{ij}$ (see Figure 2). Note that the vector $\hat{\mathbf{v}}_{ij}$ is further processed in the very same manner as an interferer signature sequence in the case of the nonlinear centralized successive cancellation scheme (SIC)[5].

3. Estimate the energy $\beta_{ij} = E[(\mathbf{r}'^{\top}_{ij} \hat{\mathbf{v}}_{ij})^2]$. Note that the estimation should be reliable because $\hat{\mathbf{v}}_{ij}$, as a component of the vector $\mathbf{r}'_{ij}$, has low variability in the energy (due to the term $(1-\mu)\alpha_1(\mathbf{u})$ in (2)).

4. Detect the sign of $\mathbf{r}'^{\top}_{ij} \hat{\mathbf{v}}_{ij}$. Note that detection should be reliable, because the component $\hat{\mathbf{v}}_{ij}$ has significant mean energy (due to the term $-\mu\, \alpha_2(\mathbf{u})$ in (2)) and low variability.

5. Perform nonlinear cancellation as

$$\mathbf{r}_{ij+1} = \mathbf{r}'_{ij} - \mathbf{x}_{ij} \tag{16}$$

where (see Figure 3)

$$\mathbf{x}_{ij} = sgn(\mathbf{r}'^{\top}_{ij} \hat{\mathbf{v}}_{ij}) \sqrt{\hat{\beta}_{ij}}\, \hat{\mathbf{v}}_{ij} \tag{17}$$

The above procedure is executed successively (within the i^{th} row of the matrix), where for the new stage $\mathbf{IC}_{ij+1}$, the input vector is $\mathbf{r}_{ij+1}$ (see equation (16)). The structure of the i^{th} row (i.e., horizontal topology) is depicted in Figure 4. From the above, each row may be viewed as a blind equivalent to the nonlinear centralized SIC scheme, where the components $\hat{\mathbf{v}}_{ij}$ replace the actual signature sequence. After sufficient number Q of the stages in the i^{th} row, cancellation is repeated in the $(i+1)^{th}$ row (see Figure 5). The input vector $\mathbf{r}_{i+11}$ of the $(i+1)^{th}$ row is $\mathbf{r}_{iQ+1}$. The stage $\mathbf{IC}_{i+1j}$ is used to iteratively refine the cancellation which is executed in the earlier stage $\mathbf{IC}_{ij}$ ($j = 1, \ldots, Q$). With appropriate delay, the vector $\mathbf{x}_{ij}$, that is canceled in the stage $\mathbf{IC}_{ij}$ is added back (step 1), and within the stage $\mathbf{IC}_{i+1j}$ processing is performed again (steps 2 to 5).

Q is selected to be equal to the number of dominant interferers, but in the more general case, this number might not be known at the receiver. A number of different schemes can be employed in order to determine the number of IC stages

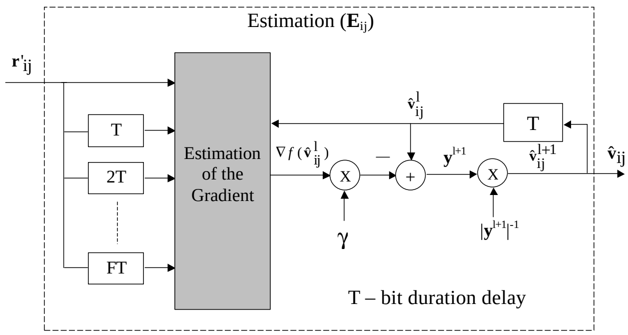

Figure 2: Block scheme: estimation of the vector $\mathbf{v}_{ij}$.

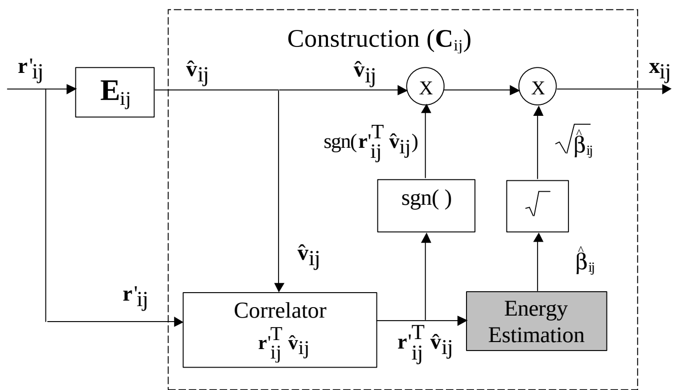

Figure 3: Block scheme: construction of the vector $\mathbf{x}_{ij}$.

within each row of this receiver. Here, we propose the following simple scheme. In the first row $i = 1$, the stage $\mathbf{IC}_{1j}$ may be determined as the last stage in the row $(Q = j)$, if the estimate of the energy $\hat{\beta}_{1j}$ drops below a certain threshold T_e. In other words

$$\hat{\beta}_{1j} < T_e \Rightarrow Q = j \tag{18}$$

This simple scheme assumes that $\hat{\beta}_{ij} \geq \hat{\beta}_{ij+1}$ (i.e., the energy estimate is decreasing with column index j). In addition, the scheme is based on the assumption that the component $\hat{\mathbf{v}}_{ij}$, that corresponds to the mean energy $\beta_{ij} = E[(\mathbf{r}'^{\top}_{ij}\hat{\mathbf{v}}_{ij})^2]$, which is below the threshold T_e, is not relevant for the cancellation. Furthermore, the number of the rows P is directly related to the performance of the receiver. Thus, the trade-off in performance versus complexity can be controlled by the number P. After sufficient number P of the rows, detection of the desired user is performed using a linear detector (e.g., matched filter).

Having all P rows and Q columns executed, and knowing just the nominal signature sequence $\mathbf{c}_1$ of the desired user ($k = 1$), we now select (i.e., estimate) effective signature sequence $\mathbf{s}_1$ as

$$G = \arg\max_j \left\{ |\mathbf{c}_1^{\top}\hat{\mathbf{v}}_{Pj}| \right\},\ \ j = 1, \cdots, Q \tag{19}$$

$$\hat{\mathbf{s}}_1 = sgn(\mathbf{c}_1^{\top}\hat{\mathbf{v}}_{PG})\hat{\mathbf{v}}_{PG} \tag{20}$$

Further detection of the desired user is performed using $\hat{\mathbf{s}}_1$ as the desired user information bearer in the vector $\mathbf{r}_{PQ+1} + \mathbf{x}_{PG}$. In other words, by executing the above step the channel is implicitly estimated and the addition is performed as follows

$$\mathbf{r}'_{PQ+1} = \mathbf{r}_{PQ+1} + \mathbf{x}_{PG} \tag{21}$$

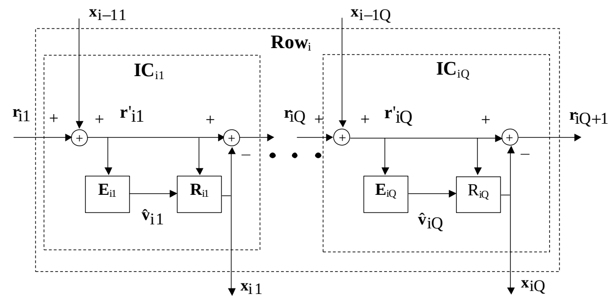

Figure 4: Horizontal topology of the BICCE receiver.

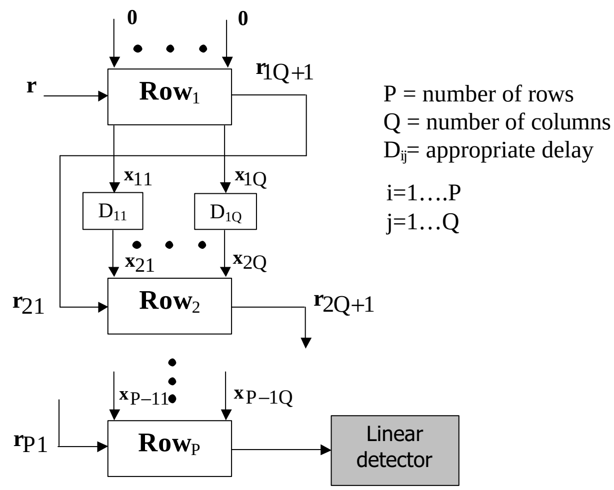

Figure 5: Vertical topology of the BICCE receiver.

Further, detection of the desired user is performed using $\mathbf{r}'_{PQ+1}$ as the input signal.

IV. Simulation Results

We consider a synchronous DS-CDMA system using Walsh-Hadamard signature sequences with processing gain $M = 8$. The system is fully loaded $K = 8$. Users are assumed to be equal in transmit energy. The channel delay spread is assumed to be $D = 7$. Channel coefficients are generated from a uniform distribution $U[-1, 1]$ and the channel response is normalized to have unit energy.

The performance of the conventional matched filter (MF), blind MMSE receiver (BMMSE) and the single user case (SU) are used as benchmarks for evaluation of the BICCE receiver. The blind MMSE receiver (BMMSE) is realized by projecting the received signal onto the vector $\hat{\mathbf{c}} = \hat{\mathbf{R}}_r^{-1}\mathbf{s}_1$, where $\hat{\mathbf{R}}_r$ is an estimate of the covariance matrix $\mathbf{R}_r = E[\mathbf{r}\,\mathbf{r}^{\top}]$. Note that in the SU case, shown in the example, the ISI is present. The above receivers assume ideal knowledge of the channel response, i.e. effective signature sequence $\mathbf{s}_1$. The performance of the BICCE is evaluated using the matched filter as the linear detector shown in Figure 5. The BICCE assumes just the knowledge of nominal signature sequence $\mathbf{c}_1$. The results are obtained after a total of $P = 3$ rows and $Q = 8$ columns. In each IC stage, the performance is measured after 2000 symbols used for the estimation in (10), and $F = 5$ in (9) and (12).

Figure 6 depicts BER as a function of signal to background noise ratio (SNR) (with respect to the desired user). Figure 7

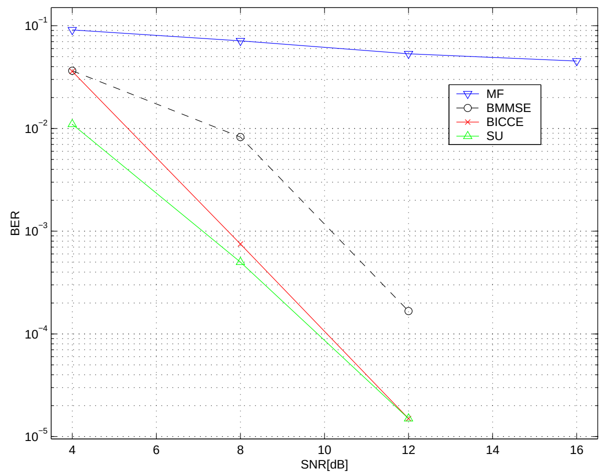

Figure 6: BER vs. SNR, spreading $M = 8$, $K = 8$ users (orthogonal Walsh-Hadamard codes are used for $\mathbf{c}_i, i = 1, \cdots, 8$, which corresponds to a synchronous downlink), channel delay spread $D = 7$.

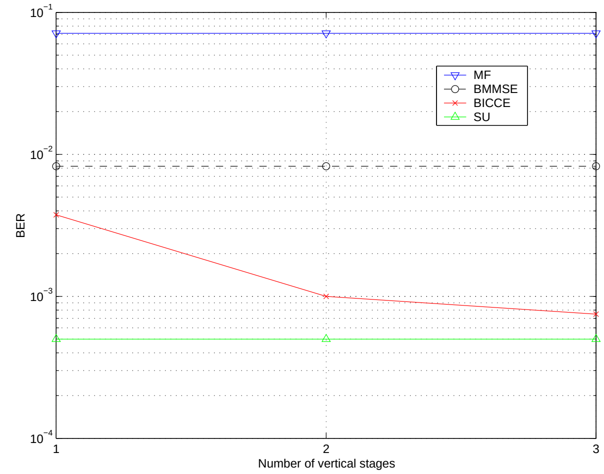

Figure 7: BER vs. Number of rows P (i.e., vertical stages), $SNR = 8\,dB$, spreading $M = 8$, $K = 8$ users (orthogonal Walsh-Hadamard codes are used for $\mathbf{c}_i, i = 1, \cdots, 8$, which corresponds to a synchronous downlink), channel delay spread $D = 7$.

depicts BER measured at an $SNR = 8\,dB$ after each row of the IC stages.

From these results, it is seen that the BICCE outperforms linear receivers, even though the linear receivers are assumed to have knowledge of the channel response. These results suggest that the BICCE may be applied as a blind solution in the case of fully loaded or even overloaded systems (presented in [8]), where it cancels MAI and estimates the channel.

V. Conclusion

In this paper we have presented a nonlinear blind interference cancellation and channel estimation scheme using higher order statistics (second and fourth moments) of the received signal. Specifically, we developed a multidimensional and iterative receiver that outperforms conventional receivers even though these receivers are assumed to know channel response perfectly, while the BICCE scheme is fully decentralized (i.e., blind). Complexity of implementation is one of the major issues which is related to this particular scheme and demands further study. In addition, the behavior of the scheme in the case of time-varying environments is to be analyzed.

References

[1] Edited by Harri Holma and Antti Toskala, "WCDMA for UMTS, Radio Access For Third Generation Mobile Communications", John Wiley and Sons Ltd. First Edition, 2000.

[2] S. Verdu, "Minimum Probability of Error for Asynchronous Gaussian Multiple-access Channels", *IEEE Transactions on Information Theory*, vol. 32, pp. 85–96, January 1986.

[3] R. Lupas and S. Verdu, "Linear Multiuser Detectors for Synchronous Code-Division Multiple-Access Channels", *IEEE Transactions on Information Theory*, vol. 35, pp. 123–136, January 1989.

[4] U. Madhow and M. L. Honig, "MMSE Interference Suppression for Direct-Sequence Spread-Spectrum CDMA", *IEEE Transactions on Communications*, vol. 42, pp. 3178–3188, December 1994.

[5] P. Patel and J. M. Holtzman, "Analysis of a Simple Successive Interference Cancellation Scheme in DS/CDMA Systems", *IEEE JSAC, Special Issue on CDMA*, vol. 12, pp. 796–807, June 1994.

[6] S. L. Miller, "An Adaptive Direct-Sequence Code-Division Multiple-Access Receiver for Multiuser Interference Rejection", *IEEE Transactions on Communications*, vol. 43, pp. 1746–1755, February/March/April 1995.

[7] P. Rapajic and B. Vucetic, "Adaptive Receiver Structure for Asynchronous CDMA Systems", *IEEE JSAC*, vol. 12, pp. 685–697, May 1994.

[8] D. Samardzija and N. Mandayam and I. Seskar, " Nonlinear Adaptive Blind Interference Cancellation for DS-CDMA Systems",*The IEEE Vehicular Technology Conference (VTC)*, September, Boston 2001.

[9] D. Samardzija, N. Mandayam and I. Seskar, "Blind Successive Interference Cancellation for CDMA Systems ", *Accepted to IEEE Transactions on Communications*, 2000.

[10] D. Samardzija and N. Mandayam and I. Seskar, "Blind Interference Cancellation for the Downlink of CDMA Systems", *Conference on Information Sciences and Systems*, vol. 2, March, TP3.17-TP3.22, Princeton University

[11] D. Godard, "Self-Recovering Equalization and Carrier Tracking in Two-Dimensional Communication Systems", *IEEE Transactions on Communications*, vol. 28, number 11, pp. 1867–1875, 1980.

[12] Edited by Simon Haykin, "Unsupervised Adaptive Filtering, Blind Deconvolution", Wiley Interscience, first edition, vol. 2, 2000.