# A VCM Approach to Multiuser Detection for DS-CDMA Frequency-Selective Fading Channels

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**Abstract— A new multiuser detector for direct-sequence code-division multiple-access (DS-CDMA) systems is proposed. In this detector, the detection is carried out by solving a linear-constrained optimization problem where the objective function is formulated based on the vector constant modulus (VCM) criterion. Two adaptation algorithms are developed for solving the optimization problem and computer simulations are conducted to evaluate the performance of the VCM detector. It is shown that this detector can effectively suppress multi-access interference (MAI) and intersymbol interference (ISI) present in the received signal. More importantly, the VCM detector offers robust detection performance against discrete-time signature distortion caused by aliasing at the receiver.**

## I. Introduction

Blind multiuser detection in direct-sequence code-division multiple access (DS-CDMA) systems has received a great deal of attention since the work of Honig *et al.* [1]. In wireless communication systems, the effective signatures can be distorted during multipath propagation and can thus become unknown to the receiver. Simulation results presented in [1] have indicated that the performance of the blind detector is very sensitive to the distortion of the effective signatures. One possible remedy for this problem is to first estimate the impulse responses of the unknown multipath channels and then to reconstruct the effective user signatures. This idea has been pursued by several authors using subspace methods [2][3] on the one hand and constrained optimization methods [4] on the other. In both methods, it is assumed that the discrete-time effective signature can be expressed as the linear convolution of the corresponding nominal signature and channel impulse response [2-4]. In typical DS-CDMA systems, however, the sampling frequency at the receiver can be lower than the *Nyquist rate* of the effective signature waveform if the highest frequency of the channel impulse response is significantly higher relative to the chip frequency of the user signatures. In this case, aliasing arises in the samples of the effective signatures and, as a result, the linear convolution relationship assumed in the above two methods breaks down. In this paper, we focus our attention on the multiuser detection problem for frequency-selective fading channels when the discrete-time effective signatures are distorted by aliasing.

As is known, the effect of aliasing can be described by using an additive term. Hence, the discrete-time effective signature can be described as the linear convolution of the nominal signature and the channel impulse response plus a distortion term that represents aliasing. In a time-varying communication channel, the distortion term may change very quickly along with the channel impulse response. For this reason, it is very difficult to timely and accurately estimate the distortion due to aliasing. Our simulation results show that detectors based on existing subspace and constrained optimization methods are very sensitive to the presence of the signature distortion caused by aliasing.

In this paper, a new multiuser detector is proposed in which the detection is carried out by solving a linear-constrained optimization problem whose objective function is formulated based on the vector constant modulus (VCM) criterion. Two adaptation algorithms are developed and computer simulations are conducted to evaluate the performance of the VCM detector. It is shown that the proposed detector can suppress multi-access interference (MAI) and intersymbol interference (ISI) effectively. More importantly, the proposed detector offers robust performance against the discrete-time signature distortion caused by aliasing at the receiver.

## II. Signal Model

Consider a $K$-user DS-CDMA system where each user is assigned a distinct signature waveform $s_k(t)$, $k = 1, 2, \ldots, K$, namely,

$$s_k(t) = \sum_{i=1}^{N} s_k(i) p_{T_c}[t-(i-1)T_c] \quad \text{for } t \in [0,\ T_b] \tag{1}$$

where $p_{T_c}(t)$ is the chip waveform which assumes nonzero values between $0 \le t \le T_c$ and is zero elsewhere, $N = T_b/T_c$ is the spreading gain and $\mathbf{s}_k = [s_k(1)\ s_k(2)\ \cdots\ s_k(N)]^T$ is the signature sequence assigned for user $k$. The signature waveforms are usually normalized to unit energy, i.e., $||s_k(t)||^2 = 1$, for $k = 1, 2, \ldots, K$. The transmitted signal of user $k$ is expressed as

$$x_k(t) = \sum_{i=-\infty}^{+\infty} A_k b_k^i s_k(t - iT_b - d_k^c) \tag{2}$$

where $b_k^i$ denotes the $i$th binary information bit, $A_k$ is the amplitude, and $d_k^c$ is the transmission delay for user $k$, respectively. For the sake of simplicity, we consider synchronous systems by assuming $d_1^c = d_2^c = \cdots = d_K^c = 0$.

The signals are transmitted through a frequency-selective fading channel and the impulse response for the signal of user $k$ can be expressed as [5]

$$g_k(t) = \sum_{m=1}^{M_k} \alpha_{km} \exp(-j\theta_{km})\, \delta(t - \tau_{km}) \tag{3}$$

where $\delta(t)$ denotes the unit impulse function, $M_k$ denotes the number of resolvable propagation paths for the signal of user $k$, $\alpha_{km}$ denotes the real amplitudes, $\tau_{km}$ denotes the excess delay, and $\theta_{km}$ denotes the additional phase shift of the $m$th propagation path for the signal of user $k$. From (2) and (3), the noise-free signal of user $k$ can be expressed as

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$$y_k(t) = x_k(t) * g_k(t) = \sum_{i=-\infty}^{+\infty} A_k b_k^i h_k(t - iT_b) \quad (4)$$

where '$*$' denotes linear convolution and $h_k(t) = s_k(t) * g_k(t)$ denotes the effective signature waveform of user $k$ due to multipath propagation. By taking all user signals and channel noise into account, the received signal $y(t)$ can be expressed as

$$y(t) = \sum_{k=1}^{K} y_k(t) + v(t) \quad (5)$$

where $v(t)$ denotes a complex-valued additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_v^2$.

At the receiver, $y(t)$ is sampled to generate $P$ samples in each chip duration. The sampled signal is given by

$$y(n) = \sum_{i=-\infty}^{\infty} \sum_{k=1}^{K} A_k b_k^i h_k(n - iPN) + v(n) \quad (6)$$

where $y(n) = y(t)|_{t=nT_c/P}$, $h_k(n) = h_k(t)_{t=nT_c/P}$, and $v(n) = v(t)|_{t=nT_c/P}$ denote the discrete-time counterparts of $y(t)$, $h(t)$, and $v(t)$, respectively. Note that when the sampling frequency, $P/T_c$, is equal to or higher than the Nyquist rate of $h_k(t)$, then $h_k(n)$ can be expressed as

$$h_k(n) = \{s_k(n)\} * \{g_k(n)\} = \sum_{m=-\infty}^{\infty} s_k(m) g_k(n - m) \quad (7)$$

where $s_k(n) = s_k(t)|_{t=nT_c/P}$ and $g_k(n) = g_k(t)|_{t=nT_c/P}$ denote the discrete-time counterparts of $s_k(t)$ and $g_k(t)$, respectively. When the sampling frequency is lower than the Nyquist rate of $h_k(t)$, however, aliasing arises in $h_k(n)$ and (7) is modified as

$$h_k(n) = \sum_{m=-\infty}^{\infty} s_k(m) g_k(n - m) + e_k(n) \quad (8)$$

where $\{e_k(n)\}$ denotes an aliasing term introduced in the discrete-time effective signatures. Note that in a frequency-selective fading channel, $e_k(n)$ stays the same within the coherent time duration but may change dramatically beyond this period. In the rest of this paper, we make the following assumptions:

1) The sampler generates one sample per chip duration, i.e., $P = 1$.
2) $\{g_k(n), n = 1, 2 \ldots\}$ for $k = 1, 2, \ldots, K$ are normalized and of finite duration with lengths no greater than $M$, where $M < N$.
3) The first user is the desired one and a coherent detection is conducted, i.e., $\theta_{1m}$ for $m = 1, \ldots, M$ are known at the receiver.

The second assumption implies that the detection of the current symbol only depends on the signal samples in the previous, the current, and the subsequent symbol durations. By collecting $N + M - 1$ samples of $y(n)$ to form a vector $\mathbf{y} = [y(1)\ y(2)\ \cdots\ y(N + M - 1)]^T$, (5) can be expressed in a matrix form as

$$\mathbf{y} = \sum_{j=-1}^{1} \sum_{k=1}^{K} A_k b_{k,j} \mathbf{h}_{k,j} + \mathbf{v} \quad (9)$$

where the subscripts $j = -1, 0$, and 1 denote the previous, the current, and the subsequent symbol duration, $b_{k,j}$ and $\mathbf{h}_{k,j}$ denote the information bit and the discrete-time effective signature of the $j$th symbol duration of user $k$, and $\mathbf{v} = [v(1)\ v(2)\ \cdots\ v(N+M-1)]^T$ is a vector of complex-valued white Gaussian noise source with zero-mean and covariance matrix $\sigma_v^2\mathbf{I}$. Specifically, $\mathbf{h}_{k,0}$ can be expressed as

$$\mathbf{h}_{k,0} = \mathbf{S}_k \mathbf{g}_k + \mathbf{e}_k \qquad \text{for} \quad k = 1, 2, \ldots, K \quad (10)$$

where $\mathbf{g}_k = [g_k(1)\ g_k(2)\ \cdots\ g_k(M)]^T$, $\mathbf{e}_k = [e_k(1)\ e_k(2)\ \cdots\ e_k(N+M-1)]^T$, and $\mathbf{S}_k$ is defined as an $(N+M-1) \times M$ Toeplitz matrix whose first column and the first row vectors are $[\mathbf{s}_k^T\ 0 \cdots 0]^T$ and $[s_k(1)\ 0\ \cdots\ 0]$, respectively.

## III. A VCM-Based Blind Multiuser Detector

### *A. Brief Review of VCM Approach*

The VCM approach was first proposed for blind channel equalization whereby the source signal has a near-Gaussian distribution and a channel equalizer using a constant modulus (CM) approach fails to converge. It has been shown that the performance of the equalizer based on the VCM approach is superior to that of the equalizer based on the CM based approach [9].

Let $\mathbf{a} = \{a(n)\}$, $\mathbf{c} = \{c(n)\}$, $\mathbf{x} = \{x(n)\}$, $\mathbf{w} = [w_1\ w_2 \cdots w_L]^T$, and $\mathbf{z} = \{z(n)\}$ denote the transmitted signal, the channel impulse response, the received signal, the equalization vector, and the equalized signal, respectively. On the basis of these assumptions, we have $\mathbf{x} = \mathbf{a} * \mathbf{c}$ and $\mathbf{z} = \mathbf{w} * \mathbf{x}$. The VCM-based channel equalizer is characterized by the solution of the minimization problem [9]

$$\text{minimize}: \quad \mathcal{J}(\mathbf{w}) = \mathrm{E}\ \left[\|\mathbf{z}\|^2 - \alpha^2\right]^2 \quad (11)$$

where $\|\mathbf{z}\|$ denotes the norm of $\mathbf{z}$ and $\alpha = \mathrm{E}(\mathbf{a}^4)/\mathrm{E}(\mathbf{a}^2)$ is a constant denoting the modulus of source signal.

### *B. VCM-Based Multiuser Detector*

Consider suppressing the interference in DS-CDMA systems by using a VCM approach. By regarding the signals of the previous and the subsequent symbol durations as the signals of the current symbol duration of additional $2K$ users, (9) can be written as

$$\mathbf{y} = \sum_{k=1}^{3K} \bar{A}_k \bar{b}_k \bar{\mathbf{h}}_k + \mathbf{v} \quad (12)$$

In (12), $\bar{A}_k$ is the amplitude, $\bar{b}_k$ is the information bit, and $\bar{\mathbf{h}}_k$ is the discrete-time effective signature of the $k$th equivalent user, which are defined in Table 1.

TABLE I
DEFINITIONS OF $\bar{A}_k$, $\bar{b}_k$, AND $\bar{\mathbf{h}}_k$ FOR (12)

| $k$ | $k \in [1,\ K]$ | $k \in [K+1,\ 2K]$ | $k \in [2K+1,\ 3K]$ |
|---|---|---|---|
| $\bar{A}_k$ | $A_k$ | $A_{k-K}$ | $A_{k-2K}$ |
| $\bar{b}_k$ | $b_{k,0}$ | $b_{k,-1}$ | $b_{k,+1}$ |
| $\bar{\mathbf{h}}_k$ | $\mathbf{h}_{k,0}$ | $\mathbf{h}_{k,-1}$ | $\mathbf{h}_{k,1}$ |

Note that after the reformulation, the ISI of the previous and subsequent symbol durations in (9) becomes the MAI from $2K$ equivalent users in (12). According to Table 1, the current information bit of the desired user corresponds to the first equivalent user in (12). If we denote the detection vector of the VCM detector as $\mathbf{w}$, it is easy to see that

$$\mathbf{w} * \mathbf{y} = \mathbf{w}^H [\mathbf{y}_1\ \mathbf{y}_2\ \cdots\ \mathbf{y}_M] \tag{13}$$

where, $\mathbf{y}_m = [y(m)\ y(m+1)\ \cdots\ y(m+N-1)]^T$ is a $N \times 1$ column vector which, according to (12), can be expressed as

$$\mathbf{y}_m = \sum_{k=1}^{3K} \bar{A}_k \bar{b}_k \bar{\mathbf{h}}_{k,m} + \mathbf{v}_m \tag{14}$$

In (14), $\bar{\mathbf{h}}_{m,k} = [\bar{\mathbf{h}}_k(m)\ \bar{\mathbf{h}}_k(m+1)\ \cdots\ \bar{\mathbf{h}}_k(m+N-1)]^T$ and $\mathbf{v}_m = [\mathbf{v}(m)\ \mathbf{v}(m+1)\ \cdots\ \mathbf{v}(m+N-1)]^T$ are truncated counterparts of $\bar{\mathbf{h}}_k$ and $\mathbf{v}$ in (12), respectively.

According to (12)-(14), the proposed VCM based detector is characterized by the solution of the optimization problem

$$\text{minimize} \quad \mathrm{E}\left[||\mathbf{w}^H \mathbf{Y}||^2 - \bar{A}_1^2\right]^2 \tag{15a}$$

$$\text{subject to:} \quad \mathbf{C}^H \mathbf{w} = \mathbf{u} \tag{15b}$$

where $\mathbf{Y} = [\mathbf{y}_1\ \mathbf{y}_2\ \cdots\ \mathbf{y}_M]$, $\bar{A}_1^2 = A_1^2$ denotes the modulus of the signal of the desired equivalent user, $\mathbf{C}$ is a $N \times (2M-1)$ Toeplitz matrix where the first column and the first row vectors are given by $[s_1(M)\ s_1(M+1)\ \cdots s_1(N)\ 0\ \cdots\ 0]^T$ and $[s_1(M)\ s_1(M-1)\ \cdots s_1(1)\ 0 \cdots 0]$, respectively, $\mathbf{u}$ is a $(2M-1) \times 1$ vector with its $M$th component being one and all other components being zeros.

There are two purposes for introducing the linear constraint in (15) into the optimization problem. The first is to fix $\mathbf{w}^H \mathbf{s}_1 = 1$ and the second is to force the orthogonality of $\mathbf{w}$ to all other shifted and truncated counterparts of $\mathbf{s}_1$. In doing so, the term $\mathbf{w}^H \bar{\mathbf{h}}_{1,m}$ included in the objective function in (15a) can be expressed as

$$\mathbf{w}^H \bar{\mathbf{h}}_{1,m} = g_1(m) + \mathbf{w}^H \mathbf{e}_{1,m} \tag{16}$$

where $\mathbf{e}_{1,m} = [e_1(m)\ e_1(m)\ \cdots\ e_1(m+N-1)]^T$ is a truncated counterpart of $\mathbf{e}_1$. If we temporarily ignore the error term in (16), it can be shown that minimizing the objective function in (15a) leads to the suppression of the terms $\mathbf{w}^H \bar{\mathbf{h}}_{k,m}$ for $k = 2, 3, \ldots, 3K$ and $m = 1, 2, \ldots, M$. In other words, the MAI signal of the other equivalent users can be effectively suppressed by $\mathbf{w}$.

Once the optimization problem in (15) is solved, the information bit of user one can be demodulated according to the *maximum ratio combination* (MRC) criterion as [7]

$$\hat{b}_1(i) = \mathrm{sign}\left[\mathrm{Re}(\mathbf{w}^H \mathbf{Y} \cdot \hat{\mathbf{g}}_1^*)\right] \tag{17}$$

where $\mathrm{Re}(\cdot)$ denotes the real part of a complex quantity, $\mathrm{sign}(\cdot)$ denotes the sign of a scalar, and $\hat{\mathbf{g}}_1^* = [\hat{\mathbf{g}}_1^*(1)\ \hat{\mathbf{g}}_1^*(2)\ \cdots\ \hat{\mathbf{g}}_1^*(M)]^T$ is an approximation of the channel impulse response of user one, which can be computed as

$$\hat{\mathbf{g}}_1^*(m) = \mathrm{E}\left|\mathbf{w}^H \mathbf{y}_m\right| \exp(-j\theta_{1m}) \quad \text{for} \quad m = 1, 2, \ldots, M \tag{18}$$

We conclude this section with two remarks:

1) *Channel Order Selection*: Though it is assumed that the maximum channel length for all users is $M$, it does NOT imply that the channels should be of the maximum length exactly. In fact, if the number of nonzero components in $\mathbf{g}_1$ is less than $M$ and their positions are known *a priori*, then the redundant constraints can be removed from (15b) to reduce the amount of computation required.

2) *Group-Blind Detectors*: In uplink CDMA systems, the nominal signatures of other users may be known at base station. In this case, the performance of the proposed detector can be improved by expanding the linear constraint in (15b) in a way that forcing $\mathbf{w}$ to be orthogonal to the shifted and truncated counterparts of the nominal signatures of the other users known at receiver. Interested readers are referred to [6] for more details.

## IV. Adaptation Algorithms

In this section, two adaptation algorithms, namely, the constrained stochastic gradient (CSG) algorithm and the recursive VCM (RVCM) algorithm, are proposed for solving the optimization problem in (15).

In the CSG algorithm, the detection vector $\mathbf{w}$ is initialized as $\mathbf{w}(0) = \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{u}$, which is one of the solutions for the equality in (15b). In each iteration of the CSG algorithm, we first compute the instantaneous gradient of the objective function, denoted as $\mathbf{g}(i)$. Then $\mathbf{g}(i)$ is projected onto $\mathbf{\Pi}_c^\perp$ so that the updated detection vector can still satisfy the constraint in (15b) in the next iteration. The step-size used for the adaptation algorithm is normalized to improve the convergence rate of the algorithm. A step-by-step description of the algorithm is presented in Table 2 where $\mathbf{Y}(i)$ is formulated based on the observation of $\mathbf{y}$ at the $i$th symbol duration according to (15).

TABLE II
CONSTRAINED STOCHASTIC GRADIENT ALGORITHM

| | |
|---|---|
| Step 1: | Compute the initial solution as $\mathbf{w}(0) = \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{u}$. |
| Step 2: | Compute $\mathbf{\Pi}_\mathbf{C}^\perp = \mathbf{I} - \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{C}^H$. |
| Step 3: | For $i = 0, 1, 2, \ldots$<br>(1) Compute $e(i) = \|\|\mathbf{w}^H(i)\mathbf{Y}(i)\|\|^2 - A_1^2$.<br>(2) Compute the stochastic gradient as $\mathbf{g}(i) = e(i) \cdot \mathbf{Y}(i)\mathbf{Y}^H(i)\mathbf{w}(i)$ and its projection on $\mathbf{\Pi}_\mathbf{C}^\perp$ as $\tilde{\mathbf{g}}(i) = \mathbf{\Pi}_\mathbf{C}^\perp\ \mathbf{g}(i)$, respectively.<br>(3) Compute the normalized step-size as $\mu(i) = \|\|\tilde{\mathbf{g}}(i)\|\|^2 / \left[e(i) \cdot \|\|\tilde{\mathbf{g}}^H(i)\mathbf{Y}(i)\|\|^2\right]$<br>(4) Update the detection vector as $\mathbf{w}(i+1) = \mathbf{w}(i) - \mu(i) \cdot \tilde{\mathbf{g}}(i)$ |

Because the objective function in (15a) involves fourth-order statistics of the received signal, the convergence rate of the stochastic gradient type algorithms can be rather slow [8]. When the statistics of the received signal experience dramatical change in a fast frequency-selective fading channel, the CGS algorithm may fail to track the variation of the received signal. In what follows, a recursive VCM (RVCM) algorithm is proposed which offers faster convergence rate at the cost of increased amount of computation.

The RVCM algorithm is developed on the basis of the well-known recursive least square (RLS) algorithm [8]. The initialization for the RVCM algorithm is the same as that for the CGS algorithm. Two key formulas for the RVCM algorithm are given by

$$\mathbf{k}(i) = \frac{1}{\lambda + \mathbf{s}^H(i)\mathbf{P}(i-1)\mathbf{s}(i)} \cdot \mathbf{P}(i-1)\ \mathbf{s}(i) \tag{19a}$$

$$\mathbf{P}(i) = \frac{1}{\lambda} \cdot \left[\mathbf{P}(i-1) - \mathbf{k}(i)\mathbf{s}^H(i)\mathbf{P}(i-1)\right] \tag{19b}$$

where $\mathbf{s}(i) = \mathbf{\Pi}_\mathbf{C}^\perp \mathbf{Y}(i)\mathbf{Y}^H(i)\mathbf{w}(i)$, $\mathbf{P}(i)$ is a matrix to approximate the inverse of the crosscorrelation matrix of $\mathbf{s}(i)$, and $0 \le \lambda \le 1$ is a forgetting factor. A step-by-step description of the RVCM algorithm is presented in Table 3.

## V. Simulation Results

Two Monte-Carlo computer simulations were conducted to investigate the performance of the VCM detector when $\mathbf{e}_k$ for $k = 1, \ldots, K$ were present at receiver. The performance measure in the

TABLE III
RECURSIVE VCM ALGORITHM

Step 1: Initialize $\mathbf{P}(0) = \delta\mathbf{I}$ with $\delta$ to be a positive scalar and
$\mathbf{w}(0) = \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{u}$.
Step 2: Compute $\mathbf{\Pi}_{\mathbf{C}}^{\perp} = \mathbf{I} - \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{C}^H$.
Step 3: For $i = 0, 1, 2, \ldots$
(1) Compute $e(i) = ||\mathbf{w}(i)^H\mathbf{Y}(i)||^2 - A_1^2$.
(2) Compute $\mathbf{s}(i) = \mathbf{\Pi}_{\mathbf{C}}^{\perp}\mathbf{Y}(i)\mathbf{Y}^H(i)\mathbf{w}(i)$.
(3) Update $\mathbf{k}(i)$ as $\mathbf{k}(i) = \mathbf{P}(i)\mathbf{s}(i)/\left[\lambda + \mathbf{s}^H(i)\mathbf{P}(i)\mathbf{s}(i)\right]$.
(4) Update the detection vector as
$\mathbf{w}(i+1) = \mathbf{w}(i) - e(i)\cdot\mathbf{k}(i)$
(5) Update $\mathbf{P}(i+1) = (1/\lambda)\cdot\left[\mathbf{P}(i) - \mathbf{k}(i)\mathbf{s}^H(i)\mathbf{P}(i)\right]$.

simulations is the bit-error-rate (BER) averaged over 100 runs. In each run, the detector coefficients for both algorithms were obtained after convergence and the BERs were obtained based on the detection of $10^5$ information bits. In both simulations, $\mathbf{s}_k$ and $\mathbf{g}_k$ were modeled as vectors of zero-mean Gaussian variables of unity norm, and $A_k$ was assumed to be a log-normally distributed random variable whose logarithmic variance is denoted by $\sigma_a^2$. For the sake of simplicity, $\mathbf{e}_k$ for $k = 1, \ldots, K$ were modeled as vectors of Gaussian variables with zero-mean and variance $\gamma$. These parameters remain unchanged in a single run but were distinct in different runs. For comparison purposes, the BERs obtained by the constrained optimization method and the subspace method were also evaluated.

In the first example, we considered a 6-user DS-CDMA system with light near-far problem where $\sigma_a^2$, $N$, and $M$ were assumed to be $\sigma_a^2 = 10$, $N = 63$, and $M = 4$, respectively. In the second example, we considered an 8-user DS-CDMA system with more severe near-far problem where $\sigma_a^2$, $N$, and $M$ were assumed to be $\sigma_a^2 = 10^3$, $N = 127$, $M = 5$, respectively. The BERs of various detectors versus the magnitude of $\gamma$ obtained in the two examples are plotted in Figs. 1 and 2 where the dash-dot, dot, and dash lines denote the BERs obtained for $\gamma = 0.01$, 0.03, and 0.05, respectively.

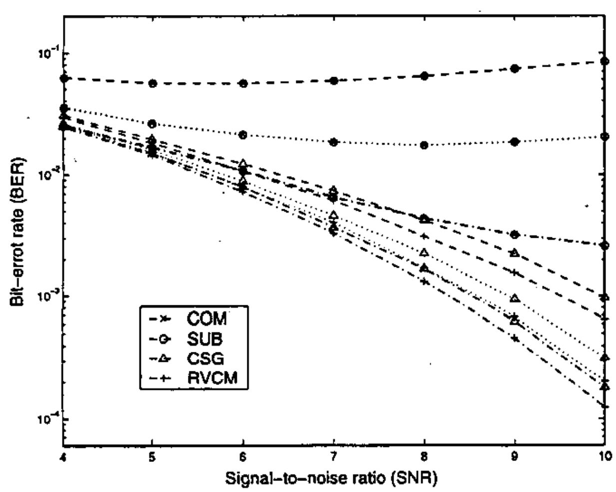


Fig. 1. Demodulation bit-error rates in the first example.

It can be seen from Figs. 1 and 2 that the VCM detectors offer improved BERs relative to the other two detectors for nonzero values of $\gamma$. In addition, the BER performance offered by the VCM detector using the RVCM algorithm is slightly better relative to that of the VCM detector using the CGS algorithm.

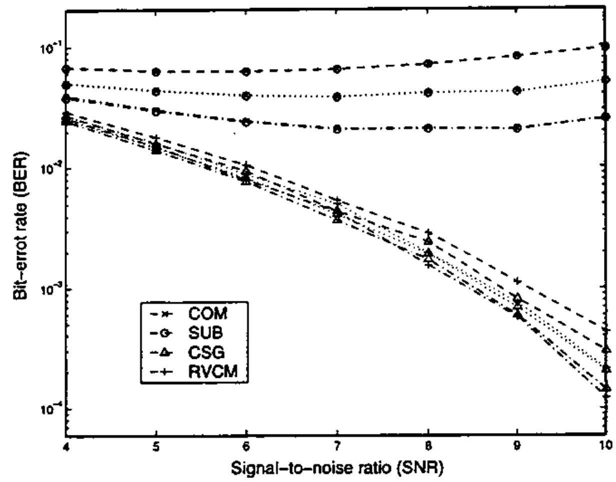


Fig. 2. Demodulation bit-error rates in the second example.

## VI. CONCLUSIONS

A new multiuser detector for direct-sequence code-division multiple-access (DS-CDMA) systems has been proposed based on the VCM criterion. Two adaptation algorithms have been developed and computer simulations have been conducted to evaluate the performance of the VCM detector. It has been shown that the VCM detector can effectively suppress the MAI and ISI present in the received signal. More importantly, this detector offers robust performance against discrete-time signature distortion caused by aliasing at the receiver.

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## REFERENCES

[1] M. Honig, U. Madhow, and S. Verdù, "Blind adaptive multiuser detection," *IEEE Trans. Inform. Theory*, vol. 41, pp. 944-960, July 1995.

[2] H. Liu and G. Xu, "A subspace method for signature waveform estimation in synchronous CDMA systems," *IEEE Trans. Commun.*, vol. 44, pp. 1346-1354, Oct. 1996.

[3] S. E. Bensley and B. Aazhang, "Subspace-based channel estimation for code division multiple access communication systems," *IEEE Trans. Commun.*, vol. 44, pp. 1009-1020, Aug. 1996.

[4] M. K. Tsatsanis and Z. Xu, "Performance analysis of minimum variance CDMA receivers," *IEEE Trans. Signal. Processing*, vol. 46, pp. 3014-3022, Nov. 1998.

[5] T. S. Rappaport, *Wireless Communications: Principles & Practice*, Upper Saddle River: Prentice Hall, NJ, 1996.

[6] X. Wang and A. Host-Madsen, "Group-blind multiuser detection for uplink CDMA," *IEEE Journal on Selected Areas in Commun.*, vol. 17, no. 11, Nov. 1999.

[7] J. G. Proakis, *Digital Communications*, 3rd ed., New York: McGraw-Hill, 1995.

[8] S. Haykin, *Adaptive Filter Theory*, 3rd ed., Englewood Cliffs, NJ: Prentice-Hall, 1996.

[9] V. Y. Yang and D. L. Jones, "A vector constant modulus algorithm for shaped constellation equalization," *IEEE Sigal Processing Letters*, vol. 5, No. 4, pp. 89-91, Apr. 1998.