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A low complexity partially adaptive CDMA receiver for downlink mobile satellite communications

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SUMMARY

A novel CDMA receiver with enhanced interference suppression is proposed for pilot symbols assisted mobile satellite systems in the presence of frequency offset. The design of the receiver involves the following procedure. First, adaptive correlators are constructed at different fingers, based on the scheme of generalized sidelobe canceller (GSC), to collect the multipath signals and suppress multi-access interference (MAI). In particular, a partially adaptive (PA) realization of the GSC correlators is proposed based on the Krylov subspace technique, leading to an efficient algorithm without the need of complicated matrix computations. Second, pilot symbols assisted frequency offset estimation, channel estimation and RAKE combining give the estimate of signal symbols. Finally, further performance enhancement is achieved by an iterative scheme in which the signal is reconstructed and subtracted from the GSC correlators input, leading to faster convergence of the receiver. The proposed low complexity PA receiver is suitable or the downlink of mobile satellite CDMA systems, and shown to outperform the conventional fully adaptive MMSE receiver by using a small number of pilot symbols. Copyright © 2003 John Wiley & Sons, Ltd.

KEY WORDS: CDMA; mobile satellite; interference suppression; generalized sidelobe canceller; partial adaptivity; Krylov subspace technique

1. INTRODUCTION

In order to improve mobility and guarantee worldwide access, satellite based systems have been proposed for the third generation mobile communications [1]. In areas with a small population or low infrastructure, satellite communications are especially superior to terrestrial mobile communications. Satellite based systems can also be used as a complement to existing communication networks in order to increase the availability of services to mobile users. Worldwide access provisioning can be achieved by developing the mobile satellite systems in the form of multi-satellite constellation in non-geostationary earth orbits. For example, the low earth orbit (LEO) satellite systems are a promising solution. The realization of handover

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between different satellites and choosing of a multiple access scheme are two important issues for a LEO satellite communication system. Both problems can be managed by using the code division multiple access (CDMA) technology with multi-satellite diversity. In the present and next generation mobile satellite communication systems, CDMA has been proposed as a major multiple access scheme [1, 2]. However, two factors that limit the overall capacity of a CDMA system are the multiple access interference (MAI) and multipath fading. In the worst case, strong MAI causes the near-far problem and severe multipath propagation induces deep fading and/or inter-symbol interference (ISI). In mobile satellite communications the propagation channel is typically a mild Ricean channel with a short delay spread. Path diversity is usually exploited by introducing artificial delayed paths from multiple satellites. On the other hand, some form of interference mitigation can be employed to boost the system capacity significantly [1].

In mobile satellite systems, diversity can be accomplished by simultaneous transmission to multiple satellites. The waveforms are then retransmitted to an earth station, where they are combined to yield diversity gain [3]. In wideband CDMA systems, the multipath environment can be exploited through the RAKE receiver, allowing signals arriving at the receiver with different propagation delays to be independently received and coherently combined by exploiting the temporal signature of the channel. On the other hand, in order to successfully detect data from the desired user, the MAI need to be suppressed effectively. Adaptive multi-user detectors (MUD) and interference cancellers have been suggested which provide full or partial immunity to the near-far effect [4]. The performance of an optimal MUD [4] in a multi-user system can approach that in a single-user environment. Unfortunately, the optimal MUD is impractically complex. As an alternative, the sub-optimal linear multi-user detector is an improved version of the conventional RAKE receiver, with the improvement due to better MAI suppression via either post- or pre-despread processing [5]. The post-despread MUD works with the outputs of a bank of filters, each matched to a user of interest. The pre-despread MUD can be regarded as an adaptive matched filter that performs despreading and MAI suppression simultaneously. Popular pre-despread MUDs include the minimum mean squared error (MMSE) [6] and minimum output energy (MOE) [7] receivers. In particular, the MOE receiver derives its filter weights by minimizing the output energy subject to a unit response constraint for the desired signal. It is similar in structure to the linearly constrained minimum variance (LCMV) beamformer in array processing [8, 9], and is shown to offer the performance of the MMSE receiver without the need of channel information [7]. Unfortunately, the MOE receiver exhibits high sensitivity to channel mismatch and does not perform reliably in the presence of multipath propagation. Although the pre-despread CDMA receivers provide excellent MAI suppression, they requires an $(M-1)$-dimensional adaptive processing, where M is the processing gain. To reduce the complexity due to a large M, partially adaptive (PA) realization is suggested as an alternative with which the number of adaptive weights is reduced [8–10]. The advantages of PA implementation include not only reduced complexity but also faster convergence.

In this paper, a novel CDMA receiver with enhanced interference suppression is proposed for pilot symbols assisted mobile satellite systems in the presence of frequency offset. The design of the receiver involves the following procedure. First, a set of adaptive correlators is constructed to collect multipath signals with different delays. The tap weights of each correlator are determined in accordance with the LCMV criterion so that strong MAI can be effectively suppressed blindly. To avoid signal cancellation incurred with channel mismatch, these LCMV correlators are realized in the form of generalized sidelobe canceller (GSC) [8, 9]. For reduced complexity processing, partial adaptivity is incorporated which is done by selecting a reduced dimension subspace of the column space of the blocking matrix by using the Krylov subspace technique [11]. Second, a simple coherent RAKE combiner with pilot aided channel estimation gives the desired user's symbol decisions. Since strong interference has been removed, channel estimation can be done accurately with a small number of pilot symbols. Finally, further performance enhancement is achieved by an iterative scheme in which the signal is reconstructed and subtracted from the GSC correlators input, leading to faster convergence of the receiver. The proposed low complexity PA receiver is suitable for the downlink of mobile satellite CDMA systems, and is shown to outperform the conventional fully adaptive MMSE receiver by using a relatively small number of pilot symbols.

2. DATA MODEL AND LINEAR CDMA RECEIVERS

Consider a mobile satellite communications system in which each satellite is equipped with S spot beams. The ground gateways are equipped with directional antennas, one for each satellite as shown in Figure 1. The transmitted field from the satellite is received by a mobile terminal in three basic ways: (1) the direct component, which is the line-of-sight (LOS) wave; (2) the specular component, which represents the field collected from a single reflection and arrives as a delayed version of the direct component; (3) the diffuse component. For simplicity, the downlink transmission channel is modelled as with L resolved Rayleigh or Rician fading paths due to either satellite diversity or multipath. The Rician probability density function is commonly used to model a clear LOS path, while the Rayleigh probability density function models a blocked LOS path with which the received signal comes from multipath. Furthermore, in order to account for users' mobility when evaluating the performance of a mobile satellite system, a time-shared combination of a 'good' state fading for the LOS path and a 'bad' fading

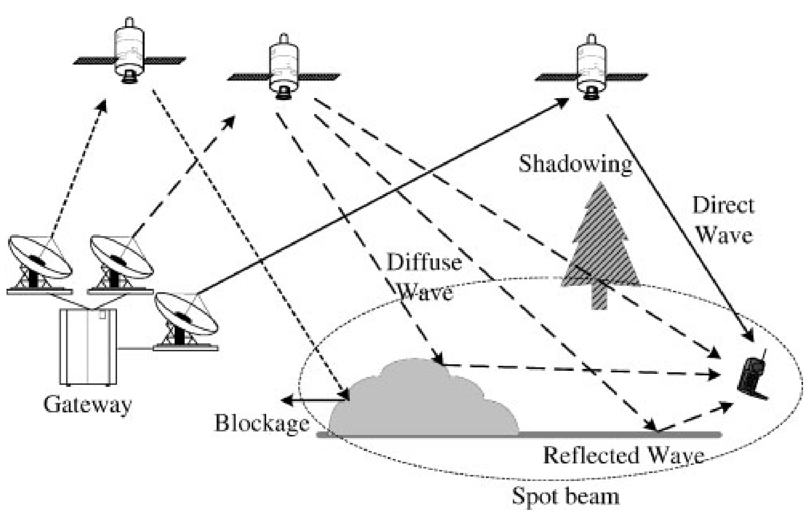

Figure 1. Illustration of mobile satellite communications.

for the non-LOS path is introduced. This is described by the mixture envelop probability density function [12,13]:

$$f_\alpha(\alpha) = B\frac{\alpha}{\sigma^2}\,\mathrm{e}^{-\frac{\alpha}{2\sigma^2}} + (1-B)\frac{\alpha}{\sigma^2}\,\mathrm{e}^{-\frac{\alpha^2+A_s^2}{2\sigma^2}} I_0\left(\frac{\alpha A_s}{\sigma^2}\right) \tag{1}$$

where B is defined as the fraction of time that a path is in a bad fading state, while $(1-B)$ is the fraction of time that the path is in a good fading state. A_s is the amplitude of the specular component of the Rician part of the density, $2\sigma^2$ is the average power of the diffuse component, and $I_0(\cdot)$ is the modified Bessel function of the first kind and zeroth order [13].

Consider a scenario in which K active CDMA users are present in the downlink of the system. The kth user's contribution to the received signal can be written as

$$r_k(t) = \sigma_k \sum_i d_k(i) c_k(t - iT) \tag{2}$$

where $d_k(i)$ denotes the ith transmitted information symbol assumed to be i.i.d. with zero-mean and unit variance, T is the symbol duration, σ_k^2 is the transmit power, and $c_k(t)$ is the signature waveform given by

$$c_k(t) = \sum_{m=0}^{M-1} c_k[m]\, p(t - mT_c) \tag{3}$$

where $c_k[m]$ is the spreading sequence of the kth user, M is the spreading factor, $p(t)$ is the chip waveform, and T_c is the chip duration. Putting the K user signals together, the received baseband data can be expressed in the following form:

$$x(t) = \sum_{k=1}^{K}\sum_{l=1}^{L} \alpha_{k,l}\mathrm{e}^{\mathrm{j}2\pi\Delta f_k t} r_k(t-\tau_{k,l}) + n(t) \tag{4}$$

where Δf_k is the frequency offset associated with the kth user (due to oscillator drifting or Doppler shift), $\tau_{k,l}$ and $\alpha_{k,l}$ are the delay and complex gain, respectively, of the lth path of the kth user, and $n(t)$ is the additive white noise process with power σ_n^2. It is assumed that the L paths arrive within a delay spread of L chips, with each path having a different delay of integer number of chips. It is also assumed that initial acquisition is performed properly such that a rough estimate of timing/frequency offset is available for each user. In this case, Δf_k is considered the residual frequency offset. To fully exploit the temporal signature, $x(t)$ is chip matched filtered and then chip rate sampled at $t = iT_s + mT_c$ over one symbol duration plus delay spread, i.e. $m = 0, 1, \ldots, M+L-2$. The resulting discrete-time data over the ith symbol is given by

$$x_m(i) = \sum_{k=1}^{K} \sigma_k \sum_{l=1}^{L} \alpha_{k,l}\mathrm{e}^{\mathrm{j}2\pi\Delta f_k(iT_s+mT_c)} r_{k,m}(i) + n_m(i) \tag{5}$$

where $r_{k,m}(i) = r_k(t-\tau_{k,l})|_{t=iT_s+mT_c}$ and $n_m(i) = n(t)|_{t=iT_s+mT_c}$. Assuming that the user 1 is the desired user, and putting the chip-sampled data over the ith symbol into an $(M+L-1)\times 1$

vector, we have

$$
\begin{aligned}
\mathbf{x}(i) &= [x_0(i), x_1(i), \ldots, x_{M+L-2}(i)]^{\mathrm{T}} \\
&= \sum_{k=1}^{K} \sigma_k \sum_{l=1}^{L} \alpha_{k,l}(\mathbf{c}_{k,l} \odot \Delta\mathbf{f}_k) d_k(i) \mathrm{e}^{\mathrm{j}2\pi\Delta f_k i T_s} + \mathbf{n}(i) \\
&= \mathbf{h}_1 d_{1,\delta}(i) + \sum_{k=2}^{K} \mathbf{h}_k d_{k,\delta}(i) + \mathbf{n}(i) \\
&= \mathbf{s}_1(i) + \mathbf{i}(i) + \mathbf{n}(i)
\end{aligned} \tag{6}
$$

where T denotes the transpose,

$$\mathbf{c}_{k,l} = [\mathbf{0}_{l-1}^{\mathrm{T}}, c[0], c[1], \ldots, c[M-1], \mathbf{0}_{L-l}^{\mathrm{T}}]^{\mathrm{T}} \tag{7}$$

$$\Delta\mathbf{f}_k = [1, \mathrm{e}^{\mathrm{j}2\pi\Delta f_k T_c}, \ldots, \mathrm{e}^{\mathrm{j}2\pi\Delta f_k (M+L-2) T_c}]^{\mathrm{T}} \tag{8}$$

$\odot$ denotes the Hadamard (elementwise) product and $\mathbf{0}_n$ is the $n \times 1$ zero vector. The $\mathbf{h}_k$ is the effective composite signature vector (CSV) of user k given by

$$\mathbf{h}_k = \sigma_k \sum_{l=1}^{L} \alpha_{k,l}(\mathbf{c}_{k,l} \odot \Delta\mathbf{f}_k) \tag{9}$$

$$d_{k,\delta}(i) = d_k(i) \mathrm{e}^{\mathrm{j}2\pi\Delta f_k i T_s} \tag{10}$$

is the 'frequency shifted' symbol varying with time index i. Finally, $\mathbf{s}_1(i) = \mathbf{h}_1 d_1(i) \mathrm{e}^{\mathrm{j}2\pi\Delta f_1 i T_s}$ is the signal vector, $\mathbf{i}(i) = \sum_{k=2}^{K} \mathbf{h}_k d_k \mathrm{e}^{\mathrm{j}2\pi\Delta f_k i T_s}(i)$ is the MAI vector, and $\mathbf{n}(i)$ is the noise vector.

A receiver for user 1 is designed to identify and remove $\mathbf{h}_1$ to retrieve $d_1(i)$ from $\mathbf{i}(i)$ and $\mathbf{n}(i)$. In particular, a linear receiver combines $\mathbf{x}(i)$ using a weight vector $\mathbf{w}_k$ to obtain

$$\hat{d}_{1,\delta}(i) = \mathbf{w}_1^{\mathrm{H}} \mathbf{x}(i) \tag{11}$$

where H denotes the complex conjugate transpose. A popular criteria for choosing $\mathbf{w}_1$ leads to the MMSE receiver:

$$\mathbf{w}_{\mathrm{MMSE}} = \mathbf{R}_x^{-1} \hat{\mathbf{h}}_1 \tag{12}$$

where $\hat{\mathbf{h}}_1$ is an estimate of $\mathbf{h}_1$ and $\mathbf{R}_x$ is the data correlation matrix given by

$$\mathbf{R}_x = E\{\mathbf{x}(i)\mathbf{x}(i)^{\mathrm{H}}\} = \mathbf{R}_s + \mathbf{R}_{in} \tag{13}$$

where

$$\mathbf{R}_s = E\{\mathbf{s}_1(i)\mathbf{s}_1(i)^{\mathrm{H}}\} = \mathbf{h}_1 \mathbf{h}_1^{\mathrm{H}} \tag{14}$$

$$\mathbf{R}_{in} = E\{(\mathbf{i}(i) + \mathbf{n}(i))(\mathbf{i}(i) + \mathbf{n}(i))^{\mathrm{H}}\} = \sum_{k=2}^{K} \mathbf{h}_k \mathbf{h}_k^{\mathrm{H}} + \sigma_n^2 \mathbf{I} \tag{15}$$

Another type of optimal receiver is the maximum SINR (MSINR) receiver given by

$$\mathbf{w}_{\mathrm{MSINR}} = \mathbf{R}_{in}^{-1} \hat{\mathbf{h}}_1 \tag{16}$$

However, $\mathbf{R}_{in}$ is not available in practice, and is usually estimated by decision aided schemes.

Finally, from (6), (11), with the frequency offset Δf_1 estimated as $\Delta\hat{f}_1$, the symbol decision $\hat{d}_1(i)$ can be obtained by

$$\hat{d}_1(i) = \mathrm{dec}\{\hat{d}_{1,\delta}(i)\mathrm{e}^{-\mathrm{j}2\pi\Delta\hat{f}_1 iT_\mathrm{s}}\} \tag{17}$$

Most existing frequency offset estimators are developed based on the assumption of no or little interference (i.e. AWGN). With the presence of strong MAI, these estimators often degrade seriously. It is thus necessary to perform interference suppression before frequency offset estimation.

3. DEVELOPMENT OF PARTIALLY ADAPTIVE CDMA RECEIVER

In this section, an efficient pre-despread adaptive CDMA receiver is developed which offers the performance of the MMSE or MSINR receiver. The receiver consists of a set of adaptive correlators and a RAKE combiner for exploiting path diversity. A decision aided scheme is included for performance enhancement. The schematic diagram of the receiver is depicted in Figure 2.

3.1. Construction of blind adaptive GSC correlators

A set of adaptive correlators is used to perform despreading and MAI suppression. They are realized in the form of GSC, and require no pilot symbols for channel estimation. In other words, these correlators are 'blind' and can utilize the entire received symbols, including data and pilot, to compute the adaptive weights. This is in contrast to non-blind pilot aided methods

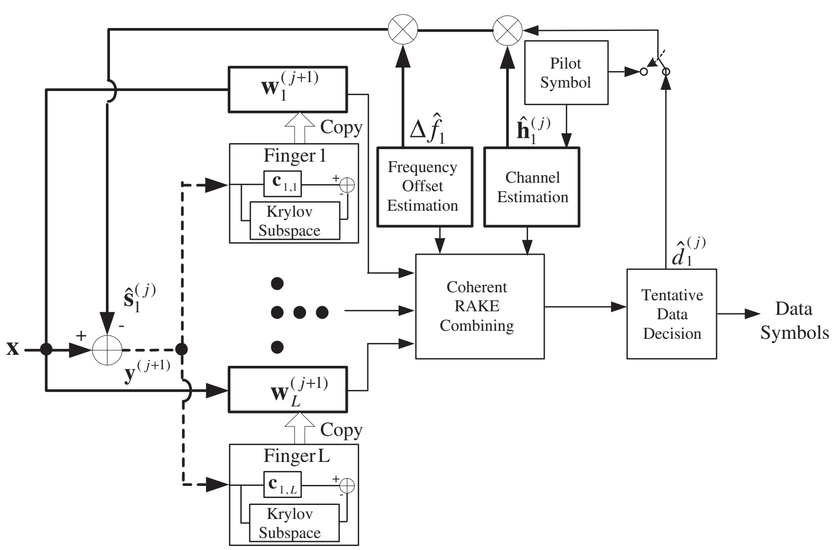

Figure 2. Schematic diagram of proposed decision aided CDMA receiver with partially adaptive interference cancellation.

(e.g. MMSE) which cannot achieve reliable channel estimation in the presence of strong MAI by using the limited number of pilot symbols.

In order to restore the processing gain and retain the path diversity, $\mathbf{x}(i)$ is despread at each of the L fingers using a set of discrete-time correlators:

$$z_{1,l}(i) = \mathbf{w}_l^{\mathrm{H}}\mathbf{x}(i) = \mathbf{w}_l^{\mathrm{H}}\mathbf{h}_1 d_1(i) + \mathbf{w}_l^{\mathrm{H}}\mathbf{i}(i) + \mathbf{w}_l^{\mathrm{H}}\mathbf{n}(i) \tag{18}$$

for $l = 1, \ldots, L$, where $\mathbf{w}_l$ is the correlator weight vector at the lth finger. For an effective suppression of MAI, these weight vectors can be determined in accordance with the LCMV criterion:

$$\min_{\mathbf{w}_l} \mathbf{w}_l^{\mathrm{H}}\mathbf{R}_x\mathbf{w}_l \quad \text{subject to } \mathbf{c}_{1,l}^{\mathrm{H}}\mathbf{w}_l = 1 \tag{19}$$

However, the adverse phenomenon of signal cancellation usually occurs with the solution in (19) due to the mismatch of signature vectors (i.e. mismatch between $\mathbf{c}_{1,l}$ and $\mathbf{h}_1$). With such a mismatch present, the signal can be treated as interference and receive a very small gain. To avoid such signal cancellation, the LCMV correlators can be implemented with multiple constraints [14]. Here an alternative solution is suggested based on the GSC technique. The GSC is essentially an indirect but simpler implementation of the LCMV receiver. It is a widely used structure that allows a constrained adaptive algorithm to be implemented in an unconstrained fashion [8, 9].

The concept of GSC, as depicted in Figure 3(a), is to decompose the weight vector into two orthogonal components as $\mathbf{w}_l = \mathbf{c}_{1,l} - \mathbf{B}\mathbf{u}_l$. The matrix $\mathbf{B}$ is a pre-designed signal 'blocking matrix' which removes user 1's signal before filtering. The goal is then to choose the adaptive weight vector $\mathbf{u}_l$ to cancel the interference in $\mathbf{x}(i)$. According to the GSC scheme, $\mathbf{u}_l$ is determined via the MMSE criterion:

$$\min_{\mathbf{u}_l} E\{|\mathbf{c}_{1,l}^{\mathrm{H}}\mathbf{x}(i) - \mathbf{u}_l^{\mathrm{H}}\mathbf{B}^{\mathrm{H}}\mathbf{x}(i)|^2\} \tag{20}$$

Since the signal has been removed in the lower branch by $\mathbf{B}$, the only way to minimize the MSE is such that $\mathbf{u}_l$ performs a mutual cancellation of the MAI between the upper and lower

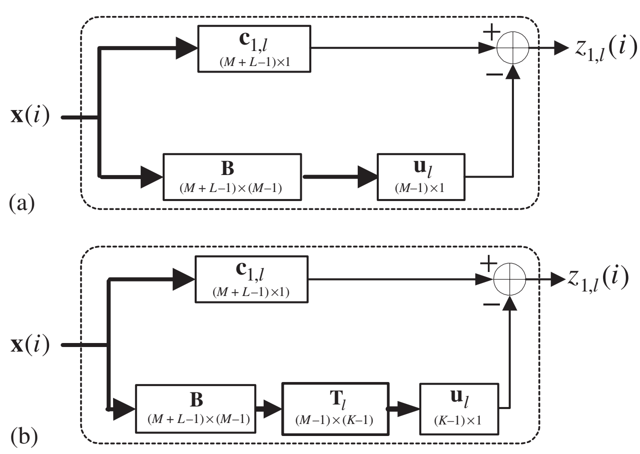

Figure 3. Illustration of (a) fully adaptive GSC and (b) partially adaptive GSC.

branches. Solving for $\mathbf{u}_l$ and substituting in $\mathbf{w}_l = \mathbf{c}_{1,l} - \mathbf{B}\mathbf{u}_l$, we get

$$\mathbf{w}_l = [\mathbf{I} - \mathbf{B}(\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{B})^{-1}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x]\mathbf{c}_{1,l} \tag{21}$$

This is called the direct-matrix-inversion (DMI) implementation of the fully adaptive (FA) GSC correlators. Note that $\mathbf{B}$ must block signals from the entire delay spread in order to avoid signal cancellation. It can be chosen to be a full rank $(M+L-1)\times(M-1)$ matrix whose columns are orthogonal to $\{\mathbf{c}_{1,1},\ldots,\mathbf{c}_{1,L}\}$, i.e. $\mathbf{B}^{\mathrm{H}}\mathbf{c}_{1,l} = \mathbf{0}$, $l = 1,\ldots,L$. The distortion of signature vectors $\mathbf{c}_{1,l}$'s due to frequency offset is typically tolerable in signal blocking, i.e. the signal component can be reliably removed by the above designed $\mathbf{B}$ under a moderately small frequency offset.

In the DMI implementation, the computation of adaptive weight vectors in (21) involves the inversion of $\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{B}$, which is $(M-1)\times(M-1)$. With a large M, this requires a high computational load and is likely to incur numerical instability and poor convergence behaviours [8, 9]. To alleviate this problem, the partially adaptive (PA) GSC is proposed which uses only a portion of the available degrees of freedom offered by the adaptive weights. Specifically, the PA techniques can be employed to reduce the size of $\mathbf{B}$ or dimension of $\mathbf{u}_l$'s [8–10]. For example, the Cross-Spectral PA (CS-PA) technique is developed by working with a smaller blocking matrix constructed from a reduced-dimensional subspace of *Range*($\mathbf{B}$) to provide the lowest MMSE [10], and requires complicated eigen-computation. In the following, a simple and effective PA technique is proposed which is suitable for the downlink of mobile satellite scenarios.

3.2. Partially adaptive implementation

The PA GSC, as shown in Figure 3(b), works with P ($P < M-1$) adaptive weights through the use of an $(M-1)\times P$ linear transformation $\mathbf{T}_l$ for the lth finger [8]. This leads to a reduced size blocking matrix $\tilde{\mathbf{B}}_l = \mathbf{B}\mathbf{T}_l$. The criteria for the selection of $\mathbf{T}_l$ include: (i) $\tilde{\mathbf{B}}_l$ should be as small as possible (ii) MAI should be retained as much as possible in the lower branch. Criterion (i) is for complexity reduction and (ii) is for optimal mutual cancellation of MAI in the upper and lower branches [15]. Criterion (ii) is equivalent to saying that a reduced size blocking matrix should be chosen such that the upper and lower branch outputs of the GSC have a large crosscorrelation [15]. Since the lower branch contains no signal, the only way to maximize the crosscorrelation is to retain as much MAI as possible in the lower branch. By doing so, a maximum mutual cancellation of interference can be achieved between the upper and lower branches. In the following, an efficient method for finding $\tilde{\mathbf{B}}_l$'s is developed based on the Krylov subspace technique.

According to Reference [16], a reliable reduced rank MMSE solution can be found by projecting the data vector $\mathbf{x}(i)$ onto a P-dimensional subspace represented by the Krylov subspace span$\{\hat{\mathbf{h}}_1, \mathbf{R}_x\hat{\mathbf{h}}_1, \ldots, \mathbf{R}_x^{(P-1)}\hat{\mathbf{h}}_1\}$:

$$\tilde{\mathbf{x}}(i) = \mathbf{S}_P^{\mathrm{H}}\mathbf{x}(i) \tag{22}$$

where $\mathbf{S}_P = [\hat{\mathbf{h}}_1, \mathbf{R}_x\hat{\mathbf{h}}_1, \ldots, \mathbf{R}_x^{(P-1)}\hat{\mathbf{h}}_1]$ is the $(M+L-1)\times P$ dimension reduction transformation. The reduced rank solution is then given by $\tilde{\mathbf{w}}_{\mathrm{MMSE}} = (\mathbf{S}_P^{\mathrm{H}}\mathbf{R}_x\mathbf{S}_P)^{-1}\mathbf{S}_P^{\mathrm{H}}\hat{\mathbf{h}}_1$ [16]. The same technique can be applied to the GSC problem by considering $\mathbf{B}^{\mathrm{H}}\mathbf{x}(i)$ as the data vector and $\mathbf{T}_l$ as the transformation. Comparing $\mathbf{u}_l = (\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{B})^{-1}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{c}_{1,l}$ in (21) with (12), and using $\tilde{\mathbf{B}}_l = \mathbf{B}\mathbf{T}_l$, it is straightforward to see that a reduced size blocking matrix can be chosen as

$$\begin{aligned}\tilde{\mathbf{B}}_l &= \mathbf{B}[\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{c}_{1,l}, (\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{B})\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{c}_{1,l}, \ldots, (\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{B})^{(P-1)}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{c}_{1,l}] \\ &= [\mathbf{B}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x\mathbf{c}_{1,l}, (\mathbf{B}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x)^2\mathbf{c}_{1,l}, \ldots, (\mathbf{B}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x)^P\mathbf{c}_{1,l}]\end{aligned} \tag{23}$$

The computation of adaptive weight vectors in (21) requires a matrix inversion, which may be a demanding task even the reduced size $\tilde{\mathbf{B}}_l$ is used in place of $\mathbf{B}$. In order to avoid such computation, a scheme is proposed based on a decorrelating (Gram-Schmidt) process that is applied to reconstruct $\tilde{\mathbf{B}}_l = [\tilde{\mathbf{b}}_{1,l}, \ldots, \tilde{\mathbf{b}}_{P,l}]$:

1. Initialization: $\mathbf{P}_0^{\perp} = \mathbf{B}\mathbf{B}^{\mathrm{H}}$ and
2. For $p = 1, \ldots, P$:

$$\tilde{\mathbf{b}}_{p,l} = \mathbf{P}_{p-1}^{\perp}(\mathbf{B}\mathbf{B}^{\mathrm{H}}\mathbf{R}_x)^p\mathbf{c}_{1,l}$$

$$\mathbf{P}_p^{\perp} = \mathbf{P}_{p-1}^{\perp} - \frac{\tilde{\mathbf{b}}_{p,l}\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}}{\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}\tilde{\mathbf{b}}_{p,l}}$$

An interesting observation gleaned from the above procedure is that $\tilde{\mathbf{b}}_{i,l}^{\mathrm{H}}\mathbf{R}_x\tilde{\mathbf{b}}_{j,l} = 0$ for $|i-j| > 1$, i.e. $\tilde{\mathbf{B}}_l^{\mathrm{H}}\mathbf{R}_x\mathbf{B}_l$ has a symmetric tri-diagonal structure. The following procedure then 'diagonizes' $\tilde{\mathbf{B}}_l^{\mathrm{H}}\mathbf{R}_x\mathbf{B}_l$ by decorrelating $\tilde{\mathbf{b}}_{i,l}$ and $\tilde{\mathbf{b}}_{j,l}$ for $|i-j| = 1$:

$$\tilde{u}_{p,l} = \frac{\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}\mathbf{R}_x\tilde{\mathbf{b}}_{p-1,l}}{\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}\mathbf{R}_x\tilde{\mathbf{b}}_{p,l}}$$

$$\tilde{\mathbf{b}}_{p-1,l} = \tilde{\mathbf{b}}_{p-1,l} - \tilde{u}_{p,l}\tilde{\mathbf{b}}_{p,l} \tag{24}$$

for $p = P, \ldots, 1$. With the modification in (24), the columns of $\tilde{\mathbf{B}}_l$ satisfies the $\mathbf{R}_x$-conjugacy property [11], i.e.:

$$\tilde{\mathbf{b}}_{r,l}^{\mathrm{H}}\mathbf{R}_x\tilde{\mathbf{b}}_{s,l} = E\{\tilde{\mathbf{b}}_{r,l}^{\mathrm{H}}\mathbf{x}(i)(\tilde{\mathbf{b}}_{s,l}^{\mathrm{H}}\mathbf{x}(i))^*\} = 0 \tag{25}$$

for $r \neq s$. It follows that the outputs from different columns of $\tilde{\mathbf{B}}_l$ are uncorrelated with each other. This leads to a significant simplification in the computation of GSC weight vector in (21). Replacing $\mathbf{B}$ in (21) by $\tilde{\mathbf{B}}_l$, we have

$$\mathbf{w}_l = \left[\mathbf{I} - \left(\sum_{p=1}^{K} d_p\tilde{\mathbf{b}}_{p,l}\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}\right)\mathbf{R}_x\right]\mathbf{c}_{1,l} \tag{26}$$

where $d_p = (\tilde{\mathbf{b}}_{p,l}^{\mathrm{H}}\mathbf{R}_x\tilde{\mathbf{b}}_{p,l})^{-1}$. The new GSC weight vector based on $\tilde{\mathbf{B}}_l$ involves no matrix inversion as desired.

3.3. RAKE combining and decision aided symbol detection

With the adaptive correlator bank constructed, the next step is to perform a maximum ratio combining of the correlator outputs to collect the multipath energy. Since the MAI has been removed, channel estimation (i.e. $\hat{\alpha}_{1,l}$'s) and frequency offset estimation (i.e. $\Delta\hat{f}_1$'s) for the desired user can be done accurately, leading to improved performance as compared to the conventional RAKE receiver. However, the GSC is blind in nature and usually exhibits slow convergence due to the residual signal effect [17]. To remedy this, an iterative decision aided scheme is introduced in which the signal is estimated and then subtracted from the input data before the computation of GSC adaptive weights.

First, assume that at the jth iteration, the received data $\mathbf{x}(i)$ is despread at the L fingers into:

$$\hat{z}_{1,l}^{(j)}(i) = \mathbf{w}_l^{(j)\mathrm{H}}\mathbf{x}(i) \tag{27}$$

for $l = 1, \ldots, L$, where $\mathbf{w}_l^{(j)}$ is obtained by (21) or (26) using the 'signal-subtracted' data vector $\mathbf{y}^{(j)}(i)$ as the GSC input:

$$\mathbf{y}^{(j)}(i) = \mathbf{x}(i) - \hat{\mathbf{s}}_1^{(j-1)}(i) \tag{28}$$

with $\hat{\mathbf{s}}_1^{(j-1)}(i)$ being the desired signal estimated at the $(j-1)$th iteration ($\hat{\mathbf{s}}_1^{(0)}(i) = \mathbf{0}$). That is, the correlation matrix $\mathbf{R}_x$ in (21) or (26) is replaced by $\mathbf{R}_y^{(j)} = E\{\mathbf{y}^{(j)}(i)\mathbf{y}^{(j)}(i)^{\mathrm{H}}\}$. After filtering, the MAI is suppressed to a certain extent, and the frequency offset estimate $\Delta\hat{f}_1$ can be obtained reliably by either the discrete Fourier transform or maximum likelihood method [18], and the channel gain estimates at the L fingers can be obtained using a sequence of N_{p} pilot symbols:

$$\hat{\alpha}_{1,l}^{(j)} = \frac{1}{MN_{\mathrm{p}}} \sum_{i=1}^{N_{\mathrm{p}}} \hat{z}_{1,l}^{(j)}(i) d_1^*(i) \mathrm{e}^{-\mathrm{j}2\pi\Delta\hat{f}_1 i T_{\mathrm{s}}} \tag{29}$$

for $l = 1, \ldots, L$, where M is the normalizing factor accounting for the processing gain. Note that $\hat{\alpha}_{1,l}^{(j)}$ includes the effect of transmit power σ_1^2. Using these channel estimates, a coherent RAKE combining of $\hat{z}_{1,l}^{(j)}(i)$'s is achieved by

$$\hat{z}_1^{(j)}(i) = \sum_{l=1}^{L} \hat{\alpha}_{1,l}^{(j)*} \hat{z}_{1,l}^{(j)}(i) \tag{30}$$

which is then sent to the data decision device:

$$\hat{d}_1^{(j)}(i) = \mathrm{dec}\{\hat{z}_1^{(j)}(i)\mathrm{e}^{-\mathrm{j}2\pi\Delta\hat{f}_1 i T_{\mathrm{s}}}\} \tag{31}$$

Second, signal reconstruction is done by exploiting the channel estimates $\hat{\alpha}_{1,l}^{(j)}$'s, $\Delta\hat{f}_1$'s, the desired user's signature $\mathbf{c}_{1,l}$ and symbol decisions $\hat{d}_1^{(j)}(i)$ as follows:

$$\hat{\mathbf{s}}_1^{(j)}(i) = \left(\sum_{l=1}^{L} \hat{\alpha}_{1,l}^{(j)} \mathbf{c}_{1,l}\right) \hat{d}_1^{(j)}(i) \mathrm{e}^{\mathrm{j}2\pi\Delta\hat{f}_1 i T_{\mathrm{s}}} \tag{32}$$

Note that $\hat{\alpha}_{1,l}^{(j)}$'s are used for both signal reconstruction and symbol detection. Finally, the reconstructed signal is subtracted from the data sent to the $(j+1)$th iteration, which yields

$$\mathbf{y}^{(j+1)}(i) = \mathbf{x}(i) - \hat{\mathbf{s}}_1^{(j)}(i) \tag{33}$$

By using $\mathbf{y}^{(j+1)}(i)$ as the GSC input, the adverse slow convergence can be effectively improved, and the PA CDMA multi-user receiver can achieve its optimal performance with a moderate size of data samples. Due to signal subtraction, the receiver will act like the optimal MSINR receiver operating on $\mathbf{R}_{in}$, which offers the best comprise between MAI plus noise suppression and signal reception. The above steps can be iterated $J > 2$ times, if necessary.

4. COMPUTER SIMULATIONS

Simulation results are demonstrated to confirm the performance of the proposed PA receiver in a time-multiplexed pilot symbols assisted system. The receiver output SINR is used as the evaluation index. Also, the input SNR is defined as $\mathrm{SNR}_i = \sigma_1^2/\sigma_n^2$, and the near-far-ratio is defined as $\mathrm{NFR} = \sigma_k^2/\sigma_1^2, k = 2, \ldots, K$, where we assume equal power MAI for convenience. It is assumed that the Ricean factor $A_s^2/2\sigma^2 = 6$ dB and the fraction of time of fading state $B = 0.3$ in (1). The path gains $\alpha_{k,l}$'s are assumed independent, identically distributed unit variance complex Gaussian random variables, the path delays $\tau_{k,l}$'s are uniform over $[0, 3T_c]$, and the number of paths is $L = 4$. All CDMA signals are generated with BPSK data modulation and random codes of length $M = 32$ are used as the spreading codes. The chip rate is assumed to be 3.84 Mcps, corresponding to a chip period of $T_c = 0.26$ µs. For each trial, N_s symbols (including data and pilot) are used to obtain the sample estimate of $\mathbf{R}_x$ and $\mathbf{R}_y$, and N_p pilot symbols are used to obtain $\hat{\alpha}_{1,l}$ and $\Delta\hat{f}_1$. In particular, the ML method is used for frequency offset estimation. Each simulation result is obtained by 200 independent trials, with each trial using a different set of $\alpha_{k,l}$'s and data/noise sequence. Unless otherwise mentioned, the following parameters are assumed: $K = 10$, $\mathrm{SNR}_i = 0$ dB, $\mathrm{NFR} = 10$ dB, $N_s = 100$, $N_p = 20$, $\Delta\hat{f}_1 = 20$ KHz (or $\Delta\hat{f}_1 T_s = 1/6$), PA dimension $P = \lceil (K-1)/2 \rceil$ and the number of iterations is $J = 3$ in Section 3.3. For comparison, we also include the results obtained with the optimal, MMSE and MOE receivers. The optimal receiver is defined to be the MSINR receiver with $\mathbf{R}_{in}$ obtained by artificially removing $\mathbf{s}_1(i)$ from $\mathbf{x}(i)$ and true CSV $\mathbf{h}_1$ used. The MMSE receiver is given by (12), with $\hat{\mathbf{h}}_1$ and $\Delta\hat{f}_1$ obtained using N_p pilot symbols. The MOE receiver is based on the method presented in Reference [14]. The proposed receiver uses $N_p = N_s/5$ pilot symbols, and the MMSE receiver uses either $N_p = N_s/2$ (1/2) or $N_p = N_s$ (full) pilot symbols. The MOE receiver is blind without using any pilot symbols ($N_p = 0$).

In the first simulation, the output SINR performance of the proposed receiver is evaluated as a function of iteration number J with $P = 5$. Included are the FA receiver (FA dimension 32) and the proposed PA receiver. For channel estimation, $N_p = N_s/5$ pilot symbols are used. The results in Figure 4 show that the proposed two receivers successively approach the optimal receiver in three iterations. After convergence, the PA receivers have almost the same performance of the FA receive, confirming that the reduced dimension $\tilde{\mathbf{B}}_l$ retains the full interference suppression capability of the FA receiver. The second simulation, the output SINR performance versus dimension of blocking matrix of PA receiver is demonstrated. The results given in Figure 5 show that the proposed PA receiver successively approach the proposed FA receiver at PA dimension $P = 5$ and reaches the performance of MMSE receiver using full pilot symbols at $P = 2$. The simulation results confirm that the proposed PA receiver is able to offer the performance of the FA receiver with a $P = \lceil (K-1)/2 \rceil$ dimensions.

In the third simulation, the tolerance of the proposed PA receiver against different frequency offsets is evaluated. The resulting SINR curves as a function of $\Delta f_1 T_s$ are plotted in Figure 6. They show that the proposed receiver performs reliably within a wide offset range, indicating that with successful signal reception and MAI suppression by the adaptive GSC correlators, an accurate frequency offset estimate can be obtained to guarantee a satisfactory performance. In the fourth simulation, the output SINR performance is evaluated as a function of input SNR. The results shown in Figure 7 indicate that the proposed PA receiver successively approaches the optimal receiver within a wide range of input SNR. In the fifth simulation, the near-far resistance is evaluated with different NFR values. Figure 8 shows the output SINR curves. It is

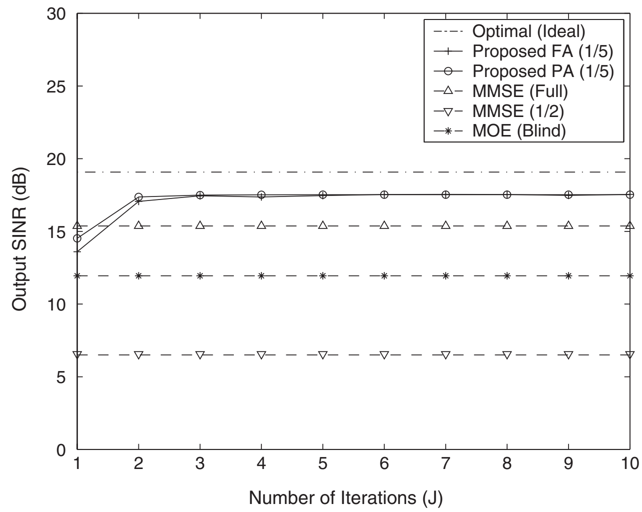

Figure 4. Receiver output SINR versus number of iterations J, with $K = 10$, $\mathrm{SNR}_i = 0$ dB, $\mathrm{NFR} = 10$ dB, $N_s = 100$, $\Delta f_1 T_s = 1/6$ and $P = 5$.

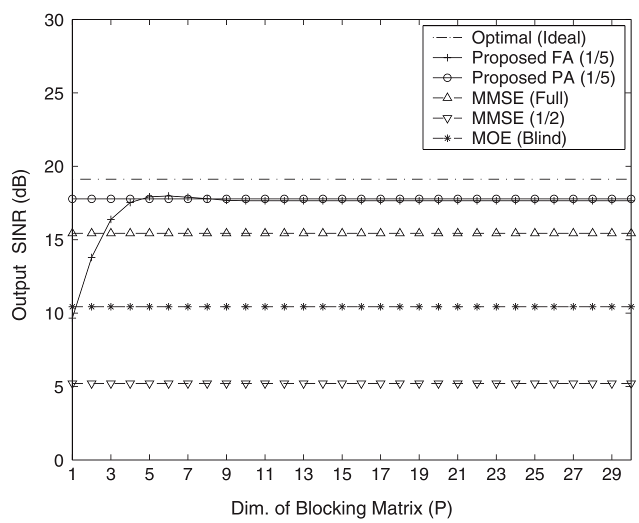

Figure 5. Receiver output SINR versus PA dimension P, with $K = 10$, $\mathrm{SNR}_i = 0$ dB, $\mathrm{NFR} = 10$ dB, $N_s = 100$, $\Delta f_1 T_s = 1/6$ and $J = 3$.

observed that the proposed PA receiver achieves its excellent near-far resistance by successfully canceling the MAI using the temporal degree of freedom offered by the pre-despread data. The system capacity is then evaluated with different values of K. As shown in Figure 9, the proposed PA receiver is able to offer the performance of the optimal receiver in a heavily loaded system with effective MAI suppression using the smallest dimension for adaptive filtering.

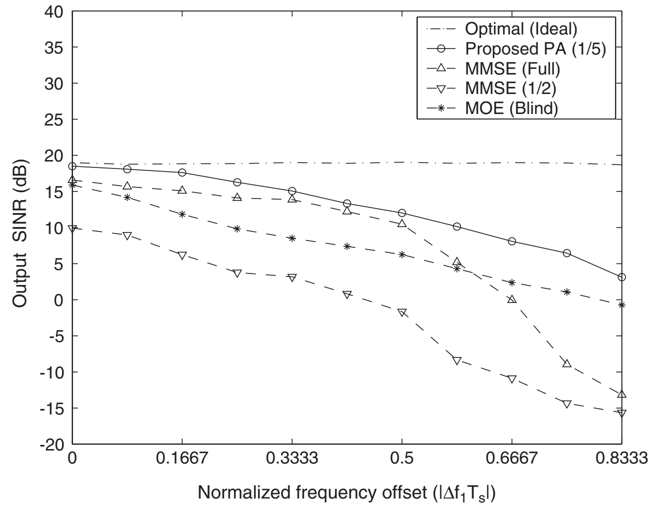

Figure 6. Receiver output SINR versus normalized frequency offset $\Delta f_1 T_s$, with $K = 10$, $\mathrm{SNR}_i = 0$ dB, NFR = 10 dB, $N_s = 100$, $J = 3$ and $P = 5$.

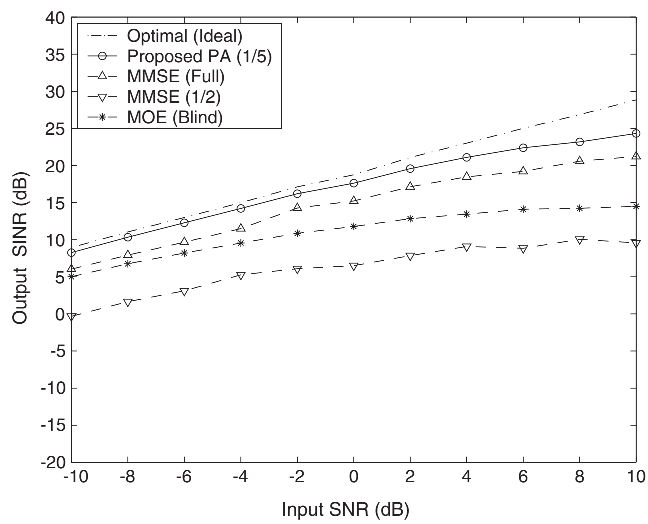

Figure 7. Receiver output SINR versus input SNR, with $K = 10$, NFR = 10 dB, $N_s = 100$, $\Delta f_1 T_s = 1/6$, $J = 3$ and $P = 5$.

Finally, the convergence behaviour of the proposed PA receiver is compared with the optimal, MMSE and MOE receivers. The results given in Figure 10 show that the proposed receiver with $1/5$ pilot symbols converges in about $N_s = 100$ data symbols, and is only 1.3 dB away from the optimal receiver. On the other hand, the MMSE receiver using full pilot symbols offers nearly the optimal performance, but degrades significantly if only $1/2$ pilot symbols are available.

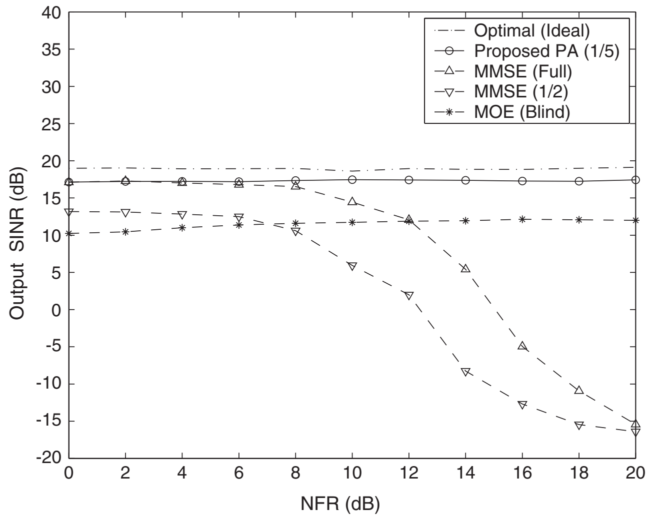

Figure 8. Receiver output SINR versus NFR, with $K = 10$, $\mathrm{SNR}_i = 0$ dB, $N_s = 100$, $\Delta f_1 T_s = 1/6$, $J = 3$ and $P = 5$.

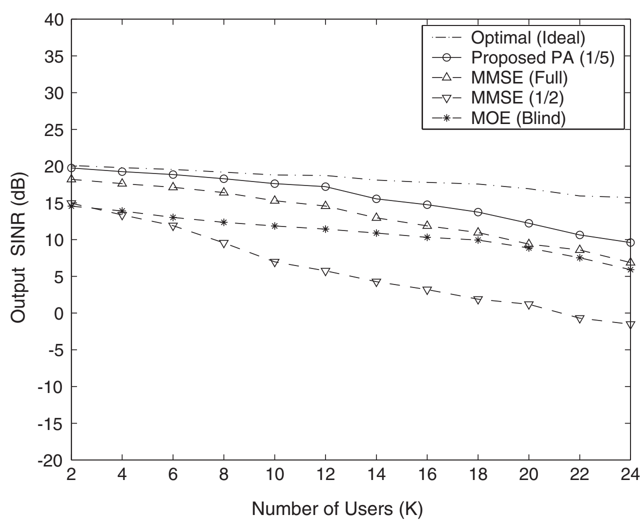

Figure 9. Receiver output SINR versus user number K, with $\mathrm{SNR}_i = 0$ dB, NFR = 10 dB, $N_s = 100$, $\Delta f_1 T_s = 1/6$, $J = 3$ and $P = \lceil (K-1)/2 \rceil$.

Again, the reasons for the significant discrepancy between the proposed and MMSE receivers with a low pilot symbol ratio is that the proposed receiver cancels the MAI before channel and frequency offset estimation, whereas the MMSE receiver estimates the channel and frequency offset in the presence of strong MAI.

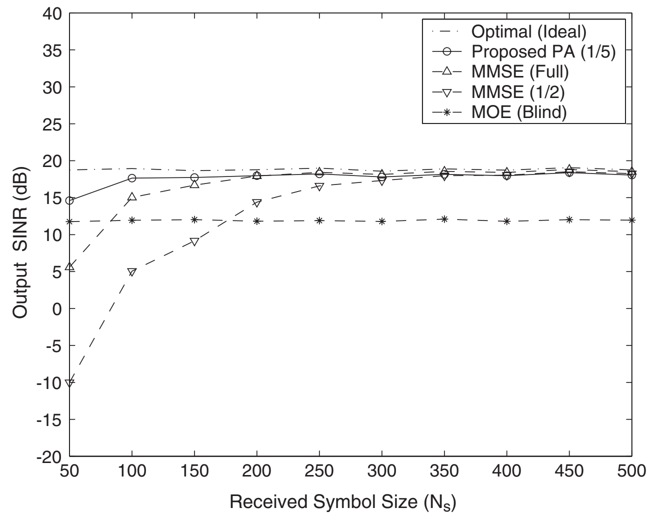

Figure 10. Receiver output SINR versus data sample size N_s, with $K = 10$, $\mathrm{SNR}_i = 0$ dB, NFR = 10 dB, $\Delta f_1 T_s = 1/6$, $J = 3$ and $P = 5$.

5. CONCLUSION

A decision aided CDMA receiver with partially adaptive interference suppression is proposed for downlink mobile satellite communications in the presence of frequency offset. The new receiver is developed with the following procedure. First, blind adaptive correlators are constructed at different fingers based on the GSC scheme to collect multipath signals and suppress strong interference. For reduced complexity implementation, partial adaptivity is incorporated into the GSC based on the Krylov subspace technique, leading to an efficient algorithm without the need of matrix inversion. Second, pilot symbols assisted frequency offset estimation, channel estimation and RAKE combining give the estimate of signal symbols. Finally, for further performance enhancement, an iterative decision aided scheme is introduced which reconstructs and subtracts the signal from the GSC input data. This effectively eliminates the performance drop due to finite data samples effect. Simulation study shows that the proposed partially adaptive CDMA receiver is very robust to frequency offset, and can achieve nearly the same performance of the optimal MSINR and MMSE receivers under severe system conditions. The main advantages of the proposed receiver over others lie in a lower implementation complexity and overhead for pilot symbols.

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