

Adaptive Space-Time Processing For Multiuser Detection in Multipath CDMA Systems

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Abstract

Wireless communications poses some unique challenges including multipath fading and co-channel interference. Diversity techniques, among which space diversity, are overwhelmingly used in wireless communication systems to enhance capacity, coverage and quality. We have considered sample-by-sample adaptive space-time multiuser detectors for multipath CDMA channels with multiple receive antennas. Fully exploiting diversities through space-time processing and multiuser detection offers substantial improvement in the performance of CDMA systems.

Keywords: Code Division Multiple Access (CDMA), Adaptive MMSE ST MUD.

I. INTRODUCTION

The presence of both multiple-access interference (MAI) and intersymbol interference (ISI) constitutes a major impediment to reliable high-data-rate CDMA communications in multipath channels. These phenomena present challenges as well as opportunities for receiver designers; through multiuser detection (MUD) [1] and space time (ST) processing [2], the inherent code, spatial, temporal and spectral diversities of multipath multi-antenna CDMA channels can be exploited to achieve substantial gain.

Advanced signal processing typically improves system performance at the cost of computational complexity. It is well known that the optimal maximum likelihood (ML) multiuser detector has prohibitive computational requirements for most current applications. A variety of linear and nonlinear multiuser detectors have been proposed to ease this computational burden while maintaining satisfactory performance. However, in asynchronous multipath CDMA channels with receive antenna arrays and large data frame lengths, direct implementation of these suboptimal techniques still proves to be very complex.

Techniques for efficient space-time multiuser detection includes sample-by-sample adaptive methods, which require knowledge only of the signal and (possibly) channel of a desired user. Sample-by sample adaptive methods are suitable for mobile end processing, which entails decentralized data detection, and for base station processing due to the time varying nature of wireless communications. We may think of the sample-by-sample adaptive method discussed here as being most suitable for application at the base station, where it is more practical to install an antenna array. However, most of the described blind techniques are readily applied to the mobile user end when multiple antennas can be applied at mobile terminals.

This paper is organized as follows. In Section II a space-time multiuser signal model is presented. while sample by-sample adaptive methods are dealt with in Section III. Computer simulation examples are given in Section IV. and Section V provides the Conclusions.

II. SPACE-TIME SIGNAL Model

Consider a direct-sequence CDMA communication system with K users employing normalized spreading waveforms S_1, \dots, S_K given by:

$$s_k(t) = \frac{1}{\sqrt{N}} \sum_{j=0}^{N-1} c_k(j) \Psi(t - jT_c) \quad , 0 \leq t \leq T, 1 \leq k \leq K \quad (1)$$

where, N is the processing gain, $\{c_k(j); 0 \leq j \leq N-1\}$ is a signature sequence of ± 1 's assigned to the k^{th} user, and $\psi(\cdot)$ is a normalized chip waveform of duration $T_c = T/N$ with T the symbol interval. User k (for $1 \leq k \leq K$) transmits a frame of M independent equiprobable BPSK symbols

$b_k(i) \in \{+1, -1\}$, $0 \leq i \leq M - 1$; and the symbol sequences from different users are assumed to be mutually independent. The transmitted baseband signal due to the k^{th} user is thus given by:

$$x_k(t) = A_k \sum_{i=0}^{M-1} b_k(i) S_k(t - iT), \quad 1 \leq k \leq K, \quad (2)$$

Where A_k is the amplitude associated with user k^{th} transmission. The transmitted signal of each user passes through a multipath channel before it is received by a uniform linear antenna array (ULA) of P elements with inter-element spacing d . Then the single-input multiple-output (SIMO) vector impulse response between the k^{th} user and the receive array can be modeled as:

$$\mathbf{h}_k(t) = \sum_{l=1}^L \mathbf{a}_{kl} g_{kl} \delta(t - \tau_{kl}) \quad (3)$$

where L is the maximum number of resolvable paths between each user and the receive array (for simplicity we assume L is the same for each user), g_{kl} and τ_{kl} are respectively the complex gain and delay of the l^{th} path of the k^{th} user, and

$$\mathbf{a}_{kl} = \begin{pmatrix} a_{kl,1} \\ a_{kl,2} \\ \vdots \\ a_{kl,P} \end{pmatrix} = \begin{pmatrix} 1 \\ e^{j 2\pi d \sin(\theta_{kl})/\lambda} \\ \vdots \\ e^{j 2\pi d (P-1) \sin(\theta_{kl})/\lambda} \end{pmatrix} \quad (4)$$

is the ULA response corresponding to the signal of the l^{th} path of the k^{th} user with direction of arrival (DOA) θ_{kl} and carrier wavelength λ . $\delta(t)$ denotes the Dirac delta function. The received signal at the antenna array is the superposition of the channel distorted signals from the K users together with additive Gaussian noise, which is assumed to be spatially and temporally white. This leads to the vector received signal model

$$\mathbf{r}(t) = \sum_{k=1}^K x_k(t) \otimes \mathbf{h}_k(t) + \sigma \mathbf{n}(t) \quad (5)$$

where \otimes denotes convolution and σ^2 is the spectral height of the ambient Gaussian noise at each antenna element.

A sufficient statistic for demodulating the multiuser symbols from the space-time signal (5) is given by [3]:

$$Y = [y_1(0), \dots, y_k(0), y_1(1), \dots, y_1(M-1), \dots, y_k(M-1)]^T \quad (6)$$

Where the elements $\{y_k(i)\}$ are defined as follows:

$$y_k(i) = \sum_{l=1}^L g_{kl}^* \mathbf{a}_{kl}^H \underbrace{\int_{-\infty}^{\infty} \mathbf{r}(t) S_k(t - iT - \tau_{kl}) dt}_{Z_{kl}(i)} \quad 1 \leq k \leq K, \quad 0 \leq i \leq M - 1 \quad (7)$$

To produce this sufficient statistic, the received signal vector $\mathbf{r}(t)$ is first match-filtered for each path of each user to form the vector observables, $\{Z_{kl}(i)\}$, after which beams are formed on each path of each user via the

dot products with the array responses $\{\mathbf{a}_{kl}\}$, and then all the paths of each user are combined with a RAKE receiver. This process produces one observation for each symbol of each user. Since the system is in general asynchronous and the users are not orthogonal, we need to collect the statistic for all users over the entire data frame. The observable $y_k(i)$ corresponds to the output of a conventional space-time matched filter, matched to the i^{th} symbol of user k . Therefore, a general space-time multiuser receiver is a space-time matched filter bank, followed by a decision algorithm as shown in Figure 1. In the following, we will present, a new ST MUD receiver structure will also be introduced, in which chip-level observables are exploited. The sufficient statistic (6) can be written as (see [1]).

$$Y = \mathbf{H}\mathbf{A}\mathbf{b} + \sigma\mathbf{v} \tag{8}$$

Where \mathbf{H} is a $KM \times KM$ matrix capturing the cross-correlations between different symbols and different users, \mathbf{A} is the $KM \times KM$ diagonal matrix whose $k+iK$ diagonal elements are equal to A_k

$\mathbf{b} = [b_1(0), \dots, b_K(0), b_1(1), \dots, b_1(M-1), \dots, b_K(M-1)]^T$ and $\mathbf{v} \sim N(0, \mathbf{H})$ (i.e., \mathbf{v} is Gaussian with zero mean and covariance matrix \mathbf{H}). An optimal ML space time multiuser detector will maximize the following log-likelihood function [1]

$$\Omega(\mathbf{b}) = 2 \text{Re}\{\mathbf{b}^T \mathbf{A}\mathbf{y}\} - \mathbf{b}^T \mathbf{A}\mathbf{H}\mathbf{A}\mathbf{b} \tag{9}$$

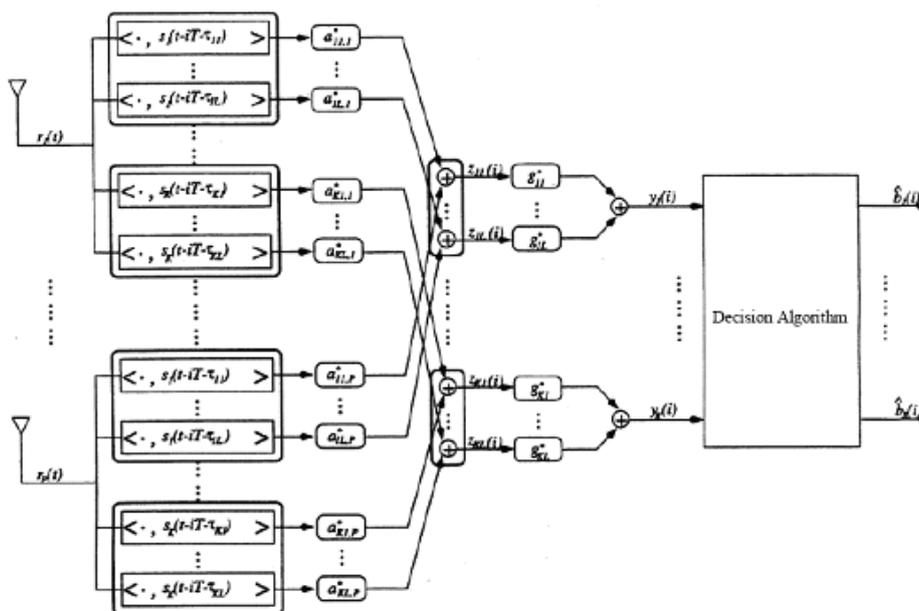


Figure 1: A conventional space-time multiuser receiver structure

III. ADAPTIVE MMSE ST MUD

Figure 2 depicts the structure of a decentralized adaptive space-time multiuser detector of interest in detecting the i^{th} symbol of k^{th} user. Each antenna element is equipped with a chip matched filter followed by a chip-interval-spaced adaptive finite-impulse-response (FIR) filter. The outputs of all FIR filters are summed and sampled at the symbol rate to form a soft decision output, which serves two purposes: to form an estimate for the desired bit through a decision device, and to form an error signal for adjustment of adaptive filter coefficients.

Collect the weights of the FIR filter banks at the p^{th} antenna element into an N -vector

$$\mathbf{w}_p^{(k)} = [w_{p,0}^{(k)}, w_{p,1}^{(k)}, \dots, w_{p,N-1}^{(k)}]^T$$

and then collect such vectors from all antenna elements into a PN -vector $\mathbf{W}_k = [(\mathbf{w}_1^k)^T, (\mathbf{w}_2^k)^T, \dots, (\mathbf{w}_P^k)^T]^T$. \mathbf{W}_k is thus applied to the signal vector $\mathbf{r}^{(k)}$ to make

a decision about b_k . A useful performance metric for the receiver of Figure 2 is the output signal-to-noise ratio (SINR), which can be estimated as:

$$SINR_k = 10 \log_{10} \left(\frac{1 - MSE(\mathbf{W}_k)}{MSE(\mathbf{W}_k)} \right) \quad (10)$$

with mean square error defined as: $MSE(\mathbf{W}_k) = E \left\{ \left(b_k - (\mathbf{W}_k)^H \mathbf{r}^{(k)} \right)^2 \right\} = 1 - (\mathbf{W}_k)^H \mathbf{h}_k - (\mathbf{h}_k)^H \mathbf{W}_k + (\mathbf{W}_k)^H \mathbf{R}_k \mathbf{W}_k$ (11)

Where $\mathbf{R}_k = E \left\{ \mathbf{r}^{(k)} \mathbf{r}^{(k)H} \right\}$ is the autocorrelation matrix of the signal vector $\mathbf{r}^{(k)}$ and $\mathbf{h}_k = E \left\{ \mathbf{r}^{(k)} b_k \right\}$ is the crosscorrelation vector between $\mathbf{r}^{(k)}$ and the desired bit b_k . An optimum choice for \mathbf{W}_k is that which minimizes the mean square error $MSE(\mathbf{W}_k)$. This choice, known as the MMSE detector, is given by the Wiener-Hopf solution

$$\mathbf{W}_k^{opt} = \mathbf{R}_k^{-1} \mathbf{h}_k \quad (12)$$

For this theoretical optimum solution, the achieved minimum value of the mean square error is given by:

$$MMSE_k \square MSE(\mathbf{W}_k^{opt}) = E \left\{ \left(b_k - (\mathbf{W}_k^{opt})^H \mathbf{r}^{(k)} \right)^2 \right\} = 1 - (\mathbf{W}_k^{opt})^H \mathbf{R}_k \mathbf{W}_k^{opt} = 1 - (\mathbf{h}_k)^H \mathbf{R}_k^{-1} \mathbf{h}_k \quad (13)$$

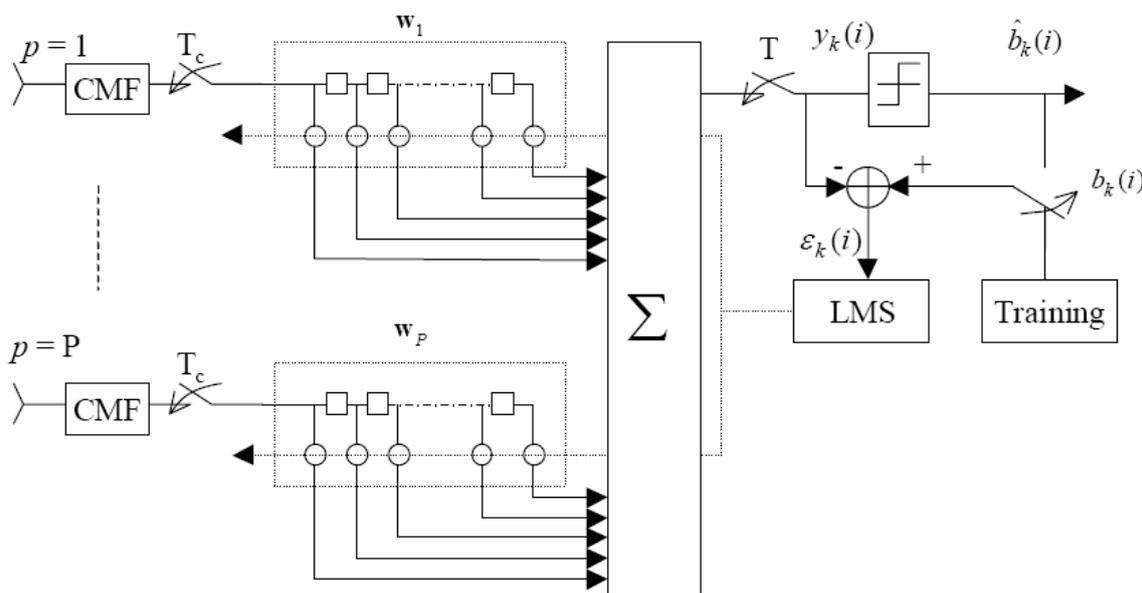


Figure 2: Structure of an adaptive MMSE space-time multiuser detector

A number of algorithms are available to seek the solution (12) adaptively, from the simple least-mean-squares (LMS) algorithm to various fast yet complex recursive-least squares (RLS) methods. The properties and behavior of these algorithms are well known and documented [4]. Here we adopt the LMS algorithm as a simple tool to obtain MMSE FIR filter banks. This choice is illustrated as follows. The soft decision output is given by:

$$y_k(i) = \mathbf{W}_k^H(i) \mathbf{r}^{(k)}(i) \quad (14)$$

from which a bit estimate is formed as:

$$\hat{b}_k(i) = \text{sgn} \left\{ \text{Re} \left(y_k(i) \right) \right\} \quad (15)$$

where “Re” indicates the real part. An error signal is then formed as:

$$\varepsilon_k(i) = b_k(i) - y_k(i) \quad (16)$$

and the filter coefficients are updated as:

$$\mathbf{W}_k(i+1) = \mathbf{W}_k(i) + \mu \varepsilon_k^*(i) \mathbf{r}^{(k)}(i) \quad (17)$$

Where μ is the step size of the adaptive algorithm. Note that after the training period, the receiver is switched to decision-directed mode and the error signal is formed as:

$$\varepsilon_k(i) = \hat{b}_k(i) - y_k(i) \quad (18)$$

IV. COMPUTER SIMULATIONS.

The performance of the above described adaptive space-time multiuser detectors is examined through computer simulations. We assume a $K = 16$ -user CDMA system with spreading gain $N = 16$, which is heavily loaded with severe near-far problem. Each user travels through $L = 3$ paths before it reaches a ULA with $P = 3$ elements and half-wavelength spacing. The maximum delay spread is set to be $4T$. The complex gains and delays of the multipath and the directions of arrival are randomly generated and kept fixed for all the simulations. We assume $A_1 = \dots = A_K$ for simplicity, but the received signal powers of different users are unequal due to the effects of multipath. The number of symbols per frame is $M = 250$. The step size of the LMS algorithm is fixed to be $\mu = 0.001$.

Figure 3 shows the learning curve for the decentralized adaptive MMSE ST MUD. The user of interest is user 1. The theoretical MMSE is also plotted in the figure (as the dashed line) for comparison. Figure 4 compares the steady-state bit error rate (BER) of the adaptive MMSE ST MUD with that of the batch iterative MMSE ST MUD. The error is counted and averaged for consecutive 400 data frames after an initial 4 data frames (1000 iterations) of adaptation. These results show that this adaptive ST MUD structure approaches the optimum MMSE ST MUD, while using only knowledge of the timing and training sequence of the desired user. This simple adaptive structure effectively combines the function of beamforming, RAKE combining and multiuser detection.

V. CONCLUSIONS

The adaptive space-time multiuser receivers combine the functions of adaptive beamforming, RAKE combining and multiuser detection with no side information needed other than the timing and training sequences of the desired user. The ST MUD performance these results show that this adaptive ST MUD structure approaches the optimum MMSE ST MUD, while using only knowledge of the timing and training sequence of the desired user.

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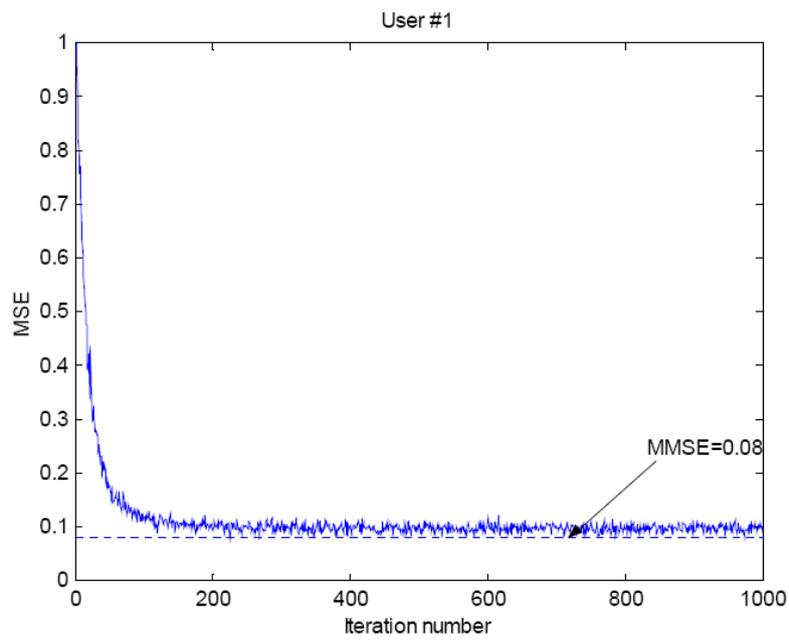


Figure 3. Convergence of the decentralized adaptive MMSE space-time multiuser detector

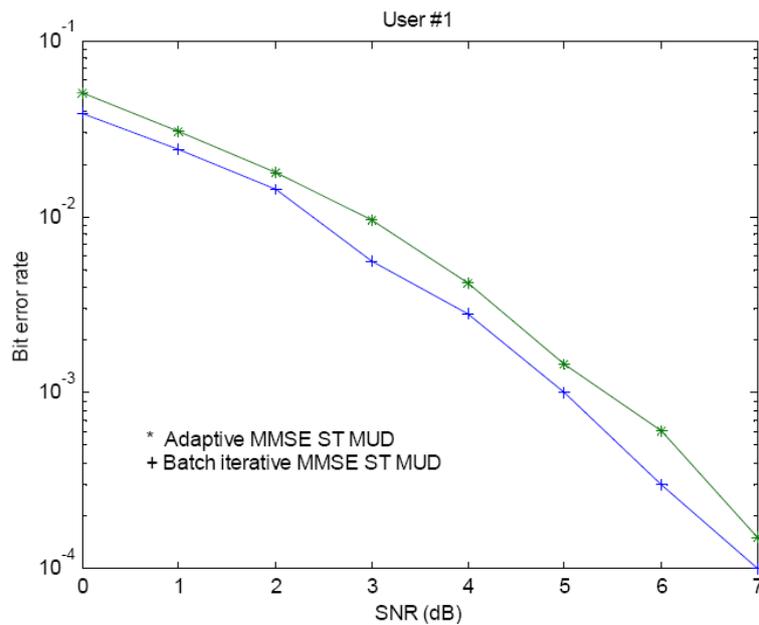


Figure 4. Bit error rate of the decentralized adaptive MMSE space-time multiuser detector in the steady state