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New Array Processing Algorithms for Maximizing Capacity of Multi-Media Spread-Spectrum Multi-Access Communications

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NEW ARRAY PROCESSING ALGORITHMS FOR MAXIMIZING CAPACITY OF MULTI-MEDIA SPREAD-SPECTRUM MULTI-ACCESS COMMUNICATIONS

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ABSTRACT

Adaptive arrays are a key technique for maximizing the capacity of wireless multimedia CDMA networks. In this paper, we present two approaches for blind adaptive weight control in a CDMA environment which offer low implementation complexity. The first method is based on the concept of a self-generated reference signal combined with traditional LMS and RLS adaptive algorithms. The second method is an eigenspace algorithm which is based on eigenvalue decomposition and interference cancellation. Simulation results for both methods are presented for a low-mobility multipath environment and show reliable convergence with significant SINR improvements in the reception of a desired signal.

INTRODUCTION

Adaptive antenna arrays are a promising technique for maximizing the capacity of wireless CDMA networks. The major challenge to implementing adaptive arrays in a CDMA network is the development of robust adaptive array techniques capable of acquiring and tracking a desired user's signal in a time-varying environment with a *large number* of active users. Blind adaptive array techniques are particularly attractive because they eliminate the need for training sequences which often reduce overall transmission rates and require additional synchronization between the transmitter and receiver. However, existing blind adaptive array methods focus on scenarios for which the number of signals arriving at the array is small (i.e., less than the number of antenna elements), and thus are not suitable for a CDMA environment. Therefore, recently there has been growing interest in blind adaptive array techniques for CDMA. Furthermore, the current trends toward multimedia services requires robust adaptive methods suitable for both high and low data rate users. Blind methods have been proposed in [3, 4] for DS/CDMA networks, but suffer from high complexities.

With this motivation, we have been pursuing two promising approaches for blind antenna weight control in CDMA systems which offer low implementation complexity. We will begin with a brief description of the signal model. Then, present each approach along with simulation results. Finally, we conclude with some brief remarks.

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SYSTEM MODEL

Consider a single cell CDMA network supporting S types of service characterized by data rates $(R_1, R_2, \ldots, R_S)$ and corresponding quality of service requirements $(Q_1, Q_2, \ldots, Q_S)$. For simplicity, the k^{th} user of service type-i is denoted as user (i,k). The CDMA network under consideration employs a Variable Spreading Gain (VSG) technique for accommodating different data rate services. In VSG, each user has a common carrier frequency, f_c and common chip duration, T_c. This means all users in the network have their signals spread over the entire available bandwidth, $B = \frac{1}{T_c}$. As a result, the processing gain for each service type (N_i) is dependent on its data rate (i.e., $N_i = \frac{1}{R_i T_c}$).

The cell base station is sectorized and each sector has a uniformly spaced linear array of M elements. If we consider a CDMA system for which the maximum signal propagation time across the array, τ_{prop}, satisfies the condition: $\tau_{prop} \ll B^{-1}$, we can make a narrowband array approximation and model time delays across the array as phase shifts. Under this assumption, the complex baseband representation of the received signal from user (i,k) can be written as:

$$\tilde{\mathbf{x}}_{i,k}(t) = \sum_{l=1}^{L} \underbrace{\sqrt{P_{i,k}^{(l)}}\, c_{i,k}(t-\tau_{i,k}^{(l)})\, b_{i,k}(t-\tau_{i,k}^{(l)})\, e^{j\theta_{i,k}^{(l)}} \mathbf{a}_{i,k}^{(l)}}_{\tilde{\mathbf{x}}_{i,k}^{(l)}(t)} \quad (1)$$

where L is the number of signal paths received from each user. $P_{i,k}^{(l)}$, $\tau_{i,k}^{(l)}$, $\theta_{i,k}^{(l)}$, and $\mathbf{a}_{i,k}^{(l)}$ represent the received power, propagation delay, signal phase, and antenna response vector for the l^{th} signal path of user (i,k). $b_{i,k}(t)$ represents the data waveform of user (i,k) and consists of an i.i.d sequence of rectangular pulses of amplitude ± 1 with duration $T_b^{(i)} = R_i^{-1}$. Similarly, $c_{i,k}(t)$ represents the code waveform for user (i,k) consisting of an i.i.d sequence of rectangular pulses of amplitude ± 1 with duration T_c. In this model, we assume that each signal path from a user arrives at the array from a random angular direction and that all signal paths for a user

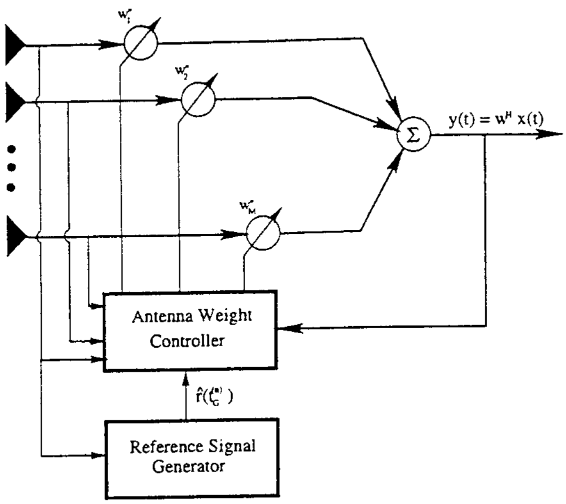

Figure 1: Proposed Adaptive Array Implementation.

have arrival times separated by greater than a chip duration (i.e., $|\tau_{i,k}^{(l)} - \tau_{i,k}^{(p)}| > T_c$).

Now, suppose the number of active users of each service type are given by $(K_1, K_2, \ldots, K_S)$. The total received signal vector at the array is:

$$\mathbf{x}(t) = \sum_{i=1}^{S}\sum_{k=1}^{K_i} \tilde{\mathbf{x}}_{i,k}(t) \quad + \quad \mathbf{n}(t) \tag{2}$$

where $\mathbf{n}(t)$ represents the noise at each antenna element.

SELF-GENERATED REFERENCE SIGNAL APPROACH

Description of Implementation

Our first proposed approach to blind antenna weight control for an adaptive antenna array in a CDMA network is based on a self-generated reference signal concept. Our proposed implementation is illustrated in Figure 1 and consists of a reference signal generator and antenna weight controller. The reference signal generator samples and processes the received signal from one antenna element over a portion of the n^{th} data bit of the desired user's signal to obtain a reference signal $\hat{r}(t_G^{(n)})$ for some future time $t_G^{(n)}$ in the n^{th} data bit (see Figure 2). The antenna weight controller in Figure 1 employs adaptive algorithms that recursively compute the antenna weights which minimize the mean square error between the array output $y(t_G^{(n)}) = \mathbf{w}^H\mathbf{x}(t_G^{(n)})$ and our generated reference signal $\hat{r}(t_G^{(n)})$. This process of reference signal generation and antenna weight update can be repeated for each data bit of the desired signal. However, to reduce computational requirements we could also update antenna weights every N^{th} data bit. Since our proposed approach obtains a reference signal from the received signal and does not require a training sequence, this represents a blind method of antenna weight control.

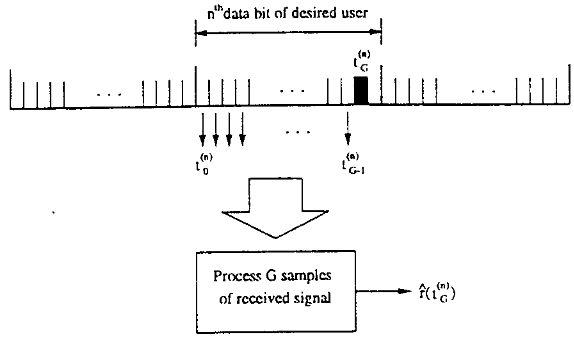

Figure 2: Conceptual illustration of reference signal generation process.

Without loss of generality assume our desired signal is $\tilde{\mathbf{x}}_{1,1}^{(1)}(t)$ and assume we have a code lock on it. The processing performed to obtain $\hat{r}(t_G^{(n)})$ from the received signal of antenna element 1 is summerized as:

(1) The received signal from antenna element 1 is sampled once per chip over G chips of the n^{th} data bit of $\tilde{\mathbf{x}}_{1,1}^{(1)}(t)$ where G ¡ N_1.

(2) Each sample is multiplied by the corresponding desired user's code for that sample time.

(3) The G samples are averaged and the result is multiplied by the desired user's code chip for time $t_G^{(n)}$.

Based on this philosophy, our generated reference signal is given by:

$$\hat{r}(t_G^{(n)}) = \underbrace{\sqrt{P_{1,1}^{(1)}}\, e^{j\theta_{1,1}^{(1)}} b_{1,1}(n) c_{1,1}(\lfloor \frac{t_G^{(n)}}{T_c} \rfloor)}_{r(t_G^{(n)})} \quad + \quad i(t_G^{(n)}) \tag{3}$$

where $r(t_G^{(n)})$ is a replica of $\tilde{\mathbf{x}}_{1,1}^{(1)}(t)$ at time $t_G^{(n)}$ and represents an ideal reference signal. The interference $i(t_G^{(n)})$ is a zero-mean random variable which represents the contribution of other user interference and noise to our generated reference signal. Since it is assume that the code sequences for each user are i.i.d sequences and $|\tau_{i,k}^{(l)} - \tau_{i,k}^{(m)}| > T_c$ for $l \neq m$, it can be verified that $E[\mathbf{x}(t_G^{(n)}) i^*(t_G^{(n)})] = \underline{0}$. Thus, $i(t_G^{(n)})$ is uncorrelated with $\mathbf{x}(t_G^{(n)})$. We define a reference signal quality metric denoted as Q_{ref} as the ratio of the power of $r(t_G^{(n)})$ to the power of $i(t_G^{(n)})$ in $\hat{r}(t_G^{(n)})$. An ideal reference signal has $Q_{ref} = \infty$.

The optimal antenna weights, $\mathbf{w}_{\hat{r}}$, which minimize the mean square error between $\hat{r}(t_G^{(n)})$ and $y(t_G^{(n)})$ are given by [2] as

$$\mathbf{w}_{\hat{r}} = R_{xx}^{-1} E[\mathbf{x}(t_G^{(n)}) \hat{r}^*(t_G^{(n)})] \tag{4}$$

where $R_{xx} = E[\mathbf{x}(t_G^{(n)})\mathbf{x}^H(t_G^{(n)})]$ is the signal correlation matrix. Substituting (3) into (4) and using that $i(t_G^{(n)})$ is uncorrelated with $\mathbf{x}(t_G^{(n)})$, we see that

$$\mathbf{w}_{\hat{r}} = R_{xx}^{-1} E[\mathbf{x}(t_G^{(n)}) r^*(t_G^{(n)})] = \mathbf{w}_r \quad (5)$$

where $\mathbf{w}_r$ are the optimal antenna weights associated with an ideal reference signal. Thus, the optimal antenna weight associated with our generated reference signal are equivalent to the optimal antenna weights associated with an ideal reference signal (training). Furthermore, since $\tilde{\mathbf{x}}_{i,k}^{(l)}(t_G^{(n)})$ is uncorrelated with $\tilde{\mathbf{x}}_{\hat{i},\hat{k}}^{(\hat{l})}(t_G^{(n)})$ for $(i,k,l) \neq (\hat{i},\hat{k},\hat{l})$, the antenna weights $\mathbf{w}_{\hat{r}}$ will also maximize the SINR at the output of the array for the desired signal $\tilde{\mathbf{x}}_{1,1}^{(1)}(t)$.

Simulation Results

With the description of our proposed implementation complete, we are now prepared to examine its performance for a multimedia CDMA network. In our simulations we consider two classical reference signal-based adaptive algorithms for the antenna weight controller: Least Mean Square (LMS) and Recursive Least Squares (RLS) [1]. For simplicity, let us denote our proposed implementations as illustrated in Figure 1 employing RLS and LMS algorithms for the antenna weight controller as Array System I(RLS) and Array System I(LMS). The criteria we will use to evaluate array system performance is SINR at the array output. Using this performance criteria, we compare the performance of Array System I(RLS) and Array System I(LMS) to the performance of baseline adaptive array systems employing RLS and LMS algorithms with an ideal reference signal. These baseline systems denoted as Array System II(LMS) and Array System II(RLS) are representative of an adaptive array system using training for antenna weight control and provide an upper bound on the performance of Array System I.

The communication network for which we will evaluate array performance is a 1.25 MHz two-media CDMA system with M=7 antenna elements. We assume each user has two signal paths arriving at the base station antenna array (i.e., L=2), and both signal paths arrive with equal power, $P_{i,k}^{(1)} = P_{i,k}^{(2)}$. Further, we assume perfect power control such that $P_{i,k}^{(1)} + P_{i,k}^{(2)} = P_i$, where P_i is chosen based on type-i service requirements. Table 1 provides a brief overview of our multimedia network's specifications.

service type (i)	R_i (Kbps)	(N_i)	$\frac{E_b^{(i)}}{N_o} = \frac{P_i T_b^{(i)}}{N_o}$ (dB)
1	9.6	128	7
2	19.2	64	10

Table 1: Multimedia network specifications.

For our simulation, we have chosen a randomly generated user scenario comprised of 30 service type-1 users and 10 service type-2 users. The signal paths from each user are assumed to arrive at the base station antenna array from a random angle uniformly distributed over $[-60°, 60°]$. Since each service type has distinct characteristics (i.e., signal power and processing gain), we evaluate array performance for both service types.

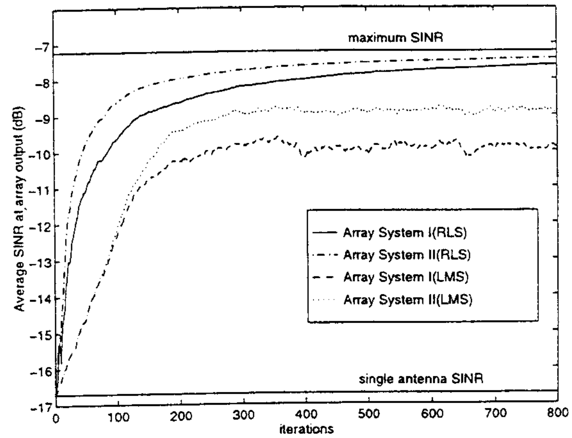

Figure 3: Array Performance for an arbitrary service type-2 user's signal.

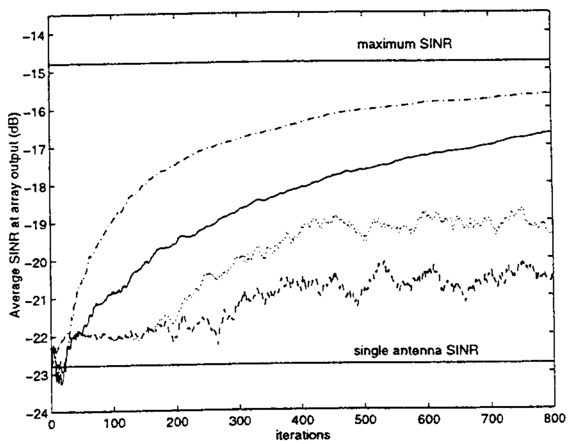

Figure 4: Array Performance for an arbitrary service type-1 user's signal.

Figure 3 shows the SINR results averaged over 100 trials for an arbitrarily selected signal path of a service type-2 user arriving from a angle of $-41.5°$. The single antenna SINR for this selected path is -16.7 dB and is illustrated in the Figure 3 along with the maximum SINR obtained using the optimal antenna weights. Since $N_1 = 64$ and G is constrained by N_2, we have chosen G=60 giving a maximum reference signal quality, Q_{ref}, of 1 dB. Similarly, Figure 4 shows the SINR results for an arbitrarily selected signal path of a service type-1 user arriving from an angle of 7.6°. The single antenna SINR for this selected path is -22.8 dB. Since $N_1 = 128$, we have chosen G=125 giving Q_{ref}= -1.8 dB. In both cases the RLS forgetting factor (λ) is 1, and the LMS step (μ) is .001.

From our simulation results given by Figures 3 and 4, we observe the SINR gains of our proposed implementation over a single antenna, as well as array convergence properties. In addition, by comparing Array System I performance to Array System II performance, we can note the effect of our self-generated reference signal on array performance. In Figure 3, we observe that Array System I(LMS) converges in approximately 200 iterations to an average SINR of -10 dB. This represents a 6 dB improvement over a single antenna element. Note that both Array System I(LMS) and Array System II(LMS) converge to an average SINR which is below the maximum SINR. This represents a *misadjustment* commonly associated with the LMS algorithm. The misadjustment of Array System I(LMS) is determined by a combination of the SINR at the antenna elements and the reference signal quality, and is lower bounded by Array System II(LMS) misadjustment.

The RLS algorithm does not suffer from a misadjustment and converges asymptotically to the maximum SINR. From Figure 3, we observe Array System II(RLS) provides approximately an additional 2 dB SINR improvement over Array System I(LMS). Furthermore, the effect of the self-generated reference signal results in a slightly slower convergence than the ideal reference signal case given by Array System II(RLS).

Figure 4 illustrates the impact of lower SINR and degraded reference signal quality associated with service type-1 on array performance. For LMS, the lower SINR results in slower convergence, and both lower SINR and degraded reference signal quality contribute to a larger misadjustment. As a result, Array System I(LMS) provides only a 2 dB gain over a single antenna element. Array System II(RLS) experiences a decrease in the convergence rate, but still appears to be converging to the maximum SINR. After 800 iterations Array System II(RLS) yields about a 6 dB improvement in SINR over a single antenna element which is 4 dB better than Array System I(LMS).

The SINR gains obtained with our array implementation translate directly to increases in communication system performance. Although reference signal quality does determine the closeness of our proposed array implementation performance to the upper bound given by Array System II, array performance is primarily limited by the SINR at the antenna elements. In a future paper, we will discuss modifications to our proposed implementation intended to improve array performance by utilizing spread-spectrum processing gains to increase the SINR at the individual antenna elements.

EIGENSPACE METHOD

Our second approach to blind adaptive weight control is based on eigenvalue decomposition and interference cancellation (EDIC). Figure 5(a) illustrates our proposed receiver implementation for which adaptive weight control is accomplished by a combination of code filtering, interference cancellation, and Dominant Mode Determination. Also, depicted is the concept of combining spatial and temporal processing of the received signal to improve performance in a multipath environment. In this section, we describe our proposed EDIC approach to antenna weight control and present simulation results for a single-media CDMA network.

At the receiver, the received signals at the antenna elements are processed by a new code filter (shown in Figure 5(b)) which uses the known spreading code of the desired user to generate a signal $\mathbf{y}$, and an interference signal $\mathbf{z}$. The desired signal is a major component of $\mathbf{y}$, while not present in $\mathbf{z}$. If we consider the first path of user 1 as the desired signal, the discrete time of signal $\mathbf{x}_{1,1}^{(1)}(n)$ can be obtained by

$$\mathbf{x}_{1,1}^{(1)}(n) = \int_{\tau_{1,1}^{(1)}+(n-1)T_c}^{\tau_{1,1}^{(1)}+nT_c} \mathbf{x}(t) C_{1,1}(t-\tau_{1,1}^{(1)})dt \qquad (6)$$

The signal space is constructed by $\mathbf{y}_{1,1}^{(1)}(m)$ which is the summation of signal $\mathbf{x}_{1,1}^{(1)}$ over a bit duration.

$$\begin{aligned} \mathbf{y}_{1,1}^{(1)}(m) &= \sum_{n=1}^{n=N} \mathbf{x}_{1,1}^{(1)}(Nm+n) \\ &= \sqrt{P_{1,1}^{(1)}} T_b b_{1,1}(m) e^{j\phi_{1,1}^{(1)}} \mathbf{a}_{1,1}^{(1)} + \mathbf{u}_{1,1}^{(1)}(m) \qquad (7) \end{aligned}$$

The covariance matrix of $\mathbf{y}_{1,1}^{(1)}$ can be written as

$$\begin{aligned} \mathbf{R}_{yy,1,1}^{(1)}(m) &= E[\mathbf{y}_{1,1}^{(1)}(m)\mathbf{y}_{1,1}^{(1)}(m)^H] \\ &= T_c^2(\mathbf{A}\mathbf{D}_y\mathbf{A}^H + \sigma^2\mathbf{I}) \qquad (8) \end{aligned}$$

where the columns of the channel matrix $\mathbf{A}$ consists of the channel response vector for each user,$\mathbf{a}_{i,k}^{(l)}$, and σ^2 represents the thermal noise power at each antenna element. The matrix $\mathbf{D}_y$ is a KL-byKL power matrix consisting of K nonzero L-by-L matrices along its diagonal. The $(1,1)$ element of $\mathbf{D}_y$ is equal to $NP_{1,1}^{(1)}$ which is the received power of the desired user's signal amplified by the processing gain. The interference subspace is constructed by the signal $\mathbf{z}_{1,1}^{(1)}(n)$ which is defined as

$$\mathbf{z}_{1,1}^{(1)}(n) = \mathbf{x}_{1,1}^{(1)}(2n) - \mathbf{x}_{1,1}^{(1)}(2n-1). \qquad (9)$$

The reader can easily verify that the desired signal is not contained in $\mathbf{z}_{1,1}^{(1)}(n)$. We now introduce beamforming algorithms that utilize the information contained in signals $\mathbf{y}_{1,1}^{(1)}$ and $\mathbf{z}_{1,1}^{(1)}$ to generate the antenna weights maximizing the SINR.

Beamforming Algorithms

GED method

If the total interference $\mathbf{u}_{1,1}^{(1)}(m)$ in equation (7) is known, the beamformer which maximizes the signal to interference and noise ratio (SINR) equals to the dominant eigenvector of the matrix pencil $(\mathbf{R}_{yy,1,1}^{(1)} - \lambda\mathbf{R}_{uu,1,1}^{(1)})$[5][6]. However, since the exact interference can not be obtained in practical systems, we estimate it as $\mathbf{z}_{1,1}^{(1)}$ and compute the antenna weights as the dominant eigenvector of $(\mathbf{R}_{yy,1,1}^{(1)} - \lambda\mathbf{R}_{zz,1,1}^{(1)})$. When applied adaptively, the GED will suffers from high hardware cost and unreliable convergence speed.

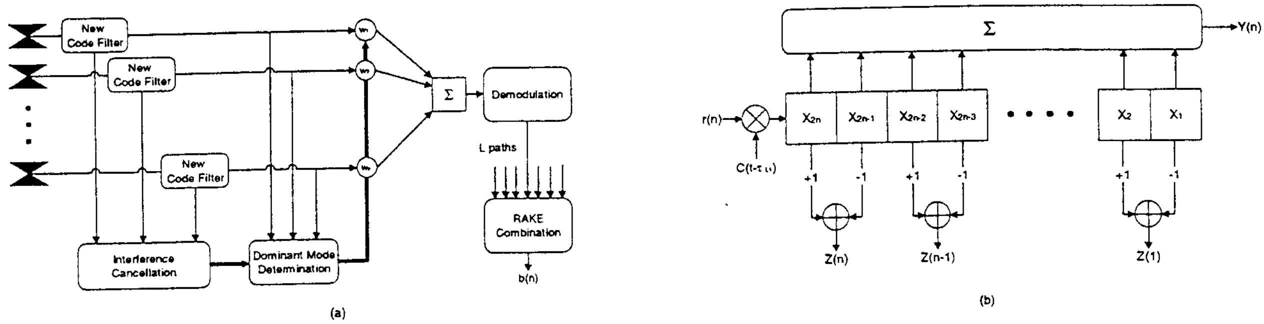

Figure 5: (a) Rake-beamforming receiver. (b) New code filter

EDIC Beamformer

The received signal from M antenna elements generates a power field in C^M space. The power of desired signal is $O(N)$ times larger than any other signals in DS/CDMA system. The largest power direction $\hat{\mathbf{a}}$ in this C^M space is known as the dominant eigenvector in the covariance matrix $\mathbf{R}^{(1)}_{yy,1,1}$.

Assume the $(\lambda_1, \dots, \lambda_p)$ and $\mathbf{Q} = [\mathbf{q}_1, \dots, \mathbf{q}_p]$ represent the eigenvalue (power) and the eigenvector (directions) of the interference correlation matrix $\mathbf{R}^{(1)}_{zz,1,1}$. We compute the antenna weights as a projection of $\hat{\mathbf{a}}$ on the domain of the least interference.

$$\begin{aligned}\mathbf{w}_{EDIC} &= \lambda_1^{-1}(\mathbf{q}_1^H\hat{\mathbf{a}})\mathbf{q}_1 + \dots + \lambda_p^{-1}(\mathbf{q}_p^H\hat{\mathbf{a}})\mathbf{q}_p \\ &= \mathbf{Q}\Lambda^{-1}\mathbf{Q}^H\hat{\mathbf{a}} \\ &= \mathbf{R}^{-1}_{zz,1,1}\cdot\hat{\mathbf{a}} \qquad (10)\end{aligned}$$

If $\hat{\mathbf{a}}$ is correctly estimated as a scalar factor away from the desired channel response and $\mathbf{R}^{(1)}_{zz,1,1}$ equals to the exact interference, the above beamforming weights will be the same as the ideal maximum SINR solution.

EDIC Recursive Algorithms

Since we are interested in antenna weight adaptation in a time-varying environment, a recursive algorithm is developed for our proposed EDIC approach. We assume that the correlation matrix $\hat{\mathbf{R}}_{zz}(n)$ and $\hat{\mathbf{R}}_{yy}(n)$ can be estimated over an exponential window. A forgetting factor $\mu(n)$ can be either time varying or a constant value between 0 and 1. For convenience of notation, we let

$$\mathbf{P}(n) = \hat{\mathbf{R}}^{-1}_{zz}(n) \qquad (11)$$

and cite the updating equations of matrix $\mathbf{P}(n)$ from the RLS algorithm [1]. The dominant mode $(\lambda_{max}, \hat{\mathbf{a}})$ of matrix $\hat{\mathbf{R}}_{yy}(n)$ can be found by using the power method [7]. If λ_2 denotes the second largest eigenvalue, it is shown that the power iterations will converge in exponential rate with factor

$$\frac{\lambda_{max}}{\lambda_2} \geq \frac{\lambda_{max}}{\lambda_2 + \dots + \lambda_M} \approx SINR_y \qquad (12)$$

The power method should converge from several to ten iterations. The recursive algorithm is summarized as follows:

Initialize : $n = 1$

- $\hat{\mathbf{R}}_{yy}(1) = \delta\mathbf{I} + \mathbf{y}(1)\mathbf{y}^H(1)$, and δ is small.
- $\mathbf{P}(1) = \hat{\mathbf{R}}^{-1}_{zz}(1) = (\delta\mathbf{I} + \mathbf{z}(1)\mathbf{z}^H(1))^{-1}$.
- $\hat{\mathbf{a}}(1) = \frac{\mathbf{y}(1)}{\|\mathbf{y}(1)\|}$.
- $\lambda_{max} = \|\mathbf{y}(1)\|^2$.

When $n = 2, 3, \dots$

1. if $(n = 2)$, then $\mu(n) = 1$
   else $\mu(n) = \hat{\mathbf{a}}^H(n-2)\cdot\hat{\mathbf{a}}(n-1)$.
2. $\mathbf{c}(n) = \frac{\mu^{-1}(n)\mathbf{P}(n-1)\mathbf{z}(n)}{1+\mu^{-1}(n)\mathbf{z}^H(n)\mathbf{P}(n-1)\mathbf{z}(n)}$.
3. $\mathbf{P}(n) = \mu^{-1}(n)[\mathbf{I} - \mathbf{c}(n)\mathbf{z}^H(n)]\mathbf{P}(n-1)$.
4. $\hat{\mathbf{R}}_{yy}(n) = \mu(n)\hat{\mathbf{R}}_{yy}(n-1) + \mathbf{y}(n)\mathbf{y}^H(n)$.
5. Calculate $\hat{\mathbf{a}}(n)$ from $(\hat{\mathbf{R}}_{yy}(n)$ & $\hat{\mathbf{a}}(n-1))$ using power iteration.
6. $\hat{\mathbf{w}}(n) = \mathbf{P}(n)\cdot\hat{\mathbf{a}}(n)$.

Table 2 shows the total number of multiplications in each updates of the EDIC recursive algorithm. As a comparison, the flops used in GED [3] are $(27+i)M^2 + (13+2i)M$ where i is the power iteration number. We note that our EDIC approach offers significant reductions in hardware complexity (about 70%) when compared to the GED beamformer. Another advantage of the EDIC beamformer over the GED beamformer is the convergence rate of the power iteration. In equation (12), we indicated the convergence rate of the EDIC beamformer depends on the SINR of the receiving signal and the antenna number, which is fixed by the power control and the architecture of the antenna. However, the GED algorithm finds the dominant mode of the matrix $\mathbf{R}^{-1}_{uu}(n)\mathbf{R}_{yy}(n)$ in the power iteration, which is adversely affected by the condition of the interference matrix $\mathbf{R}^{-1}_{uu}(n)$. Therefore, the convergence factor becomes variable in every update. Simulation results will compare the performance of these two updating methods in the next section.

Simulation Results

To study the performance of the algorithms in the above section, we first assume a single cell DS/CDMA system which uses DQPSK as the modulation scheme with $K = 20$ users randomly distributed in azimuth around the basestation over $[0, \pi]$. The arrival angle diversity [8] is assumed to be $\Delta\theta =$

Step #	Number of Flops
1	M
2	$2M^2 + 2M$
3	M^2
4	$2M^2$
5	$i(M^2 + 2M)$
6	M^2
Total	$(6+i)M^2 + (3+2i)M$

Table 2: Number of multiplication in EDIC recursive algorithm

Path #	1st	2nd
Arriving angle	$\pi/4$	$5\pi/8$
Relative delay	0	$4T_c$
Receiving power	1	0.8

Table 3: Desired user's arrival parameters

$\frac{\pi}{16}$. At the basestation, we consider the different cases in which antenna array has $M = 2, 4, 6, 8, 10$ elements separated equally by a half carrier wavelength. Each user has two signal paths arriving at the base station array, and we assume perfect power control such that $P_{1,1}^{(1)} + P_{1,1}^{(2)} = constant$. In addition, the power in each path is assumed to be Rayleigh distributed. We assume the spreading codes of each user are known and arriving delay is well estimated. The desired signal to thermal noise ratio is 3 dB, and the receiving SINR equals -14.8 dB. The processing gain, $N = 64$. In Table 3, we provide the simulation parameters for the desired users' received signals.

When simulating the adaptive algorithms, we fix the forgetting factor $\mu = 1$ and show the mean square error (MSE) of the estimated signal versus bit iterations. Fig. 6 shows that the EDIC recursive algorithm has better performance and converge faster than the GED beamformer. A lower bound on MSE performance can be found from the Wiener solution assuming that the desired channel response and the training bits can be obtained accurately. An upper performance bound is taken as the Maximum Ratio Combining (MRC) of each antenna output. In Figure 7 we plot the performance of our proposed EDIC method and the GED method along with the upper and lower bounds for $M = 10$. From these results, we note EDIC offers a 5 dB performance improvement over the GED method.

CONCLUSION

In this paper, we have presented two new adaptive array approaches for communications in a DS/CDMA network. The proposed approaches offer significant improvements in communication system performance and/or network capacity through SINR gains realized by array beamforming. In addition, both approaches blindly update antenna weights and offer reasonable convergence rates with low computational complexity. Although, up to this point we have focused on applications for a centralized network with a base station, the adaptive techniques have obvious extensions to a distributed network.

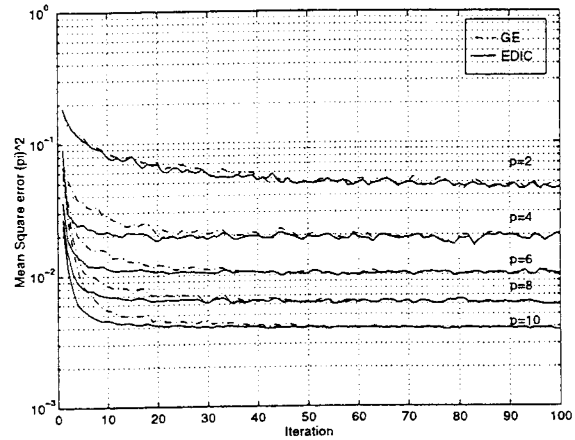

Figure 6: The EDIC and GED beamformer.

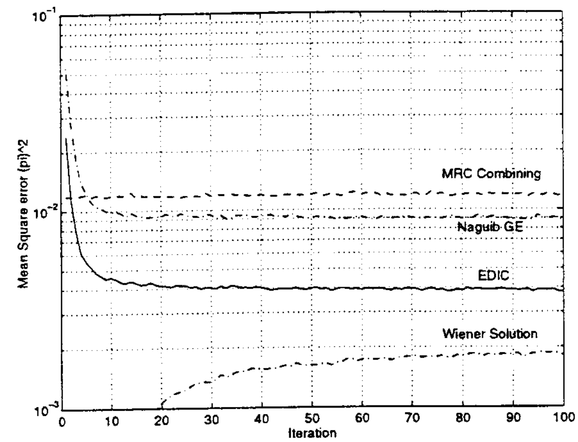

Figure 7: The EDIC and sub-EDIC method to the upper and lower bound.

While the techniques proposed here have applicability to commercial cellular/PCS systems, they also have appeal for maximizing the capacity of future wireless army communication systems. Our current proposed implementations address operation in a multi-user access interference (MAI) environment only. Military systems have the additional requirement to operate in a hostile jamming environment which we expect will degrade our array's performance. Thus, we are currently investigating modifications which are intended to provide improved performance in a MAI/jammer environment.[1]

[1]The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government.

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