ADAPTIVE ANTENNA ARRAY ALGORITHMS AND THEIR IMPACT ON CODE DIVISION MULTIPLE ACCESS SYSTEMS (CDMA)

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ABSTRACT

In mobile communications there is a need to increase the channel capacity. The increasing demand for mobile communication services without a corresponding increase in RF spectrum allocation (channel capacity) motivates the need for new techniques to improve spectrum utilization. The CDMA and adaptive antenna array are two approaches that shows real promise for increasing spectrum efficiency. This paper focuses on the application of adaptive arrays to the Code Division Multiple Access (CDMA) cellular systems. The adaptive antenna has an intelligent control unit, so the antenna can follow the user, direct the radiation pattern towards the desired user, adapt to varying channel conditions and minimize the interference. Therefore there can be several users in the same channel in the same cell. The driving force of this intelligent control unit are special kinds of algorithms and we are going to investigate the performance of these different adaptive array algorithms in the CDMA systems.

In this paper four each blind adaptive array algorithms are developed, and their performance under different test situations (e. g. AWGN (Additive White Gaussian Noise) channel, and multipath environment) is studied. A MATLAB test bed is created to show their performance on these two test situations and an optimum one can be selected. We shall also try to show the adaptive nature of the beam former in response to the change in the direction of arrival of the signal on the antenna array. The matlab program will plot a rectangular and polar plot for the signals of different users.

Key words:
Code Division Multiple Access (CDMA), Adaptive(Smart Antenna), and Adaptive Array Algorithms.

INTRODUCTION

The concept of cellular or mobile communication was developed in the 1970's at Bell Labs in the U.S. The idea behind the concept was simple: Instead of providing communication services in a centralized fashion through a single high-power transmission / receiver station, they are provided in a distributed fashion via several low power stations.

The geographical area that the communication system serves is divided into smaller subareas, called cells.within each cell, all the communication is carried out via the basestation serving that particular cell.when a mobile-phone user wants to make a call or download data from a server, he or she must first connect to the appropriate wireless network. The connection is made using radio links (i.e em waves) between the phone or terminal and the nearest basestation operated by that network provider. In turn the baseststion is connected to a high capacity fiber-optic "backbone"that links together many other networks. It is via this backbone network that the user can connect to any other conventional phone (PSTN); mobile phone or additional service within the public network.

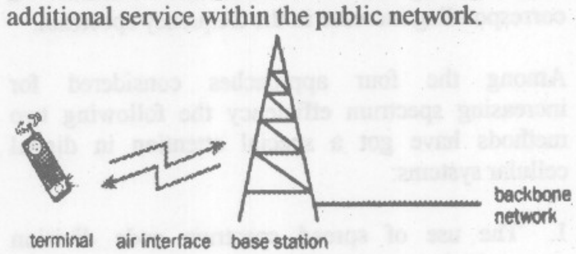


Figure 1 Mobile phones make the connection

The basic idea behind wireless-communication system. The caller connects to the appropriate network by first sending signals to the nearest base station, which is in turn connected to the backbone network (Fig. 1).

The most important factor in the success of the cellular concept has been the relative ease with which the total system capacity can be increased. The rapid growth in the number of users of mobile communications means that many operators must find new ways of increasing the capacity of their networks. A higher demand in wireless communications calls for higher system capacities. The capacity of a wireless communication system can be increased by different methods.

These methods include:

1. By directly enlarging the bandwidth of the existing communication channels or by allocating new frequencies to the service in question.

2. By the division of a geographical area into cells.

3. By using Multiple-Access technique.

4. By using Adaptive Antenna.

The radio frequency spectrum allocated for mobile communication services (which is 800-900 MHz) is very limited, scarce and costy. And cellular operators have 25MHz each, split between the two directions of communication (i.e transmission and receiving). Due to this, the services given for mobile communication are bounded. Hence there comes a need or Motivation for new technologies to improve effective spectrum utilization without a corresponding increase in the frequency spectrum.

Among the four approaches considered for increasing spectrum efficiency the following two methods have got a special attention in digital cellular systems:

1. The use of spread spectrum code division multiple access(CDMA)technology,

2. The use of adaptive antenna array in the cellsite basestaion.

This paper presents the application of Adaptive Antenna on the performance improvement of a Code Division Multiple Access (CDMA).

CDMA is the channel in which multiple users communicate with the nearest basestation, and an adaptive antenna array is a system comprised of a number antenna elements (called arrays) together with a signal processor. The arrays are used to receive communication signals and the adaptive signal processor is used to make them smart. i.e the adaptive antenna is capable of automatically forming beams in the directions of the desired signals and forming nulls in the direction of the interfering signals. Hence by using the adaptive antenna in a CDMA system we can reduce the amount of co-channel interference from other users with in its own cell and from neighboring cells, and therefore increase the system capacity.

The signal processor, which is the intelligent part of the adaptive antenna, can be preprogrammed but usually uses special kinds of adaptive algorithms. There are different kinds adaptive algorithms developed having different performance. Based upon their performance algorithms are chosen and an optimum one is chosen to be used on adaptive antenna in CDMA. And this is the second task of this paper.

In CDMA, signals from different callers are transmitted at the same time and in the same frequency band. In this case, the signals can be distinguished from each other by a so called spreading code that is allocated to each user. This spreading code (which is a kind of pseudo-noise) is applied to the signal before it is transmitted. The signals from a particular user can be separated from each other at the receiver by correlating them with the desired spreading code. CDMA employs spreading spectrum modulation (i.e. each user's signal wave form is spread over the entire frequency spectrum by applying the code sequence to the signal). The intended receiver then uses the appropriate code to detect the signal of his or her choice.

Adaptive Antenna Array

An adaptive antenna is a system comprised of set of antenna elements called arrays and a signal processor. The antenna elements (arrays) are used to receive communication signals and the signal processor is used to make them smart.

The antenna elements can be arranged in varying geometries: Linear array, Circular array, and A Planar array.In this paper a special type of linear array called ULA is considered. In ULA the centers of elements are spaced equally.

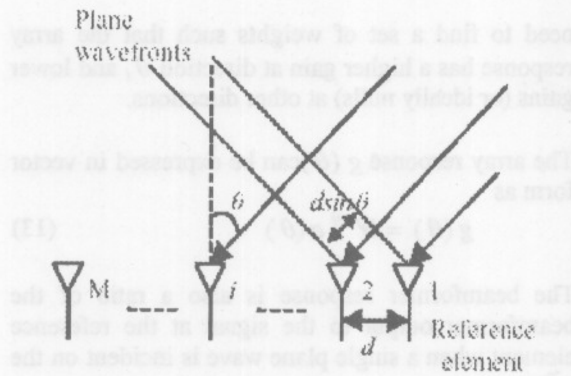


Figure 2 A simple narrow band adaptive array

Consider an M-element uniformly linear array as shown in Fig. 2 and the array elements are equally spaced by a distance 'd', and plane wave arrives at the array from a direction θ off the array broadside. The angle θ is called the direction-of-arrival (DOA) or angle of arrival (AOA) of the received signal, and is measured clockwise from the broadside of the array.

The received signal at the first element can be expressed as

$$\widetilde{X}_1(t) = u(t)\cos(2\pi f_c t + \gamma(t) + \beta) \qquad (1)$$

and the complex representation of $\widetilde{X}_1(t)$ is given by

$$X_1(t) = u(t)\exp\{j(\gamma(t) + \beta)\} \qquad (2)$$

f_c - is the carrier frequency of the modulated signal ($f_c = c/\lambda$),

$\gamma(t)$ - is the information carrying component,

β -is the random phase,

$u(t)$ - is the amplitude of the signal.

The complex envelope representation of the received signal for element 'i' is given by :

$$X_i(t) = x_1(t)\exp\{j(\frac{2\pi}{\lambda}(i-1)d\sin\theta)\},\ i=1,2,3.. \qquad (3)$$

Eq. (1.3) can be expressed in vector form as:

$$X(t) = a(\theta)X_1(t) \qquad (4)$$

The vector **x** (t) is often referred to as the *array input data vector or the illumination vector*, and **a** *(θ) is called the steering vector*.

General case: Suppose there are 'q' narrowband signals $s_1(t), \ldots\ldots, s_q(t)$, all centered around a known frequency, say fc, impinging on the array with a DOA θ_i, i=1,2, ……., q. The received signal at the array is a superposition of all the impinging signals and noise. Therefore, the input data vector may be expressed as

$$X(t) = \sum_{i=1}^{q} a(\theta_i)s_i(t) + n(t) \qquad (5)$$

and **n**(t) denotes the Mx1 vector of the noise at the array elements, and

$$a(\theta_i) = \begin{bmatrix} 1 \\ e^{-j\frac{2\pi}{\lambda}d\sin\theta_i} \\ \vdots \\ e^{-j\frac{2\pi}{\lambda}(m-1)d\sin\theta_i} \end{bmatrix}$$

is the steering vector. (6)

In matrix notation, Eq. (5) becomes

$$X(t) = A(\Theta)s(t) + n(t) \qquad (7)$$

Where $A(\Theta)$ is the Mxq matrix of the steering vectors

$$A(\Theta) = [a(\theta 1), \ldots\ldots, a(\theta q)] \qquad (8)$$

and

$$s(t) = \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_q(t) \end{bmatrix} \qquad (9)$$

Equation (7) represents the most commonly used **narrowband input data model.**

With the data model created above, most array processing problems may be categorized as follows. Given the sampled data **X** in a wireless system, determine:

1. the number of signals q
2. the DOAs $\theta 1, \ldots\ldots, \theta_q$
3. the signal waveforms s(1),……., s(K).

We shall refer to (1) as the detection problem, to (2) as the localization problem, and to (3) as the **beamforming** problem, which is the focus of this research.

A narrowband beamformer, shown in Fig. 3, combines the spatially sampled time series from each sensor to obtain a scalar output time series i.e the signals received at the different antenna elements are multiplied with complex weights, and then summed up; the weights are chosen adaptively by the processor.

The output of the beamformer at time k is given by;

$$y(k) = w_1^* x_1(k) + w_2^* x_2(k) + \ldots\ldots\ldots, w_m^* x_m(k), \\ = \sum_{i=1}^{M} w_i^* \, x_i(k) \qquad (10)$$

w_i is called the complex weight.

The vector form of eqn (1.10) is by

$$Y(k) = W^H X(k) \qquad (11)$$
$$W = [w_1, w_2, \ldots\ldots\ldots, w_M]^T.$$

The output of the beamformer (adaptive antenna) is in the form a beam or radiation pattern and its radiation pattern is determined by the radiation pattern of the individual elements, their orientation and relative position in space, and the amplitude and phase of feeding currents. In our case we assumed that each element of the array is an isotropic point source, and the radiation pattern of the array will depend solely on the geometry and feeding currents of the array, and the radiation pattern so obtained is called **beamformer response** given by:

$$g(\theta) = \sum_{i=1}^{M} w_i^* \exp\{-j(\frac{2\pi}{\lambda})(i-1)d \sin\theta \qquad (12)$$

where $g(\theta)$ represents the response of the array to a signal with DOA equal to θ, so if there are several signals coming from different directions, and if we want to extract the signal with direction θ_i, we need to find a set of weights such that the array response has a higher gain at direction θ_i and lower gains (or ideally nulls) at other directions.

The array response $g(\theta)$ can be expressed in vector form as

$$g(\theta) = W^H a(\theta) \qquad (13)$$

The beamformer response is also a ratio of the beamformer output to the signal at the reference element when a single plane wave is incident on the array

$$g(\theta) = W^H a(\theta) = \frac{Y}{x_1(t)} \qquad (14)$$

The beampattern is defined as the magnitude of $g(\theta)$

$$G(\theta) = |g(\theta)| \qquad (15)$$

We can define the normalized beamformer response as:

$$g_n(\theta) = \frac{g(\theta)}{\max\{G(\theta)\}} \qquad (16)$$

where $g_n(\theta)$ is also known as the normalized radiation pattern or array factor of the array.

Adaptive Beamforming Algorithms.

In a mobile communication system, the mobile is generally moving; therefore the DOAs of the received signals in the base station are time varying. Also, due to the time-varying wireless channel between the mobile and the base station, and the existence of the cochannel interference, multipath, and noise, the parameters of each impinging signal are varied with time. For a beamformer with constant weights, the resulting beampattern cannot track these time-varying factors. However, an adaptive array may change its patterns automatically in response to the signal environment. An adaptive array is an antenna system that can modify its beampattern or other parameters, by means of internal feedback control while the antenna system is operating. Adaptive arrays are also known as adaptive beamformers, or adaptive antennas. A simple narrowband adaptive array is shown in Fig. 3.

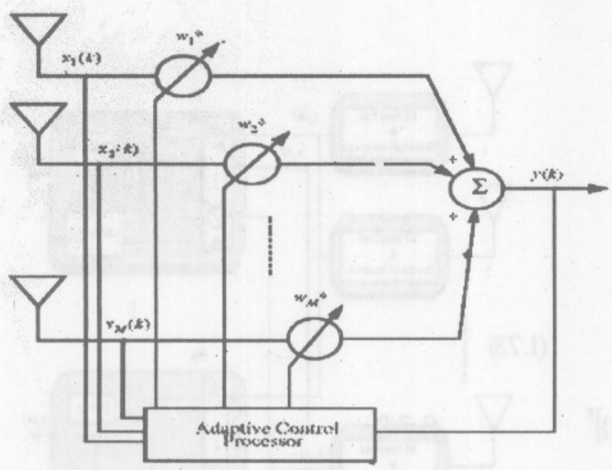


Figure 3 An adaptive array

In Fig. 3, the complex weights $w_1, \ldots, w_M$ are adjusted by the adaptive control processor. The method used by the adaptive control processor to change the weights is called the **adaptive algorithm**. For one adaptive array, there may exist several adaptive algorithms that could be used to adjust the weight vector.

Most adaptive algorithms may be categorized into two classes. One class of these algorithms is the **non-blind adaptive algorithm** (such as Wiener solution, Steepest Descent solution, and Least Mean Square)in which a training signal is used to adjust the array weight vector. Another technique is to use a **blind adaptive algorithm** (DOA's estimation, Property restoral) which does not require a training signal.

Since the non-blind algorithms use a training signal, during the training period, data cannot be sent over the radio channel. This reduces the spectral efficiency of the system. Therefore, the blind algorithms are of more research interest.

Blind Adaptive Algorithms

Blind adaptive algorithms do not require a training sequence. Instead, they exploit some known properties of the desired received signal. Most of the blind algorithms may be categorized into the following three classes or combinations of them:

- Algorithms based on estimation of the DOAs of the received signals.
- Algorithms based on property-restoral techniques.
- Algorithms based on the discrete-alphabet structure of digital signals.

Each of the above three category is a vast research by it self, hence in our case we particularly focus our attention towards the second.

In this paper four types of blind adaptive algorithms are considered and their performance under different test condition is studied.

(a) Multitarget Least-Squares Constant Modulus Algorithm (MT-LSCMA).

In here the number of output ports is equal to the number of antenna elements, and the weight vectors $w_1, w_2, \ldots\ldots, w_M$ are initialized with a set of different vectors, for ex, the column vectors of MxM identity matrix.

In MT-LSCMA, after the algorithm converges, a sorting procedure must be performed to relate the port outputs to each user's signal. In a CDMA system, the pseudo-noise (PN) sequence assigned to each user can be utilized in the sorting procedure. For a CDMA system with p users, the complex envelope of the signal transmitted by the *i*th user can be expressed as

$$s_i(t)=\sqrt{2p_i}\,b_i(t)c_i(t)\exp\{-j\phi_i\},\quad i=1,2,\ldots,p, \tag{17}$$

where $p_i(t)$, $bi(t)$, $ci(t)$ and $\phi_i(t)$,are the power, the data signal, the spreading signal (PN sequence), and the random phase of the *i*th user signal, respectively.

The output of port *i* in the beamformer is then given by

$$y_i(t)=\alpha_i\sqrt{2P_j}\,b_j(t-\tau_j)\exp\{-j(\phi_j+\gamma_i)\}+n_i(t) \tag{18}$$

Figure 4, $y(t)$ is -a vector containing the port outputs of the beamformer and is given by

$$Y(t)=[y_1(t), y_2(t), \ldots\ldots, y_M(t)]^T \tag{19}$$

(b) Multitarget Decision-Directed Algorithm

By replacing LS-CMA in the MT-LSCMA with decision-directed (DD) algorithm described previously, we obtain the MT-DD algorithm

$$Y(l) = \left[W^H(l)X(l)\right]^T \qquad (1.73)$$

$$= \left[y(1+lk), y(2+lk), \ldots\ldots, y((l+1)k)\right]^T,$$

$$r(l) = \left[\mathrm{sgn}\{\mathrm{Re}(y(1+lk))\}, \ldots\ldots\ldots, \mathrm{sgn}\{\mathrm{Re}(y((l+1)k))\}\right]^T \qquad (1.74)$$

$$W(l+1) = \left[X(l)X^H(l)\right]^{-1} X(l) r^*(l) \qquad (1.75)$$

where l is the iteration number, and K is the number of samples in one data block.

(c) Least-Squares Despread Respread Multitarget Array (LS-DRMTA)

The multitarget adaptive algorithms discussed to date do not utilize any information of the spreading signal of each user in the CDMA system. However, in a CDMA system, it is these spreading signals that distinguish different users occupying the same frequency band. Therefore it will be very useful if the information of these spreading signals can be utilized in the multitarget adaptive algorithm. The algorithm discussed in this section is called least-squares despread respread multitarget array (LS-DRMTA).

In a conventional CDMA system, the PN sequence is repeated every bit period, therefore both $c_i(t)$ and $ri(t)$ have a time period T_b.

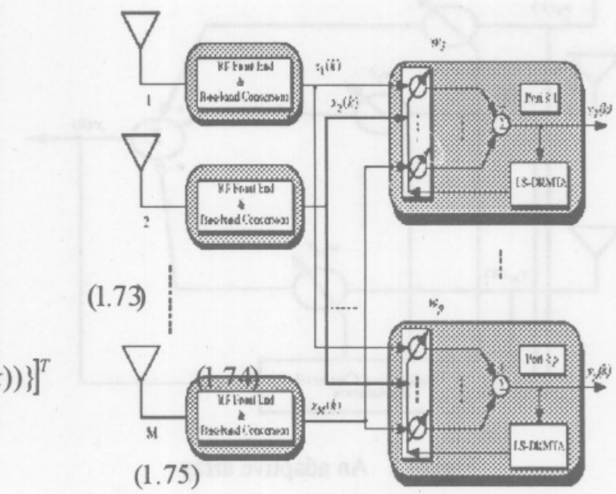


Figure 4 Structure of a beamformer using LS-DRMTA

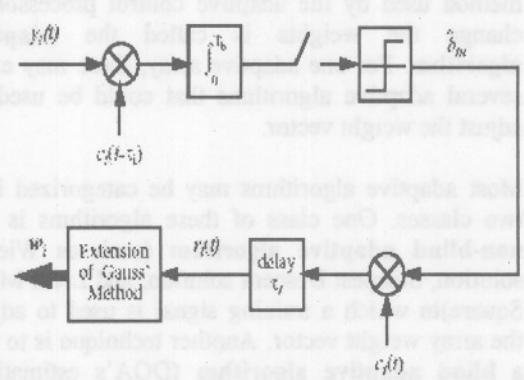


Figure 5 LS-DRMTA block diagram for user i

Using the extension of Gauss' method again the iterative equation for updating of the weight as:

$$W_i(l+1) = w_i(l) - \left[XX^H\right]^{-1} X\left(y_i(l) - r_i(l)\right)^*$$

$$= w_i(l) - \left[XX^H\right]^{-1} XX^H w_i(l) + \left[XX^H\right]^{-1} X r_i(l)^*$$

$$= \left[XX^H\right]^{-1} X r_i^*(l),$$

where $y_i(l)$ *and* $r_i(l)$ are the output data vector and estimate of signal waveform of user i over one bit period corresponding to the weight vector w_i in the lth iteration, respectively.

Similar to the dynamic LS-CMA, LS-DRMTA can adapt the weight vectors using different input data blocks in each iteration.

Let

$$X(l)=[x(1+lk),x(2+lk),\ldots\ldots\ldots\ldots,x((l+1)k)] \qquad l=0,1,\ldots,L, \tag{20}$$

where L is the number of iterations required for the algorithm to converge, and K is the number of data samples per bit (NcNs) if the data samples over one bit period are all used for the adaptation. In Fig. 4, the LS-DRMTA for the ith user can be described by the following equations:

$$y_i(l)=\left[w_i^H(l)X(l)\right]^T$$

$$=\left[y_i(1+lk),y_i(2+lk),\ldots\ldots\ldots,y_i((l+1)k)\right]^T,$$

$$\widehat{b}_{il}=\operatorname{sgn}\left\{\operatorname{Re}\left(\sum_{k=1+lk}^{(l+1)k} y_i(k)c_i(k-k_{\tau_i})\right)\right\} \tag{21}$$

$$r_i(l)=\widehat{b}_{il}\left[c_i(1+lk-k_{\tau_i}),\widehat{b}_{il}c_i(2+lk-k_{\tau_i}),\ldots,\widehat{b}_{il}c_i((l+1)k-k_{\tau_i})\right]^T, \tag{22}$$

$$W_i(l+1)=\left[X(l)X^H(l)\right]^{-1}X(l)r_i^*(l) \tag{23}$$

where $c_i(k)$ is the kth sample of the spreading signal of user i, $k\tau_i$ is the number of samples corresponding to τ_i, the delay of user i, and $\widehat{b}_{il}$ l is the estimate of lth bit for user i. The accumulated sum in Eq. (21) is equivalent to integration in the continuous time domain.

(d) Least-Squares Despread Respread Multitarget Constant Modulus Algorithm

LS-DRMTCMA combines the spreading signal and the constant modulus property of the transmitted signal to adapt the weight vector. The algorithm using this kind of combination in the adaptation of the weight vector is referred to as least-squares despread respread multitarget constant modulus algorithm (LS-DRMTCMA) in this research. Fig. 4 shows the structure of a beamformer using the LS-DRMTCMA and Fig. 5 shows the block diagram of the LS-DRMTCMA for user i.

We obtain the following equations for LS-DRMTCMA:

$$y_i(l)=\left[w_i^H(l)X(l)\right]^T$$

$$=\left[y_i(1+lk),y_i(2+lk),\ldots\ldots\ldots,y_i((l+1)k)\right]^T,$$

$$\widehat{b}_{il}=\operatorname{sgn}\left\{\operatorname{Re}\left(\sum_{k=1+lk}^{(l+1)k} y_i(k)c_i(k-k_{\tau_i})\right)\right\}$$

$$r_i(l)=\widehat{b}_{il}\left[c_i(1+lk-k_{\tau_i}),\widehat{b}_{il}c_i(2+lk-k_{\tau_i}),\ldots,\widehat{b}_{il}c_i((l+1)k-k_{\tau_i})\right]^T,$$

$$r_{iCM}(l)=\left[\frac{y(1+lk)}{|y(1+lk)|},\frac{y(2+lk)}{|y(2+lk)|},\ldots\ldots,\frac{y((1+l)k)}{|y((1+l)k)|}\right]^T$$

$$r_i(l)=a_{PN}\,r_{iPN}(l)+a_{CM}\,r_{iCM}(l)$$

$$W_i(l+1)=\left[X(l)X^H(l)\right]^{-1}X(l)r_i^*(l) \tag{24}$$

From the above equations we see that if a_{CM} is set to zero, the LS-DRMTCMA becomes the LS-DRMTA, therefore the LS-DRMTA can be viewed as a special case of the LS-DRMTCMA.

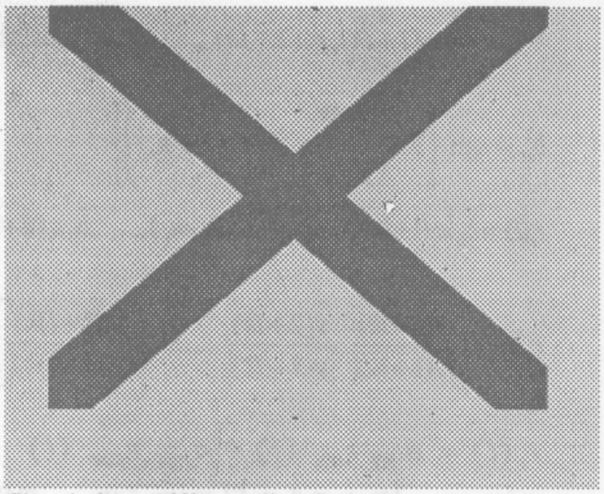
Also we see that if a_{PN} is set to zero and the GSO procedure is performed during the adaptation, the algorithm becomes MT-LSCMA. The choice of a_{PN} and a_{CM} can affect the resulting beampattern and thus the performance of the system.

Results Obtained and Discussion

This section provides the simulation results on the performance of the algorithms under two test conditions (AWGN channel, and Multipath channel). Our comparison of the algorithms will focus on the BER performance of different algorithms.

Let's first consider one case where there are 8 users in the system transmitting CDMA signals from different directions. The DOAs of the signals are equally spaced between -70^0 and 90^0. Fig. 6 shows the distribution of these 8 users. We assume that there is no multipath and the radio channel only introduces the additive white Gaussian noise (AWGN). We also assume perfect power control in the base station, so all the signals impinging on the array have the same power. The input signal to noise ratio per bit (E_b/N_0) is set to 20dB. Table 1 shows the signal parameters of the user's entire signal.

Table 1: Signal Parameters of 8 Users Transmitting



Signals from Different directions

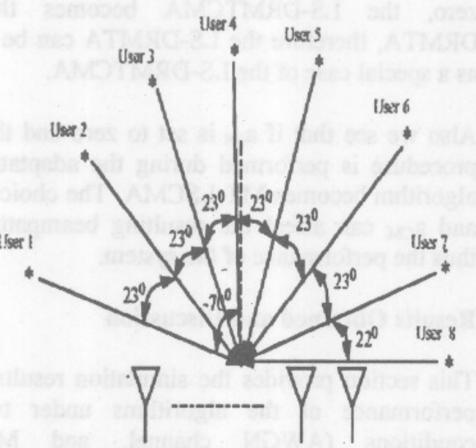


Figure 6 Illustration of eight users with DOAs equally spaced between -70^0 and 90^0

BER Performance for AWGN Channel

In this section, we will compare the BER performance of different algorithms under different conditions. We will consider two E_b / N_0 cases, E_b / N_0 = 8 dB, and E_b / N_0 = 4 dB. For each E_b / N_0 case, we will also consider two different DOA distribution cases. One case is the non-crowded case with all the DOAs of the signals equally spaced between -70^0 and 90^0 . Another one is the crowded case with all the DOAs equally spaced between 0^0 to 90^0

The DOA distribution of all the users for both the non-crowded and crowded cases is illustrated in Fig.7. We assume perfect power control, so all the signals impinging on the array have the same power unless specifed otherwise. Fig. 8 shows the BER performance of different algorithms for Eb/N_0 = 8 dB, non-crowded DOA case.For the MT-SDDD, when the system is under-loaded (with the number of users less than the number of antenna elements of the array), the BER increases sharply as the number of users increases. This is because the MT-SDDD uses the estimate of the data sample as the desired signal to adapt the weight vectors of the beamformer. When the number of users increases, the error rate of the data sample estimate becomes larger, and the algorithm cannot adapt the weight vectors correctly, therefore the improvement due to the spatial filtering becomes smaller and the BER increases. However, comparing the BER performance of the MT-SDDD with that of the conventional receiver, we see that a large improvement can still be achieved when the system is under-loaded. When the system is fully-loaded (with the number of users equal to the number of antenna elements of the array) or overloaded (with the number of users greater than the number of antenna elements of the array), the BER changes smoothly as the number of users increases, and the improvement of the BER performance over that of the conventional receiver is small. This is because under

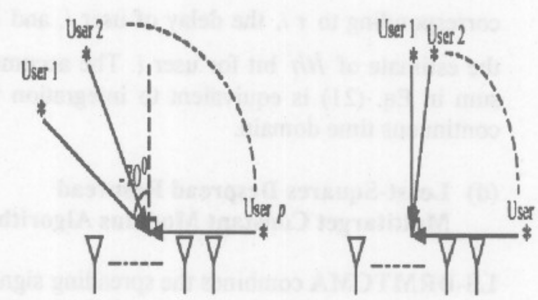


Figure 7

D
OA distribution of all the users for both the non-crowded and crowded cases respectively.

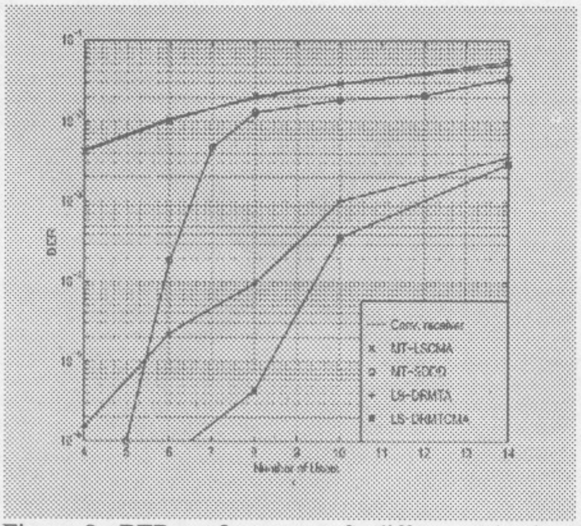


Figure 8 BER performance of different adaptive algorithms. In this case, $E_b/N_0 = 8$ dB, the DOAs of all the users are equally spaced between -70^0 and 90^0. The ratio of the coefficients a_{PN}/a_{CM} used in the LS-DRMTCMA is set to 2.

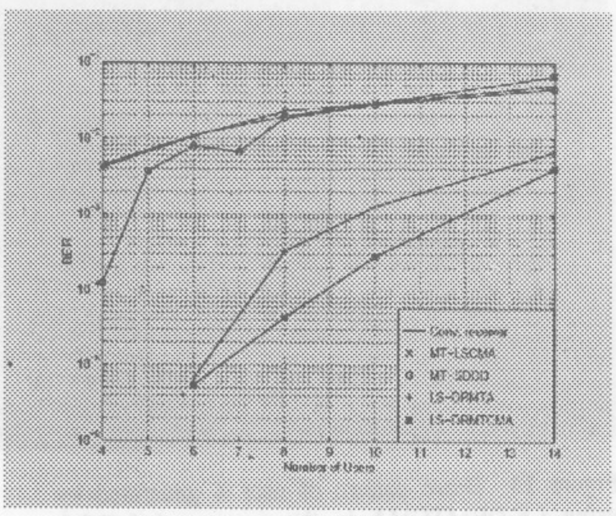


Figure 9 BER performance of different adaptive algorithms. In this case, $Eb / N0 = 8$ dB, the DOAs of all the users are equally spaced between 0^0 and 90^0.

The ratio of the coefficients a_{PN} / a_{CM} used in the LS-DRMTCMA is set to 2 the fully-loaded and over-loaded situations, the MT-SDDD cannot form deep nulls in the DOAs of the interference. Also, several signals may fall into a main beam of one output port, therefore the interference level cannot be reduced to a very low point, and the BER performance is thus close to that of the conventional receiver.

For LS-DRMTA and LS-DRMTCMA, however, since these two algorithms utilize the information of the PN sequences of all the users to adapt the weight vectors, they can construct deeper nulls in the DOAs of the interference than the MT-SDDD, therefore the BER of these two algorithms is much lower than that of the MT-SDDD. Figs. 10 and 14 show the beampatterns of user 5 generated by using the LS-DRMTCMA and the MT-SDDD algorithm, respectively. Comparing Figs. 10 and 14 we see that the LS-DRMTCMA can generate deeper null in the DOAs of the interference than the MT-SDDD, therefore can reduce the interference to a lower level. Also, since the LS-DRMTCMA uses the constant modulus property of the transmitted signal in addition to the PN sequences of all the users to adapt the weight vectors, it can achieve a lower BER than the LS-DRMTA. However, the improvement of the LS-DRMTCMA over th LS-DRMTA becomes smaller when the system is over-loaded.

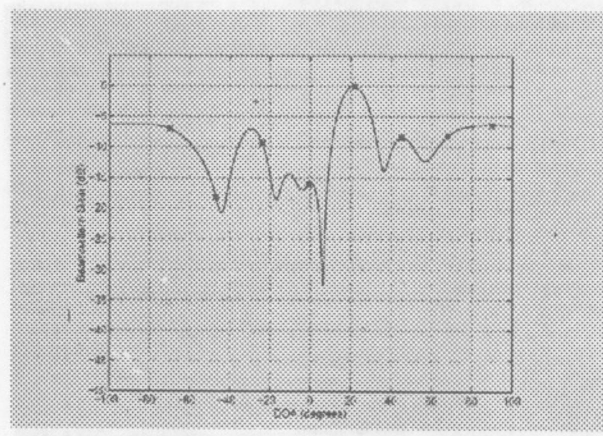


Figure 10 Beampattern of user 5 generated by using MT-SDDD.

The BER performance of different algorithms for the *Eb* /N0 = 8 dB, crowded DOA case is shown in Fig. 9. From Fig. 9 we see that the MT-LSCMA still cannot work under this crowded DOA situation. It was found from experiments that the MT-LSCMA can only work for high Eb / N0 (e. g., Eb/ N0 = 20 dB) and far under-loaded (e. g., number of users equal to 4) case. Comparing Fig. 9 with Fig. 8, we see that the BER increases as the DOAs of the signals becomes crowded for almost all the test cases. This is because more and more interference can fall into the main beam of one output port if the DOAs of the signals becomes crowded. However, in the crowded DOA case, the angle separation becomes 12.86^{O}, which is smaller than $\theta_H = 14.5^0$, thus even for the desired user close to the broadside of the array, two interference will fall into the main beam of the desired user.

Figures 13 and 14 show the beampatterns of user 4 generated by using LS-DRMTCMA for both the non-crowded and crowded case, respectively. Comparing Figs. 13 and 14, we see that in the crowded case, two more interference fall into the main beam of user 4, thus the interference level increases and the BER becomes higher. From Figs. 8 and 9, we see that when the number of users is equal to 8, the BER for LS-DRMTCMA in the non-crowded DOA case is about 4 X10^{-6} while the BER for LS-DRMTCMA in the crowded DOA case becomes approximately 4 X 10^{-5}, which is 10 times of that in the non-crowded DOA case. In this situation, however, the LS-DRMTCMA and LS-DRMTA can still achieve a large improvement over the BER performance of the MT-SDDD.

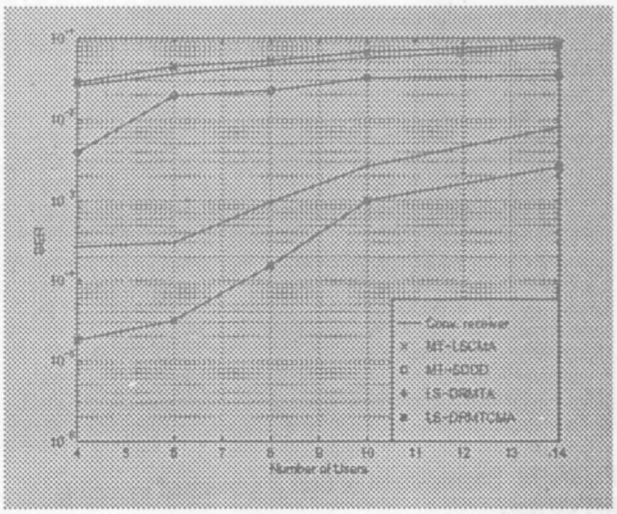


Figure 11 BER performance of different adaptive algorithms

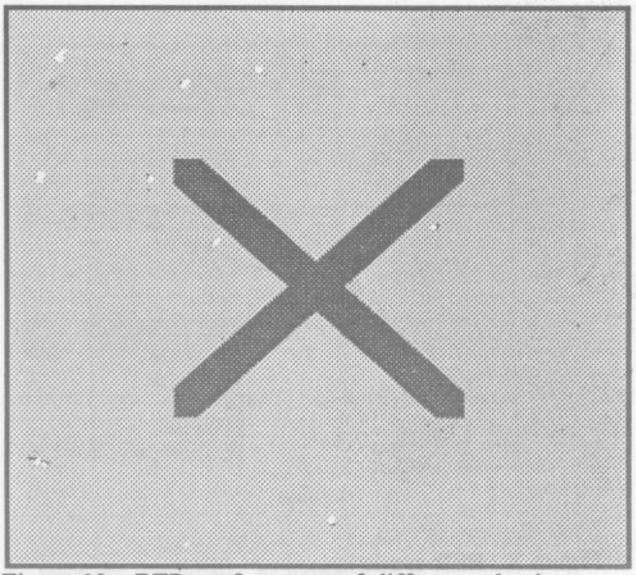


Figure 12 BER performance of different adaptive algorithms

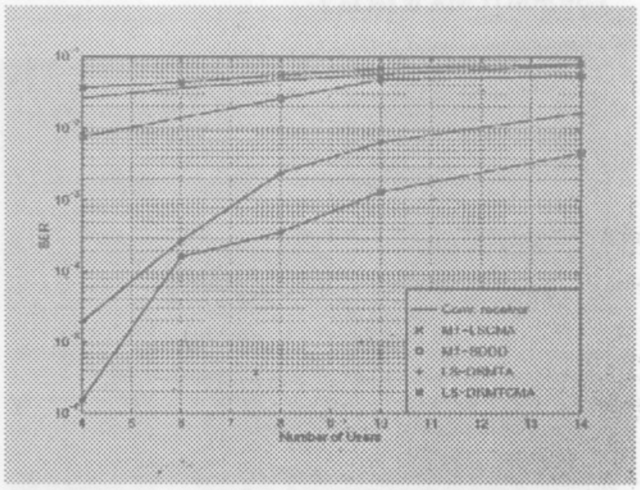


Figure 13 Beam pattern of user 4 generated by using LS-DRMTCMA in the non-crowded DOA case.

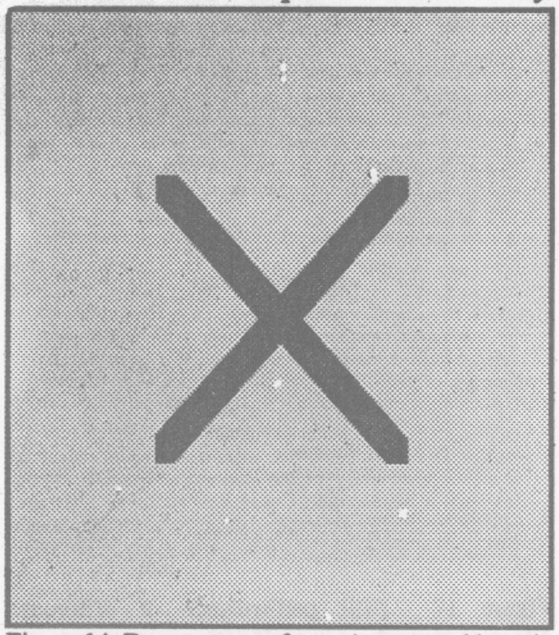


Figure 14 Beampattern of user 4 generated by using LS-DRMTCMA in the non-crowded DOA case.

BER Performance in Multipath Environment

In a wireless radio channel, the transmitted signal may arrive at the receiver through different paths with different time delays. These multipaths will cause the intersymbol interference (ISI) and degrade the BER performance of the system. However, if these multipaths are coming from different DOAs, we can use an adaptive array in the receiver to extract the path with the strongest power and reject the other ones, therefore reducing the ISI and improving the BER performance. In this section, we will examine the BER performance of different algorithms in the multipath environment.

The signal parameters of the multipaths in different simulation cases are shown in.

The BER performance of different algorithms for cases 1, 2 and 3 are illustrated in Figs. 15, 16, and 17, respectively. Comparing Figs. 15, 16, and 17 with Fig. 8, we see that the BER performance is indeed degraded by the multipath in all the cases. Comparing Figs. 15, 16, and 17, we note that decreasing the power ratio between the multipaths will result in a higher BER. This is what we expect since in these three simulation cases, the angle separation between the multipaths is equal to 10^0, which is less than $\theta H = 14.5^0$. hence both of the multipaths fall into the main beam of the output port, and a lower power ratio between the multipaths means a higher ISI level, which will result in a worse BER performance. However, from Figs. 15, 16, and 17, we see that even for such a small multipath angle separation, using the adaptive array in the receiver can still reduce the multipath effect and improve the BER performance, although the improvement becomes smaller when the power ratio between the multipaths decreases.

The BER performance of different algorithms for cases 4, 5 and 6 are illustrated in Figs. 18, 19, and 20, respectively. From Figs. 18, 19, and 20, we see that although the angle separation between the multipaths is now equal to 20^0, which is greater than $\theta H = 14.5^0$, as in the close multipath DOA case, decreasing the power ratio between the multipaths will also result in a higher BER. The reason is that the beamformer cannot ideally form a null in the direction of the second path, so decreasing the power ratio between the multipaths still will result in a higher ISI level. Also since the angle separation is now equal to 20^0, the multipaths of one user may fall into the main beam constructed for another user, hence decreasing the power ratio between the multipaths will increase the interference level of the desired user. The higher ISI and interference level will then cause a worse BER performance. Comparing Figs. 18, 19, and 20 with Figs. 15, 16, and 17, we see that the BER of the well-separated multipath DOA case is lower than that of the close multipath DOA case, and the improvement obtained by using the adaptive array is larger in the well-separated DOA case. The reason is that in the close DOA case where the DOAs of the multipaths are separated by only 10^0, all the multipaths tend to fall into the main beam of the output port, and thus the adaptive array cannot rejected the multipath effectively. However, in the well-separated multipath DOA case, for most of the users, only one multipath can fall into the main beam of the output port, therefore the multipath effect can be reduced by the array to a very low level.

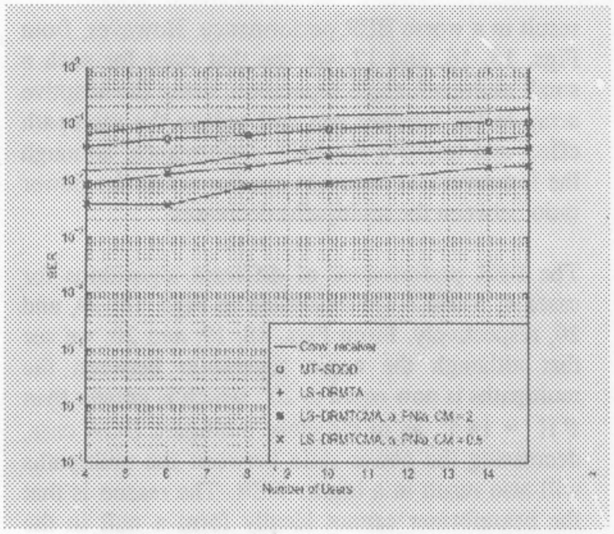


Figure 15 BER performances of different adaptive algorithms in multipath environment

In this case, Eb / N0 = 8 dB, the DOAs of the first paths of all the users are equally spaced between -70^0 and 90^0. The DOA of the second path is 10^0 less than that of the first path. The power ratio of the first path to the second path is 0 dB, and the time delay between these two paths is 0.5Tc.

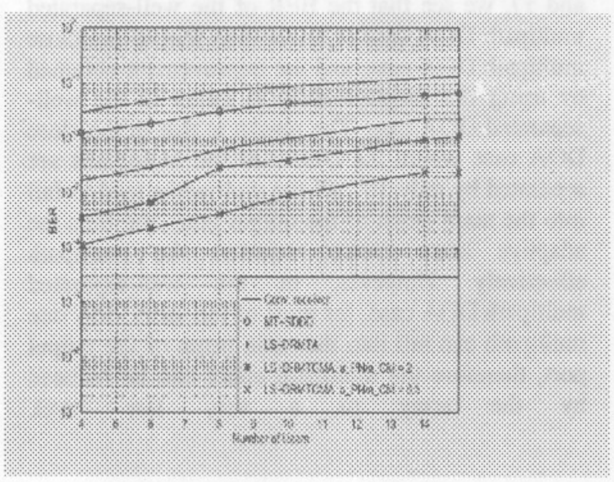


Figure 16 BER performance of different adaptive algorithms in multipath environment. In this case, Eb / N0 = 8 dB, the DOAs of the first paths of all the users are equally spaced between -70^0 and 90^0. The DOA of the second path is10^0 less than that of the first path. The power ratio of the first path to the second path is 6 dB, and the time delay between these two paths is 0.5Tc.

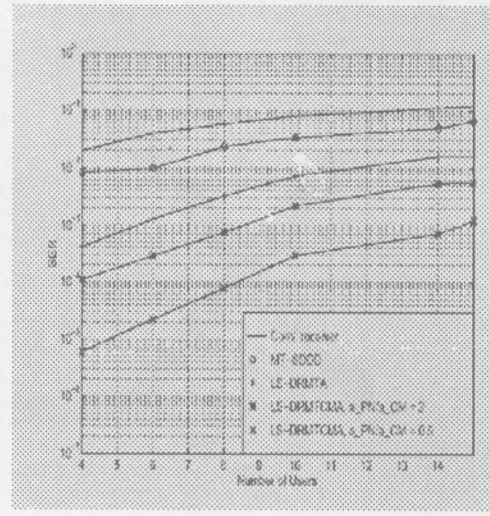


Figure 17 BER performance of different adaptive algorithms in multipath environment.

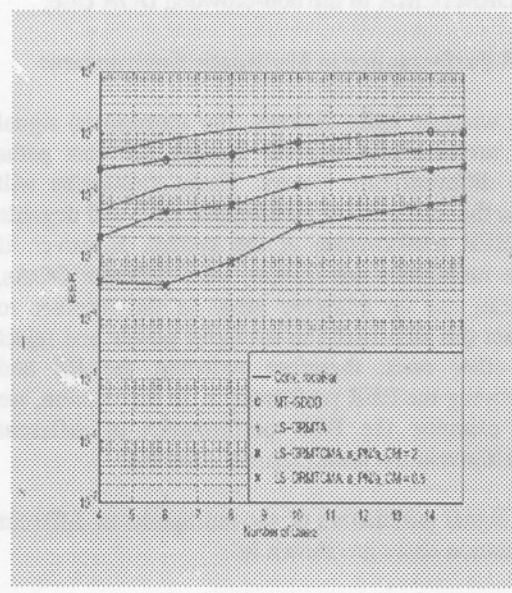


Figure 18 BER performances of different adaptive algorithms in multipath environment.

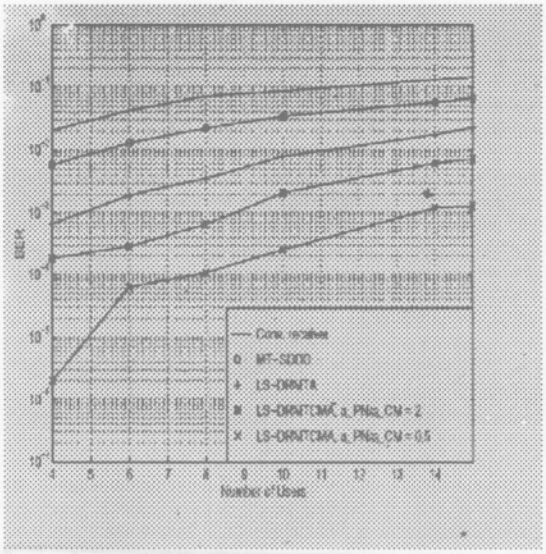


Figure 19 BER performances of different adaptive algorithms in multipath environment.

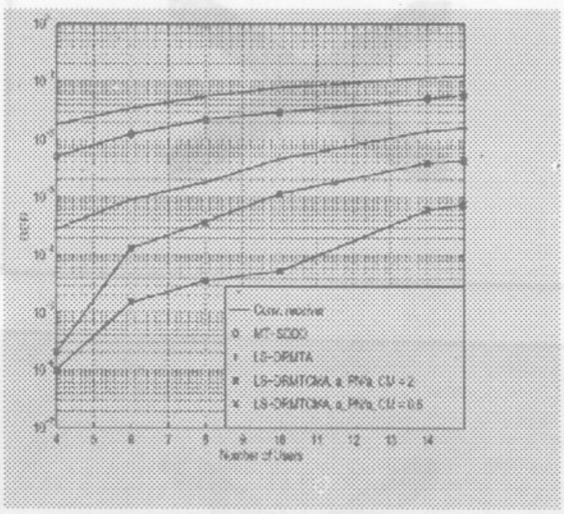
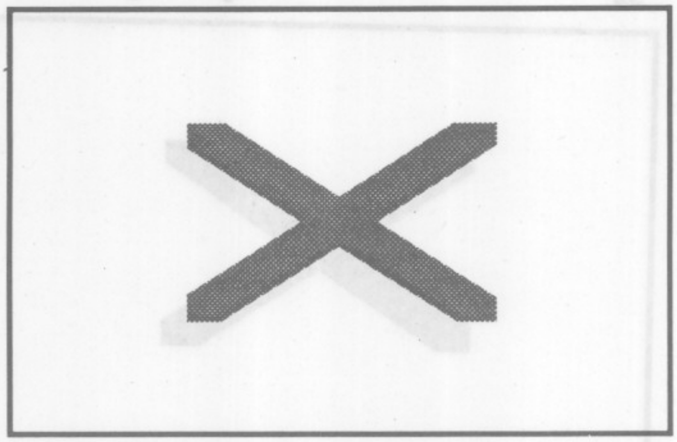
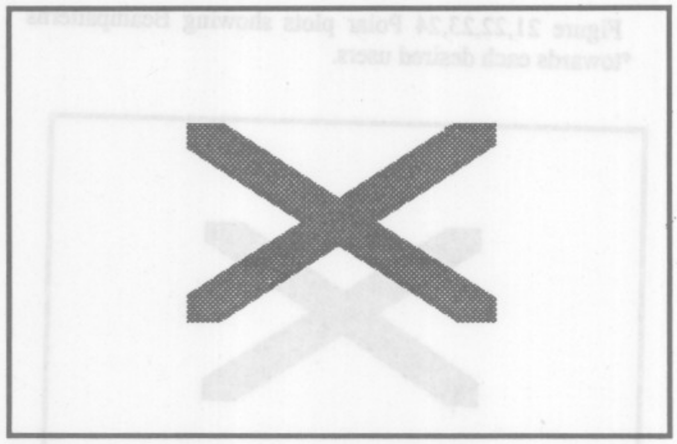
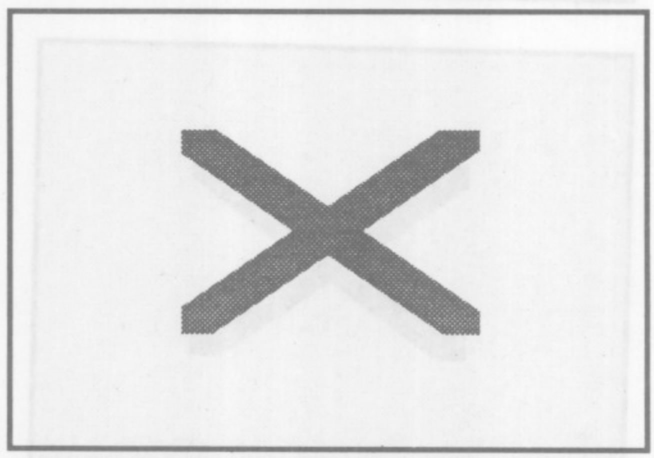


Figure 20 BER performance of different adaptive algorithms in multipath environment. In this case, Eb / N0 = 8 dB, the DOAs of the first paths of all the users are equally spaced between -70^0 and 90^0. The DOA of the second path is 20^0 less than that of the first path.

The following polar plots are a clear simulation results that shows the ability of the beamformer in tracking a user as the user changes its direction of arrival. The signal processor uses the LS-DRMTA and LS-DRMTCMA algorithms and these shows their interference nulling capability towards the undesired user.







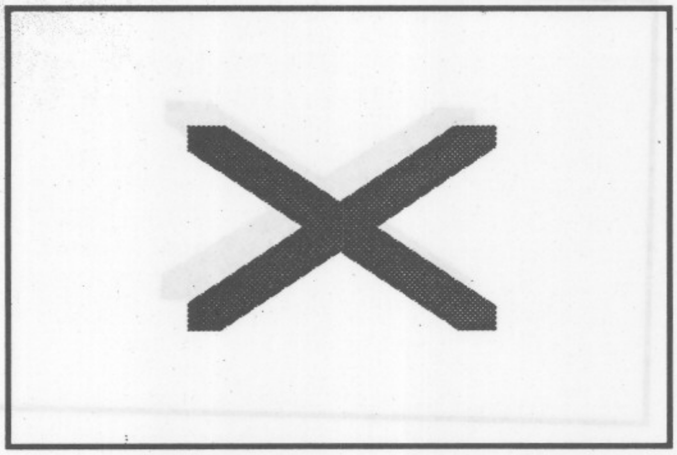
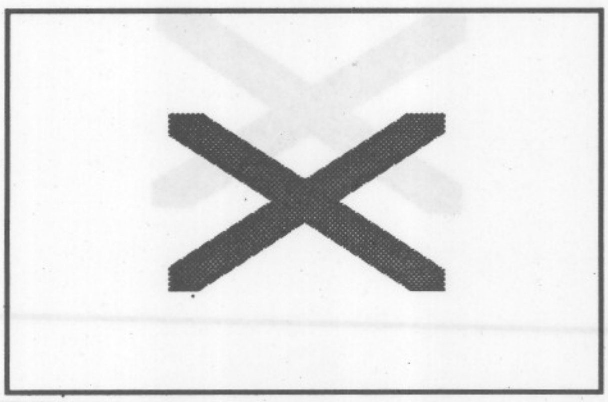
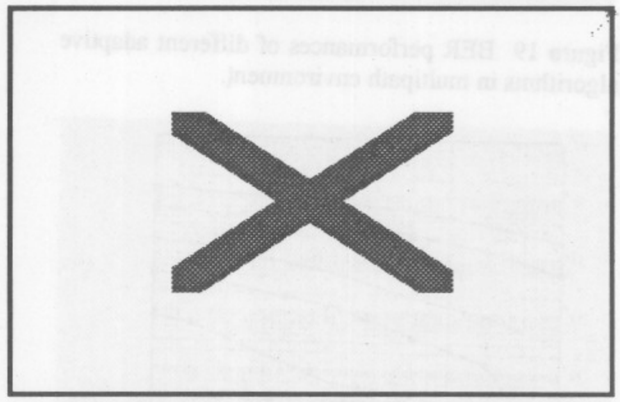
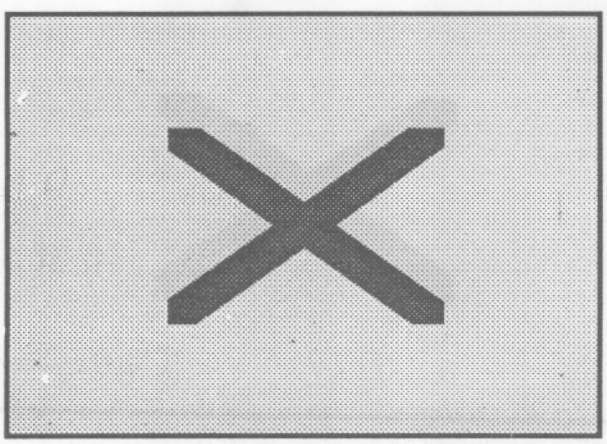


Figure 21,22,23,24 Polar plots showing Beampatterns towards each desired users.







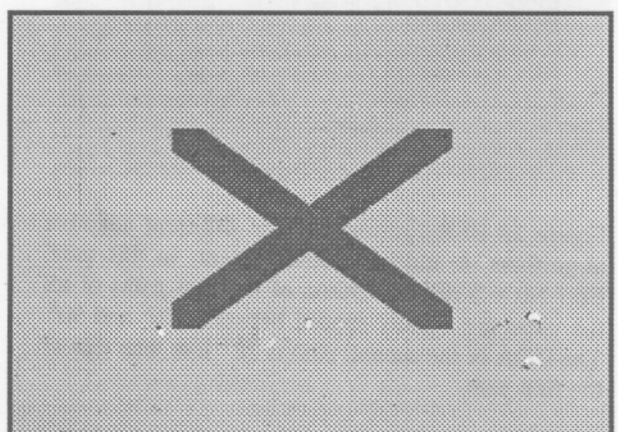


Figure 25,26,27.28 Polar plots showing towards each desired users.

CONCLUSION

We compare the BER performance of different algorithms in various channel environments (e. g. the AWGN channel and in the multipath environment). From the comparisons we see that the LSDRMTA and the LS-DRMTCMA, the two algorithms developed, can outperform the other algorithms in both channel environments.

We've first tried to show the performance capability of these four algorithms in different environment. And we see that the BER of the two algorithms (i.e. LS-DRMTA and LS-DRMTCMA) is better than that of the other two (i.e. MT-LSCMA and MT-DD). This is clearly shown by the observation in the simulation. Hence we see that LS-DRMTA and LS-DRMTCMA has the ability to form deep nulls towards the interfering signals and developing major radiation pattern towards the desired signal under both the non-crowded and crowded situation.

SUMMARY

In this thesis, four adaptive algorithms are discussed for the beamformer used in a CDMA system. We provide a derivation of these algorithms and create a MATLAB simulation testbed to compare the performance of these algorithms.

The BER performance of all these algorithms is compared under different conditions (e. g, the AWGN channel, and the multipath environment). It was shown from the simulation results that the two algorithms, LS-DRMTA and LS-DRMTCMA, can outperform the other algorithms in all the test conditions no matter if the system is over-loaded (i. e., even if the number of users is greater than the number of antenna elements of the array). It was also shown that the LS-DRMTA and LS-DRMTCMA does not need to perform the GSO and sorting procedure which are required in the MT-LSCMA and MT-SDDD, therefore can reduce the system complexity. We also show that unlike that in the MT-LSCMA and MT-SDDD, the number of output ports is not limited by the number of antenna elements in LS-DRMTA and LS-DRMTCMA, which can result in a lower interference level in the beamformer output and make the expansion of the system easier. It has also been tried to show the interference nulling capability of these two algorithms and creating major radiation pattern towards the desired user. This is clearly shown from the polar plots and we can observe that the radiation pattern follows the user as it changes the DOA and this shows the adaptive nature of the beamformer. We also examine the convergence property of different algorithms and show that the two algorithms can converge faster than the other algorithms. In this thesis, we also provide a detailed survey of the adaptive beamformer algorithms, which is very useful for the researchers working in this area.

Future Work

1. Currently the two algorithms (LS-DRMTA and LS-DRMTCMA) are only simulated in the workstation using the MATLAB code. It will be useful if these two algorithms can be implemented in a DSP chip and the 8-element antenna array can be constructed for field trial measurement.

2. In this thesis, the performance of all the algorithms is evaluated by using a uniform linear array. In the future, we can use different array geometries, e. g., a circular array, to examine the performance of the algorithms.

3. The spreading signal used in this research is a short PN sequence (e. g., only 15 chips per bit). In a realistic CDMA system, a longer PN sequence is always used. To reduce the computational complexity of the algorithms, we can use only part of the PN sequence in the LS-DRMTA and LS-DRMTCMA for the adaptation. The effect of using only one segment of the PN sequence on the performance of the algorithms should be examined in the future.

4. In this research, we only use a simple channel model to evaluate the performance of the algorithms. It may be useful if a channel model including the DOA, the time delay, the power level, and the time-varying property of each multipath can be used in the simulation.

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