Algorithm Comparison for Smart Antennas in Mobile Communication

by

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بسم الله الرحمن الرحيم

Dedicated to my parents and loved ones

Certificate of Approval

It is certified that we have read the project report submitted by **Shafqat Ullah Khan [121-FET/MSEE/F-07]**. It is our judgment that this report is of sufficient standard to warrant its acceptance by the International Islamic University, Islamabad for degree of MS Electronic Engineering (MSEE).

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Abstract

In this dissertation, smart antenna techniques are being investigated using two algorithms Least Mean Square (LMS) and Sample Matrix Inversion (SMI). The main role of smart antenna is to mitigate Multiple Access Interference (MAI) by beam forming operation. There fore, irrespective of a particular wireless communication system, it is important to consider whether a chosen array configuration will give optimum performance.

Wireless cellular communication has experienced rapid growth in the demand for provision of high data rate wireless services. This fact motivates the need to find ways to improve the spectrum efficiency of wireless communication system. Smart or adaptive antennas have emerged as a promising technology to enhance the spectrum efficiency of present and future wireless communication system by exploiting the spatial domain. In this dissertation, we study different smart antenna approaches, especially a fully adaptive beam forming approach based on smart antennas. Various adaptive algorithms used to compute the complex weights are investigated. This includes a study of two algorithms the Least Mean Square (LMS) and Sample Matrix Inversion (SMI) algorithm.

Acknowledgment

First of all I am grateful to my Almighty Allah, The Kind and Merciful, Who enabled me to complete this work. Then, I would like thank to my supervisor Dr. I. M. Qureshi, for his continual encouragements and enthusiasm. His enthusiasm in searching for new ideas in digital signal processing has always inspired and motivated to reach new horizons of research, and this blessing is not stopped, in fact this was a very nice start of my research carrier. I never saw a person, who always treated me as his own child and pay special attention to me, my studies and my research in all stages. What I have been learning from him is not just a range of solutions to the communication problems, but his inspirational insight, his way of conducting research and his art of living.My sincere thanks go to my teachers Dr. A. N. Malik, Dr. T. A. Cheema and Dr. Abdul Jalil. I am also indebted to Shujaat Hussain, Atta-ur-Rahman, Majid Ali Shah and Malik Ghayas, for their wonderful friendship and warm encouragement.

At the end I would like to thank my mother for providing me psychological strength to bear the mental stress and hardships during the study and research period.

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CHAPTER 1

Introduction

Wireless communication has the invention of the wireless concept by Marconi in 1897.In recent years there is a large number of users in the area of mobile communication. This growth will demand for capacity and coverage. Several new technologies are explored to make effective use of limited resources. To improve capacity we divide a large coverage zone into small cells, and in this way high power transmitter [1] is replaced with low power transmitter. Each cell is allocated a set of frequency channel that are different from those allocated to the neighboring cells. The same set of frequencies can be reused by another cell as they are separated.

In FDMA, different carrier frequencies are assign to different users. But in the TDMA different users using the same frequency channel are allocated different time slot. Third generation cellular system uses another type of access technique known as Code Division Multiple Access (CDMA) [2] technique. It is based on the spread spectrum technology where individual users are identified by the use of signature codes and occupy the same bandwidth. These technologies have brought tremendous increase in wireless network capacity. Therefore new technologies are required in the field of mobile communication to accommodate future capacity needs.

Space division multiple access (SDMA) [3] has emerged as a new technology. SDMA exploits the spatial domain of the mobile radio channel to bring about increase in network capacity in the existing wireless system. SDMA based system uses smart antennas or adaptive arrays that are dynamically able to adapt to the changing traffic requirement. Smart antennas usually employed at the base station, radiate narrow beams to serve different users, as long as the users are well separated spatially the same frequency can be reused, even if the users are in same cell. Smart antenna techniques are new in the field of mobile communication. Early smart antenna technology was deployed in military communication system where narrow beams were used to avoid interference arising from noise and other jamming signals [4].

Switched beam forming is a smart antenna approach in its simplest form. Multiple fixed beams in predetermined directions is used to serve the users. In this approach the base station switches between several beams that gives the best performance as the mobile user moves through the cell. Most advanced approach based on smart antenna technique known as adaptive beam forming uses antenna arrays backed by strong signal processing capability to automatically change the beam pattern in accordance with the changing signal environment. It not only directs maximum radiation in the direction of the desired mobile user but also introduces nulls at interfering directions while tracking the desired mobile user at the same time. The adaption is achieved by multiplying the incoming signal with complex weights and then summing them together to obtain the desired radiation pattern [5]. These weights are computed adaptively to adapt to the changes in the signal environment. The adaptation is achieved by multiplying the incoming signal with complex weights and then summing them together to obtain the desired radiation pattern. These weights are computed adaptively to adapt to the changes in the signal environment.

Adaptive algorithm forms the heart of the array processing network. Several algorithm have been developed based on different criteria top compute the complex weights [6]. They have their own disadvantages and advantages as far as complexity and convergence speed. The arrays by themselves are not smart it is the digital signal processing DSP block that makes them smart. SDMA based system using smart antennas or adaptive arrays to achieve to maximum radiation in the direction of desired user and nulls in the direction of interferer signals.

1.1 Contribution

The major contribution made in this Thesis is given below:

i. Least Mean Square (LMS) and Sample Matrix Inversion (SMI) algorithm were used to investigate smart antenna approaches and compared both the algorithm.

ii. The criteria for comparison of algorithm are the convergence of the two algorithms.

1.2 Organization

This Thesis is outlined as:

1. **Chapter 2:** This chapter provides brief discussion on different access technique including the space division multiple accesses (SDMA) in relevance with smart antennas.
2. **Chapter 3:** In this chapter I discussed the array theory and various array definitions which is main component of the smart antenna structure.
3. **Chapter 4:** This chapter explains the concept of switched beam approach and adaptive beam approach.
4. **Chapter 5:** This chapter discusses the problem setup of adaptive arrays.
5. **Chapter 6:** This chapter is devoted for the working of the Least Mean Square (LMS) algorithm.
6. **Chapter 7:** This chapter provides an understanding of the working of Sample Matrix Inversion (SMI) algorithm.
7. **Chapter 8:** This chapter concludes the thesis with a summary and scope for future work in the area of adaptive algorithm for mobile communication.

CHAPTER 2

Code Division Multiple Access

A limited amount of bandwidth is allocated for wireless services. wireless system is required to accommodate as many users as possible by effectively sharing A finite amount of radio spectrum shared simultaneously by many users is called multiple access techniques. There are three major access techniques used to share the available bandwidth in a wireless communication system. These are Frequency Division Multiple Access (FDMA) [13], Time Division Multiple Access (TDMA) [13], Code Division Multiple Access (CDMA) [14] [15], and Space Division Multiple Access (SDMA) [16] [17].

2.1.1 Frequency Division Multiple Access (FDMA)

In Frequency Division Multiple Access (FDMA), individual channels are assigned to individual users, as can be seen from Figure 2.1.

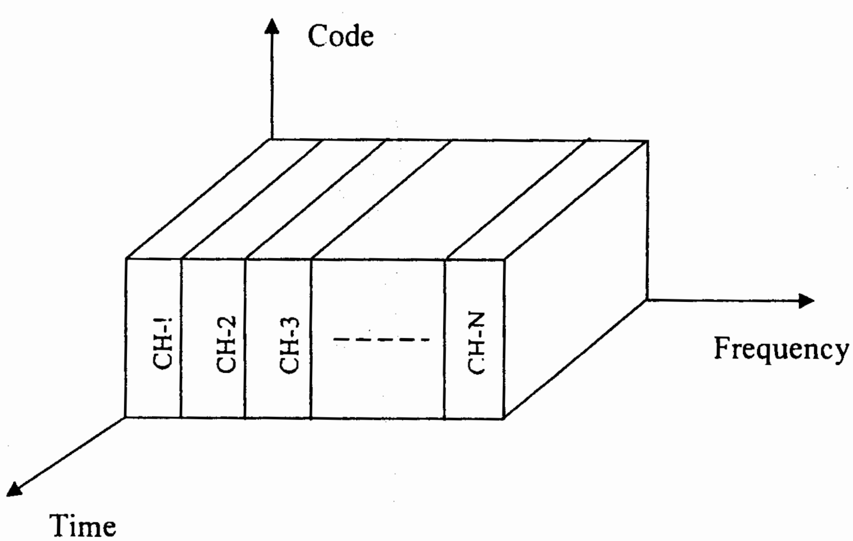

Figure 2.1: FDMA Scheme

Here a unique frequency band is assigned to each user. Advanced Mobile Phone System (AMPS), which is the first generation US analogue system, is based on FDMA. In this technique the bandwidth divided into a number of channels and each user is assigned a finite portion of bandwidth for permanent use. The channels are assigned only when demands by the users. Therefore a channel is assigned on request. FDMA channels have narrow band width (30 KHz) and usually implemented in narrow band system. In FDMA, we partition the available frequency into a number of sub-bands, where each user has a dedicated frequency band for its communication.

FDMA does not require synchronization or timing control, which makes it algorithmically simple, at the same time two users can not use the same frequency. FDMA achieves simultaneous transmission and reception by using frequency division duplexing (FDA), in order for both the transmitter and the receiver to operate at the same time, FDD requires duplexer. The requirement of duplexer in the FDMA system makes it expensive.

2.1.2 Time Division Multiple Access (TDMA)

TDMA requires time synchronization; users share the bandwidth in the frequency domain. The number of channels is less, internal channel frequency is almost negligible, and hence the guard time between the channels is considerably smaller. In cellular communication when a user moves from one cell to another cell there is a chance that user could experience a call loss if there are no free timeslots available. TDMA uses different time slot for transmission and reception.

The division of radio spectrum into the time slots is called the Time Division Multiple Access (TDMA) system. A dedicated time slot is assigned to each user to communicate either it transmit or receive, as shown in Figure 2.2. A Global System for Mobile Communication GSM [18], which uses the both TDMA and Frequency Division Duplexing i.e. TDMA/FDD. FDD is a system where pair of frequencies are assigned to the users as a channel i.e. one is uplink channel and the other is down link channel.

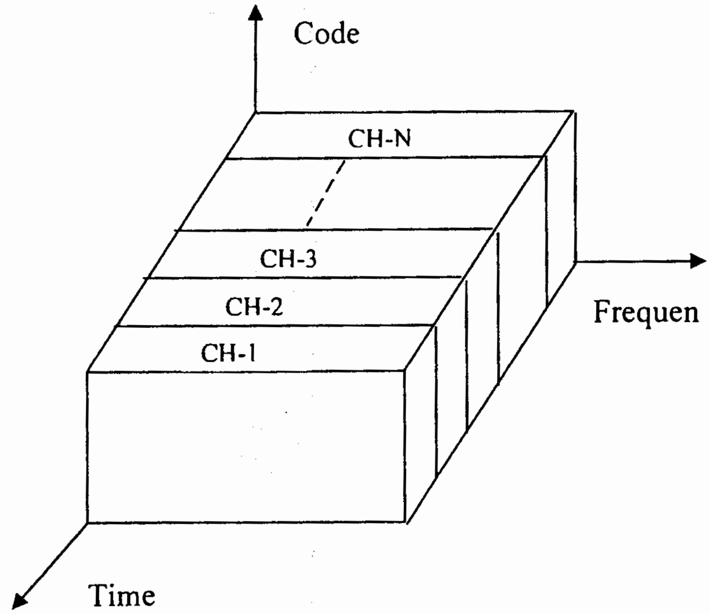

Figure 2.2: TDMA Scheme

In digital system continuous transmission is not required because users do not use the allocated bandwidth all the time. In such system, TDMA is a complementary access technique to FDMA. Global System for Mobile communication uses the TDMA technique. A combination of TDMA and frequency division uplink/downlink duplexing was used in the digital mobile standard, known as Global System for Mobile communication, which was the first representative of second generation in mobile communication system. In TDMA the entire bandwidth is available to the user but only for a finite period of time.

2.1.3 Code Division Multiple Access (CDMA)

Code Division Multiple Access (CDMA) is more sophisticated from FDMA and TDMA. Here all the users share the same carrier frequency when they transmit. Here each user is assigned a unique code sequence or signature sequence called pseudo-random code words and all of these code words are orthogonal to each other. As can seen from figure 2.3. In the receiver end time correlation operation is applied and it will detect only the specific desired code word. While due to decorrelation operation all the other code words are considered as noise. CDMA is some time called the Spread Spectrum Multiple Access (SSMA). Spread Spectrum signals means that for the transmission of digital information, their bandwidth W is

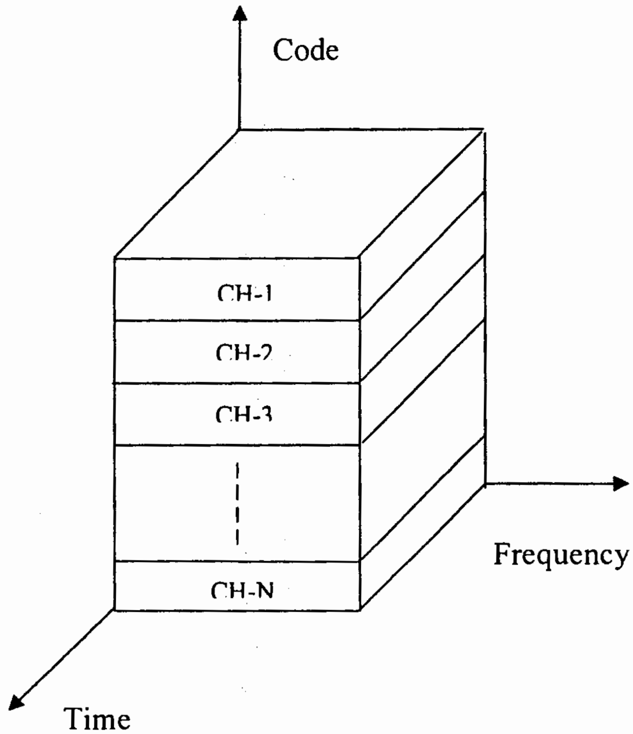

Figure 2.3: CDMA Scheme.

higher then the information rate R. Direct Sequence CDMA (DS-CDMA) [15], Frequency Hopping CDMA (FH-CDMA) [16], and Time Hopping CDMA (TH-CDMA) [19], are the three common technique of the spread spectrum communication system. Besides these techniques some hybrid techniques are also available by combining these techniques. These are Multi-carrier CDMA (MC-CDMA) [20], Direct Sequence CDMA/Frequency Hopping CDMA (DS/FH), Time Hopping CDMA/Frequency Hopping CDMA (TH/FH) and Direct Sequence CDMA/Frequency Hopping CDMA/Time Hopping CDMA (DS/FH/TH). Besides this MC-CDMA [16], is further subdivided into MC-DS-CDMA [15], and Multi tone CDMA (MT-CDMA) [13].

In DS-CDMA, information bits are directly modulated, which uses a pseudo-random noise sequence and in a result a bandwidth DS-spread signal appeared. In Frequency Hopping CDMA (FH-CDMA), the available channel bandwidth is sub divided into number of frequency slots. The available frequency slots are occupied by the transmitted signal and these are handled by the frequency hopping techniques. FH-CDMA are sub divided into two parts these are Slow Frequency Hopping (SFH) and Fast Frequency Hopping (FFH). Slow

Frequency Hopping (SFH) is performed at symbol rate while in Fast Frequency Hopping (FFH) there are multiple hops per symbol. Besides DS-CDMA and FH-CDMA, there is another Hopping technique which is called Time Hopping CDMA (TH-CDMA) [19]. The time interval which is larger then the information rate reciprocal, is subdivide into a large number of time slots is called TH-CDMA. The information symbol which are coded are transmitted as a block of one or more code words in a time slot which are pseudo-randomly selected.

There are various CDMA techniques which are deployed in the context of Second Generation (2G) [21], and the Third Generation (3G) [15], systems. In 1995, the United State has deployed the popular 2 G CDMA standard called as Interim Standard 95 IS-95 [15] [21], technique also known as CDMA-ONE. In 1998, the Wide band CDMA (W-CDMA) [15] [22], is deployed. It is also called Universal mobile Telecommunication Service (UMTS) [15] [23], and also CDMA 2000 [15] [24], is deployed. These both are 3G based technologies. The Chinese technology named as Time-Duplex Smart Antenna aided CDMA (TD-SCDMA) [25], was also improved by ITU.

2.1.4 Space Division Multiple Access (SDMA)

The latest Wireless Access technology is the Space Division Multiple Access (SDMA) [15] [16]. Controlling the radiated signal in space for each user is done by Space Division Multiple Access (SDMA). Spot beam antenna are used in SDMA system. For reducing the Multiple Access Interference (MAI) in SDMA, TD-SCDMA [25] standard is used. In SDMA sectorized antenna and adaptive antenna are used.

SDMA utilizes the spatial separation of users in order to optimize the use of the frequency spectrum. A primitive form of the SDMA is when the same frequency is re-used in different cells in a cellular wireless network. It is required for limited co-channel interference that the cells be sufficiently separated. This limits the number of cells a region can be divided into and hence limits the frequency re-use factor.

This technique would enable frequency re-use within the cell. It uses smart antenna technique that employs antenna arrays backed by some intelligent signal processing to steer the antenna pattern in the direction of the desired user and places nulls in the direction of interfering signals. since these arrays can produce narrow spot beams, the frequency can be reused within the cells as long as the spatial separation between the users is sufficient.

CHAPTER 3

Array Theory

An antenna array is a configuration of individual radiating elements that are arranged in space and can be used to produce a directional pattern. Single-element antennas have radiation patterns that are broad and have a low directivity that is not suitable for long distance communications. A high directivity can be still achieved with single-element antennas by increasing the electrical dimensions (in terms of wavelength) and hence the physical size of the antenna [14]. Antenna arrays come in various geometrical configurations, the most common being; linear arrays (ID). Arrays usually employ identical antenna elements. The radiating pattern of the array depends on the configuration, the distance between the elements, the amplitude and phase excitation of the elements, and also the radiation pattern of individual elements.

3.1 Some Antenna parameter definitions

It is worthwhile to have a brief understanding of some of the antenna parameters before discussing antenna arrays in detail. Some of the parameters discussed in are explained below.

3.1.1 Radiation Power density

Radiation power density W_r gives a measure of the average power radiated by the antenna in a particular direction and is obtained by time-averaging the Poynting vector.

$$W_r(r,\theta,\phi) = \frac{1}{2}\mathrm{Re}\left[E \times H^*\right] = \frac{1}{2\eta}\left|E(r,\theta,\phi)\right|^2 \left(Watts/m^2\right) \tag{3.1}$$

where E is the electric field intensity, H is the magnetic field intensity, and η is the intrinsic impedance.

3.1.2 Radiation Intensity

Radiation intensity U in a given directions is the power radiated by the antenna per unit solid angle. It is given by the product of the radiation density and the square of the distance r.

$$U = r^2 W_r \quad \text{(Watts/ unit solid angle)} \tag{3.2}$$

3.1.3 Total power radiated

The total power radiated P_{tot} by the antenna in all the direction is given by,

$$P_{tot} = \int_0^{2\pi}\int_0^{\pi} W_r(r,\theta,\phi) r^2 \sin(\theta)\, d\theta d\phi \tag{3.3}$$

$$= \int_0^{2\pi}\int_0^{\pi} U(\theta,\phi)\sin(\theta)\, d\theta d\phi \quad \text{Watts} \tag{3.4}$$

3.1.4 Directivity

The Directive gain D_g is the ratio of the radiation intensity in a given direction to the radiation intensity in all the directions. i.e.

$$D_g = \frac{4\pi U(\theta,\phi)}{P_{tot}}$$

$$= \frac{4\pi U(\theta,\phi)}{\int_0^{2\pi}\int_0^{\pi} U(\theta,\phi)\sin(\theta)\, d\theta d\phi} \tag{3.5}$$

The Directivity D_0 is the maximum value of the direction gain D_g for a given direction. i.e.

$$D_0 = \frac{4\pi U_{max}(\theta,\phi)}{P_{tot}} \tag{3.6}$$

where U_{max} is the maximum radiation intensity.

3.1.5 Radiation Pattern

The radiation pattern of an antenna can be defined as the variation in field intensity as a function of position or angle. Let us consider an isotropic radiator, which has stonger the radiation in one direction than in another. One of the lobe has the strongest radiation intensity compared to another lobes. It is referred to as the major lobes, but all other lobes are called minor lobes. In most radar system, low side ratios are very important to minimize false target indications through side lobes [19].

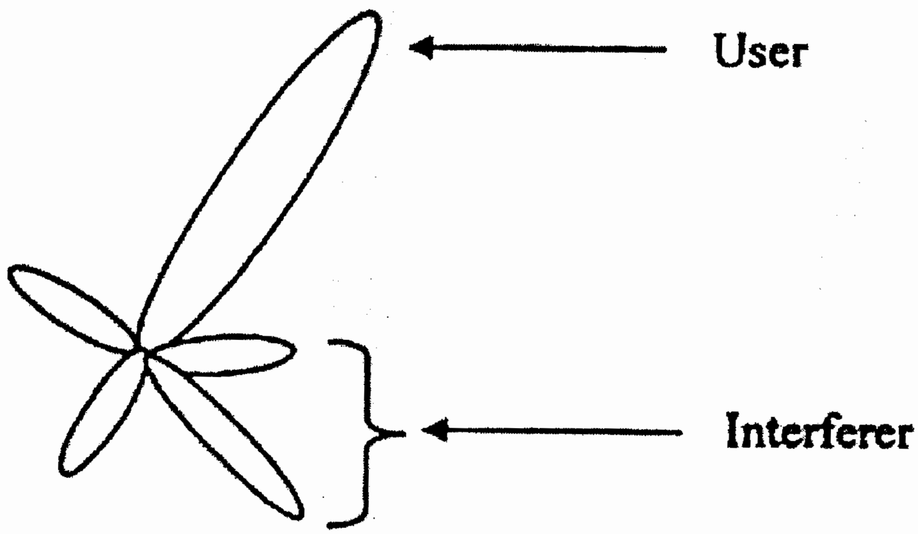

Fig. 3.1 Radiation pattern

3.2 Linear Array Analysis

When antenna array has elements arranged in a straight line it is known as a linear array. Let us consider a linear array with two elements shown in Fig. 3.2. The elements are placed on either side of the origin at a distance $\frac{d}{2}$ from it. The electric field radiated by these two elements in the far field region at point P is due to element 1;

$$\bar{E}_1 = w_1 f_1(\theta_1, \phi_1) \frac{e^{-j\left(kr_1 - \frac{\beta}{2}\right)}}{r_1} \tag{3.7}$$

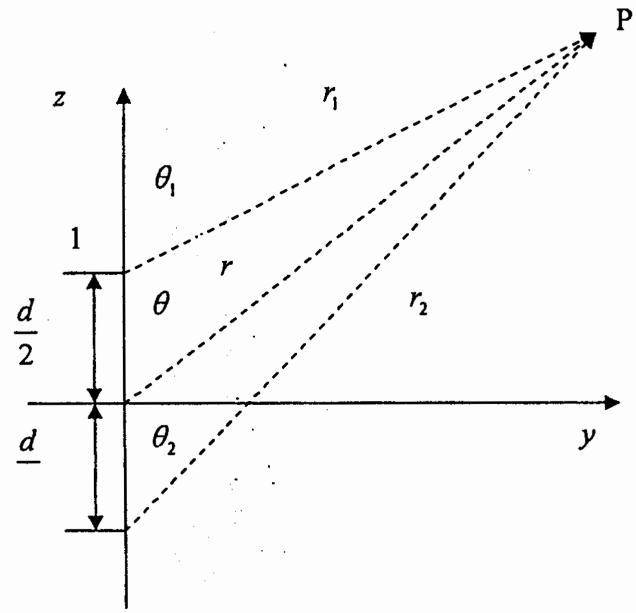

Fig. 3.2 a two-element linear array

$$\bar{E}_1 = w_1 f_1(\theta_1, \phi_1) \frac{e^{-j(kr1 - \frac{\beta}{2})}}{r_1} \tag{3.7}$$

Electric field at P due to element 2:

$$\bar{E}_2 = w_2 f_2(\theta_2, \phi_2) \frac{e^{-j(kr2 + \frac{\beta}{2})}}{r_2} \tag{3.8}$$

where w_1, w_2 are the weights; f_1, f_2 are the normalized field patterns for each antenna element; r_1, r_2 are the distances of element 1 and element 2 from the observation point P; β is the phase difference between the feed of the two array elements. The magnitude excitation of the radiators are identical. To make the far field approximation the above Fig. can be re-drawn as shown in Fig. 3.3. Assuming far-field observations and referring to Fig.3.3:

$$\theta_1 \cong \theta_2 \cong \theta$$

$$r_1 = r_2 = r \qquad \text{For amplitude variation}$$

$$r_1 \cong r - \frac{d}{2}\cos\theta \qquad \text{For phase variation} \tag{3.9}$$

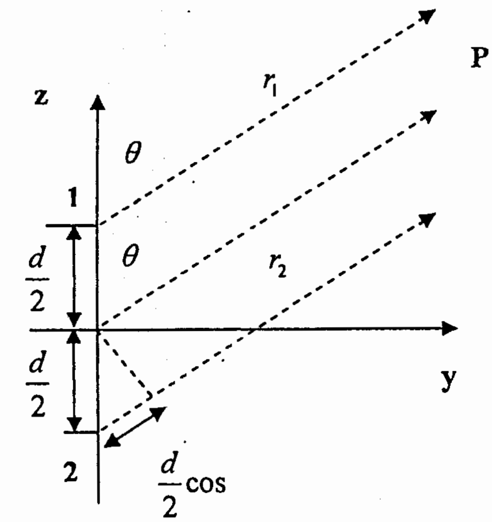

Fig. 3.3 Far-field geometry of a two-element linear array

$$r_2 \cong r + \frac{d}{2}\cos\theta$$

Now the array elements are identical we can assume the following;

$$F_1(\theta_1, \phi_1) = F_2(\theta_2, \phi_2) = F(\theta, \phi)$$

The total field E at point P is the vector sum of the fields radiated by the individual elements and can be illustrated as follows:

$$\overline{E} = \overline{E}_1 + \overline{E}_2$$

$$\overline{E} = w_1 f(\theta,\phi)\frac{e^{-j(k(r-\frac{d}{2}\cos)-\frac{\beta}{2})}}{r} + w_2 f(\theta,\phi)\frac{e^{-j(k(r+\frac{d}{2}\cos)+\frac{\beta}{2}}}{r} \tag{3.10}$$

$$\overline{E} = \frac{e^{-jkr}}{r} f(\theta,\phi)\left[w_1 e^{j(k\frac{d}{2}\cos\theta+\frac{\beta}{2}} + w_2 e^{-j(k\frac{d}{2}\cos\theta+\frac{\beta}{2})} \right] \tag{3.11}$$

for uniform weighting

$$w_1 = w_2 = w \tag{3.12}$$

$$\overline{E} = w\frac{e^{-jkr}}{r} f(\theta,\phi) \times 2\cos(\frac{kd\cos\theta + \beta}{2}) \tag{3.13}$$

The above relation as often referred to as pattern multiplication which indicates that the total field of the array is equal to the product of the field due to the single element located at the origin and a factor called array factor, AF. i.e.

$$\bar{E} = w\frac{e^{-jkr}}{r} f(\theta,\phi) \times 2\cos\left(\frac{kd\cos\theta + \beta}{2}\right) \tag{3.13}$$

The above relation as often referred to as pattern multiplication which indicates that the total field of the array is equal to the product of the field due to the single element located at the origin and a factor called array factor, AF. i.e.

$$(Total) = [\text{E(single element at reference signal)}] \times [\text{array factor}] \tag{3.14}$$

The pattern multiplication rule only applies for an array consisting of identical elements.

The normalized array factor for the above two-element array can be written as follows:

$$AF_n = \cos\left(\frac{kd\cos\theta + \beta}{2}\right) \tag{3.15}$$

Therefore from the above discussion it is evident that the AF depends on:

i. The number of elements

ii. The geometrical arrangement

iii. The relative excitation magnitudes

iv. The relative phase between elements

3.3 Uniform Linear Array

A uniform array consists of equi spaced elements which fed with current of equal amplitude. The uniform linear array consists of N elements equally spaced at distance $\frac{d}{2}$ apart with identical amplitude excitation and has a progressive phase difference of β between the successive elements. An array of identical elements all of identical amplitude and each with progressive phases referred to as a uniform array [22].

The total field of the array is determined by the vector addition of the fields radiated by the of the isolated element. This depend upon the separation between the elements , it is necessary that the fields form the elements of the array interfere constructively in the remaining space.

The array factor can be written as,

$$AF = \frac{\sin\left[\frac{N}{2}\psi\right]}{\sin\left[\frac{\psi}{2}\right]} \tag{3.16}$$

For small values of ψ the above equation can be written as

$$AF = \frac{\sin\left[\frac{N}{2}\psi\right]}{\frac{\psi}{2}}$$

The maximum value of the array factor is equal to N. To normalize the array factor so that the maximum value of each is equal to unity.

$$AF = \frac{1}{N}\left[\frac{\sin\left[\frac{N}{2}\psi\right]}{\sin\left[\frac{\psi}{2}\right]}\right] \tag{3.17}$$

3.3.1 Nulls and Maxima of the Array factor

To find the nulls of the AF, the above equation is set to zero.

$$\sin\left[\frac{N}{2}\psi\right] = 0 \Rightarrow \frac{N}{2}\psi = \pm n\pi \Rightarrow \frac{N}{2}\left(kd\cos\theta_n + \beta\right) = \pm n\pi \tag{3.18}$$

$$\theta_n = \cos^{-1}\left[\frac{\lambda}{2\pi d}\left(-\beta \pm \frac{2n}{N}\right)\right] \tag{3.19}$$

where $n = 1,2,3..(n \neq N,2N,3N)$

The angles θ_m at which the maxima occurs can be obtained as

$$\theta_m = \cos^{-1}\left[\frac{\lambda}{2\pi d}\left(-\beta \pm \frac{2n}{N}\right)\right] \tag{3.20}$$

If $\frac{d}{2}$ is chosen to be sufficiently small the AF in Eq. (3.17) has only one maximum and it occurs when m=0 in Eq. (3.20) i-e.

$$\theta_m = \cos^{-1}\left[\frac{\lambda\beta}{2\pi d}\right] \tag{3.21}$$

For m=1,2,... the argument of the arccosine in Eq.(3.20) becomes greater than unity.

CHAPTER 4

Smart Antenna Technology

In mobile communication systems, capacity and performance ate usually limited by two major impairments. They are multipath and co-channel interference [15]. Multipath is a condition which arises when a transmitted signal undergoes reflection from various obstacles in the propagation environment. This gives rise to multiple signals arriving from different directions. Since the multipath signals follow different paths, they have different phases when they are arrive at the receiver. The result is degradation in signal quality when they are combined at the receiver due to the phase mismatch. Co-channel interference is the interference between two signals that operate at the same frequency. In cellular communication the interference is usually caused by a signal from a different cell occupying the same frequency band.

Smart antenna is one of the most promising technologies that will enable a higher capacity in wireless networks by effectively reducing multipath and co-channel interference [15] [16]. This is achieved by focusing the radiation only in the desired direction and adjusting radiating elements arranged in the form of an array. The signals from these elements are combined to form a movable or switch able beam pattern that follows the desired user. In a Smart antenna system the arrays by themselves are not smart, it is the digital signal processing that makes them smart. The process of combining the signals and then focusing the radiation in a particular direction is often referred to as digital beam forming [23]. This term will be extensively used in the following sections.

The early smart antenna systems were designed for use in military applications to suppress interfering or jamming signals from the enemy. Since interference suppression was a feature in this system, this technology was borrowed to apply to personal wireless communications where interference was limiting the number4 of users that a network could handle. It is a major challenge to apply smart antenna technology to personal wireless communications since the traffic is denser. Also, the time available for complex computations is limited. However, the advent of powerful, low-cost, digital processing components and the development of software-based techniques have made smart antenna systems a practical reality for cellular communications systems [23].

4.1 Types of Smart Antenna Systems

There are basically two approaches [24] to implement antennas that dynamically change their antenna pattern to mitigate interference and multipath affects while increasing coverage and range [25]. They are

- Switched beam
- Adaptive Arrays

The switched beam approach is simpler compared to the fully adaptive approach. It provides a considerable increase in network capacity when compared to traditional omni directional antenna systems or sector-based systems. In this approach, an antenna array generates overlapping beams that cover the surrounding area. When an incoming signal is detected, the base station determines the beam that is best aligned in the signal-of-interest direction and then switches to that beam to communicate with the user [27]. A switched beam antenna can be thought of as an extension of the conventional sector antenna in that it divides a sector into several micro-sectors. It is the simplest technique and easiest to retro-fit to existing wireless technologies. Switched beam antenna systems are effective only in low to moderate co-channel interfering environment owing to their lack of ability to distinguish a desired user from an interferer environment owing to their lack of ability to distinguish a desired user from an interfere, e.g. if a strong interfering signal is at the center of the selected beam and the desired user is away from the centre of the selected beam, the interfering signal can be enhanced far more than the desired signal.

The Adaptive array system is the "smarter" of the two approaches. This system tracks the mobile user continuously by steering the main beam towards the user and at the same time forming nulls in the directions of the interfering signal. Like switched beam systems, they also incorporate arrays [14]. Typically, the received signal from each of the spatially distributed antenna elements is multiplied by a weight. The weights are complex in nature and adjust the amplitude and phase. These signals are combined to yield the array output. These complex weights are computed by a complicated adaptive algorithm, which is pre-programmed into the digital signal-processing unit that manages the signal radiated by the base station.

4.1.1 Switched Beam Systems

This type of adaptive technique actually does not steer or scan the beam in the direction of the desired signal. Switched beam [15] employs an antenna array which radiates several overlapping fixed beams covering a designated angular area. It subdivides the sector inro many narrow beams. Each beam can be treated as individual sensors serving individual user or a group of users.

The spatially separated directional beam leads to increase in the possible reuse of a frequency channel by reducing potential interference and also increases the range. These antennas don not have a uniform gain in all directions but when compared to a conventional antenna system they have increased gain in preferred directions. The switched beam antenna has switching mechanism that enables it to select and then switch the right beam which gives the best reception for a mobile user under consideration. The selection is usually based on maximum received power for that user. Note that same beam can be used both for uplink and downlink communication. A typical switched beam system for a base station would consist of multiple arrays with each array covering a certain sector in the cell. Consider a switched beam forming system. It consists of a phase shifting network; whish forms multiple beams looking in certain directions. The RF switch actuates the right beam in the desired direction. The selection of the right beam is made by the control logic, the control logic is governed by an algorithm which scans all the beams and selects the one receiving the strongest signal based on a measurement made by the detector. This technique is simple in operation but is not suitable for high interference areas.

Let us consider a scenario where User 1 who is at the side-edge of the beam which he is being served by. If a second user were at the direction of the null then there would be no interference but if the second user moves into the same area of the beam as the first user he could cause interference to the first user. Therefore switched beam systems are best suited for a little or zero-interference environment. In case of a multipath signal [21] there is a chance that the system would switch the beam to the indirect path signal rather that the direct path signal coming form the user. This leads to this ambiguity in the perception of the direction of

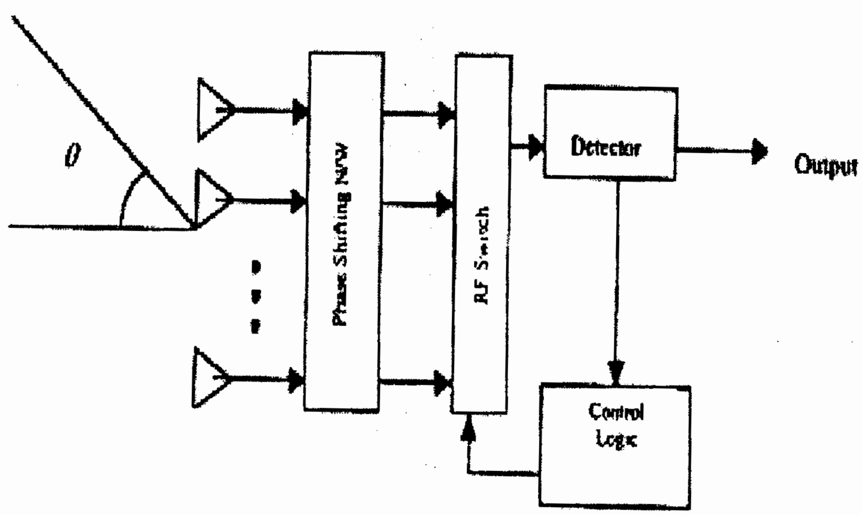

Fig. 4.1 block diagram of Switched beam systems.

the received signal, thus, switched beam systems are only used for the reception of signals. Since these antennas have a non-uniform gain between the beams the mobile user when moving away from the edge of the beam is likely to suffer from a call loss before he is handed of to the next beam because there is no beam serving that area. Also, these systems lead to frequent hand-offs when the mobile user is actively moving from the area of one beam to another. Therefore these intra-cell hand-offs have to be controlled. Switched beam systems cannot reduce multipath interference components with a direction of arrival close to that of the desired signal. Despite of all these disadvantages, the switched beam approach is less complicated (compared to the completely adaptive systems) and provides a significant range extension, increase in capacity, and a considerable interference rejection when the desired user is at the center of the beam. Also, it less expensive and can be easily implemented in older systems.

4.1.2 Adaptive Array Systems

From the previous discussion it was quite apparent that switched beam systems offer limited performance enhancement when compared to conventional antenna system in wireless communication.

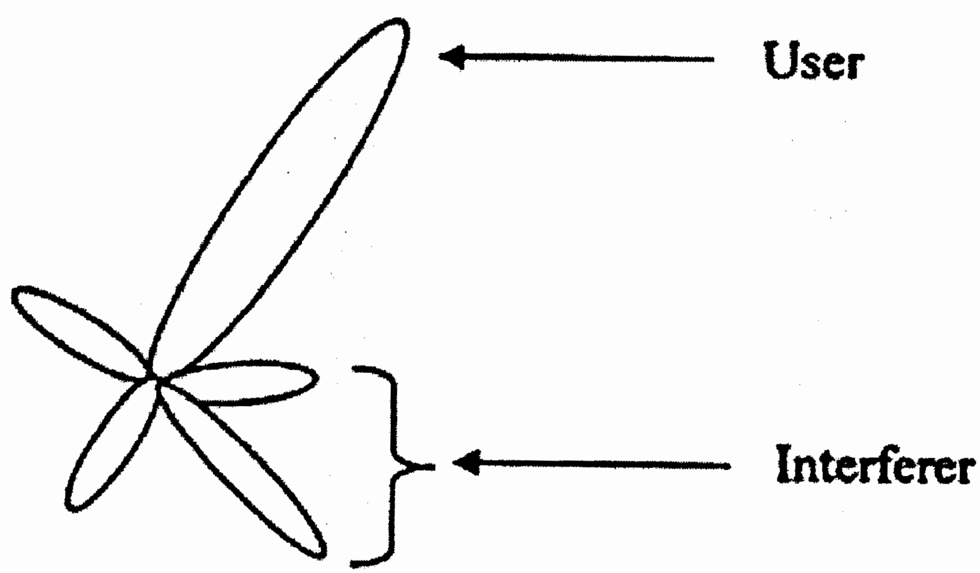

Fig. 4.2 Beam formations for adaptive array antenna system

However, greater performance improvements can be achieved by implementing advanced signal processing techniques to process the information obtains by the antenna arrays. Unlike switched beam systems, the adaptive array systems are really smart because they are able to dynamically react to the changing RF environment. They have a multitude of radiation patterns compared to fixed finite patterns in switched beam systems to adapt to the ever-changing RF environment. An adaptive array, like a switched beam system uses antenna arrays but it is controlled by signal processing. This signal processing steers the radiation beam towards a desired mobile user, follows the user as he moves, and at the same time minimizes interference arising from other users by introducing nulls in their directions. This is illustrated in a simple diagram.

The adaptive array [22] systems are really intelligent in the true sense and can actually be referred to as smart antennas. The smartness in these systems comes from the intelligent digital processor that is incorporated in the system. The processing is mainly governed by complex computationally intensive algorithms. Fully adaptive system use advanced signal processing algorithms to locate and track the desired and interfering signals to dynamically minimize interference and maximize signal reception, and also adaptive arrays can provide greater range (received signal gain) or require fewer antennas to achieve a given range.

4.1.2.1 Basic Working Mechanism

A smart antenna system can perform the following functions, first the direction of arrival of all the incoming signals including the interfering signals and the multipath signals are estimated using the Direction of Arrival [27] algorithms. Secondly, the desired user signal is identified and separated from the rest of the unwanted incoming signals. Lastly a beam is steered in the direction of the desired signal and the user is tracked as he moves while pacing nulls at interfering signal directions by constantly updating the complex weights.

In case of phased arrays it is quite evident that the direction f radiation of the main beam in an array depends upon the phase difference between the element5s of the array. Therefore it is possible to continuously steer the main beam in any direction by adjusting the progressive phase difference β between the elements. The same concept forms the basis in adaptive array systems in which the phase is adjusted to achieve maximum radiation in the desired direction.

To have a better understanding of how an adaptive array system works, let us consider a typical adaptive digital beam forming [28] network.

In a beam forming network typically the signals incident at the individual elements are combined intelligently to form a signal desired beam formed output. Before the incoming signals are weighted they are brought down to base band or intermediate frequencies (IF's). the receivers provided at the output of each element perform the necessary frequency down conversion. Adaptive antenna array systems use digital signal processors (DSP's) to weight the incoming signal. Therefore it is required that the down-converted signal be converted into digital format before they are processed by the DSP (Digital Signal Processing). Analog-to-digital converters (ADC's) are provided for this purpose. For accurate performance, they are required to provide accurate translation of the RF signal from the analog to the digital domain. The digital signal processor forms the heat of the system, which accepts the intermediate frequencies (IF's) signal in digital format and he processing of the digital data is driven by software. The processor interprets the incoming data information, determines the complex weights (amplification and phase information) and multiplies the weights to each element output to optimize the array pattern. The optimization is based on a particular criterion, which minimizes the contribution from noise and interference while producing maximum beam gain at the desired direction. There are several algorithms based on different criteria for updating and computing the optimum weights.

4.2 Comparison between switched beam and adaptive array systems

4.2.1 Switched beam system

The switched beam system can be summarized as follows:

i. it uses multiple fixed directional beams with narrow beam widths.

ii. The required phase shifts are provided by simple fixed phase shifting networks like the butler matrix.

iii. They do not require complex algorithms; simple algorithms are used for beam selection.

iv. It requires only moderate interaction between mobile unit and base station as compared to adaptive array system.

v. Since low technology is used it has lesser cost and complexity.

vi. Integration into existing cellular system is easy and cheap.

vii. It provides significant increase in coverage and capacity compared conventional antenna based systems.

viii. Since multiple narrow beams are used, frequent intra-cell hand-offs between beams have to be handled as mobile moves from one beam to another.

ix. It cannot distinguish between direct signal and interfering and/or multipath signals, this leading to undesired enhancement of the interfering signal more than the desired signal.

x. Since there is no null steering involved; switched beam systems offers limited co-channel interference suppression as compared to the adaptive array system.

4.2.2 Adaptive array system

Adaptive array system can be summarized as follows

v. A complete adaptive system; steers the beam towards desired signal-of-interest and places nulls at the interfering signal directions.

vi. It requires implementation of DSP technology.

vii. It requires implementation of DSP technology.

viii. It has better interference rejection capacity compared to switched beam systems.

ix. It is not easy to implement in existing systems, i.e. up gradation is difficult and expensive.

x. Since continuous steering of the beam is required as the mobile moves; high interaction between mobile unit and base station is required.

xi. Since the beam continuously follows the user; intra-cell hand-offs are less.

xii. It provides better coverage and increased capacity because of improved interference rejection as compared to the Switched beam system.

xiii. It can either reject multipath components or add them by correcting the delays to enhance the signal quality.

4.3 Benefits of Smart Antenna Technology

4.3.1 Reduction in co-channel interference

Smart antennas have a property of spatial filtering to focus radiated energy in the form of narrow beams only in the direction of the desired mobile user and no other direction. In addition they also have nulls in their radiation pattern in the direction of other mobile users in the vicinity. Therefore there is often negligible co-channel interference [26].

4.3.2 Range improvement

Smart antennas employs collection of individual elements in the form of an array they give rise to narrow beam with increased gain when compared to conventional antennas using the same power [29]. The increase in gain leads to increase in range and the coverage of the system. Therefore fewer base stations are required to cover a given are.

4.3.3 Increase in capacity

Smart antennas enable reduction in co-channel interference, which leads to increase in the frequency reuse factor. That is smart antennas allow more users to use the same frequency spectrum at the same time bringing about tremendous increase in capacity.

4.3.4 Reduction in transmitted power

Ordinary antennas radiate energy in all directions leading to a waste of power. Comparatively smart antennas radiate energy only in the desired direction [27]. Therefore less power is required for radiation at the base station. Reduction in transmitted power also implies reduction in interference towards other users.

4.3.5 Reduction in handoff

To improve the capacity in a crowed cellular network, congested cells are further broken into micro cells to enable increase in the frequency reuse factor. This results in frequent handoffs, as the cell size is smaller [21]. Using smart antennas at the base station, there is no need to split the cells since the capacity is increased by using independent spot beams. Therefore, handoffs occur rarely, only when two beams using the same frequency cross each other.

4.3.6 Mitigation of multipath effects

Smart antennas can either reject multipath components as interference, thus mitigating its effects in terms of fading or it can use the multipath components and add them constructively to enhance system performance.

4.3.7 Compatibility

Smart antenna technology can be applied to various multiple access techniques such as TDMA, FDMA, and CDMA [28]. It is compatible with almost any modulation method and bandwidth or frequency band.

CHAPTER 5

Adaptive Beamforming

Adaptive beamforming is a technique in which an array of antenna is exploited to achieve maximum reception in a specified direction by estimating the signal arrival from a desired direction (in the presence of noise) while signals of the same frequency from other directions are rejected. This is achieved by varying the weights of each of the sensors used in the array. The weights may changed adaptively and used to provide optimal beamforming in the sense that it reduced the MMSE between the desired and actual beam pattern formed. It basically uses the idea that the signals emanating from different transmitters occupy the same frequency channel, they still arrive from different directions. This spatial separation is exploited to separate the desired signals from the interfering signals. In adaptive beamforming the optimum weights are iteratively computed using complex algorithms based upon different criteria.

Beamforming is generally accomplished by phasing the feed to each element of an array so that signals received or transmitted from all elements will be in phase in particular directions. The phases and amplitude are adjusted to optimize the received signal.Beamforming is the latest technology used for various purposes .The array factor for an N-element equally spaced linear array is given,

$$AF(\phi) = \sum_{n=0}^{N-1} A_n e^{jn\left(\frac{2\pi d}{\lambda}\cos\phi + \alpha\right)} \tag{5.1}$$

The inter element phase shift is given by,

$$\alpha = -\frac{2\pi d}{\lambda_0} cos\phi_0$$

ϕ_0 is the desired beam direction. At λ_0 wavelength the phase shift corresponds to a time delay that will steer the beam to ϕ_0.

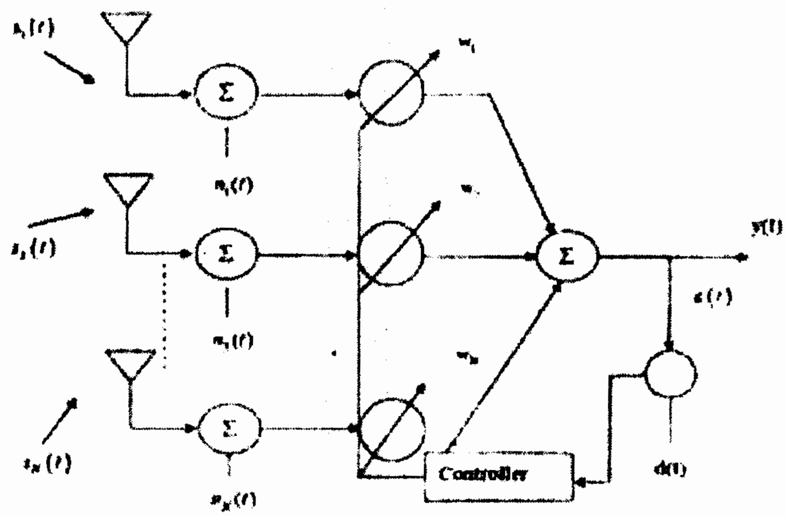

Fig. 5.1 An Adaptive array system

5.1 Adaptive beam forming problem setup

To illustrate different beamforming aspects, let us consider an adaptive beam forming configuration shown above in Fig. 5.1. The output of the array $y(t)$ with variable element weights is the weighted sum of the received signals $s_i(t)$ at the array elements and the noise $\eta(t)$ at the receiver connected to each element. The weights $\mathbf{w}$ are iteratively computed based on the array output $y(t)$, a reference signal $d(t)$ that approximate the desired signal. The reference signal is approximated to the desired signal using a training sequence or a spreading code, which is known at the receiver. The format of the reference signal varies and depends upon the system where adaptive beam forming is implemented. The reference signal usually has a good correlation with the desired signal and the degree of correlation influences the accuracy and the convergence of the algorithm. The output of the beam former is given by

$$y(t)=\mathbf{w}^H\mathbf{x}(t) \tag{5.2}$$

where $\mathbf{w}^H$ denotes the complex conjugate transpose of the weighted vector $\mathbf{w}$.

In order to compute the optimum weights, the array response vector from the sampled data of the array output has to be known. The received signal at the *nth* antenna can be expressed as,

$$x_n(t)=\sum_{k=1}^{K} s_k(t)e^{-jkd(n-1)\sin\theta_k+\eta_n(t)} \tag{5.3}$$

where ... is the wave number $=\frac{2\pi}{\lambda}$, λ =wavelength of the carrier frequency of the signals, d= uniformed inter element distance, $s_k(t)$ = signal transmitted by the *kth* source as received by the reference antenna, θ_k= AOA of the *kth* source as measure and $\eta_n(t)$ = Additive White Gaussian Noise (AWGN) at the antenna elements. Using vector notation, the received signal can be expressed as,

$$\mathbf{x}(t)=\sum_{k=1}^{K}\mathbf{a}(\theta_k)\mathbf{s}_k(t)+\eta(t)=\mathbf{A}(\theta)\mathbf{s}(t)+\eta(t) \tag{5.4}$$

where $\mathbf{x}(t)$ is $N\times 1$ received signal vector, $s(t)$ is $K\times 1$ transmitted signal vector, $\eta(t)$ noise vector , $\mathbf{a}(\theta_k)$ is the $N\times 1$ steering vector and $\mathbf{A}(\theta)=[\mathbf{a}(\theta_1),\mathbf{a}(\theta_2),\ldots,\mathbf{a}(\theta_K)]$ is $N\times K$ matrix whose columns are steering vectors of the sources. The array correlation matrix associated with vector $\mathbf{x}(t)$ contain formation about how signals from element are correlated with each other and is given by

$$\mathbf{R}=E\left[\mathbf{x}(t)\mathbf{x}^H(t)\right] \tag{5.5}$$

Let $s_1(t)$ be the desired user signal arriving form direction θ_1 and consider the rest of the signals $s_k(t), k = 2,3,...K$ as interferences arriving from their respective direction. The array output is given by

$$y(n) = \mathbf{w}^H \mathbf{x}(t) \tag{5.6}$$

where $\mathbf{w}$ is the weight vctor that is applied to the antenna array to produced the beam pattern with its main lobe in the direction of the desired user. Substituting (5.5) in (5.7) and simplifying we get.

$$y(t) = \sum_{k=1}^{K} \mathbf{w}^H \mathbf{a}(\theta_k) s_k(t) + \mathbf{w}^H \eta(t) \tag{5.7}$$

Let $d^*(t)$ represent a signal that is closely correlated to the original desired signal $s(t)$.and

$d^*(t)$ is referred to as the reference signal, the mean square error (MSE) $e^2(t)$ between the beam former output and the reference signal can now be computed as follws,

$$e^2(t) = \left[d^*(t) - \mathbf{w}^H \mathbf{x}(t)\right]^2 \tag{5.8}$$

After taking an expectation on both sides of the equation we get,

$$E\{e^2(t)\} = E\left\{\left[d^*(t) - \mathbf{w}^H \mathbf{x}(t)\right]^2\right\} \tag{5.9}$$

$$E\{e^2(t)\} = E\{d^2(t)\} - 2\mathbf{w}^H \mathbf{r} + \mathbf{w}^H \mathbf{R} \mathbf{w} \tag{5.10}$$

Where $\mathbf{r} = E\left[d^*(t)\mathbf{x}(t)\right]$ is the cross correlation matrix between the desired signal and the received signal and $\mathbf{R} = E\left[\mathbf{x}(t)\mathbf{x}^H(t)\right]$ is the auto correlation matrix of the received signal also known as the covariance matrix. The minimum MSE can be obtained by setting the gradient vecto of the above equation with respect to equal to zero, i.e.

$$\nabla_w \left(E\{s^*(t)\}\right) = -2\mathbf{r} + 2\mathbf{R}\mathbf{w} \tag{5.11}$$

$$=0$$

Therefore the optimum solution for the weight w_{opt} is given by

$$\mathbf{w}_{opt} = \mathbf{R}^{-1}\mathbf{r} \tag{5.12}$$

This equation is referred to as the optimum weiner solution.

5.2 Sample matrix inversion in (SMI) Algorithm.

In this algorithm the weights are chosen such that the mean square error between the beam former output and the reference signal is minimized. The mean square error is given by,

$$E\left|\left\{d(t) - \mathbf{w}^H\mathbf{x}(t)\right\}^2\right| = E\left[d^2(t)\right] - 2\mathbf{w}^H\mathbf{R}_r + \mathbf{w}^H\mathbf{R}_0\mathbf{w} \tag{5.13}$$

$\mathbf{x}(t)$ is the array output at time $t; d(t)$ is the reference signal $\mathbf{R}_m = E\left[\mathbf{x}(t)\mathbf{x}^H(t)\right]$ is the signal covariance matrix ,$\mathbf{R}_r = E\left[d(t)\mathbf{x}(t)\right]$ defines the covariance between the reference signal and the data signal. The weight vector, for which the above equation becomes minimum, is obtained by setting its radiant vector with respect to w to zero , i.e.

$$\nabla_w\left\{E\left[\left\{d(t) - \mathbf{w}^H\mathbf{x}(t)\right\}^2\right]\right\} = -2\mathbf{R}_r + \mathbf{R}_0\mathbf{w} \tag{5.14}$$

$$=0$$

Therefore,

$$\mathbf{w}_{opt} = \mathbf{R}_m^{-1}\mathbf{R}_r \tag{5.15}$$

The optimum weights can be easily obtained by direct inversion of the covariance matrix. This algorithm requires a reference signal and is computational intensive. It is definitely faster than LMS.

5.3 Least Mean Squares (LMS)

The LMS algorithm is an important member of a family of stochastic gradient algorithm. The term “stochastic gradient” is intended to distinguish in a recursive computation of the Wiener filter for stochastic inputs. A significant feature of the LMS algorithm is its simplicity. Moreover, it does not require measurement of the correlation functions, nor does it require matrix inversion. This algorithm like the preceding one requires a reference signal and it computes weight vector,

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu\mathbf{x}(n)\left[d^{*}(n)-\mathbf{x}^{H}(n)\mathbf{w}(n)\right] \tag{5.16}$$

Using the above equation, where $\mathbf{w}(n+1)$ denotes weight computed at $(n+1)th$ iteration, and μ is the gain constant that controls the rate of adaptation, i.e. how fast estimated weights approach the optimal weights. The convergence of the algorithm depends upon eigen values of $\mathbf{R}$, the array correlation matrix, Note that the second term, $\mu\mathbf{x}(n)e^{*}(n)$ on the right hand of Eq. 5.16 represents the adjustment that is applied to the current estimate of the tap weight vector. The iterative procedure is started with an initial guess.

The algorithm described by Eq. 5.15 is the complex form of the adaptive least mean square (LMS) algorithm. At each iteration or time update, this algorithm is a member of the family of stochastic gradient algorithm. In particular, when the LMS algorithm operates on stochastic inputs, the allowed set of direction along which we step from one iteration cycle to the next is quite random and can not therefore be thought of as consisting of true gradient direction. In reality, exact measurement of the gradient vector is not possible, since that would require prior knowledge of both the correlation matrix and the cross correlation vector. Consequently, the gradient vector must be estimated from the available data when we operate in an unknown environment.

In a digital system, the reference signal is obtained by periodically transmitting a training sequence that is known to a receiver, or using the spread code in the case of direct sequence CDMA system [29]. The LMS algorithm describes here is a basic structure for most dynamic adaptive algorithm. This method requires information about a reference signal. In deed, it is the simplicity of the LMS algorithm that has made it the standard against which other linear adaptive filtering algorithm.

5.4 MUSIC Algorithm

MUSIC is an abbreviation for MUltiple Signal Classification; MUSIC is essentially a method of characterizing the range of self-adjoint operator. Suppose A is a self-adjoint operator with eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots$ and corresponding eigenvectors. suppose the eigenvalues are all zero, so that the vectors $v_1, v_2, \ldots,$ span the null space A. Alternatively $\lambda_{M+1}, \lambda_{M+2}, \ldots,$ could be merely very small below the noise level of the system represented by A, in this case we say that the vectors v_{M+1}, v_{M+2} span the noise subspace of A. We can form the projection onto the noise subspace; this projection is given explicitly by

$$P_{noise} = \sum_{j \rangle M} v_j \bar{v}^T{}_j \tag{5.17}$$

where the subscript T denotes transpose, the bar denotes the complex conjugate. The range of A is spanned by the vectors $v_1, v_2, \ldots, v_M$ We know that the noise subspace is orthogonal to the range. Therefore a vector **f** is in the range if and only if its projection onto the noise subspace is zero. i.e. if $\|P_{noise}\mathbf{f}\| = 0$ and this in turn happen only if

$$\frac{1}{\|P_{noise}\mathbf{f}\|} = \infty \tag{5.18}$$

The above equation is the MUSIC characterization of the range of A.

5.5 MUSIC Algorithm in Signal Processing

MUSIC is generally used in signal processing problems. In this case make measurement of some signal $\mathbf{x}(t)$ at discrete time $t_n = n$ the resulting sampl $x_n = x(t_n)$ are considered random variables. The correlation matrix is $\mathbf{A}_{n,m} = E\left(x_n \bar{x}_m\right)$ where E denotes the expected value.

We consider the case when the signal is composed of two time harmonic signals of different frequencies plus noise. Thus $x_n = \alpha_1 e^{iw_1 n} + \alpha_2 e^{iw_2 n}, \ldots, w_n$. We assume that the random variables

w_n are identically distributed, because the different terms of x_n are mutually independent. The self-adjoint matrix A can be written as,

$$\mathbf{A} = E\left(\left|\alpha_1\right|^2\right) s^1 \overline{s^1}^T + E\left(\left|\alpha_2\right|^2\right) s^2 \overline{s^2}^T + \sigma_0^2 \mathbf{I} \tag{5.19}$$

Where the nth component of the vector s^j is given by $s_n{}^j = e^{iw_n j}$. I denotes the identically operator and $\sigma_0^2 = E\left(\left|w_n\right|^2\right)$.The MUSIC algorithm for estimating the frequiencies w_1 and w_2 is

$$\frac{1}{\left\|P_{noise} S^w\right\|} \tag{5.20}$$

Where s^w is the vector whose nth component is the e^{iwn}. MUSIC is a method for estimating the individual frequencies of multiple time harmonic signals.

5.6 Normalized Least Mean Square Algorithm

The fundamental equation for NLMS is as follows

$$e(n) = d(n) - w^H(n) r(n) \tag{5.21}$$

$$w(n+1) = w(n) + \frac{\mu . e^*(n) . r(n)}{\left\|r(n)\right\|^2} \tag{5.22}$$

The constant μ is the convergence parameter that determines the degree of weight update.as shown in Eq. 1 and Eq. 2 the MMSE algorithm discriminates the desired signal from the interference signals. The beam forming consist of an MMSE weight adjuster and a beam estimator that computes the target output as the reference signal for the weight adjustor. In the NLMS algorithm the desired user signal is arriving at an angle 60 degree while interferer signal is arriving at an angles 140 degree. The main lobe will be in the direction of the desired user and minor lobe will be in the direction of the interferer signals.

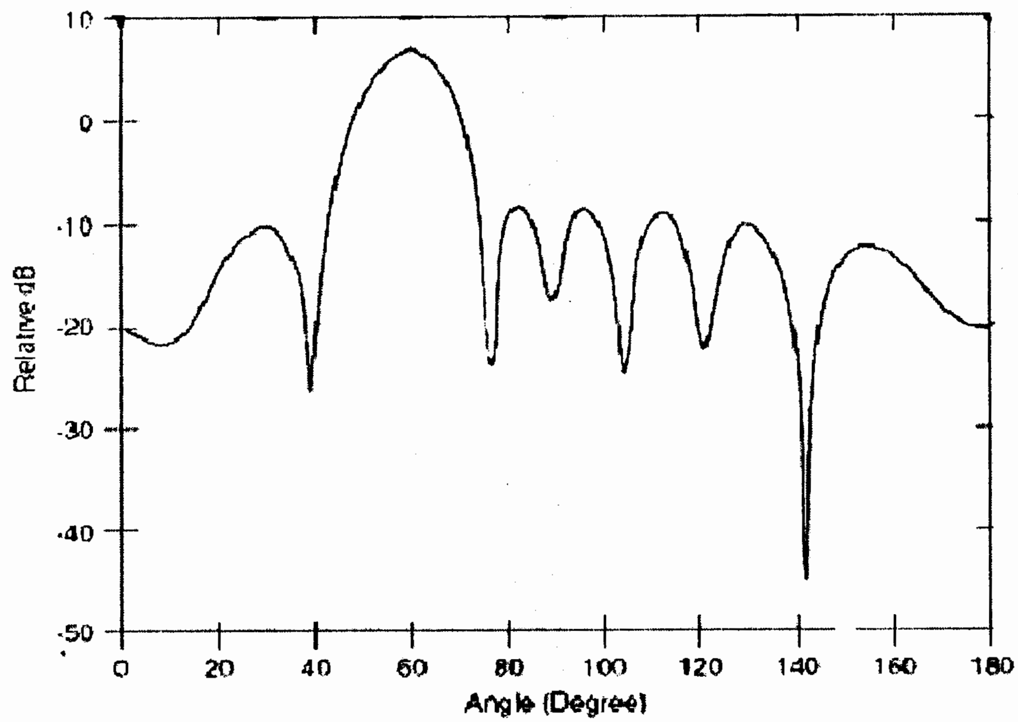

Fig. 5.3 NLMS Array factor plot for desired user arriving at an angle 60 degree while interferer signals are arriving at an angle 140 degree.

5.7 Modified Tabu Search Algorithm

The tabu search algorithm is used to steer the single, multiple and broad band nulls to the direction of interference by the amplitude and phase of each array element. Tabu search algorithm has been developed to be an effective and efficient scheme for optimization that combines search strategy based on a set of elementary moves. One characteristic of Tabu search is that it finds good near optimal solutions early in the optimization run.

The Tabu search algorithm used in this thesis is the modified Tabu search algorithm. The classical TSA uses a solution vector consisting of a string of bits. However the MTSA uses a real value solution vector and adaptive mechanism for producing neighbors. This neighbor production mechanism enables us to find to find the most promising region of the search phase. Because of these features, the MTSA is used for the pattern nulling. Nulling of the pattern is achieved by controlling the amplitude and phase of each array element.

To select the new solution from the neighbors, performance values of all neighbors are evaluated in the cost function given by Eq. 5.19 and the non-Tabu neighbor producing the highest improvement according to the present solution is then selected as the next solution. If there are some Tabu-neighbors which are better than the best solution found so-far, then those Tabu solutions are freed.

5.7 Numerical Result

In order to illustrate the capabilities of the MTSA for steering single, multiple and broad band nulls with the imposed directions by controlling the amplitude only, three example of a linear array with one-half wavelength have been performed. In the application of the MTSA, three examples of the amplitude-only control are presented. i.e. The pattern obtained by the MTSA and illustrated in Fig. 5.2. In order to show the effects of the weighting factors given in Eq. 5.19 on the pattern, in the second example, the dynamic range ratio is constrained to 3.6 by increasing only the value of the weighting factor w_4. The pattern having single null at -20° with this constrained dynamic range ratio is shown,

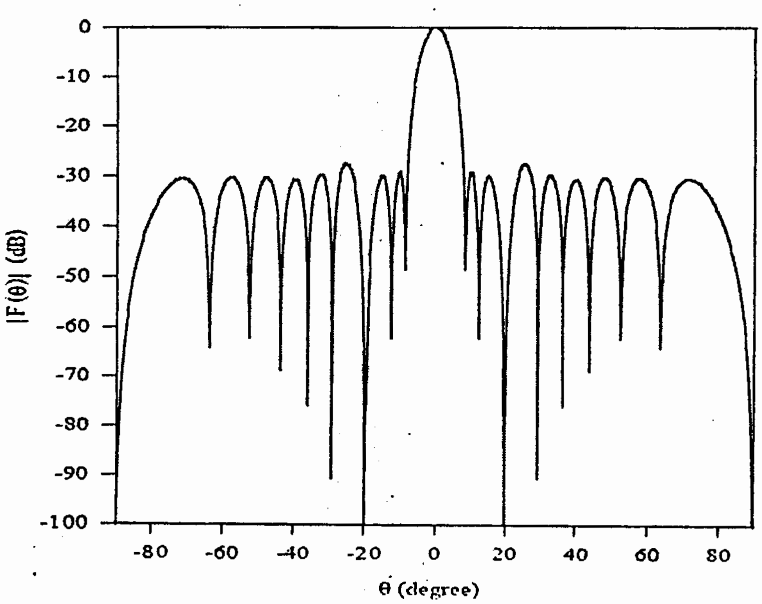

Fig. 5.2 Radiation pattern by controlling amplitude-only with one imposed null at -20°

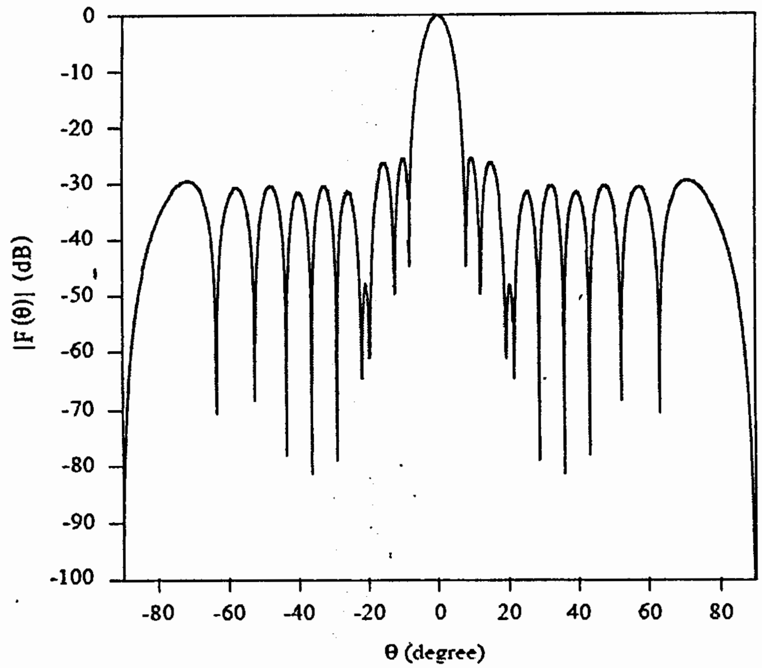

Fig. 5.3 Radiation pattern obtained by controlling amplitude-only with one imposed null at -20 degree and the constrained dynamic range of 3.6.

in Fig. 5.3. As expected, the result of first example is better than that of the second example because the smaller amplitude range means smaller degrees of freedom for the solution space hence worse side lobe and null depth performance. The null depths of Fig. 5.2 and 5.3 are 99.6 dB and 52.7 dB, respectively.

In the third example, the pattern with a broad null sector centered 30° with $\Delta\theta = 5^{\circ}$ is considered. The resulting pattern is shown in Fig. 5.4. The desired broad null is achieved with a null depth of 113 dB at the center angle of30°. In the three examples given above, since the array elements have even symmetry around the center of the array, a corresponding image nulls occurred at the other side of the main beam simultaneously As a result of this assumption, the number of attenuators required is N for the array with $2N$ elements. Table 1 gives the element amplitudes obtained by using the MTSA for Fig. 5.2–5.4 .finally this optimization approach can be helpful for antenna array.

CHAPTER 6

Least Mean Square Algorithm

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 [9] is an adaptive algorithm, which uses a gradient-based method of steepest decent [5]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions.

6.1 LMS Algorithm and Adaptive Arrays

Consider a Uniform Linear Array (ULA) with N isotropic elements, which forms the integral part of the adaptive beam forming system as shown in the Fig.6.1 below. The output of the antenna array $x(t)$ is given by,

$$x(t) = s(t)a(\theta_o) + \sum_{i=1}^{N_u} u_i(t)a(\theta_i) + \eta(t) \tag{6.1}$$

$s(t)$ denotes the desired signal arriving at angle θ_o and $u_i(t)$ denotes interfering signals arriving at angle of incidences θ_i respectively. $a(\theta_o)$ and $a(\theta_i)$ represents the steering vectors for the desired signal and interfering signals respectively. Therefore it is required to construct the desired signal from the received signal amid the interfering signal and additional noise $\eta(t)$. As shown above the outputs of the individual sensors are linearly combined after being scaled using corresponding weights such that the antenna array pattern

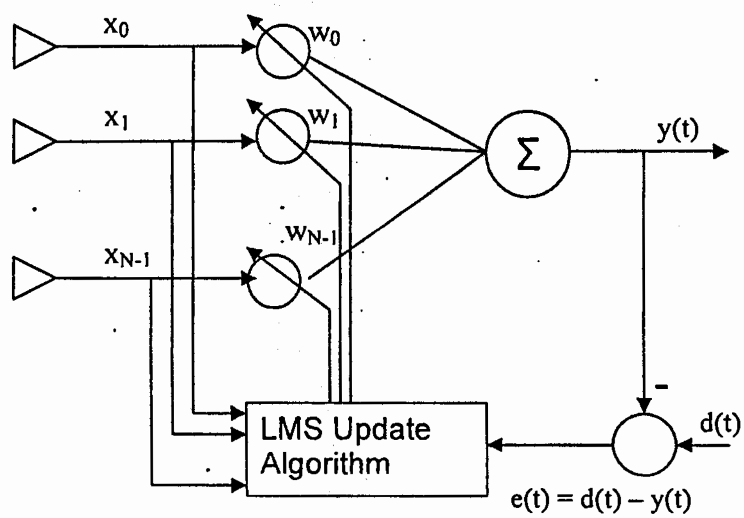

Fig. 6.1 LMS adaptive Beamforming network

is optimized to have maximum possible gain in the direction of the desired signal and nulls in the direction of the interferers. The weights here will be computed using LMS algorithm based on Minimum Mean Squared Error (MMSE) criterion. Therefore the spatial filtering problem involves estimation of signal $s(t)$ from the received signal $x(t)$ by minimizing the error between the reference signal $d(t)$ and the output of the beam former $y(t)$. This is a classical Weiner filtering problem for which the solution can be iteratively found using the LMS algorithm.

6.2 LMS algorithm formulation

From the method of steepest descent, the weight vector equation is given by [5],

$$w(n+1) = w(n) + \frac{1}{2}\mu[-\nabla(E\{e^2(n)\})] \tag{6.2}$$

where μ is the step-size parameter and controls the convergence characteristics of the LMS algorithm; $e^2(n)$ is the mean square error between the reference signal $d(t)$ and beam former output $y(n)$ which is given by,

$$e^2(n) = [d^*(n) - \mathbf{w}^H\mathbf{x}(n)]^2 \tag{6.3}$$

The gradient vector in the above weight update equation can be computed as

$$\nabla_w(E\{e^2(n)\}) = -2\mathbf{r} + 2\mathbf{R}\mathbf{w}(n) \tag{6.4}$$

In the method of steepest descent the biggest problem is the computation involved in finding the values $\mathbf{r}$ and $\mathbf{R}$ matrices in real time [9]. The LMS algorithm on the other hand simplifies this by using the instantaneous values of covariance matrices $\mathbf{r}$ and $\mathbf{R}$ instead of their actual values i.e.

$$\mathrm{R}(n) = \mathbf{x}(n)\mathbf{x}^H(n) \tag{6.5}$$

$$\mathbf{r}(n) = d^*(n)\mathbf{x}(n) \tag{6.6}$$

Therefore the weight update can be given by the following equation,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)[d^*(n) - \mathbf{x}^H(n)\mathbf{w}(n)] \tag{6.7}$$

$$= \mathbf{w}(n) + \mu\mathbf{x}(n)e^*(n)$$

The LMS algorithm is initiated with an arbitrary value $w(0)$ for the weight vector at $n = 0$. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. Therefore the LMS algorithm can be summarized in following equations;

$$y(n) = \mathbf{w}^H\mathbf{x}(n) \tag{6.8}$$

$$e(n) = d^*(n) - y(n) \tag{6.9}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)e^*(n) \tag{6.10}$$

Eq. 6.8 and 6.9 define the estimation error $e(n)$, the computation of which is based on the current estimate of the tap weight vector, the term $\mu\mathbf{x}(\mathrm{n})\mathrm{e}^*(\mathrm{n})$ represent the adjustment. The algorithm described by Eq. (6.8) through (6.10) is the complex form of the adaptive least mean square (LMS) algorithm.at each iteration, this algorithm requires knowledge of the most recent values: $\mathbf{x}(n), d(n),$ and $\mathbf{w}(n)$.

6.3 Convergence and Stability of the LMS algorithm

The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{6.11}$$

where λ_{max} is the largest eigenvalue of the correlation matrix $\mathbf{R}$. The convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix $\mathbf{R}$. When the eigen values of the correlation matrix $\mathbf{R}$ are widespread, convergence may be slow. The eigen value spread of the correlation matrix is estimated by computing the ratio of the largest eigen value to the smallest eigen value of the matrix. If μ is chosen to be very small then the algorithm converges very slowly. A large value of μ may lead to a faster convergence but may be less stable around the minimum value. LMS algorithm, improving the convergence process;naturally for that to be possible prior knowledge is required

6.4 Simulation result for the LMS algorithm

For simulation purposes a linear array is used with its individual elements spaced at half-wavelength distance. The desired signal $s(t)$ arriving at θ_0 is a simple complex sinusoidal-phase modulated signal of the following form,

$$s(t) = e^{j\sin(\omega t)} \tag{6.12}$$

The interfering signals $u_i(t)$ arriving at angles θ_i are also of the above form. By doing so it can be shown in the simulations how interfering signals of the same frequency as the desired signal can be separated to achieve rejection of co-channel interference. Illustrations are provided to give a better understanding of different aspects of the LMS algorithm with respect to adaptive beam forming. For simplicity purpose the reference signal $d(t)$ is considered to be the same as the desired signal $s(t)$.

6.4.1 Beamforming examples

Three examples are provided to show the beam forming abilities of the LMS algorithm.

Case 1:

In the first case the desired user signal is arriving at 0 degrees and the interfering signals is arriving at angles -30 degrees. The array factor plot in Fig. 6.2 shows that the LMS algorithm is able to iteratively update the weights to force deep nulls at the direction of interferers and achieve maximum in the direction of the desired signal.

At the other extreme, when the inputs are highly correlated and the eigen value spread is large, the convergence of the LMS algorithm (like the steepest-descent algorithm from which it is derived) takes on a directional nature. The speed of convergence of the algorithm

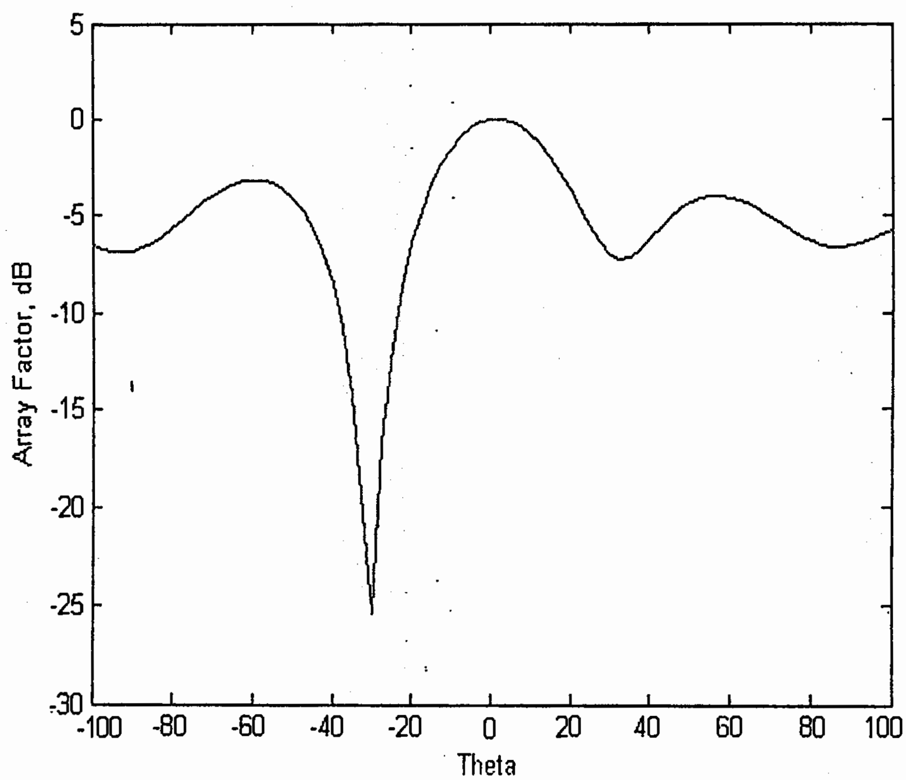

Fig. 6.2 LMS Array Factor Plot desired user signal is arriving at angle 0 degree while interferer signal is arriving at an angle -30 degree. N=4

is faster in certain directions in the algorithm weight space than in some other directions. Depending on the direction along which the convergence of the algorithm takes place, it is possible for the convergence to be accelerated by an increase in the eigenvalue spread. The main limitation of LMS is their relative slow rate of convergence.

Case 2:

Another example shown in Fig. 6.3 is provided for the case where the desired user signal is arriving at -10 degree and there are two interfering signals arriving at angles -55 and 35 degrees respectively. The array factor plot in Fig. 6.3 shows that the LMS algorithm is able to iteratively update the weights to force deep nulls at the direction of the interferer and achieve maximum in the direction of the desired signal.

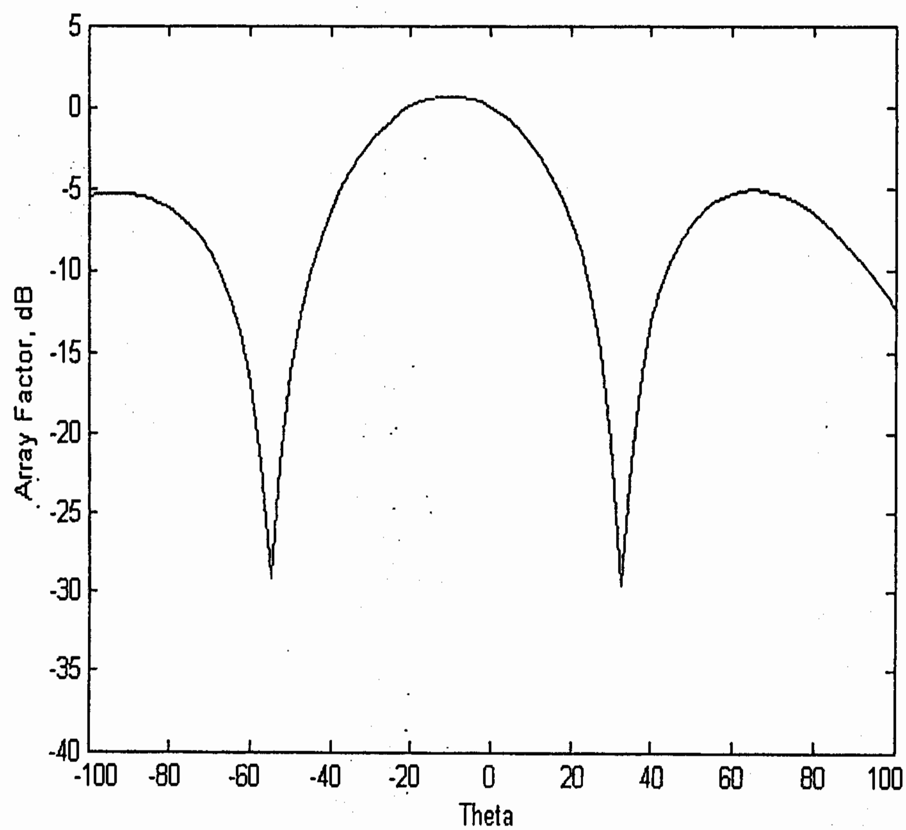

Fig. 6.3 LMS Array Factor Plot desired user is arriving at angle -10 degree while interferer is arriving at an angle - 55 degree and 35 degree respectively N=4

Case 3:

In this case the example shown in Fig. 6.4 is provided for the case where the desired user signal is arriving at 0 degree and there are three interfering signals arriving at angles -85, -35 and 40 degrees respectively. The array factor plot in Fig. 6.4 shows that the LMS algorithm is able to iteratively update the weights to force deep nulls at the direction of the interferer and achieve maximum in the direction of the desired signal.

6.4.2 Dependency of the step-size parameter

The step-size parameter or the convergence factor is the basis for the convergence speed of the LMS algorithm. For the LMS algorithm to converge and be stable Eq. (6.11) repeated below gives the allowable range of μ.

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{6.13}$$

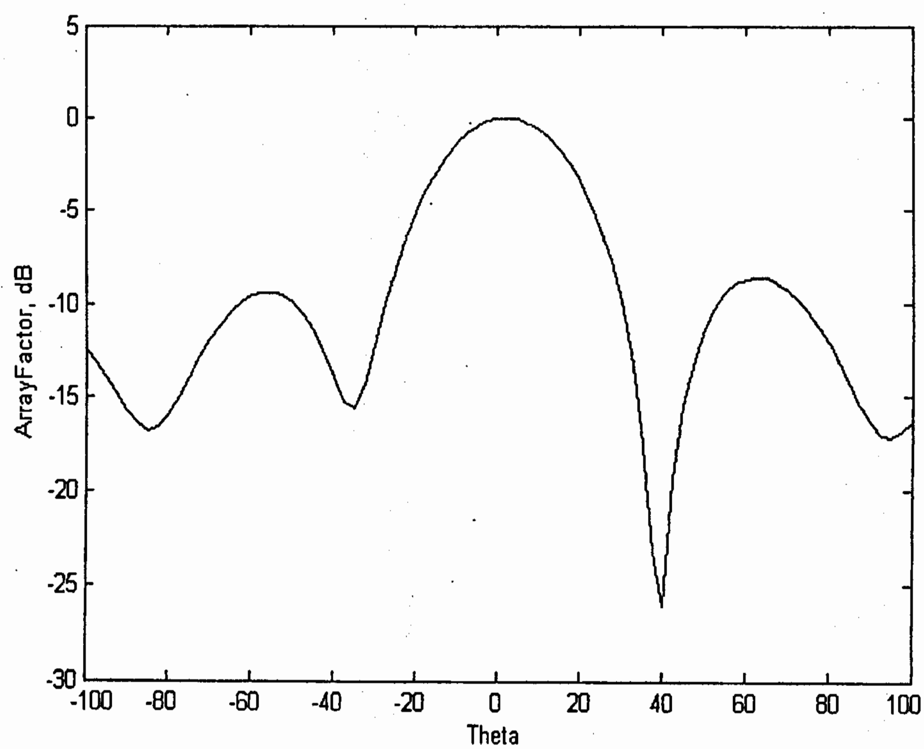

Fig. 6.4 LMS Array Factor Plot desired user signal is arriving at angle 0 degree while interferer signal is arriving at an angle -85, -35 and 40 degree respectively. N=5

where λ_{max} is the largest eigen value of the correlation matrix $\mathbf{R}$. The LMS algorithm is most commonly used adaptive algorithm because of its simplicity and a reasonable performance. Since it is an iterative algorithm it can be used in a highly time-varying signal environment. It has a stable and robust performance against different signal conditions. However it may not have a really fast convergence speed compared other complicated algorithms like the Recursive Least Square (RLS).

It converges with slow speeds when the environment yields a correlation matrix $\mathbf{R}$ possessing a large eigen spread. Usually traffic conditions are not static, the user and interferer locations and the signal environment are varying with time, in which case the weights will not have enough time to converge when adapted at an identical rate. That is the step-size needs to be varied in accordance with the varying traffic conditions. There are several variants of the LMS algorithm that deal with the shortcomings of its basic form. LMS is not a blind algorithm i.e. it requires a priori information for the reference signal.

CHAPTER 7

Sample Matrix Inversion

The LMS algorithm discussed in the previous chapter is a continuously adaptive algorithm and has a slow convergence when the eigen values of the covariance matrix are widespread. When the transmission is discontinuous, a block adaptive approach would give a better performance than a continuous approach. One such algorithm is the Sample Matrix Inversion (SMI) [3] [9] which provide good performance in a discontinuous traffic. It requires that the number of interferers and their positions remain constant during the duration of the block acquisition.

In TDMA communication systems, data is transmitted in bursts with a known training sequence occurring in each burst. A good example is GSM where there are 26 training bits [30] in middle of each burst. This training sequence is designed to have good auto-correlation and cross correlation properties for use in burst synchronization, burst identification, and equalizer training. In such bursty transmission systems, some form of block-adaptive algorithm will certainly provide a better performance than the continuously adaptive LMS algorithm. This has led to the formulation of the SMI algorithm.

7.1 SMI Formulation

The SMI algorithm has a faster convergence rate since it employs direct inversion of the covariance matrix $\mathbf{R}$. Let us recall the equations for the covariance matrix $\mathbf{R}$ and the correlation matrix $\mathbf{r}$ [12].

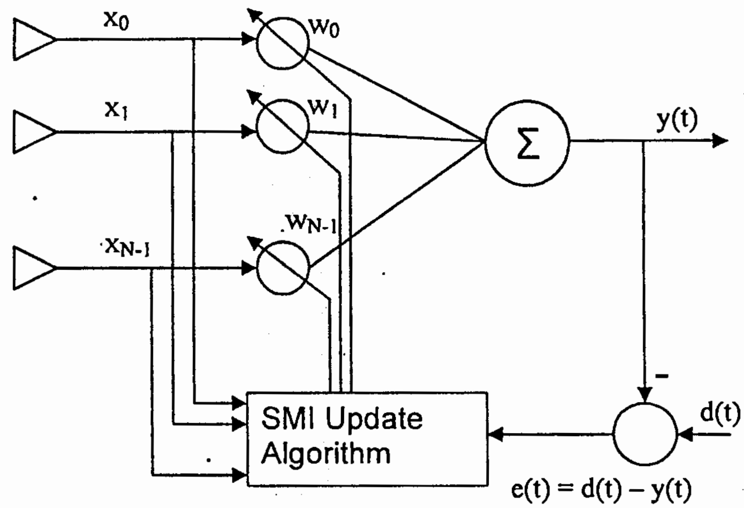

Fig. 7.1 SMI adaptive beam forming network

$$\mathbf{R} = E[\mathbf{x}(t)\mathbf{x}^H(t)] \tag{7.1}$$

$$\mathbf{r} = E[\mathbf{x}(t)d^*(t)] \tag{7.2}$$

If a priori information about the desired and the interfering signals is known, then the optimum weights can be calculated directly by using the Weiner solution,

$$\mathbf{w}_{opt} = \mathbf{R}^{-1}\mathbf{r} \tag{7.3}$$

However, in practice signals are not known and the signal environment keeps changing. Therefore optimal weights can be computed by obtaining the estimates of the covariance matrix $\mathbf{R}$ and the correlation matrix $\mathbf{r}$, by time averaging from the block of input data. The estimates of the matrices over a block size $N_2 - N_1$ are given by

$$\hat{\mathbf{R}} = \sum_{i=N_1}^{N_2} \mathbf{x}(i)\mathbf{x}^H(i) \tag{7.4}$$

$$\hat{\mathbf{r}} = \sum_{i=N_1}^{N_2} d^*(i)\mathbf{x}^H(i) \tag{7.5}$$

where N_1 and N_2 form the lower and the upper limit of the observation interval. The weight vector can now be estimated by the following equation:

$$\hat{\mathbf{w}} = \hat{\mathbf{R}}^{-1}\hat{\mathbf{r}} \tag{7.6}$$

based on the above discussion the weights will be updated.

The stability of the SMI algorithm depends on the ability to invert the large covariance matrix. In order to avoid a singularity of the covariance matrix, a zero- mean white Gaussian noise [31] is added to the array response vector. It creates a strong additive component to the diagonal of the matrix. In the absence of noise in the system, a singularity occurs when the number of signals to be resolved is less than the number of elements in the array. SMI employs direct matrix inversion the convergence of this algorithm is faster compared to the LMS algorithm. However, huge matrix inversions lead to computational complexities that cannot be easily overcome.

7.2 Weight Adaptation Techniques

Weight adaptation in the SMI algorithm can be achieved as follows [9].

7.2.1 Block adaptation

The above-mentioned block adaptive approach, where the adaptation is carried over disjoint intervals of time, is the most common type. This is well suited for a highly time varying signal environment as in mobile communications.

7.3 Simulation Results for the SMI algorithm

For simulation purposes, a similar scenario is considered as with the LMS simulation discussed in the previous chapter. A linear array is used with its individual elements spaced at half-wavelength distance. The desired signal $s(t)$ arriving at θ_0 is a simple sinusoidal-phase modulated signal of the same form as in Eq. (6.12). The interfering signals $u_i(t)$ arriving at angles θ_i are also of the same form. Simulation results with illustrations are provided to give a better understanding of different aspects of the SMI algorithm with respect to adaptive beam forming. For simplicity sake the reference signal $d(t)$ is considered to be same as the desired signal $s(t)$.

7.3.1 Beam forming example

Case 1:

In the example provided here, the desired user signal is arriving at -20 degrees and the interfering signals is arriving at angles –80 and 30 degree respectively. The array factor plot in Fig. 7.2 shows that the SMI algorithm is able to update the weights to force deep nulls in the direction of the interferer and achieve a maximum in the direction of the desired signal. The angular parameters for the desired and interfering signal used here are identical to that used in the LMS simulation in the previous chapter. It can be seen that nulls are deeper in the case of SMI when compared to LMS.

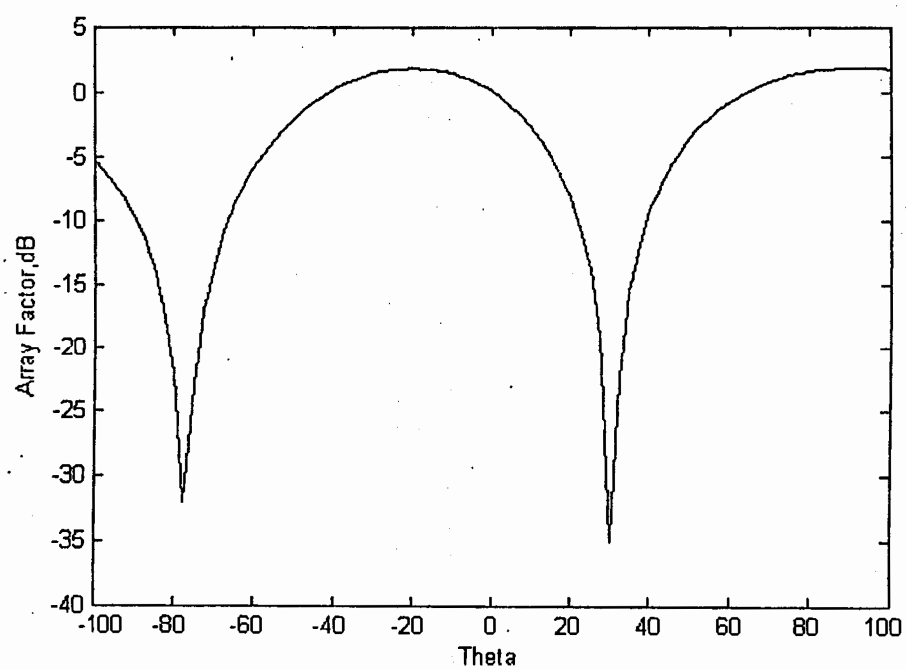

Fig. 7.2 SMI Array Factor plot desired user signal is arriving at an angle -20 degree while interferer signal is arriving at -80 and 30 degree respectively. N=4

Case 2:

Another example shown in Fig. 7.3 is provided for the case where the desired user signal is arriving at -10 degree and there are three interfering signals arriving at angles -50, 20 and 75 degrees respectively. The array factor plot in Fig. 7.3 shows that the SMI algorithm is able to iteratively update the weights to force deep nulls at the direction of the interferer and achieve maximum in the direction of the desired signal.

It quite evident that SMI has a fast convergence rate. SMI algorithm is based on matrix inversion, which tends to be computationally intensive. The high convergence rate property of the SMI algorithm is best made use of when it is used in conjunction with other algorithms. Like LMS, SMI algorithm requires information about the desired signal.

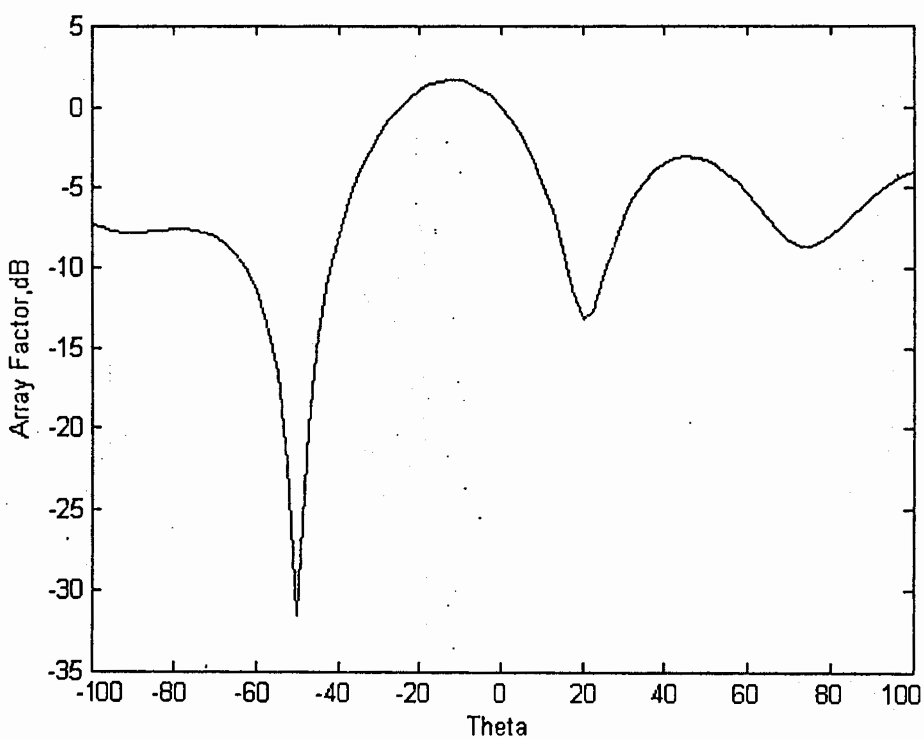

Fig. 7.3 SMI Array Factor plot desired user signal is arriving at angle -10 degree while interferer signal is arriving at -50 , 20 and 75 degree respectively N=5

CHAPTER 8

Conclusions and Future Work

8.1 Conclusions

The main purpose of this thesis is to make an in-depth study of the adaptive algorithms used in smart antennas. Two algorithms, the Least Mean Square (LMS) and the Sample Matrix Inversion (SMI) were discussed. Simulation results were also provided to understand various aspects of the algorithm such as the convergence and the stability, when the covariance matrix has a large eigenvalue spread the LMS algorithm has a slow convergence. The results obtained from the simulation showed that the LMS had poor convergence rate compared to the SMI. The fast convergence of the SMI is attributed to direct optimum weight computation using computationally intensive matrix inversions. The convergence of the algorithm depends on adaptive algorithm type. The adaptive algorithm based on least mean square (LMS) and Sample Matrix Inversion is applied, in which antenna weights are recursively obtained to minimize the mean square error.

8.2 Future Work

Future work of this study could involve an extension of the simulations performed, to different modulation technique. Also the algorithm can be tested in different signal propagation environments. A further enhancement in the algorithm performance may be achieved by incorporating a variable convergence rate rather than a constant convergence rate. Also, when used in an environment that does not require continuous transmission improved convergence rate cab be achieved by re-initializing the weights. Smart antenna approach can also be used for different algorithm like MUSIC.

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