NEURAL NETWORK BASED ROBUST ADAPTIVE BEAMFORMING FOR SMART ANTENNA SYSTEM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

in

Electrical Engineering

by

Paramanand Sharma

Roll No: 207EE104

Department of Electrical Engineering
National Institute of Technology
Rourkela

2009

NEURAL NETWORK BASED ROBUST ADAPTIVE BEAMFORMING FOR SMART ANTENNA SYSTEM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

in

Electrical Engineering

by

Paramanand Sharma

Under the Guidance of

Prof. Susmita Das

Department of Electrical Engineering
National Institute of Technology
Rourkela

2009

CERTIFICATE

This is to certify that the thesis entitled, "**NEURAL NETWORK BASED ROBUST ADAPTIVE BEAMFORMING FOR SMART ANTENNA SYSTEM**" submitted by **Mr. PARAMANAND SHARMA** in partial fulfillment of the requirements for the award of Master of Technology Degree in **Electrical Engineering** with specialization in "**Electronics System and Communication**" at the National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/ Institute for the award of any degree or diploma.

Date:

Prof. Susmita Das
Department of Electrical Engineering.
National Institute of Technology
Rourkela – 769008

Acknowledgement

I would like to express my deep sense of respect and gratitude toward my supervisor **Dr. Susmita Das**, who not only guided the academic project work but also stood as a teacher and philosopher in realizing the imagination in pragmatic way. I want to thank her for introducing me in the field of the Smart Antenna for wireless communication. Her presence and optimism have provided an invaluable influence on my career and outlook for the future. I consider it as my good fortune to have got an opportunity to work with such a wonderful person.

I express my gratitude to **Dr B.D. Subhudhi**, Professor and Head, Department of Electrical Engineering, faculty member and staff of Department of Electrical Engineering for extending all possible help in carrying out the dissertation work directly or indirectly. They have been great source of inspiration to me and I thank them from bottom of my heart. I would like to acknowledge my institute, National Institute of Technology, Rourkela, for providing good facilities to complete my thesis work.

I would also like to take this opportunity to acknowledge my friends for their support and encouragement. Without them, it would have been very difficult for me to complete my thesis work. I am especially indebted to my parents for their love, sacrifice and support. They are my teachers after I came to this world and have set great example for me about how to live, study and work.

At last, I would like to give thanks to God since He has given me wisdom, health and all the necessities that I need for all these years.

Paramanand Sharma

Contents

ABSTRACT

As the growing demand for mobile communications is constantly increasing, the need for better coverage, improved capacity, and higher transmission quality rises. Thus, a more efficient use of the radio spectrum is required. A smart antenna system is capable of efficiently utilizing the radio spectrum and is a promise for an effective solution to the present wireless system problems while achieving reliable and robust high-speed, high-data-rate transmission. Smart antenna technology offer significantly improved solution to reduce interference level and improve system capacity. With this technology, each user's signal is transmitted and received by the base station only in the direction of that particular user. Smart antenna technology attempts to address this problem via advanced signal processing technology called beamforming.

The adaptive algorithm used in the signal processing has a profound effect on the performance of a Smart Antenna system that is known to have resolution and interference rejection capability when array steering vector is precisely known. Adaptive beamforming is used for enhancing a desired signal while suppressing noise and interference at the output of an array of sensors. However the performance degradation of adaptive beamforming may become more pronounced than in an ideal case because some of underlying assumptions on environment, sources or sensor array can be violated and this may cause mismatch. There are several efficient approaches that provide an improved robustness against mismatch as like LSMI algorithm.

Neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. Neural network methods possess such advantages as general purpose nature, nonlinear property, passive parallelism, adaptive learning capability, generalization capability and fast convergence rates. Motivated by these inherent advantages of the neural network, in this thesis work, a robust adaptive beamforming algorithm using neural network is investigated which is effective in case of signal steering vector mismatch. This technique employs a three-layer radial basis function neural network (RBFNN), which treats the problem of computing the weights of an adaptive array antenna as a mapping problem. The robust adaptive beamforming algorithm using RBFNN, provides excellent robustness to signal steering vector mismatches, enhances the array system performance under non ideal conditions and makes the mean output array SINR (Signal-to-Interference-plus- Noise Ratio) consistently close to the optimal one.

List of Figures

CHAPTER 1

INTRODUCTION

Chapter 1 INTRODUCTION

1.1 Introduction

In recent years a substantial increase in development of broadband wireless access technologies for evolving wireless internet services and improved cellular system has been observed because of them there is traffic that demands on both the manufacturer and operators to provide sufficient capacity in the networks. This becomes major challenging problems for service provider to solve since there exists certain negative factors in the radiation environment contributing to limit the capacity. As the growing demand for mobile communications is constantly increasing, the need for better coverage, improved capacity, and higher transmission quality rises. Thus, a more efficient use of the radio spectrum is required. Smart antenna systems [1] are capable of efficiently utilizing the radio spectrum and are a promise for an effective solution to the present wireless systems problems while achieving reliable and robust high-speed, high-data-rate transmission. In fact, smart antenna systems comprise several critical areas such as individual antenna array design, signal processing algorithms, space-time processing, wireless channel modeling and coding, and network performance.

In order to manipulate the radiation pattern of an antenna structure with software, multiple antennas are required instead of a single antenna. Unlike a single antenna, which has a fixed radiation pattern, the radiation pattern of an antenna array can be quite flexible. The flexibility varies according to the algorithm being implemented in the system. The most straight forward approach to generate a flexible radiation pattern is the switched lobe (SL) or the switched beam technique where the antenna array contains a number of highly directional antennas. Each of the antenna points are in a slightly different direction. The system then analyzes the received signal from each of the antennas and selects the one that has the best signal. A more intelligent approach would be, instead of switching antennas, determine the direction of arrival (DoA) of the signal. Once the DoA is obtained, the system uses the antenna array to form a highly directional beam pointing toward the user. Both methods should provide

some advantages over the conventional system; however the benefit would be minimal if the signal suffers a lot of angular spread where the signal arrives at many different directions in a multipath environment. The situation would be even worse when no line-of-sight (LOS) is present between the user and the base station.

To overcome the above shortcoming, a more advanced method was developed. This method, usually called the optimum beam forming technique, fully utilizes the spatial diversity present in the multipath channel so that a stronger received signal can be generated. With optimum beam forming, signals received from multiple antennas are adjusted separately in both amplitude and phase before being combined. By doing so, the system behaves as if it has multiple adjustable radiation patterns. Each of the patterns is tuned to receive signals from a single user. An adaptive algorithm is used at the base station so that the system has the ability to determine the optimal radiation pattern for each user. As part of the training procedure, each of the users transmits a short training sequence to the base station. The algorithm then makes use of this information from a user by comparing each received signal to the original sequence to find out the correct radiation pattern for that user. With this method, all received signals from each antenna element are used and are optimally combined to enhance the desired signal and to cancel unwanted interference. During the training process, a lot of number crunching is needed at the base station. So it was not popular in the past due to the expensive cost of computation power. However, intensive signal processing is no longer an issue with the availability of low cost, extremely fast processors. Keep in mind that what actually happens in optimal beam forming is more complicated than what is shown in the diagram. It is more complicated when interference from other mobile occurs.

Though smart antenna techniques are new in the area of mobile communications, the technology itself was introduced in 1960's. Early smart antenna technology was deployed in military communication systems, where narrow beams are used in order to avoid interference arising from noise and other jamming signals. Extending the smart antenna concept further researchers worked on the technology to apply it to the personal communication industry to accommodate more users in the wireless network by suppressing interference. It increases

network capacity [2, 3] by precise control of signal nulls quality and mitigation of interference combine to frequency reuse reduce distance (or cluster size), improving capacity.

Switched beamforming is a smart antenna approach in its simplest form, where multiple fixed beams in predetermined directions are used to serve the users. In this approach the base station switches between several beams that give the best performance as the mobile user moves through the cell. Most advance approach based on smart antenna techniques, known as adaptive beamforming 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 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. The complex weight computation based on different criteria is incorporated in the signal processor in the form of software algorithms.

Adaptive Beamforming [1] is a technique in which an array of antennas 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 (antennas) used in the array. Adaptive beamforming is used for enhancing desired signal while suppressing noise and interference at output of array of sensor. It basically uses the idea that, though 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 signal from the interfering signals. In adaptive beamforming the optimum weights are iteratively computed using complex algorithms based upon different criteria. There are various methods of adaptive beamforming to optimize the array weights as Least Mean Square, Sample Matrix Inversion, Recursive Least Square, Constant Modulus algorithms.

Adaptive beamforming has wide applications in fields such as radar, sonar, seismology, radio astronomy, and wireless communications [1, 4, 5]. When adaptive arrays are applied to

practical problems, the performance of adaptive beamforming methods may become worse than in the ideal case because of violation of underlying assumptions on the environment, sources, or sensor array and this may cause a mismatch between the assumed array response and true array response. During the past two decades, many approaches have been developed to improve the robustness against even slight mismatches. The most common is linearly constrained minimum variance (LCMV) beamformer [6], which provides robustness against uncertainty in the signal look direction. But, the beamformer loses degrees of freedom for interference suppression. Diagonal loading [7] has been a popular and widely used approach to improve the robustness of the adaptive beamforming algorithms. However, a serious drawback of the approach is that it is not clear how to choose the diagonal loading level based on information about the uncertainty of the array steering vector. From the above brief review, it is clear that these approaches cannot be expected to provide sufficient robustness improvements.

Neural networks have found numerous applications in the field of signal processing [8, 9], mainly because of their general purpose nature, fast convergence rates, and new VLSI implementations. Neural network, using simple addition, multiplication, division, and threshold operations in the basic processing element, can be readily implemented in analog VLSI. Neural network methods possess such advantages as general purpose nature, nonlinear property, passive parallelism, adaptive learning capability, generalization capability and fast convergence rates. Neural network method is typically used in two steps: training phase and performance phase. Neural network is first trained with known input/output pattern pairs. It can be implemented off-line, although a large training pattern set is required for network training. After the training phase, it can be used directly to replace the complex system dynamics.

1.2 Motivation of Thesis

Smart antenna is recognized as promising technologies for higher user capacity in wireless communication system. The core of smart antenna is the adaptive beam- forming algorithms in antenna array. Adaptive Beamforming technique 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. There are several Adaptive

beamforming algorithms as SMI, RLS, CMA varying in complexity based on different criteria for updating and computing the optimum weights.

Adaptive beamforming is known to have resolution and interference rejection capability when the array steering vector is precisely known, however the performance of adaptive beamforming techniques may degrade severely in the presence of mismatches between assumed array response and true array response.

This problem can be overcome by neural network approach. In this thesis the development of a neural network- based robust adaptive beamforming algorithm, which treats the problem of computing the weights of an adaptive array antenna as a mapping problem. Using MATLAB in this thesis work, we investigated a novel approach to robust adaptive beamforming and show clearly how efficiently we compute the weight vector by using the neural network method. This algorithm provides excellent robustness to signal steering vector mismatches, enhances the array system performance under non ideal conditions and makes the mean output array SINR consistently close to the optimal one.

1.3 Literature Survey

Carl B. Dietrich has reported that Smart antennas can improve system performance, and fond increasing use of it. He experimentally reported that smart handled terminals demonstrated over 20 dB of interference rejection with single- and multi-polarized arrays and shows that Adaptive beamforming improved reliability, range, talk time, and capacity in both peer-to-peer and cellular systems [2].

Michael Chryssomallis has given the overview of smart antenna and provided a basic model for determining the angle of arrival for incoming signals, the appropriate antenna beamforming and the adaptive algorithms that are used for array processing. Moreover he shows how smart antennas, with spatial processing, can provide substantial additional improvement when used with TDMA and CDMA digital-communication systems [3].

Brennan L. E reported the ability of an AMTI (airborn moving target indication) radar to reject clutter is often seriously degraded by the motion of the radar. An adaptive receiving array can compensate for platform motion and provide excellent AMTI performance. Scattering from aircraft structure can also distort antenna patterns and reduce AMTI capability. He produced a technique that can adapt the element weights to compensate for near-field scatterers and element excitation errors [4].

Syed Shah Irfan Hussain developed a mobile tracking algorithm that has been devised for adapting the weights of the transmit antenna to attain optimal weights for a particular wireless static channel configuration. This algorithm was based on the sign gradient feedback algorithm (SGF), which was a coarse form of least mean square algorithm (LMS). This algorithm does not require knowledge of the transmit antenna configuration. It has been shown that this algorithm converges to optimum weights of the transmit beamformer as well as reduces their un-necessary perturbations around the point of convergence [15].

Mohammad Tariqul Islam developed a Matrix Inversion Normalized Least Mean Square (MI-NLMS) adaptive beam forming algorithm for smart antenna application which combined the individual good aspects of Sample Matrix Inversion (SMI) and the Normalized Least Mean Square (NLMS) algorithms and he is describe to improve the convergence speed with small BER . MI-NLMS computes the optimal weight vector based on the SMI algorithm and updates the weight vector by NLMS algorithm [16].

Ahmed H. El Zooghby used RBFNN for the direction of Arrival (DOA). He was found that networks implementing these functions were indeed successful in performing the required task and yielded good performance in the sense that the network produced actual output very close to the desired DOA. Also it was demonstrated that these networks are able to generalize, by training and testing using data sets derived from different signal conditions mainly with the effect of noise added to the data used for testing. The main advantage of the RBFNN is the substantial reduction in the CPU time needed to estimate the DOA [8]

Xin Song proposed the robust Capon beamformer (RCB) based on some types of mismatches and shows that the proposed robust Capon beamformer is much less sensitive to some types of mismatches and the small training sample size than the standard Capon beamformer (CB). Moreover, the mean output SINR of RCB is better than that of CB in a wide range of SNR and N [17].

1.4 Outline of Thesis

This thesis is organized into six chapters. Following this introduction, Chapter 2 provides Antennas and antenna system. In chapter 3, the brief overview of Smart antenna system discusses. Chapter 4 contains several Beamforming Algorithms. Chapter 5 contains neural network based robust adaptive beamforming algorithm with all the simulation and results. Chapter 6 provides conclusion remarks and scope of future work.

CHAPTER 2

ANTENNAS AND ANTENNA SYSTEMS

Chapter 2 ANTENNAS AND ANTENNA SYSTEMS

2.1 A Useful Analogy for Adaptive Smart Antenna

For an intuitive grasp of how an adaptive antenna system works, close your eyes and converse with someone as they move about the room. You will notice that you can determine their location without seeing them because of the following:

• You hear the speaker's signals through your two ears, your acoustic sensors.

• The voice arrives at each ear at a different time.

• Your brain, a specialized signal processor, does a large number of calculations to correlate information and compute the location of the speaker.

Your brain also adds the strength of the signals from each ear together, so you perceive sound in one chosen direction as being twice as loud as everything else.

Adaptive antenna systems [10] do the same thing, using antennas instead of ears. As a result, 8, 10, or 12 ears can be employed to help fine-tune and turn up signal information. Also, because antennas both listen and talk, an adaptive antenna system can send signals back in the same direction from which they came. This means that the antenna system cannot only hear 8 or 10 or 12 times louder but talk back more loudly and directly as well.

Going a step further, if additional speakers joined in, your internal signal processor could also tune out unwanted noise (interference) and alternately focus on one conversation at a time. Thus, advanced adaptive array systems have a similar ability to differentiate between desired and undesired signals.

2.2 Antennas

A device able to receive or transmit electromagnetic energy is called an “antenna”. Antennas have become ubiquitous devices and occupy a salient position in wireless system experienced the largest growth among industry systems. Antennas couple electromagnetic

energy from one medium (space) to another medium as wire, coaxial cable, or waveguide. Physical designs can vary greatly. Antenna produces complex electromagnetic fields both near to and far from antennas. Not all of the electromagnetic fields generated actually radiated into space. Some of the fields remain in the vicinity of antenna and are viewed as reactive near fields; much the same way as inductor or capacitor is a reactive storage element in lumped element circuits.

2.2.1 Omni Directional Antennas

Since the early days of wireless communications, there has been the simple dipole antenna, which radiates and receives equally well in all directions. To find its users, this single-element design broadcasts Omni directionally in a pattern resembling ripples radiating outward in a pool of water. While adequate for simple RF environments where no specific knowledge of the users where about is available, this unfocused approach scatters signals, reaching desired users with only a small percentage of the overall energy sent out into the environment.

Given this limitation, Omni directional strategies attempt to overcome environmental challenges by simply boosting the power level of the signals broadcast. In a setting of numerous users and interferers, this makes a bad situation worse in that the signals that miss the intended user become interference for those in the same or adjoining cells.

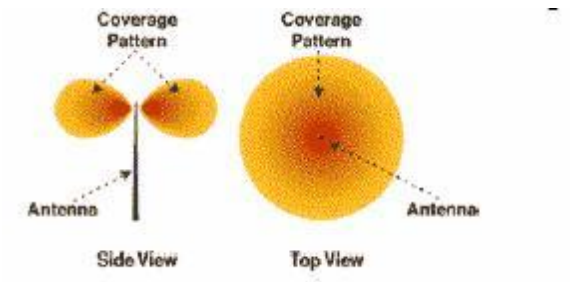

Fig.2.1. Omni directional Antenna and Coverage Patterns

In uplink applications (user to base station), Omni directional antennas offer no preferential gain for the signals of served users. In other words, users have to shout over competing signal energy. Also, this single-element approach cannot selectively reject signals interfering with those of served users and has no spatial multi-path mitigation or equalization capabilities. Omni directional strategies directly and adversely impact spectral efficiency, limiting frequency reuse. These limitations force system designers and network planners to

devise increasingly sophisticated and costly remedies. In recent years, the limitations of broadcast antenna technology on the quality, capacity, and coverage of wireless systems have prompted an evolution in the fundamental design and role of the antenna in a wireless system.

2.2.2 Directional Antennas

A single antenna can also be constructed to have certain fixed preferential transmission and reception directions. As an alternative to the brute force method of adding new transmitter sites, many conventional antenna towers today split, or sectaries cells. A 360° area is often split into three 120° subdivisions, each of which is covered by a slightly less broadcast method of transmission.

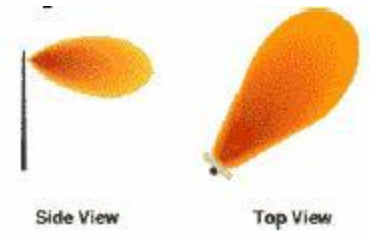

Fig.2.2. Directional Antenna and Coverage Pattern

All else being equal, sector antennas provide increased gain over a restricted range of azimuths as compared to an Omni directional antenna. This is commonly referred to as antenna element gain and should not be confused with the processing gains associated with smart antenna systems. While sectaries antennas multiply the use of channels, they do not overcome the major disadvantages of standard Omni directional antenna broadcast such as co channel Interference.

2.3 Antenna Systems

An antenna be made more intelligent by first, its physical design can be modified by adding more elements. Second, the antenna can become an antenna system that can be designed to shift signals before transmission at each of the successive elements so that the antenna has a composite effect. This basic hardware and software concept is known as the phased array antenna. The following summarizes antenna developments in order of increasing benefits and intelligence.

2.3.1 Sectorized Systems

Sectorized antenna systems take a traditional cellular area and subdivide it into sectors that are covered using directional antennas looking out from the same base station location. Operationally, each sector is treated as a different cell, the range of which is greater than in the omni directional case. Sector antennas increase the possible reuse of a frequency channel in such cellular systems by reducing potential interference across the original cell, and they are widely used for this purpose. As many as six sectors per cell have been used in practical service. When combining more than one of these directional antennas, the base station can cover all directions.

2.3.2 Diversity System

The diversity system incorporates two antenna elements at the base station, the slight physical separation (space diversity) of which has been used historically to improve reception by counteracting the negative effects of multipath. Diversity offers an improvement in the effective strength of the received signal by using one of the following two methods:

Switched diversity: Assuming that at least one antenna will be in a favorable location at a given moment, this system continually switches between antennas (connects each of the receiving channels to the best serving antenna) so as always to use the element with the largest output. While reducing the negative effects of signal fading, they do not increase gain since only one antenna is used at a time.

Diversity combining: This approach corrects the phase error in two multipath signals and effectively combines the power of both signals to produce gain. Other diversity systems, such as maximal ratio combining systems, combine the outputs of all the antennas to maximize the ratio of combined received signal energy to noise.

Because macro cell-type base stations historically put out far more power on the downlink (base station to user) than mobile terminals can generate on the reverse path, most diversity antenna systems have evolved only to perform in uplink (user to base station). Diversity antennas merely switch operation from one working element to another. Although this approach mitigates severe multipath fading, its use of one element at a time offers no uplink gain improvement over any other single element approach. In high-interference environments, the simple strategy of locking onto the strongest signal or extracting maximum signal power from the antennas is clearly inappropriate and can result in crystal-clear reception of an interferer rather than the

desired signal.

The need to transmit to numerous users more efficiently without compounding the interference problem led to the next step of the evolution antenna systems that intelligently integrate the simultaneous operation of diversity antenna elements.

2.4 Smart antenna

The concept of using multiple antennas and innovative signal processing to serve cells more intelligently has existed for many years. In fact, varying degrees of relatively costly smart antenna [10, 11] systems have already been applied in defense systems. Until recent years, cost barriers have prevented their use in commercial systems. The advent of powerful, low-cost digital signal processors (DSPs), general-purpose processors (and ASICs), as well as innovative software-based signal-processing techniques (algorithms) have made intelligent antennas practical for cellular communications systems. Smart antenna systems are the technology of uniting not only antenna technology but also two or more of other technology as digital signal processors and high function of antennas.

Today, when spectrally efficient solutions are increasingly a business imperative, these systems are providing greater coverage area for each cell site, higher rejection of interference, and substantial capacity improvements. That can overcome the problem in high speed mobile communication such as limited channel bandwidth while satisfying the demand for many mobiles in a limited channel.

CHAPTER 3

SMART ANTENNA SYSTEM

Chapter 3 SMART ANTENNA SYSTEM

In truth, antennas are not smart—antenna systems are smart. Generally collocated with a base station, a smart antenna system combines an antenna array with a digital signal-processing capability to transmit and receive in an adaptive, spatially sensitive manner. In other words, such a system can automatically change the directionality of its radiation patterns in response to its signal environment. Smart antennas also known as adaptive array antennas, multiple antennas and recently MIMO that are antenna arrays with smart signal processing algorithms used to identify spatial signal signature such as the direction of arrival (DOA) of the signal, and use it to calculate beamforming vectors, to track and locate the antenna beam on the mobile/target. The antenna could optionally be any sensor. This can dramatically increase the performance characteristics (such as capacity) of a wireless system.

3.1 Types of Smart Antenna Systems

Terms commonly heard today that embrace various aspects of a smart antenna system technology include intelligent antennas, phased array, SDMA, spatial processing, digital beam forming, adaptive antenna systems, and others. Smart antenna systems are customarily categorized, however, as either switched beam or adaptive array systems. The following are distinctions between the two major categories of smart antennas regarding the choices in transmit strategy:

• **Switched beam**. A finite number of fixed, predefined patterns or combining strategies (sectors)

• **Adaptive array**. An infinite number of patterns (scenario-based) that are adjusted in real time.

3.1.1 Switched Beam Antennas

Switched beam antenna systems form multiple fixed beams with heightened sensitivity in particular directions. These antenna systems detect signal strength, choose from one of several

predetermined, fixed beams, and switch from one beam to another as the mobile moves throughout the sector. Instead of shaping the directional antenna pattern with the metallic properties and physical design of a single element (like a sectorized antenna), switched beam systems combine the outputs of multiple antennas in such a way as to form finely sectorized (directional) beams with more spatial selectivity than can be achieved with conventional, single-element approaches.

Fig.3.1. Switched Beam System Coverage Patterns

3.1.2 Adaptive Array Antennas

Adaptive antenna technology represents the most advanced smart antenna approach to date. Using a variety of new signal-processing algorithms, the adaptive system takes advantage of its ability to effectively locate and track various types of signals to dynamically minimize interference and maximize intended signal reception.

Both systems attempt to increase gain according to the location of the user; however, only the adaptive system provides optimal gain while simultaneously identifying, tracking, and minimizing interfering signals.

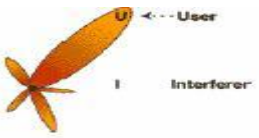

Fig3.2. Adaptive Array Coverage

Omni directional antennas are obviously distinguished from their intelligent counterparts by the number of antennas (or antenna elements) employed. Switched beam and adaptive array systems, however, share many hardware characteristics and are distinguished primarily by their

adaptive intelligence.

To process information that is directionally sensitive requires an array of antenna elements (typically 4 to 12), the inputs from which are combined to control signal transmission adaptively. Antenna elements can be arranged in linear, circular, or planar configurations and are most often installed at the base station, although they may also be used in mobile phones or laptops.

3.2 Architecture of Smart Antenna System

Traditional switched beam and adaptive array systems enable a base station to customize the beams they generate for each remote user effectively by means of internal feedback control. Generally speaking, each approach forms a main lobe toward individual users and attempts to reject interference or noise from outside of the main lobe.

3.2.1 Listening to the Cell (Uplink Processing)

It is assumed here that a smart antenna is only employed at the base station and not at the handset or subscriber unit. Such remote radio terminals transmit using omni directional antennas, leaving it to the base station to separate the desired signals from interference selectively.

Typically, the received signal from the spatially distributed antenna elements is multiplied by a weight, a complex adjustment of amplitude and a phase. These signals are combined to yield the array output. An adaptive algorithm controls the weights according to predefined objectives. For a switched beam system, this may be primarily maximum gain; for an adaptive array system, other factors may receive equal consideration. These dynamic calculations enable the system to change its radiation pattern for optimized signal reception.

3.2.2 Speaking to the Users (Downlink Processing)

The task of transmitting in a spatially selective manner is the major basis for differentiating between switched beam and adaptive array systems. As described below, switched beam systems communicate with users by changing between preset directional patterns, largely on the basis of signal strength. In comparison, adaptive arrays attempt to understand the RF environment more comprehensively and transmit more selectively.

The type of downlink processing used depends on whether the communication system uses time division duplex (TDD), which transmits and receives on the same frequency or frequency division duplex (FDD), which uses separate frequencies for transmit and receiving (e.g., GSM). In most FDD systems, the uplink and downlink fading and other propagation characteristics may be considered independent, whereas in TDD systems the uplink and downlink channels can be considered reciprocal. Hence, in TDD systems uplink channel information may be used to achieve spatially selective transmission. In FDD systems, the uplink channel information cannot be used directly and other types of downlink processing must be considered.

3.3 Switched Beam Systems

In terms of radiation patterns, switched beam is an extension of the current microcellular or cellular sectorization method of splitting a typical cell. The switched beam approach further subdivides macro sectors into several micro sectors as a means of improving range and capacity. Each micro sector contains a predetermined fixed beam pattern with the greatest sensitivity located in the center of the beam and less sensitivity elsewhere. The design of such systems involves high-gain, narrow azimuthally beam width antenna elements.

The switched beam system selects one of several predetermined fixed-beam patterns (based on weighted combinations of antenna outputs) with the greatest output power in the remote user's channel. These choices are driven by RF or base band DSP hardware and software. The system switches its beam in different directions throughout space by changing the phase differences of the signals used to feed the antenna elements or received from them. When the mobile user enters a particular macro sector, the switched beam system selects the micro sector containing the strongest signal. Throughout the call, the system monitors signal strength and switches to other fixed micro sectors as required.

Smart antenna systems communicate directionally by forming specific antenna beam patterns. When a smart antenna directs its main lobe with enhanced gain in the direction of the user, it naturally forms side lobes and nulls or areas of medium and minimal gain respectively in directions away from the main lobe. Different switched beam and adaptive smart antenna systems control the lobes and the nulls with varying degrees of accuracy and flexibility.

3.4 Adaptive Antenna System

The adaptive antenna systems approach communication between a user and base station in a different way, in effect adding a dimension of space. By adjusting to an RF environment as it changes (or the spatial origin of signals), adaptive antenna technology can dynamically alter the signal patterns to near infinity to optimize the performance of the wireless system.

Adaptive arrays utilize sophisticated signal-processing algorithms to continuously distinguish between desired signals, multipath, and interfering signals as well as calculate their directions of arrival. This approach continuously updates it's transmit strategy based on changes in both the desired and interfering signal locations. The ability to track users smoothly with main lobes and interferers with nulls ensures that the link budget is constantly maximized because there are neither micro sectors nor predefined patterns.

Both types of smart antenna systems provide significant gains over conventional sectored systems. The low level of interference on the left represents a new wireless system with lower penetration levels. The significant level of interference on the right represents either a wireless system with more users or one using more aggressive frequency reuse patterns. In this scenario, the interference rejection capability of the adaptive system provides significantly more coverage than either the conventional or switched beam system.

3.5 Relative Benefits/Tradeoffs of Switched Beam and Adaptive Array Systems

- **Integration**: ─ Switched beam systems are traditionally designed to retrofit widely deployed cellular systems. It has been commonly implemented as an add-on or appliqué technology that intelligently addresses the needs of mature networks. In comparison, adaptive array systems have been deployed with a more fully integrated approach that offers less hardware redundancy than switched beam systems but requires new build-out.

- **Range/coverage─** Switched beam systems can increase base station range from 20 to 200 percent over conventional sectored cells, depending on environmental circumstances and the hardware/software used. The added coverage can save an operator substantial infrastructure costs and means lower prices for consumers. Also, the dynamic switching from beam to beam conserves capacity because the system does not send all signals in all directions. In comparison,

adaptive array systems can cover a broader, more uniform area with the same power levels as a switched beam system.

- **Interference suppression─** Switched beam antennas suppress interference arriving from directions away from the active beam's center. Because beam patterns are fixed, however, actual interference rejection is often the gain of the selected communication beam pattern in the interferer's direction. Also, they are normally used only for reception because of the system's ambiguous perception of the location of the received signal (the consequences of transmitting in the wrong beam being obvious). Also, because their beams are predetermined, sensitivity can occasionally vary as the user moves through the sector.

Switched beam solutions work best in minimal to moderate co channel interference and have difficulty in distinguishing between a desired signal and an interferer. If the interfering signal is at approximately the center of the selected beam, and the user is away from the center of the selected beam, the interfering signal can be enhanced far more than the desired signal. In these cases, the quality is degraded for the user. Adaptive array technology currently offers more comprehensive interference rejection. Also, because it transmits an infinite, rather than finite, number of combinations, its narrower focus creates less interference to neighboring users than a switched-beam approach.

- **Spatial division multiple access (SDMA)—**Among the most sophisticated utilizations of smart antenna technology is SDMA, which employs advanced processing techniques to, in effect, locate and track fixed or mobile terminals, adaptively steering transmission signals toward users and away from interferers. This adaptive array technology achieves superior levels of interference suppression, making possible more efficient reuse of frequencies than the standard fixed hexagonal reuse patterns. In essence, the scheme can adapt the frequency allocations to where the most users are located.

Utilizing highly sophisticated algorithms and rapid processing hardware, spatial processing takes the reuse advantages that result from interference suppression to a new level. In essence, spatial processing dynamically creates a different sector for each user and conducts a frequency/channel allocation in an ongoing manner in real time.

Adaptive spatial processing integrates a higher level of measurement and analysis of the scattering aspects of the RF environment. Whereas traditional beam forming and beam-steering techniques assume one correct direction of transmission toward a user, spatial processing

maximizes the use of multiple antennas to combine signals in space in a method that transcends a one user-one beam methodology.

3.6 The Goals of the Smart Antenna System

The dual purpose of a smart antenna system is to augment the signal quality of the radio-based system through more focused transmission of radio signals while enhancing capacity through increased frequency reuse. More specifically, the features of and benefits derived from a smart antenna system include these –

3.6.1 Features:

- **Signal gain**-Inputs from multiple antennas are combined to optimize available power required to establish given level of coverage.
- **Interference rejection-** Antenna pattern can be generated toward interference sources, improving the signal- to interference ratio of the received signals. On the reverse link or uplink this reduces the interference seen by base station. It also reduces the amount of interference spread in the system forward link or downlink. Such improvements in the carrier to interference ratio to increased capacity.
- **Spatial diversity-**Composite information from the array is used to minimize fading and other undesirable effects of multipath propagation.
- **Power efficiency** -Combines the inputs to multiple elements to optimize available processing gain in the downlink (toward users).

3.6.2 Benefits:

- **Increased antenna gain-** It helps increase the base station range and coverage, extends battery life, and allows for smaller and lighter handset design.
- **Better range/coverage**-Focusing the energy sent out into the cell increases base station range and coverage. Lower power requirements also enable a greater battery life and smaller/lighter handset size.
- **Increased capacity**- Precise control of signal nulls quality and mitigation of interference combine to frequency reuse reduce distance (or cluster size), improving capacity. Certain adaptive technologies (such as space division multiple access) support the reuse of frequencies within the same cell.

- **Multipath rejection**-It can reduce the effective delay spread of the channel, allowing higher bit rates to be supported without the use of an equalizer.
- **Reduced expense**-Lower amplifier costs, power consumption, and higher reliability will result.

3.7 Drawbacks of Smart Antenna

Smart-antenna transceivers are much more complex than traditional base-station transceivers. The antenna array needs separate transceiver chains for each antenna element in the array, and accurate real-time calibration for each of them. Moreover, the antenna beam forming is computationally intensive, which means that smart-antenna base stations must be equipped with very powerful digital signal processors. This tends to increase the system costs in the short term; however, since the benefits outweigh the costs, it will be cheaper in the long run.

For a smart antenna to have a reasonable gain, an array of antenna elements is necessary. Consequently, this means that a linear array consisting of 10 elements with an inter-element spacing of $\lambda/2$, operating at 2 GHz, would be approximately 70 cm wide. This might pose problems, due to the growing public demand for less-visible base stations.

CHAPTER 4

BEAMFORMING ALGORITHM

Chapter 4 BEAMFORMING ALGORITHM

Beamforming

Beamforming is a general signal processing technique used to control the directionality of the reception or transmission of a signal on a transducer array. Beam forming creates the radiation pattern of the antenna array by adding the phases of the signals in the desired direction and by nulling the pattern in the unwanted direction. The phases and amplitudes are adjusted to optimize the received signal. A standard tool for analyzing the performance of a beam-former is the response for a given N-by-1 weight vector *W (k)* as function of θ, known as the beam response. This angular response is computed for all possible angles.

4.1 Fixed Weight Beamforming

A Fixed weight beam-former [1] as shown in fig4.1 is a smart antenna in which fixed weight is used to study the signal arriving from a specific direction. Since it optimize the signal arriving from specific direction while attenuating signals from other directions, thus it is called the spatial matched filter. In the fixed weight beamforming approach the arrival angles does not change with time, so the optimum weight would not need to be adjusted.

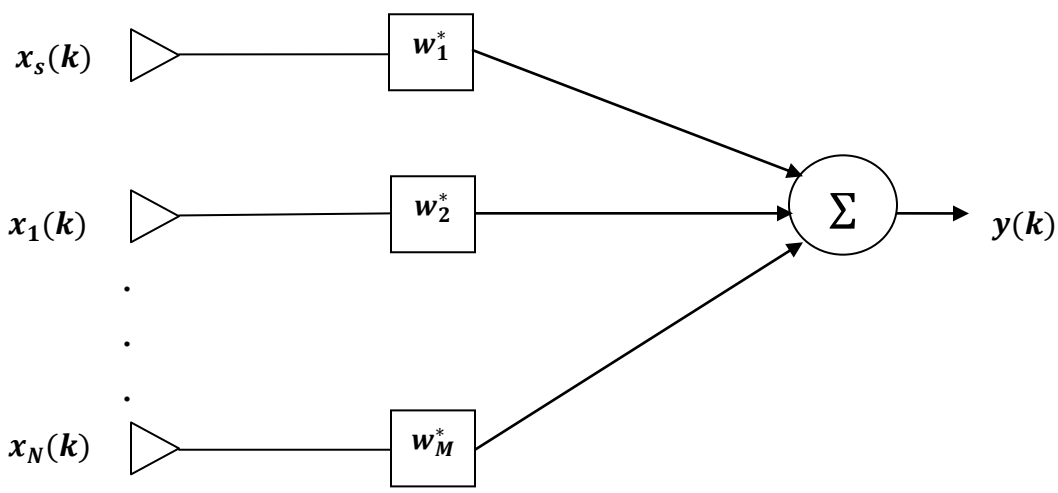

Fig. 4.1 Block diagram of Fixed weight Beamformer

4.1.1 Maximum Signal-to-Interference Ratio:

One criterion which can be applied to enhancing the received signal and minimizing interfering signals is based upon maximizing SIR. The SIR is defined as the ratio of the desired signal power and undesired signal power.

Let one desired signal arriving from angle θ_0 and N interferers arriving from angles θ_1,..., θ_N. The signal and interferers are received by an array of M elements with M potential weights. Each received signal at element m also includes additive Gaussian noise. Time is represented by the kth time smples. Thus the weighted array output can be given in the following form:

$$y(k) = \bar{w}^H . \bar{x}(k) \qquad \text{..... (4.1)}$$

Where

$$\bar{x}(k) = \bar{a}_0 s(k) + [\bar{a}_1 \ \bar{a}_2 \ldots\ldots \bar{a}_N \ ] . \begin{bmatrix} i_1(k) \\ i_2(k) \\ . \\ . \\ i_N(k) \end{bmatrix} + \bar{n}(k)$$

$$= \bar{x}_s(k) + \bar{x}_i(k) + \bar{n}(k) \qquad \text{..... (4.2)}$$

With

$\bar{w} = [w_1 \ w_2 \ \ldots . w_M \ ]^T$ = Array weights

$\bar{x}_s(k)$ = desired signal vector

$\bar{x}_i(k)$ = interfering signals vector

$\bar{n}(k)$ = zero mean Gaussian noise for each channel

$\bar{a}_i$ = M-element array steering vector for θ_i direction of arrival

The weighted array output of desired signal is

$$\sigma_s^2 = E[|\bar{w}^H . \bar{x}_s|^2] = \bar{w}^H . \bar{R}_{ss} . \bar{w} \qquad \text{..... (4.3)}$$

Where

$$\bar{R}_{ss} = E\left[\bar{x}_s \ \bar{x}_s{}^H\right] = \text{signal correlation matrix} \qquad \text{..... (4.4)}$$

The weighted array output power for undesired signals is

$$\sigma_u^2 = E[|\bar{w}^H . \ \bar{u}|^2] = \bar{w}^H . \ \bar{R}_{uu} . \ \bar{w} \qquad \text{..... (4.5)}$$

Where

$$\bar{R}_{uu} = \bar{R}_{ii} + \bar{R}_{nn} \qquad \text{..... (4.6)}$$

With

$\bar{R}_{ii}$ = correlation matrix for interferers

$\bar{R}_{nn}$ = correlation matrix for noise.

Then SIR is defined as

$$SIR = \frac{\sigma_s^2}{\sigma_u^2} = \frac{\bar{w}^H . \bar{R}_{ss} . \bar{w}}{\bar{w}^H . \bar{R}_{uu} . \bar{w}} \qquad \text{..... (4.7)}$$

The SIR can be maximized by optimizing weight, the weight vector in terms of optimum Weiner solution

$$\bar{w}_{SIR} = \beta . \bar{R}_{uu}^{-1} . \bar{a}_0 \qquad \text{..... (4.8)}$$

Where

$$\beta = \frac{E[|s|^2]}{SIR_{max}} \bar{a}_0^H . \bar{w}_{SIR} \qquad \text{..... (4.9)}$$

4.1.2. Minimum Mean-Square Error Method:

In this method array weights is found by minimizing the MSE. So the MSE adaptive system can be drawn as

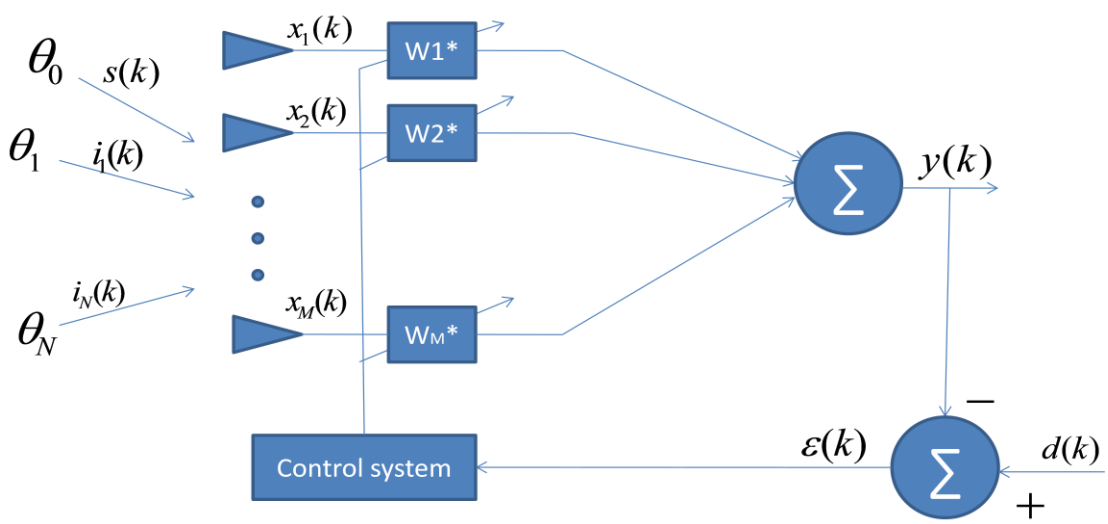

Fig. 4.2 Block diagram of MSE adaptive system

Error signal is defined as the difference of desired signal *d(k)* and output signal *y(k).*

$$\varepsilon(k) = d(k) - \bar{w}^H \bar{x}(k) \qquad \text{..... (4.10)}$$

Thus by the simple algebra MSE is

$$|\varepsilon(k)|^2 = |d(k)|^2 - 2\, d(k)\, \bar{w}^H \bar{x}(k) + \bar{w}^H \bar{x}(k)\, \bar{x}^H(k)\, \bar{w} \qquad \text{..... (4.11)}$$

Taking expected value of both sides and simplifying expression we get

$$E[|\varepsilon|^2] = E[\,|d|^2] - 2\, \bar{w}^H \bar{r} + \bar{w}^H \bar{R}_{xx}\, \bar{w} \qquad \text{..... (4.12)}$$

Where correlations are defined as

$$\bar{r} = E[d^* .\ \bar{x}] = E[d^* .\ (\bar{x}_s + \bar{x}_i + \bar{n}] \qquad \text{..... (4.13)}$$

$$\bar{R}_{xx} = E[\bar{x}\, \bar{x}^H] = \bar{R}_{ss} + \bar{R}_{uu} \qquad \text{..... (4.14)}$$

By the Weiner-Hopf solution the optimum weights provide minimum MSE. So the optimum weight is

$$\bar{w}_{MSE} = \bar{R}_{xx}^{-1}\, \bar{r} \qquad \text{..... (4.15)}$$

4.1.3. Maximum Likelihood Method:

The maximum likelihood method is predicated on the assumption that we have an unknown desired signal $\bar{x}_s$ and that unwanted signal $\bar{n}$ has a zero mean Guassian distribution. The goal of this method is to define a likelihood function which can give an estimate on desired signal. The input signal vector is given by

$$\bar{x} = \bar{a}_0\, s + \bar{n} = \bar{x}_s + \bar{n} \qquad \text{..... (4.16)}$$

The probability function can be defined as

$$p(\bar{x}/\bar{x}_s) = \frac{1}{\sqrt{2\pi\sigma_n^2}}\, e^{-\{(\bar{x}-\bar{a}_0 s)^H \bar{R}_{nn}^{-1} (\bar{x}-\bar{a}_0 s)\}} \qquad \text{..... (4.17)}$$

Where

σ_n = noise standard deviation

$$\bar{R}_{nn} = \sigma_n{}^2\, \bar{I} \text{ = noise correlation matrix} \qquad \text{..... (4.19)}$$

We can define the log-likelihood function as

$$L[\bar{x}] = -ln[p(\bar{x}/\bar{x}_s)] = C\{(\bar{x} - \bar{a}_0 s)^H \bar{R}_{nn}^{-1} (\bar{x} - \bar{a}_0 s)\} \qquad \text{..... (4.20)}$$

Where *C* is constant.

Thus the Maximum Likelihood weight is

$$\bar{w}_{ML} = \frac{\bar{R}_{nn}^{-1}\ \bar{a}_0}{\bar{a}_0^H\ \bar{R}_{nn}^{-1}\ \bar{a}_0} \qquad \text{..... (4.21)}$$

4.1.4. Minimum Variance Method:

Minimum Variance solution is also called minimum variance distortionless response (MVDR) or minimum variance performance measure. The goal of MV method is to minimize the array output noise variance.

The weighted array output is given as

$$y = \bar{w}^H \bar{x} = \bar{w}^H \bar{a}_0 s + \bar{w}^H \bar{u} \qquad \text{..... (4.22)}$$

For distortionless response, we must add the constraint that

$$\bar{w}^H \bar{a}_0 = 1 \qquad \text{..... (4.23)}$$

Applying the constraint to above eq. the array output is given as

$$y = s + \bar{w}^H \bar{u} \qquad \text{..... (4.24)}$$

The variance of y calculated as

$$\sigma_{MV}^2 = E[|\bar{w}^H \bar{x}|^2] = E[|s + \bar{w}^H \bar{u}|^2]$$
$$= \bar{w}^H \bar{R}_{uu} \bar{w} \qquad \text{..... (4.25)}$$

We can minimize variance by using the method of Lagrange. The cost function defined as

$$J(\bar{w}) = \frac{\sigma_{MV}^2}{2} + \lambda (1 - \bar{w}^H \bar{a}_0) \qquad \text{..... (4.26)}$$

$$J(\bar{w}) = \frac{\bar{w}^H \bar{R}_{uu} \bar{w}}{2} + \lambda (1 - \bar{w}^H \bar{a}_0) \qquad \text{..... (4.27)}$$

The cost function is a quadratic function and can be minimized by setting gradient equal to zero then minimum variance weight becomes

$$\bar{w}_{MV} = \lambda \bar{R}_{uu}^{-1} \bar{a}_0 \qquad \text{..... (4.28)}$$

Where λ is Lagrange multiplier and defined as

$$\lambda = \frac{1}{\bar{a}_0 \bar{R}_{uu}^{-1} \bar{a}_0} \qquad \text{..... (4.29)}$$

So the minimum variance optimum weight is

$$\bar{w}_{MV} = \frac{\bar{R}_{uu}^{-1} \bar{a}_0}{\bar{a}_0 \bar{R}_{uu}^{-1} \bar{a}_0} \qquad \text{..... (4.30)}$$

4.2 Adaptive Beamforming:

The adaptive algorithm used in the signal processing has a profound effect on the performance of a Smart Antenna system. Although the smart antenna system is sometimes called the “Space Division Multiple Access”, it is not the antenna that is smart. The function of an antenna is to convert electrical signals into electromagnetic waves or vice versa but nothing else. The adaptive algorithm is the one that gives a smart antenna system its intelligence. Without an adaptive algorithm, the original signals can no longer be extracted.

In the fixed weight beamforming approach the arrival angles does not change with time, so the optimum weight would not need to be adjusted. However, if desired arrival angles change with time, it is necessary to devise an optimization scheme that operates on-the-fly so as to keep recalculating the optimum array weight that’s done by using adaptive beamforming algorithm . The task of the algorithm in a Smart antenna system is to adjust the received signals so that the desired signals are extracted once the signals are combined. Various methods can be used in the implementation of an adaptive algorithm.

In comparison, the hearing system of a human being is much like a smart antenna system. Like the antenna, our ears pick up all sound waves from the surrounding environment. From what has been received, the human brain picks out the important information. For example, people are able to listen to a conversation even though the conversation may take place in a very noisy environment. The desired signal can be mixed with other interference like traffic noise, background music, etc., but the human brain is able to suppress the unrelated sounds and concentrate on the conversation. Furthermore, a human can even listen to sound which is weaker than the interference. The adaptive algorithm in a smart antenna system serves a similar purpose as the brain in this analogy, however it is less sophisticated. Our brain can perform the above signal selection and suppression with only two ears, but multiple antennas are required for the adaptive algorithm so that enough information on the user signals can be acquired to perform the task. In human beings, some people are more intelligent than others. In order for them to be more intelligent, they have to have a more developed brain. Similarly, some algorithms are smarter than other algorithms. A smart algorithm usually requires more resources than algorithms that are less intelligent. Unlike our brain which is a free resource, more resources in the world of technology always mean more expensive components and more complicated system.

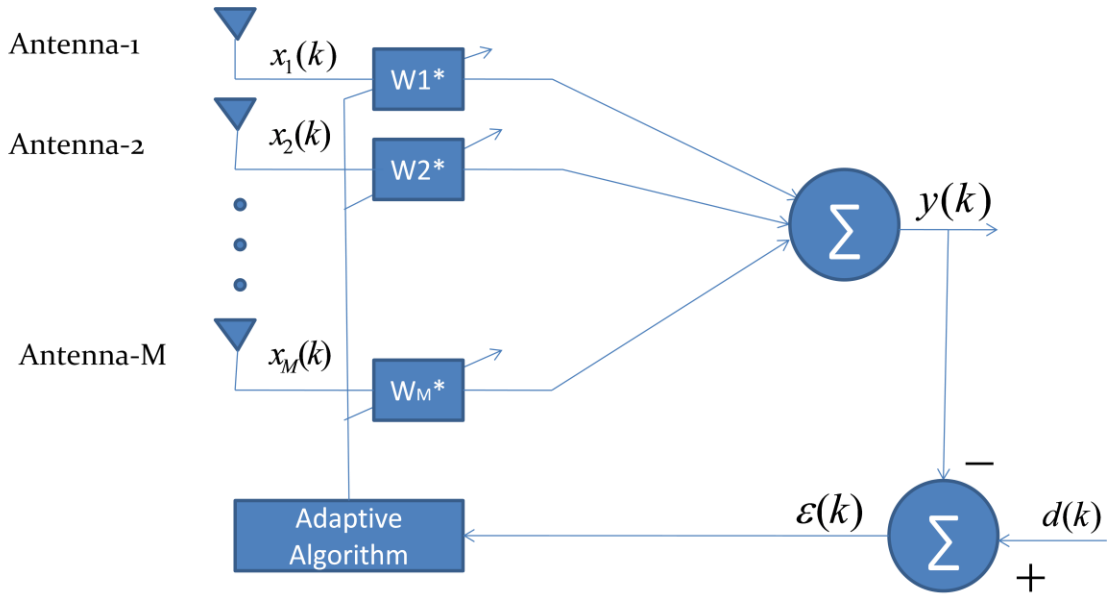

Fig. 4.3 Block diagram of Adaptive Beamforming Algorithm

4.2.1 Least Mean Square Algorithm:

This algorithm was first developed by Widrow and Hoff in 1960 [1, 12, 13]. The design of this algorithm was stimulated by the Wiener-Hopf equation. By modifying the set of Wiener-Hopf equations with the stochastic gradient approach, a simple adaptive algorithm that can be updated recursively was developed. This algorithm was later on known as the least-mean-square (LMS) algorithm.

The algorithm contains three steps in each recursion: the computation of the processed signal with the current set of weights, the generation of the error between the processed signal and the desired signal, and the adjustment of the weights with the new error information by the gradient method.

The error can be defined as desired minus output of array weight.

$$\varepsilon(k) = d(k) - \bar{w}^H \bar{x}(k) \qquad \text{..... (4.31)}$$

The squared error is

$$|\varepsilon(k)|^2 = |\varepsilon(k) = d(k) - \bar{w}^H \bar{x}(k)|^2 \qquad \text{..... (4.32)}$$

The cost function is defined as

$$J(\bar{w}) = D - 2\,\bar{w}^H \bar{r} + \bar{w}^H \bar{R}_{xx} \bar{w} \qquad \text{..... (4.33)}$$

To minimize the cost function we take gradient of above eq. and equate to zero .thus the solution for weights is optimum Weiner solution is

$$\bar{w}_{opt} = \bar{R}_{xx}^{-1} \bar{r} \qquad \text{..... (4.34)}$$

By using the gradient of cost function we have the LMS solution:

$$\bar{w}(k+1) = \bar{w}(k) + \mu\, e^{*}(k)\bar{x}(k) \qquad \text{..... (4.35)}$$

Where μ is the step size parameter that control rate of adaptation.

This algorithm is simple and easy in computation.

4.2.2. Sample Matrix Inversion:

This method is also alternatively known as direct matrix inversion (DMI). The sample matrix [1, 11] is a time average estimate of array correlation matrix using *K*-time samples. If random process is ergodic in the correlation, the time average estimate will equal the actual correlation matrix. In this method we use *K*–length block of data, so this method is called a block-adaptive approach. We are thus adapting the weight block by block.

K samples of signal vector X defined as $M \times K$ matrix as

$$\bar{X}_K(k) = \begin{bmatrix} x_1(1+kK) & x_1(2+kK) & \dots & x_1(K+kK) \\ x_2(1+kK) & x_2(2+kK) & \dots & x_M(K+kK) \\ \vdots & \vdots & & \vdots \\ x_1(1+kK) & x_2(2+kK) & \dots & x_M(K+kK) \end{bmatrix} \qquad \text{..... (4.36)}$$

Where k is the block number and K is the block-length.

Then the estimate of the array correlation matrix is:

$$\hat{R}_{xx}(k) = \frac{1}{K}\, \bar{X}_K(k)\, \bar{X}_K^H(k) \qquad \text{..... (4.37)}$$

And the estimate of correlation vector is:

$$\hat{r}(k) = \frac{1}{K}\; d^{*}(k)\, \bar{X}_K(k) \qquad \text{..... (4.38)}$$

The SMI weights can be calculated for k^{th} block of length *K* as

$$\begin{aligned} \bar{w}_{SMI}(k) &= \bar{R}_{xx}^{-1}(k)\, \bar{r}(k) \\ &= [\bar{X}_K(k)\, \bar{X}_K^H(k)]^{-1} d^{*}(k)\, \bar{X}_K(k) \qquad \text{..... (4.39)} \end{aligned}$$

4.2.3. Recursive Least Square Algorithm:

The recursive least-square (RLS) algorithm does not require any matrix inversion computations as the inverse correlation matrix is computed directly. The recursive least-squares (RLS) algorithm uses a different approach in carrying out the adaptation. Instead of minimizing the mean square error as in the LMS algorithm, the sum of the squared errors of different set of inputs is the subject of minimization. This algorithm was first derived from the Kalman filter. Although it is intended to be used in a multi-tap transversal filter where the squared error information is sampled over a varying time frame, this method also works in our system where input information originates from different elements. It requires reference signal and correlation matrix information. In RLS [1, 13] algorithm the weights are updated by the equation:

$$\bar{w}(k) = \bar{w}(k-1) + \bar{g}(k)\,[d^*(k) - \bar{x}^H(k)\,\bar{w}(k-1)] \qquad \text{..... (4.40)}$$

Where $\bar{g}_k(k)$ is the gain vector and it expressed as

$$\bar{g}(k) = \hat{R}_{xx}^{-1}(k)\,\bar{x}(k) \qquad \text{..... (4.41)}$$

Where

$$\hat{R}_{xx}\,(k) = \sum_{i=1}^{k} \bar{x}(i)\bar{x}^H(i) \qquad \text{..... (4.42)}$$

4.2.4. Constant Modulus Algorithm:

Many adaptive beamforming algorithms are based on minimizing the error between reference signal and array output. The reference signal is typically a training sequence used to train the adaptive array or a desired signal based upon a priori knowledge of nature of the arriving signals. In the case where a reference signal is not available one must resort to an assortment of optimization techniques that are blind to exact content of the incoming signals.

The Constan Modulus algorithm [1, 13] is blind algorithm where a reference signal is not available. It is a gradient-based algorithm that has a constant amplitude or modulus. Godard was the first to propose a family of constant modulus blind equalization algorithms .The algorithm contains three steps in each recursion: (1) the computation of the processed signal with the current set of weights(Initial weight *w(1)* are chosen), (2) the generation of the error , and (3) the adjustment of the weights with the new error information. The following equations summarize the above three steps.

Output signal with weight-

$$y(k) = W^H \cdot X(k) \qquad \text{..... (4.43)}$$

The resulting error signal is

$$e(k) = y(k)|y(k)|^{p-2}(R_p - |y(k)|^p) \qquad \text{..... (4.44)}$$

The Godard cost function is given as

$$J(k) = E\left[\left(|y(k)|^p - R_p\right)^q\right] \qquad \text{..... (4.45)}$$

Where p is positive integer and q is the positive integer = 1.

The R_p is defined as when gradient of cost function is zero,

$$R_p = \frac{E\left[|s(k)|^{2p}\right]}{E\left[|s(k)|^p\right]} \qquad \text{..... (4.46)}$$

The weight is updated by the equation

$$\bar{w}(k+1) = \bar{w}(k) + \mu e^*(k)\bar{x}(k) \qquad \text{..... (4.47)}$$

4.2.5. Least Square Constant Modulus:

One severe disadvantage of the Godard CMA is slow convergence time .The slow converges limits the usefulness of the algorithm in the dynamic environment where the signal must be captured quickly. This also limits the usefulness of CMA when channel conditions are rapidly changing. The previous Godrad CMA is based upon the method of steepest descent by taking the gradient of the cost function. A faster algorithm was developed by Agee [14] using the method of non-linear least square. The least square algorithm is also known as the Gauss method based upon the work of Gauss in 1795.This method is known as least square constant modulus algorithm. The least-squares constant modulus algorithm (LSCMA) is summarized as following:

$$\bar{w}(k+1) = \bar{w}(k) - (\bar{X}^*\bar{X}^H)^{-1}\,\bar{X}^*\,(\bar{y}(k) - \bar{r}(k) \qquad \text{..... (4.48)}$$

$$= (\bar{X}^*\bar{X}^H)^{-1}\,\bar{X}^*\,\bar{r}(k) \qquad \text{..... (4.49)}$$

Where X is input data matrix and $y(k)$ and $r(k)$ are output data and complex limited output data vectors.While only one block of data is used to implement the LS-CMA algorithm iterates through n values until convergence. The initial weight vector $\bar{w}(1)$ is chosen, the complex-limited output data vector $\bar{r}^*(1)$ is calculated, and then the next weight vector $\bar{w}(2)$ is calculated, and the iteration continue until satisfactory convergence is satisfied. This is called the static LS-CMA because only one block, of length K, is used for the iteration process.

CHAPTER 5

NEURAL NETWORK BASED ROBUST ADAPTIVE BEAMFORMING ALGORITHM

Chapter 5 NEURAL NETWORK BASED ROBUST ADAPTIVE BEAMFORING ALGORITHM

Adaptive Beamforming is a technique in which an array of antennas 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. Adaptive beamforming has wide applications in fields such as radar, sonar, seismology, radio astronomy, and wireless communications [4], [5]. When adaptive arrays are applied to practical problems, the performance of adaptive beamforming methods may become worse than in the ideal case because of violation of underlying assumptions on the environment, sources, or sensor array and this may cause a mismatch between the assumed array response and true array response. During the past two decades, many approaches have been developed to improve the robustness against even slight mismatches However, the performance of adaptive beamforming techniques may degrade severely in the presence of mismatches between the assumed array response and the true array response.

Neural networks have found numerous applications in the field of signal processing [8], [9], mainly because of their general purpose nature, fast convergence rates, and new VLSI implementations. The aspect of antenna array signal processing focuses on adaptive beamforming. Adaptive beamforming is used for enhancing a desired signal while suppressing noise and interference at the output of an array of sensors. When adaptive arrays are applied to practical problems, the performance degradation of adaptive beamforming techniques may become even more pronounced than in the ideal case because some of underlying assumptions on the environment, sources, or sensor array can be violated and this may cause a mismatch between the presumed and actual signal steering vectors. To account for the signal steering vector mismatches, additional linear constraints (point and derivative constraints) can be imposed to improve the robustness of adaptive beamforming [18]. But, the beamformers lose degrees of freedom for interference suppression. Diagonal loading [19] has been a popular

approach to improve the robustness of adaptive beamforming algorithms. However, a serious drawback of the approach is that there is no reliable way to choose the diagonal loading factor.

Neural network methods possess such advantages as general purpose nature, nonlinear property, passive parallelism, adaptive learning capability, generalization capability and fast convergence rates. Neural network method is typically used in two steps: training phase and performance phase. Neural network is first trained with known input/output pattern pairs.
It can be implemented off-line, although a large training pattern set is required for network training. After the training phase, it can be used directly to replace the complex system dynamics. By these inherent advantages of the neural network, this thesis presents the development of a neural network-based robust adaptive beamforming algorithm, which treats the problem of computing the weights of an adaptive array antenna as a mapping problem.

5.1 Mathematical Model

Consider a uniform linear array (ULA) with M omni directional sensors spaced by the distance d and D narrow-band incoherent plane waves, impinging from directions $\{\theta_1 , \theta_2 , \dots . \theta_{D-1} \}$.

The observation vector is given by

$$X(k) = s(k) + i(k) + n(k)$$

$$= s_0(k)a + i(k) + n(k) \qquad \text{..... (5.1)}$$

Where $X(k)$ is the complex vector of array observations and it expressed as

$$X(k) = [x_1(k), x_2(k), \dots \dots x_M(k)]^T \qquad \text{..... (5.2)}$$

$s_0(k)$ = the signal waveform, a is the signal steering vector,

$i(k)$ is the interference component, $n(k)$ is the noise component.

The output of a narrowband beamformer is

$$y(k) = w^H X(k) \qquad \text{..... (5.3)}$$

Where w is the complex vector of beamformer weight and it expressed as

$$w = [w_1, w_2, \dots . . , w_M]^T \qquad \text{..... (5.4)}$$

The signal to interference plus noise ratio (SINR) has the following form

$$SINR = \frac{w^H R_s w}{w^H R_{i+n} w} \qquad \text{..... (5.5)}$$

Where R_s is $M \times M$ signal matrix that is statistical expectation of signal vector and it is

$$R_s = E\{s(k)s^H(k)\} \qquad \text{..... (5.6)}$$

and R_{i+n} is signal plus noise covariance matrix as

$$R_{i+n} = E\{\big(i(k) + n(k)\big)\big(i(k) + n(k)\big)^H\} \qquad \text{..... (5.7)}$$

The adaptive beamformer weight vector is computed in order to optimize the performance in terms of a certain criterion. Although several criteria can be used, we limit our consideration by the output SINR criterion, which is rewritten as

$$SINR = \frac{\sigma_s^2 |w^H a|^2}{w^H R_{i+n} w} \qquad \text{..... (5.8)}$$

Where σ_s^2 is the signal power.

The problem of finding the maximum of (8) is equivalent to the following optimization problem

$$\min w^H R_{i+n} w \ \text{ subject to } w^H a = 1. \qquad \text{..... (5.9)}$$

From (9), the following solution can be found for the optimal weight vector

$$w_{opt} = \frac{R_{i+n}^{-1} a}{a^H R_{i+n}^{-1} a} \qquad \text{..... (5.10)}$$

Inserting (10) into (8), we obtain that the optimal SINR is given as

$$SINR_{opt} = \sigma_s^2 a^H R_{i+n}^{-1} a \qquad \text{..... (5.11)}$$

Where equation (11) gives an upper bound on the output SINR (8).

5.1.1 Sample matrix inversion (SMI) algorithm

The sample matrix is a time average estimate of array correlation matrix using *N*-time samples. If random process is ergodic in the correlation, the time average estimate will equal the actual correlation matrix. In this method we use *N*–length block of data. In practical applications, the

exact interference-plus-noise covariance matrix R_{i+n} is unavailable. Therefore, the sample covariance matrix $\hat{R}$ is used instead of R_{i+n}.

$$\hat{R} = \frac{1}{N}\sum_{i=1}^{N} X(i)X^{H}(i) \qquad \text{..... (5.12)}$$

Where N is the number of snapshots available.

Thus weight of SMI algorithm is

$$w_{SMI} = \alpha\hat{R}^{-1}a \qquad \text{..... (5.13)}$$

where $\alpha = a^{H}\hat{R}^{-1}a$ is the normalization constant that does not affect the output SINR.

The SMI algorithm is very sensitive to the mismatch between the presumed and actual spatial signature vectors.

5.1.2 Loaded sample matrix inversion (LSMI) algorithm

One of the most popular robust approaches is the loaded SMI (LSMI) algorithm, which attempts to improve the robustness of the SMI technique against an arbitrary spatial signature mismatch by means of diagonal loading of the sample covariance matrix [20]. The essence of LSMI algorithm is to replace the conventional sample covariance matrix $\hat{R}$ by the so-called diagonally loaded covariance matrix.

$$\hat{R}_{dl} = \hat{R} + \xi I \qquad \text{..... (5.14)}$$

where ξ is a diagonal loading factor. So that, we can write the LSMI weight vector in the following form

$$w_{LSMI} = \hat{R}_{dl}^{-1}a = (\hat{R} + \xi I)^{-1}a \qquad \text{..... (5.15)}$$

So the LSMI algorithm can improve the performance of SMI algorithm in scenarios with an arbitrary steering vector mismatch, this improvement is not significant because LSMI algorithm exploits the presumed steering vector and, therefore, its performance degrades when the norm of the error vector is large. Furthermore, the proper choice of ξ represents a serious problem in practical applications because ξ depends on the unknown signal and interference parameters.

5.1.3 Robust Adaptive Beamforming

We assume that the norm of the steering vector distortion a_e can be bounded by some known constant ϵ^2

$$\|a_e\|^2 \leq \epsilon^2 \qquad \text{..... (5.16)}$$

Then, the actual signal steering vector

$$\tilde{a} = a_e + \bar{a} \qquad \text{..... (5.17)}$$

Where $\bar{a}$ is the assumed steering vector.

Cost function of robust adaptive beamforming algorithm minimizes the mean output power subject to the inequality constraint. Thereby, the optimization problem can be formulated as

$$\min(a_e + \bar{a})^H R^{-1}(a_e + \bar{a}) \text{ subject to } \|a_e\|^2 \leq \epsilon^2 . \qquad \text{..... (5.18)}$$

The solution to (18) can be obtained using Lagrange multiplier method by minimizing the function

$$H = (a_e + \bar{a})^H R^{-1}(a_e + \bar{a}) + \lambda(a_e^H a_e - \epsilon^2) \qquad \text{..... (5.19)}$$

Where λ is Lagrange multiplier.

For finding the norm of steering vector computing this gradient of (19) and equating it to zero yields

$$a_e = -\left(\hat{R}^{-1} + \lambda I\right)^{-1} \hat{R}^{-1} \bar{a} \qquad \text{..... (5.20)}$$

So by equations (18) and (20) .we get

$$\bar{a}^H \hat{R}^{-1} \left(\hat{R}^{-1} + \lambda I\right)^{-2} \hat{R}^{-1} \bar{a} = \varepsilon^2 \qquad \text{..... (5.21)}$$

The covariance matrix decompose into Eigen value and eigenvector form as

$$\hat{R} = U \Lambda U^H \qquad \text{..... (5.22)}$$

Where columns of U are the eigenvectors and diagonal elements of Λ are known values of $\hat{R}$.

Then inserting (22) into (21), we can obtain

$$\bar{a}^H U \Lambda^{-1} (\Lambda^{-1} + \lambda I)^{-2} \Lambda^{-1} U^H \bar{a} = \varepsilon^2 \qquad \text{..... (5.23)}$$

Let $F = U^H \bar{a}$ and above equation can be simplified as

$$f(\lambda) = \sum_{i=1}^{M} \frac{|F_i|^2}{(1+\lambda\gamma_i)^2} = \varepsilon^2 \qquad \text{..... (5.24)}$$

Left side of (24) is a monotonically decreasing function of λ, and we can obtain a unique solution $\lambda > 0$. And hence λ can be obtained efficiently by Newton's method [7], [21].

From eq. (24) , we have

$$\sum_{i=1}^{M} \frac{|F_i|^2}{(1+\lambda\gamma_i)^2} = \varepsilon^2 < \sum_{i=1}^{M} \frac{|F_i|^2}{(\lambda\gamma_i)^2} \qquad \text{..... (5.25)}$$

This gives the upper bound on λ

$$\lambda < \frac{1}{\varepsilon}\left(\sum_{i=1}^{M} \frac{|F_i|^2}{\gamma_i{}^2}\right)^{\frac{1}{2}} \qquad \text{..... (5.26)}$$

By replacing the γ_i in (24) with γ_1 and $\gamma_M$respectively, we get

$$\frac{\|\bar{a}\| - \varepsilon}{\gamma_1 \varepsilon} \leq \lambda \leq \frac{\|\bar{a}\| - \varepsilon}{\gamma_M \varepsilon} \qquad \text{..... (5.27)}$$

We can combine (26) and (27) to give the following upper and lower bounds on the solution of λ

$$\frac{\|\bar{a}\| - \varepsilon}{\gamma_1 \varepsilon} \leq \lambda \leq \min\left\{\frac{\|\bar{a}\| - \varepsilon}{\gamma_M \varepsilon}, \frac{1}{\varepsilon}\left(\sum_{i=1}^{M} \frac{|F_i|^2}{\gamma_i{}^2}\right)^{\frac{1}{2}}\right\} \qquad \text{..... (5.28)}$$

Solving (22) for λ by a Newton's method using that the solution is unique and it follows the above condition. Thus the weight vector for RAB written as

$$w_{RAB} = \frac{\hat{R}^{-1}((\lambda\hat{R}+I)^{-1} - I)\bar{a}}{\bar{a}^H \hat{R}^{-1}((\lambda\hat{R}+I)^{-1} - I)^2 \bar{a}} \qquad \text{..... (5.29)}$$

$$= \frac{U\,\lambda^{-1}((\lambda\Lambda+I)^{-1} - I)U^H\,\bar{a}}{\bar{a}^H U\Lambda^{-1}((\lambda\Lambda+I)^{-1} - I)^2 U^H \bar{a}} \qquad \text{..... (5.30)}$$

5.2 Radial Basis Function Neural Network (RBFNN)

The weight vector of the above algorithm is a nonlinear function of the sample covariance matrix, and is not suitable for real-time implementation. Therefore, it can be approximated using a suitable architecture such as RBFNN in this thesis. The array outputs are preprocessed, and then applied to the RBFNN. The sample covariance matrix $\widehat{\boldsymbol{R}}$ is presented to the input layer of the RBFNN, and the vector $\boldsymbol{w}_{\mathrm{RAB}}$ is produced at the output layer. As it is the case, with most neural network, the RBFNN is designed to perform an input-output mapping, trained with examples ($\widehat{\boldsymbol{R}}$; $\boldsymbol{w}_{\mathrm{RAB}}$), l=1, 2,...., N_T , where N_T stands for the number of examples contained in the training set.

5.2.1 Radial Basis Function

Radial Basis Functions emerged as a variant of artificial neural network in late 80s. However, their roots are entrenched in much older pattern recognition techniques as for example potential functions, clustering, functional approximation, and spline interpolation and mixture models. The

RBF originated in the study for the interpolation problems of multi-variable and is still a main research area in numeric analysis. From other standpoint, the design of a neural network can also be viewed as a surface fitting (reconstruction) problem in a hyperspace where the RBF method is a nature choice. As one of the most popular neural network models, RBF network has attracted lots of attentions on the improvement of its approximation as well as the construction of its architecture. RBF's are embedded into a two-layer feed forward neural network. Such a network is characterized by a set of inputs and a set of outputs. In between the inputs and outputs there is a layer of processing units called hidden units. Each of them implements a radial basis function. The output units implement a weighted sum of hidden units outputs. The input into a RBF network is non-linear while the output is linear. Due to their nonlinear approximation properties, RBF networks are able to model complex mapping, while perceptron neural networks can only model by means of multiple intermediary layers.

In order to use a radial Basis function Network we need to specify the hidden unit activation function, the number of processing units, a criterion for modeling a given task and a training algorithm for finding the parameters of the network. Finding the RBF weights is called network training. If we have at hand a set of input-output pairs, called training set, we optimize the network parameters in order to fit the network outputs to the given inputs. The fit is evaluated by means of a cost function, usually assumed to be the mean square error. After training, the RBF network can be used with data whose underlying statistics is similar to that of training set.

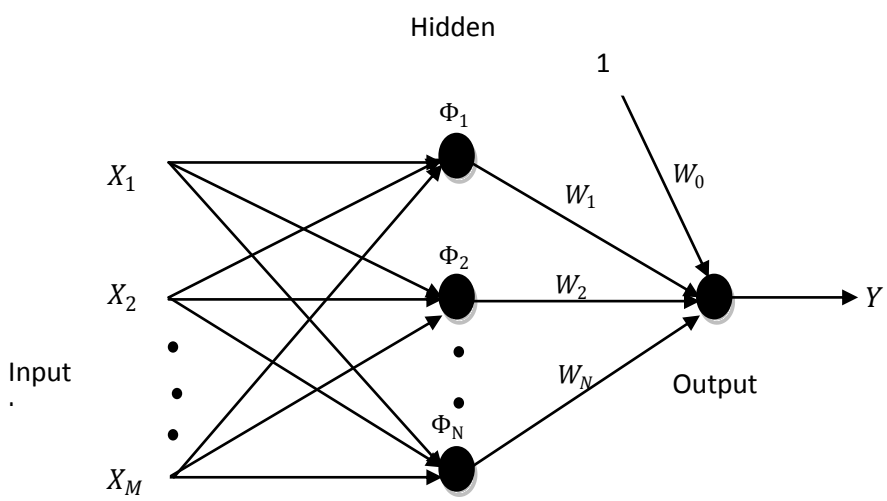

Fig.5.1 Structure of RBF Neural Network

5.2.1.1 Network Topology

Basic principle of the RBF method is detailed in the remarkable literature of Haykin [23]. The construction of a RBF network, in its most basic form, involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to its environment. The second layer, the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space; in most applications the hidden space is of high dimensionality. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer. The way in which the network is used for data modeling is different when approximating time-series and in pattern classification. In the first case, the network inputs represent data samples at certain past time-laps, while the network has only one output representing a signal value. In the pattern classification applications the inputs represent feature entries, while each output corresponds to a class. Generally, for given set of different points x, RBF technique uses a function $F^*(x)$ of the following form

$$F^*(x) = \sum_{i=1}^{m_1} w_i \, \varphi_i \, (\mathrm{x}) \qquad \text{..... (5.31)}$$

Where, $\varphi_i(x|i = 1,2, \ldots . m_1)$ is a new set of basis functions that we assume to be linearly independent without loss of generality, G(x, t_i) is a Green function centered at t_i, w_i constitute a new set of weights, and m_1 is the number of centers (or the size of the hidden layer). Typically, the number of basis functions is less than the number of data points (i.e., $m_1 \leq N$). A commonly used Green function is the multivariate Gaussian function.

$$\mathrm{G}(\mathrm{x}, \mathrm{t_i}) = exp\left(-\frac{1}{2\,\sigma_i^2}\|\mathrm{x} - \mathrm{t_i}\|^2\right) \qquad \text{..... (5.32)}$$

Where ||.|| denotes a norm that is usually Euclidean.

5.2.1.2 Learning Strategies

There are different strategies that used in the design of an RBF network, depending on how the centers of the redial basis functions of the network are specified. These design strategies pertain to an RBF network whose formulation is based on interpolation theory. Here we used Supervised Selection of Centers as a learning strategy.

In this approach, the centers of the radial basis functions and all other free parameters of the network undergo a supervised learning process; in other words, the RBF network takes on its most generalized form. A natural candidate for such a process is error-correlation learning, which is most conveniently implemented using a gradient descent procedure that represents a generalization of the LMS algorithm.

The first step in the development of such a learning procedure is to define the instantaneous value of the cost function

$$\xi = \frac{1}{2}\sum_{j=1}^{N} e_j^2 \qquad \text{..... (5.33)}$$

Where N is the size of the training sample used to do the learning, and e_j is the error signal defined by

$$e_j = \mathrm{d}_j - F^*(\mathrm{x}_j) \qquad \text{..... (5.34)}$$

$$= \mathrm{d}_j - \sum_{i=1}^{m_1} \mathrm{G}(\|\mathrm{x}_j - \mathrm{t}_i\|^2)_{C_i} \qquad \text{..... (5.35)}$$

The requirement is to find the free parameters w_i, t_i and $\sum_i^{-1}()$ (the latter being related to the norm-weighting matrix C_i) so as to minimize ξ. The results of this minimization are summarized below:

1. Linear weights (output layer)

$$\frac{\partial \xi(n)}{\partial \mathrm{w}_i(n)} = \sum_{j=1}^{N} e_j(n)\, \mathrm{G}(\|\mathrm{x}_j - \mathrm{t}_i(n)\|)_{C_i} \qquad \text{..... (5.36)}$$

$$\mathrm{w}_i(n+1) = \mathrm{w}_i(n) - \eta_1 \frac{\partial \xi(n)}{\partial \mathrm{w}_i(n)}, \qquad i = 1, 2, \dots, m_1 \qquad \text{..... (5.37)}$$

2. Positions of Centers (hidden layer)

$$\frac{\partial \xi(n)}{\partial \mathrm{t}_i(n)} = 2\,\mathrm{w}_i(\mathrm{n}) \sum_{j=1}^{N} e_j(n)\, G'(\|\mathrm{x}_j - \mathrm{t}_i(n)\|)_{C_i} \Sigma_i^{-1}[\mathrm{x}_j - \mathrm{t}_i(n)] \qquad \text{..... (5.38)}$$

$$\mathrm{t}_i(n+1) = \mathrm{t}_i(n) - \eta_2 \frac{\partial \xi(n)}{\partial \mathrm{t}_i(n)}, \qquad i = 1, 2, \dots, m_1 \qquad \text{..... (5.39)}$$

3. Spreads of centers (hidden layer)

$$\frac{\partial \xi(n)}{\partial \Sigma_i^{-1}(n)} = -\mathrm{w}_i(\mathrm{n}) \sum_{j=1}^{N} e_j(n)\, G'(\|\mathrm{x}_j - \mathrm{t}_i(n)\|)_{C_i} \mathrm{Q}_{ji}(n) \qquad \text{..... (5.40)}$$

$$\mathrm{Q}_{ji}(n) = [\mathrm{x}_j - \mathrm{t}_i(n)]\ [x\_j - t\_i\,(n)]^T \qquad \text{..... (5.41)}$$

$$\Sigma_i^{-1}(n+1) = \Sigma_i^{-1}(n) - \eta_3 \frac{\partial \xi(n)}{\partial \Sigma_i^{-1}(n)} \qquad \text{..... (5.42)}$$

Where the term $e_j(n)$ is the error signal of output unit j at time n. The term G′(.) is the first derivative of the Green's function G(.) with respect to its argument. The update equation for w_i, t_i and Σ_i^{-1} are assigned different learning-rate parameters η_1 , η_2 and η_3 , respectively. The covariance matrix Σ determines the receptive field of the Gaussian radial-basis function G ($\|x-ti\|_C$) given in the equation

$$G(\|x - t_i\|_C = exp\left[-\frac{1}{2}(x - t_i)^T \Sigma^{-1} (x - t_i)\right] \qquad \text{..... (5.43)}$$

Here the required training input/output pairs of the training set, that is $\{\hat{R}, w_{RAB}\}$. In the application, desired sources are located at elevation angels θ ranging from -90° to $+90^o$ to span the field of view of the antenna. Once the RBFNN is trained with a representative set of training input/output pairs, it is ready to function in the performance phase. In the performance phase, the RBFNN produces estimation of the weight vector w_{RAB} .

5.2.1.3 Performance Phase of the RBFNN

After the training phase is complete, the RBFNN has established an approximation of the desired input-output mapping. In the performance phase, the neural network is expected to generalize, that is, respond to inputs that has never seen before, but drawn from the same distribution as the inputs used in the training set. In the performance phase, the RBFNN produces outputs to previously unseen inputs by interpolating between the inputs used in the training phase.

(a) Generate the rearranged covariance matrix;

(b) Present the array output vector at the input layer of the trained RBFNN. The output layer of the trained RBFNN will produce the estimation of the weight vector for the array output.

Unlike the SMI, the least mean-square, or recursive least squares algorithms, where the optimization is carried out whenever the directions of the desired or interfering signals change, in our algorithm, the weight vector of the trained network can be used to produce the optimum weight vector needed to steer the narrow beams of the adaptive array to the directions of the desired signal in real time.

5.2.2 Simulation and Results

We present here some simulations to justify the performance of the SMI, LSMI and robust adaptive beamforming.

5.2.2.1 Array Factor Plots with variation of number of array elements with different element spacing-

We determined that the element spacing must be $d \leq \lambda / 2$ to prevent spatial aliasing. Here we relax this restriction and look at various element spacing with different element linear array and resulting array characteristics, namely, their beam-pattern. Here we show the beam-pattern plots for different algorithm when the angle of arrival of desired user is at 30° and interferer at -60° for different element spacing λ/2, λ/4 and λ/8 .We note that from simulation the algorithm places adaptively the maxima in the direction of desired user and nulls at the AOA of the interferer for various values of N.

(a) SMI algorithm

The array factor plots of SMI algorithm for different element spacing as λ/2, λ/4 and λ/8 with N = 5, 8, 10 are as

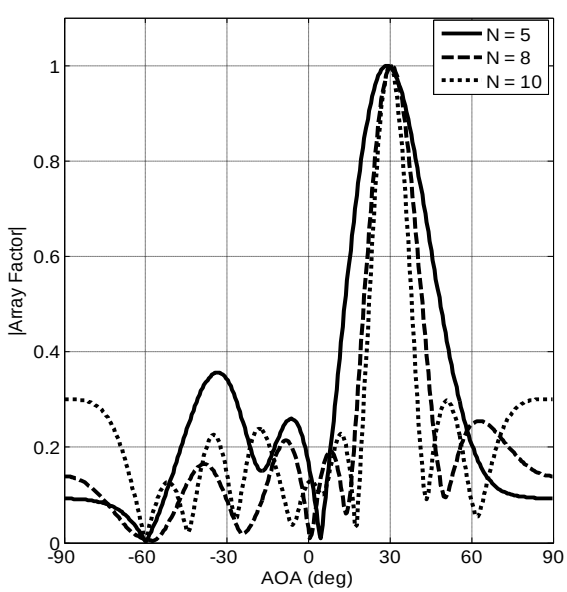

Fig 5.2 Array Factor plots for SMI algorithm (for d=0.5λ)

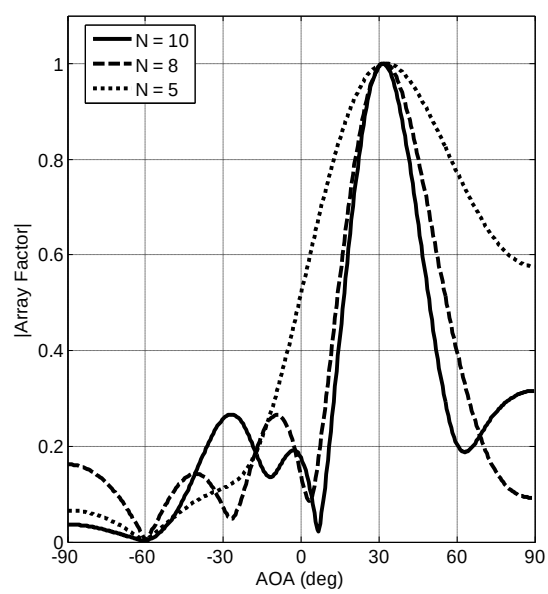

Fig 5.3 Array Factor plots SMI algorithm (for d=0.25λ)

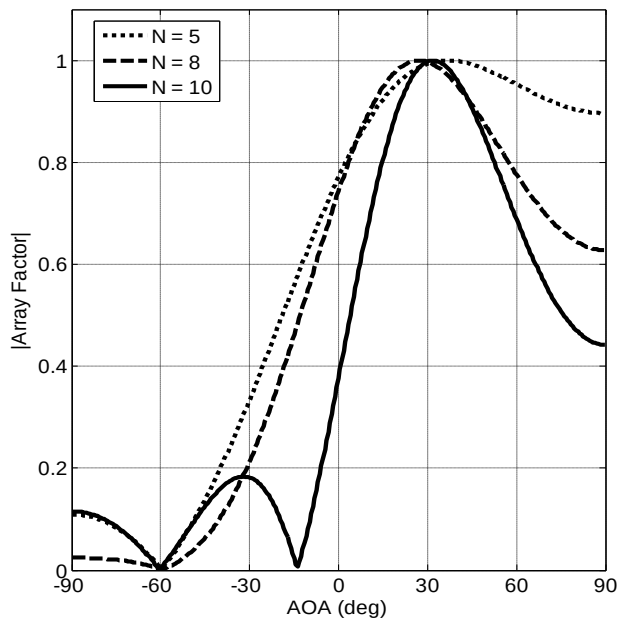

Fig 5.4 Array Factor plots for SMI algorithm (for d=0.125λ)

(b) The array factor plots of LSMI algorithm for different element spacing as λ/2, λ/4 and λ/8 with N = 5, 8, 10 are as

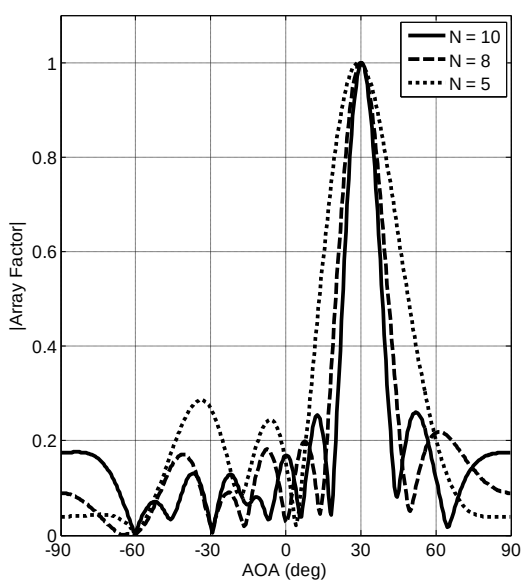

Fig 5.5 Array Factor plots for LSMI algorithm (d=0.5λ)

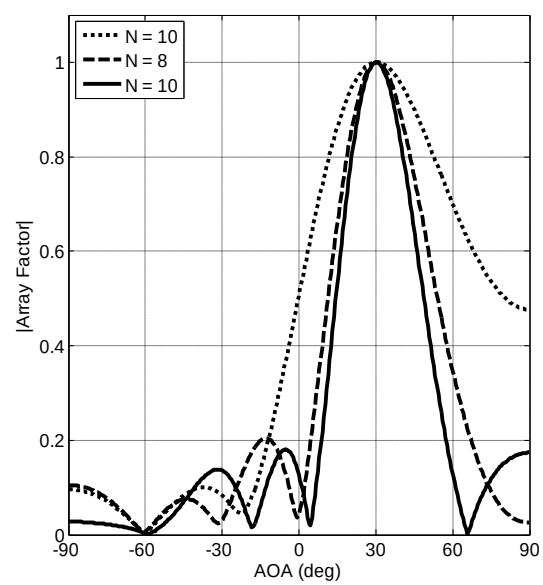

Fig 5.6 Array Factor plots for LSMI algorithm (d=0.25λ)

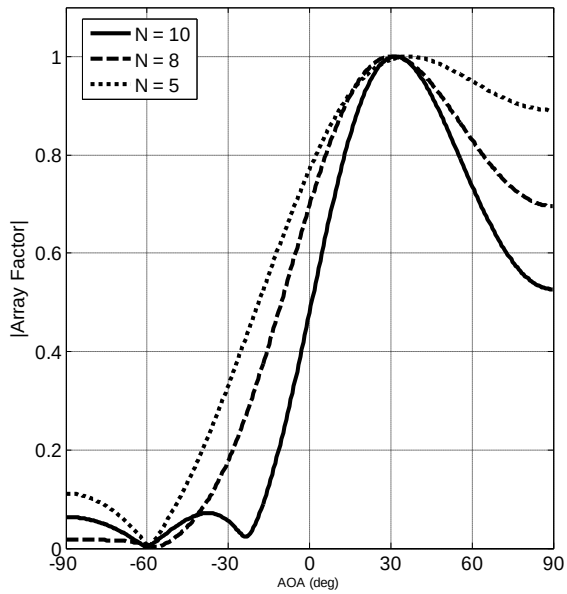

Fig 5.7 Array Factor plots for LSMI algorithm (d=0.125λ)

(c) The array factor plots of Robust Adaptive Beamforming algorithm for different element spacing as λ/2, λ/4 and λ/8 with N = 5, 8, 10 are as

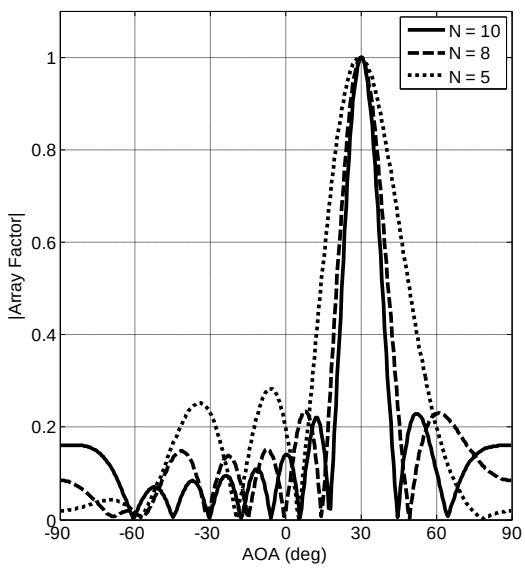

Fig 5.8 Array Factor plots for RAB algorithm (d=0.5λ)

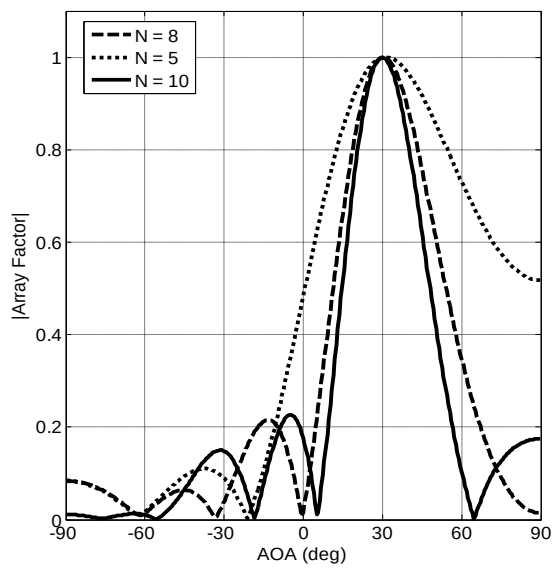

Fig 5.9 Array Factor plots for RAB algorithm (d=0.25λ)

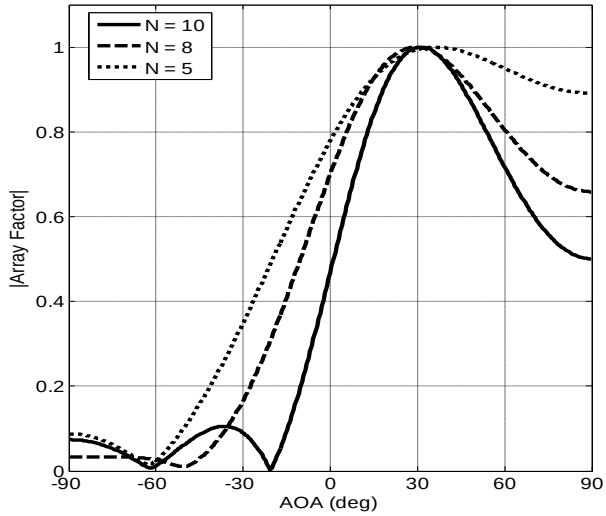

Fig 5.10 Array Factor plots for RAB algorithm (d=0.125λ)

From figures with different element spacing it is evident that the optimum spacing between elements is half wavelength and as number of element spacing increases width of main lobe decreases, this is crucial for the application of smart antennas when single narrower beam is required to track the mobile, and number of side lobes increases these represents power radiated or received in potentially unwanted directions. So in a wireless communication system side lobes will contribute to the level of interferences spreads in the cell or sector by a transmitter as well as level of interference seen by a receiver when antenna arrays are used. It is evident that more elements an array has or alternatively the larger the array gets, the better the characteristics of radiation pattern as for as its shape and degree of freedom.

From these figures we get that array factor with different element spacing λ/2, λ/4 and λ/8 for Robust Adaptive beamfoming algorithm is better than the SMI and LSMI algorithms.

5.2.2.2 Comparison of Array Beampatterns of Algorithms

We assume a uniform linear array with M =10 omnidirectional sensors spaced half a wavelength apart. For each scenario, 100 simulation runs are used to obtain each simulated point. In the training phase, desired sources are located at elevation angles θ ranging from -90° to $+90^o$. In all examples, two interfering sources are assumed to impinge on the array from the directions of arrival (DOAs) 30° and 50° , respectively. The diagonal loading factor $\xi = 10\ \sigma_n^2$ is taken in the LSMI algorithm, where σ_n^2 is the noise power.

We assume that both the presumed and actual signal spatial signatures are plane waves impinging from the DOAs 0° and 2° , respectively. Fig. 5.11 displays the beampatterns of the methods tested for the fixed SNR =10dB for the no-mismatch case.

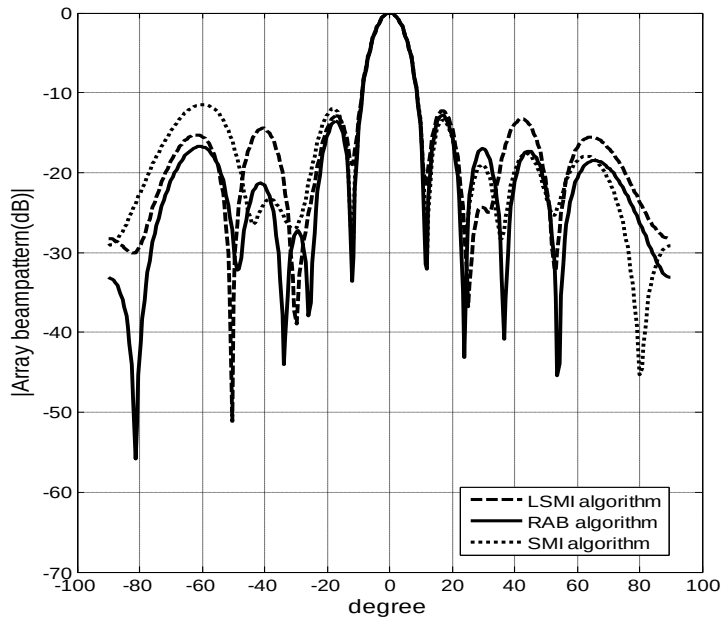

Fig 5.11 Comparison of beampatterns (for no mismatch)

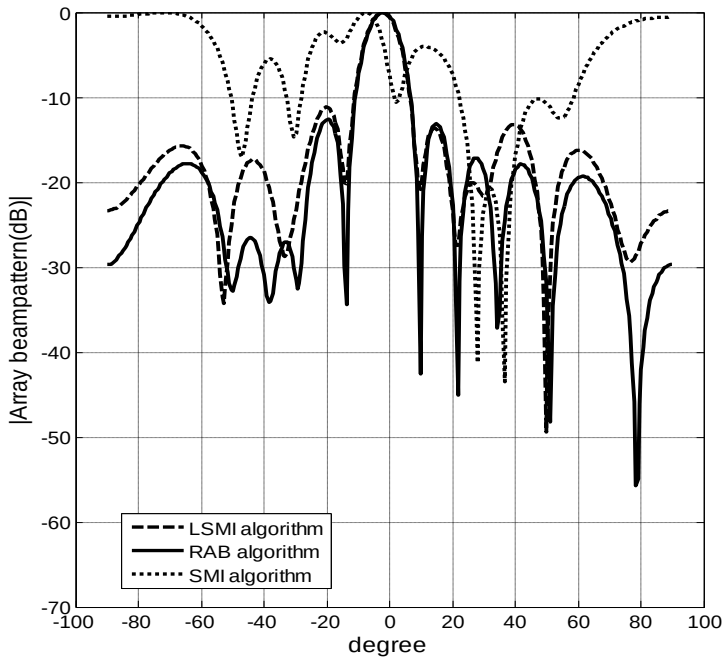

Fig 5.12 Comparison of beampatterns (for 2° mismatch)

From Fig. 5.11, we note that the robust adaptive beamforming algorithm based on RBFNN can adapt the radiation pattern of the antenna to direct narrow beam to the desired signal and nulls interfering sources. Fig. 5.12 displays the beampatterns of the methods tested for the fixed SNR =10dB for a 2° mismatch. From Fig. 5.12, we note that although the beampatterns of the robust adaptive beamforming algorithm based on RBFNN do not have nulls at the DOAs of the interferences as deep as those of the SMI algorithm, the interferences are sufficiently suppressed by our algorithm.

5.2.2.3 Comparison of Performance for known signal steering vector

The plane-wave signal is assumed to impinge on the array from $\theta = 0^o$. Fig.5.13 displays the performance of the three methods tested versus the number of snapshots for the fixed SNR =10dB. Fig. 5.14 shows the performance of these algorithms versus the SNR for the fixed training data size N = 500. In the second example, note that the performance of the robust adaptive beamforming algorithm based on RBFNN can outperform that of the other beamforming algorithms.

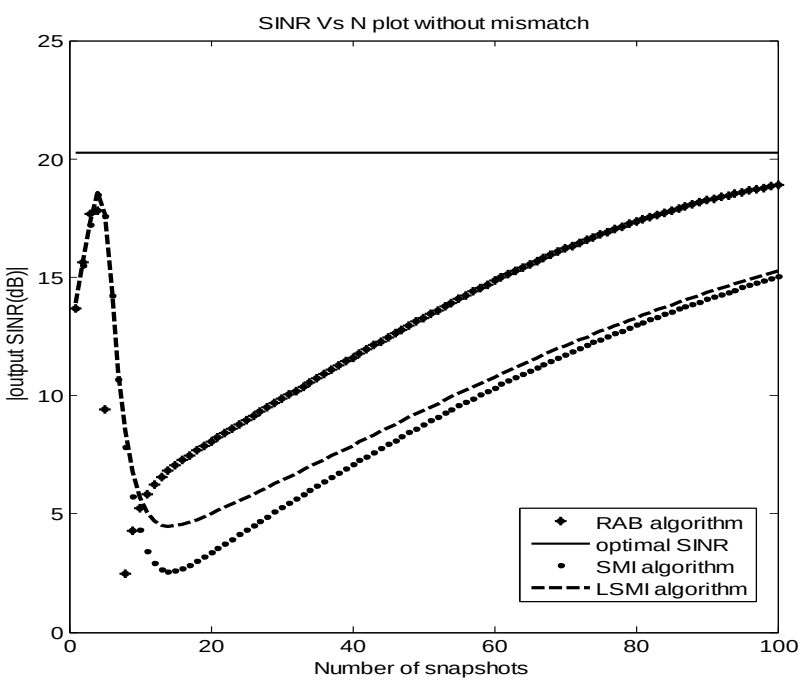

Fig 5.13 Output SINR versus N for no mismatch case

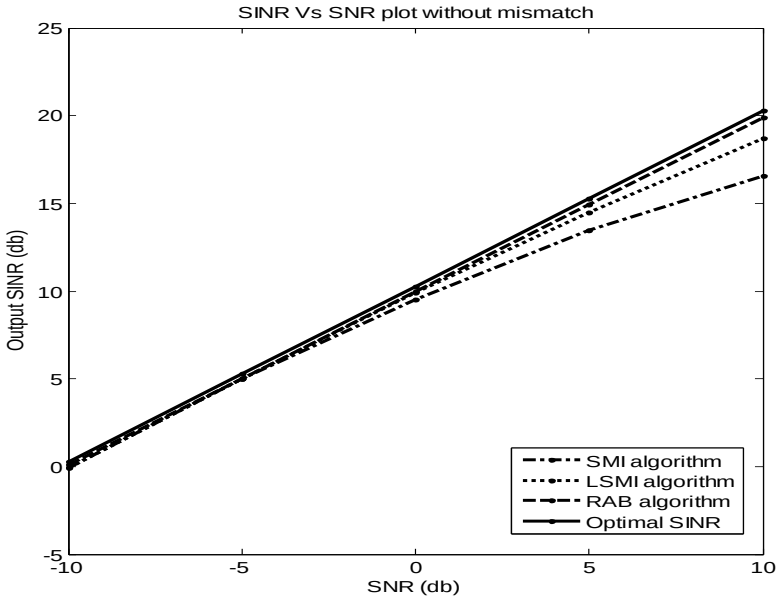

Fig 5.14 Output SINR versus SNR for no mismatch case

5.2.2.4 Comparison of Performance for Signal look direction mismatch

In the example, a scenario with the signal look direction mismatch is considered. We assume that both the presumed and actual signal spatial signatures are plane waves impinging from the DOAs 0° and 3° , respectively. This corresponds to a 3° mismatch in the signal look direction. Fig. 5.15 displays the performance of the three methods tested versus the number of snapshots for SNR =10 dB.

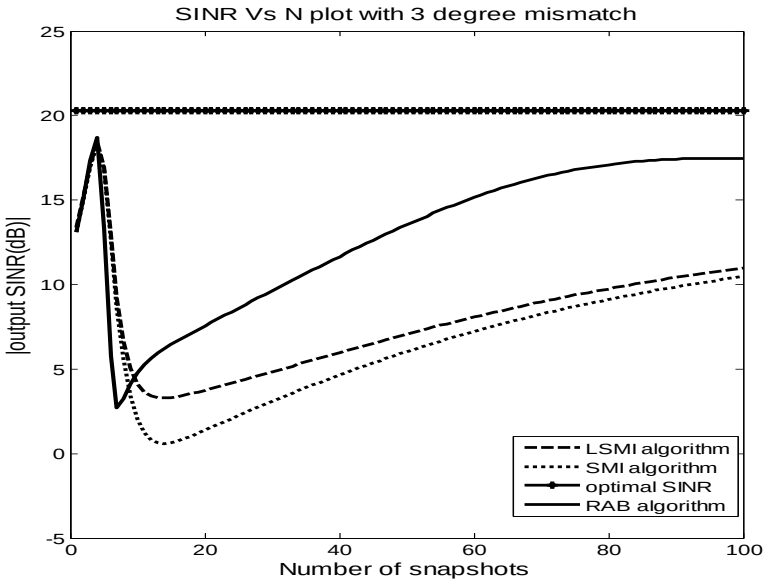

Fig 5.15 Output SINR versus N for mismatch case

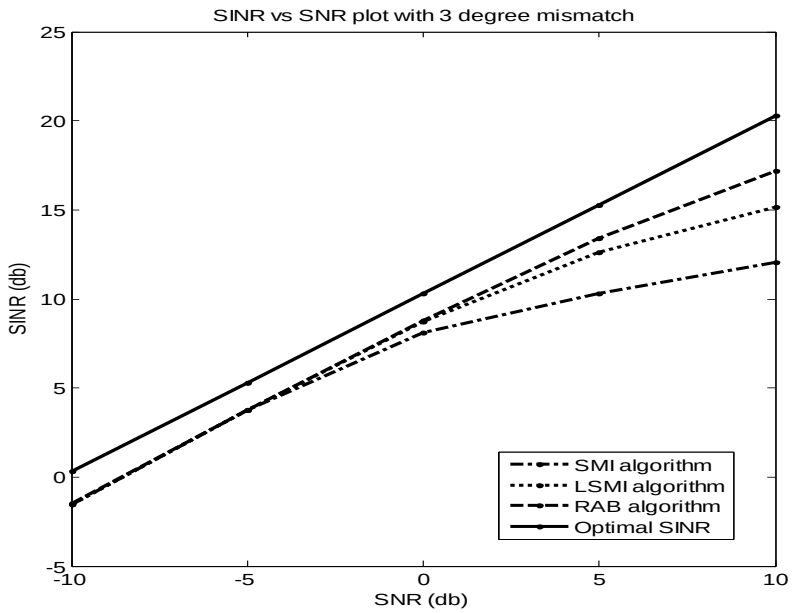

Fig 5.16 Output SINR versus SNR for mismatch

The performance of these algorithms versus the SNR for fixed training data size N = 500is shown in fig 5.16. We see that SMI algorithm is very sensitive even to slight mismatches that can easily occur in practical situations and LSMI algorithm can improve the performance of the SMI algorithm. The robust adaptive beamforming algorithm based on RBFNN provides a significantly improved robustness against signal steering vector mismatches and makes the mean output array SINR close to the optimal one at all values of the SNR and N.

CHAPTER 6

CONCLUSION AND SCOPE OF FURURE WORK

Chapter 6 CONCLUSION AND SCOPE OF FURURE WORK

6.1 Conclusion

The robust adaptive beamforming algorithm is based on explicit modeling of uncertainty in the desired signal array response and three layer radial basis function neural network which treats the problem of computing weights of an adaptive array antenna as a mapping problem. We have seen that SMI, LSMI and neural network based robust adaptive beamforming algorithm to track the desired signal while simultaneously nulling the interference sources.

- These algorithms have optimum spacing between array elements is $d = 0.5\lambda$ and it is found that more elements an array has or alternatively the larger the array gets, the better the characteristics of radiation pattern as for as its shape and degree of freedom.
- LSMI algorithm improves the performance of SMI algorithm in scenarios with an arbitrary steering vector mismatch, but choice of diagonal loading factor represents a serious problem.
- Robust adaptive beamforming algorithm based on RBFNN is much less sensitive to signal steering vector mismatch but the SMI algorithm is very sensitive even to slight mismatchs. The robust adaptive beamforming algorithm based on RBFNN adapted the radiation pattern of antenna to direct narrow beam to desired signals and nulls the interference sources.
- The robust adaptive beamforming algorithm based on RBFNN consistently enjoys excellent performance because it achieves the values of SINR that are close to the optimal one in a wide range of the SNR and N but values of SMI and LSMI algorithm did not achieve to the optimal one.

So, it is concluded that the robust adaptive beamforming algorithm based on neural network consistently enjoys a significantly improved performance as compared with other existing algorithms.

6.2 Scope of future work

- Neural network like Reurrent Neural Network (RNN) with reduced structural complexity can be incorporated for adaptive beamforming.
- Adaptive Neuro-Fuzzy Inference System (ANFIS) may be considered better robustness to the beamforming algorithms.

REFERENCES:

[1] Frank Gross,"*Smart Antenna for Wireless Communication*", Mcgraw-hill, September 14, 2005.

[2] Carl B. Dietrich, Jr., Warren L. Stutzman, Byung-Ki Kim, and Kai Dietze, *"Smart Antennas in Wireless Communications: Base-Station Diversity and Handset Beam forming"*, lEEE Antennas and Propagation Magazine, Vol. 42, No. 5, October 2000.

[3] Michael Chryssomallis, *"Smart Antennas"*, IEEE Antennas and Propagation Magazine, Vol. 42, No. 3**,** June 2000.

[4] Brennan L. E., Mallet J. D. and Reed I. S. "*Adaptive Arrays in Airborne MTI Radar*", *IEEE Trans. Antennas Propagation*, 24, pp. 607-615, 1976.

[5] Lal C. Godara, "*Application of antenna arrays to mobile communications, partΠ: beam-forming and direction-of-arrival considerations*", Proceeding of the IEEE, Vol. 85, No. 8, pp.1195-1234, August 1997.

[6] Monzingo R. A. and Miller T. W., "*Introduction to Adaptive Arrays"*, New York: Wiley, 1980.

[7] Li J., Stoica P. and Wang Z., "*On Robust Capon Beamforming and Diagonal Loading*", *IEEE Trans. Signal Processing*, 51, pp. 1702-1715, 2003.

[8] A. H. El Zooghby, C. G. Christodoulou, and M. Georgiopoulos, "*Performance of radia basis function networks for direction of arrival estimation with antenna arrays*," *IEEE Trans. Antennas Propagat.*, vol.45, pp. 1611-1617, Nov. 1997

[9] P. R. Chang, W. H. Yang and K. K. Chan, "*A neural network approach to MVDR beamforming problem*", *IEEE Trans. Antennas Propagat.*, vol.40, pp. 313-322, 1992.

[10] Salvatore Bellofiore, Consfan fine A. Balanis, Jeffrey Foufz, and Andreas S. Spanias,"*Smart-Antenna Systems for Mobile Communication Networks Part I: Overview and Antenna Design*", IEEE Antenna's and Propagation Magazine, Vol. 44, No. 3, June 2002.

[11] Dimitris G. Manolakis, Vinay K.Ingle,Stephen M. Kogon, "*Statistical and adaptive signal processing*", Mc Graw Hill Publication, 2005.

[12] Simon Haykin, "*Adaptive filter theory*", Forth edition, Pearson education asia, Second Indian reprint, 2002.

[13] Bernard widrow, Semuel D. Stearns, "*Adaptive signal processing*", Pearson education asia, Second Indian reprint, 2002.

[14] Agee, B, "*The Least-Square CMA: A New Technique for Rapid Correction of Constant Modulus Signal*", IEEE International Conference on ICASSP'86, Vol. 11, pp. 953-956, April 1986.

[15] Syed Shah Irfan Hussain,Syed Amjad Hussain Shah and Mohammad Imran Sheikh "*A Mobile Tracking Algorithm for Adaptive Array Smart Antennas by Adapting the Weights of Transmit Antenna*", IEEE transaction on Smart Antenna pp. 58-63 , jul 2004

[16] Mohammad Tariqul Islam,Zainol Abidin Abdul Rashid "*MI-NLMS adaptive beamformingalgorithm for smart antenna system applications*", Journal of Zhejiang University SCIENCE A ,vol 10, pp. 1709-1716 , Jul 2006.

[17] Xin Song, Jinkuan Wang, and Yinghua Han, "*Robust Capon Beamforming in the Presence of Mismatches*", Proceedings of ISCIT2005,pp.135-138, July2005.

[18] S. Zhang and I. L. Thng,"*Robust presteering derivative constraints for broadband antenna arrays*", *IEEE Trans. Signal Processing*, vol. 50, pp. 1-10, Jan. 2002.

[19] B. D. Carlson,"*Covariance matrix estimation errors and diagonal loading in adaptive arrays*", *IEEE Trans. Aerosp. Electron. Syst.*, vol. 24, pp. 397-401, July 1988.

[20] H. Cox, R. M. Zeskind, and M. H. Owen, "*Robust adaptive beamforming*", *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 35, pp. 1365-1376, Oct. 1987.

[21] J. Li, P. Stoica, and Z. Wang, "*Doubly constrained robust Capon beamformer*", *IEEE Trans. Signal Processing*, vol. 52, pp. 2407-2423, Sept. 2004.

[22] Xin Song Jinkuan Wang Xuefen Niu, "*Robust Adaptive Beamforming Algorithm Based on Neural Network*", Proceedings of the IEEE International Conference on Automation and Logistics, pp. 1844-1849, Sep. 2008.

[23] Simon Haykin, "*Neural Networks*", Second edition, Pearson education asia, Fourth Indian reprint, 2004.