ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

INSTITUTE OF TECHNOLOGY

ELECTRICAL AND COMPUTER ENGINEERING DEPARTMENT

Investigation of Adaptive Beamforming Algorithm for Smart Antenna system to Improve the Effect of Angle Separation

By

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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Advisor’s Name Signature

Dedicated to My sister

Hana Wondimu

And

Dr.Ing. Hailu Ayele

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Abbreviations

ADC…………………………………………………………...Analogue to Digital converter

A.F ……………………………………………………………………Array Factor

A.S……………………………………………………………….Angle of Separation

AWGN………………………………………………… Additive white Gaussian Noise

BER………………………………………………………………………Bit Error Rate

CDMA………………………………………………… code division multiple access

CMA………………………………………………………Constant Module Algorithm

CS-LMS…………………...............................Constrained-Stability Least Mean Square

DMI……………………………………………………… Direct Matrix Inversion

DOA ………………………………………………….. Direction of arrival estimation

ESPRIT…………… Estimation of signal parameters via rotational invariance techniques

LMS…………………………………………………………….. Least Mean Square

LP ……………………………………………………………….Linear prediction

LS-CMA ………………………………………Least Square constant module algorithm

LSM……………………………………………………….. Least Square Method

MI-NLMS…………………………….. Matrix Inversion Normalized Least Mean Square

ML ……………………………………………………………Maximum likelihood

MMSE……………………………………………………Minimum Mean-Squared Error

MSR ………………………………………………………...Mean Square Error

MSINR………………………………..Maximum Signal-to-Interference-plus-Noise ratio

MRVSS ………………………………………..Modified Robust Variable step size LMS

MUSIC…………………………………………………. Multiple Signal Classification

MVDRE…………………………Minimum Variance Distortionless Response Estimator

NLMS……………………………………………………..Normalized Least Mean Square

SMI………………………………………………………… Sample Matrix Inversion

SNR…………………………………………………………Signal-to-Noise Ratio

SINR…………………………………………….. Signal to Interference and Noise ratio

SCORE ……………………………………Spectral Self-Coherence Restoral algorithms

RF ………………………………………………………………. Radio Frequency

RLS………………………………………………………………..Recursive Least square

ULA ……………………………………………………………Uniform Linear Array

TEW………………………………………………..Transverse Electromagnetic Wave

Abstract

As the growing demand for wireless 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. Smart antennas combine the antenna array with signal processing to optimize automatically the beam pattern in response to the received signal. Beam forming is the method used to create the radiation pattern of the antenna arrays by adding constructively the phase of the signals in the direction of desired targets and Nulling the pattern of undesired targets.

One of the central motivations for this work comes from the observed performance degradation due to angle separation between the desired and interferer signals. This is one of the challenges that face workers in the smart antenna system. In fact, the main objective of this work is to study and recommend Antenna parameters and adaptive algorithm which can reduce the effect of angle separation. In addition effect of angle separation on the Bore sight and Nulling, comparison of Adaptive Beamfoming algorithms: LMS, SMI and RLS based on angle difference presented herein. Furthermore, the paper presents array parameters and algorithms to combat the effects of angle separation on the overall system.

Adaptive Beamforming algorithms such as: LMS, DMI and RLS are studied based on angle separation for different combination of array parameters. All the three algorithms performance degrades when the separation becomes narrow. Increasing number of array and spacing between array elements alleviate these problems but it increase computational complexity and introduce grating lobes. Among these algorithms LMS algorithm has low computational complexity and less grating lobes, so LMS algorithm which works based on angle separation is an excellent solution to this performance degradation.

Chapter 1: Introduction

1.1 Motivation and Background

The increasing demand for wireless communication services without a corresponding increase in Radio frequency (RF) spectrum allocation and a better performance motivates the need for new techniques to improve spectrum utilization and system performance. Consequently, future wireless applications are characterized by a better performance and adaptive. Traditionally fixed beam forming is employing at the base station of wireless communication system which has a drawback of system performance and lack of adaptive techniques. One approach for increasing these requirements uses spatial processing with adaptive antenna array [2], [6], and [13].

A smart antenna is an antenna array system that is aided by a processing system that processes the signals received by the array or transmitted by the array using suitable array algorithms to improve wireless system performance. A smart antenna system consists of an antenna array, associated RF hard ware, and a computer controller that changes the array pattern [2]. Smart antennas have two main functions: direction of arrival estimation (DOA) and Beamforming.

Beam forming is the method used to create the radiation pattern of the antenna arrays by adding constructively the phase of the signals in the direction of desired targets and nulling the pattern of undesired targets. In Beamforming, both the amplitude and phase of each antenna elements are controlled. Combined amplitude and phase control can be used to adjust side lobe levels and steer nulls better than can be achieved by phase control alone.

Specifically when the desire and the interferer signal have the same frequency, but having spatial deference, a better way to cancel the interferer, steer the beams towards the desire direction and to enhance signal to noise ratio is Beamforming [1]. Adaptive beam forming techniques dynamically adjust the array pattern to optimize some characteristic of the received signal. There are two types of beam forming: Fixed beam forming and adaptive beam forming. Both types use beam forming algorithms to adjust their weights. The weights of fixed Beamformer are pre-designed and it does not change in application, whereas the adaptive beam former automatically adjust its weight according to the environment. The adaptive beam forming algorithm takes the fixed beam-forming process one step further and allows for the calculation of continuously updated weights. The adaptation process must satisfy a specified optimization criterion.

Smart antennas are currently used in wireless communication system to provide interference mitigation and enhance user capacity, data rates. Current applications of smart antennas are predominately at cellular base station due to area and processing power requirement.

1.2 Problem statement

The purpose of, almost, all beam forming algorithms are to adjust the weight of beam former that the array pattern is adjusted according to the signal of interest. Although smart antenna system has numerous advantageous compared to traditional Beamforming arrays, it has limitations on the performance characteristics like computational complexity, speed of convergence, beam steering ability, nullifying capability and side lobe level.

Beam forming algorithms such as: Least mean square (LMS), Recursive least square (RLS), Normalized least mean square (NLMS) and the like are analyzed intensively. Speed of convergence, beam steering ability, nullifying capability and other performance measurements criterion are analyzed for those algorithms and suggestions are made that which one is best according to an application.

Most of the previous works uses fixed DOA of both the desire and the interferer signal for their analysis purpose. In addition to this they assume that the angle separations between the signals are large enough. However does array performance criterions and algorithms which are analyzed more for fixed DOA for large angle separation always perform well or the same for different angle of separation? What is the effect small angle separation on the Boresight and Nulling? And also which algorithm and array parameters perform well for small angle of separation? Such types of investigations are very important for antenna designer to set array parameters and select an adaptive Beamforming algorithm depending on the required conditions.

This work tries to investigate the effect of angle separation on the Bore sight and Nulling points , comparing adaptive Beamforming algorithms and suggest a possible solution to reduce the performance degradation due to angle difference between the desired and interferer signal.

1.3 Objectives of the thesis

1.3.1 General Objective

The general objective of this thesis work is to investigate adaptive Beamforming algorithms for smart antenna system and to recommend the best algorithm and parameter based on different criterion.

1.3.2 Specific Objective

Specifically the aim of this thesis is to:

- Investigate the effect of angle separation on the performance of smart antenna system for a given adaptive algorithm (Bore sight, Nulling and side lobe level).
- Study the effect of varying number of array and spacing between array elements on the system performance based on angle separation.
- To study the performance of the recommend algorithm and array parameter based on angle separation (beam steering ability, nullifying capability and side lobe level).
- Performance comparison of different adaptive Beamforming algorithms LMS, RLS and DMI (computational complexity, beam steering ability, nullifying capability, and side lobe level)

1.4 Methodology

The methods to be employed to achieve the objectives of the research are:

- **Literature review**: includes reading books, articles, simulation tools and other resources related to the topic.
- **System modeling:** involves the formulation of smart antenna systems that is used in this thesis work.
- **Simulation:** involves simulating the modeled communication system using beam forming algorithms and MATLAB.
- **Analysis and Interpretation of the results:** the results obtained from the simulation results analyzed and compared based on performance analysis criteria's.

1.5 Review of related works

So far a number of research papers have been published regarding on smart antenna system. Most of the works mainly focus on either comparing the available algorithm based on different performance criterion [3],[4],[10],[18] ,[19] or developing the new one or modifying the available algorithm to make it robust against any steering and signal vector error and to enhance the performance of the system[8],[11],[14],[15]. An algorithm with less complexity, low computational cost, good convergence rate, robust to signal and steering vector error, steer the main lobe towards the signal of interest is usually preferred [3].

The performance of adaptive beam forming algorithm such as: Least mean square, Matrix inversion normalized least mean square (MI-NLMS), Recursive least square, Constant module algorithm (CMA), Least square constant module (LS-CMA), Constrained Kalman, unconstrained and robust Kalman are studied in [3]. These adaptive algorithms are analyzed based on computational complexity, cost of implementation, beam steering ability, nullifying capability, side lobe level, beam pattern and amplitudes for different channel types. Simulation results show that LMS has low speed of convergence, successfully steer the main lobe of antenna array towards the desired signal but unsatisfactory to nullify the interference compared to the other. The other adaptive algorithms have fast speed of convergence and forming deep nulls but high computational cost. However under any environmental change except robust Kalman the performance of the system degrades. Thus the paper recommended that robust Kalman is a good choice among those robust adaptive beam forming algorithms.

Training sequence algorithms RLS, LMS, and CMA are analyzed in [4]. In addition to criterion in [3], error plot, BER and the effect of changing step size are also considered. Simulation results show that besides the computational complexity RLS has the best performance under the above performance criterions. Thus the paper proved that RLS is the best algorithm among those for base station smart antenna system.

LMS and NLMS are studied in [10] and [18] based on computational complexity, stability under variation of weight, interference rejection, beam steering ability and speed of convergence as a criteria. Simulation results show that LMS has less speed of convergence, less computational cost, good response towards the desired direction and better capability to place null towards the interferer compared to NLMS. Thus LMS is preferred for such types of condition. NLMS has high computational cost however it has high stability as a variation of weights and high speed of convergence. Hence here NLMS is preferred.

LMS, SMI, RLS, CMA and LS-CMA are studied in [19]. Number of iteration required to converge and half power beam width are used for analysis purpose. Simulation result revealed that LS-CMA is the best among the above adaptive Beamforming algorithms for smart antenna base station for cellular communication network.

[11] Presents a novel adaptive Beamforming algorithm the MI-NLMS for smart antenna system which combines the NLMS and sample matrix inversion algorithm (SMI) to improve the convergence speed with small bit error rate and (BER). Simulation result showed that the MI-NLMS algorithm provides remarkable improvements in terms of interference rejection, convergence rate and BER over those of LMS and NLMS algorithms.

[14] Proposed robust capon Beamformer and showed that RCB belongs to the class of diagonal loading approach but the amount of diagonal loading can be precisely calculated based on the uncertainty of the steering vector. Simulation results showed that the proposed robust capon Beamformer can be efficiently performs upon different array steering vector error.

Reference [15], presented a different approach to achieve fast convergence rate with an LMS based algorithm. The proposed least mean square-least mean square algorithm involves the use of two LMS algorithm section. The speed of convergence of the proposed algorithm is compared with LMS, constrained-stability least mean square (CS-LMS) and modified robust variable step size LMS (MRVSS) in Rayleigh fading and AWGN channel. Simulation results showed that the proposed algorithm has rapid convergence, typically within a few iterations. The superior performance of the proposed LLMS algorithm has been achieved with a complexity larger than twice the conventional LMS algorithm schemes and this complexity is lower than MRVSS and NLMS, and also LLMS remains stable even its reference signal is corrupted AWGN.

[5] Proposed a novel techniques and architecture for adaptive Beamforming. This self-calibration technique solving the problem associated performance degradation due to errors in the calibration of the array. [8] Consider the problem of null-steering Beamforming using neural approach for smart antenna system.

[1] Compares the performance of LMS adaptive Beamforming algorithm with respect to antenna array size, elements forming this array, physical spacing and the signal environment parameters are analyzed in terms of the number of signals incident on the antenna array and their angular separation. Simulation results showed that the performance LMS adaptive Beamforming improves as more are used in the antenna array. The improvement is seen in the form of sharper beams directed towards the desire users. Regarding the spacing between the antenna elements, it was reported that using small or large spacing values could degrade the performance, an element spacing values of 0.5λ was found to be a good values that to ensure successful performance of the LMS Beamformer. The effect of incident signals on the antenna array has been studied too and

it was concluded that the performance of the Beamformer degrades as more signals are incident on the linear array.

[2], [6] and [16] studies how antenna array used in communication system and suggest ways of improving system performance. [9], [12] and [16] analyzed how smart antenna system estimates the direction of arrival of the signal using different techniques such as: MUSIC, ESPRIT and compares these algorithms to suggest which one are best under a given circumstance.

Basically, this works mainly focuses on studying the effect of angle separation on the performance criterions (Boresight and Nulling) which are not analyzed more based on varying the array parameters for smart antenna system. Such types of issues need to be analyzed more to recommend an algorithm and array parameters which is best, under a given performance criterion.

1.6 Assumptions taken and notation used in this thesis

- There are M directional source
- The signals are uncorrelated
- The medium is homogenous
- The array consists of identical distortion free element
- Equ-spaced element spacing between arrays (d)
- The first element is situated at the origin
- The signals are narrow bands
- There are L linear array in the system
- The effect of the propagation from a source to an element is a pure time delay.

1.7 Contribution of the thesis

Some of the major contributions of the thesis are listed below

- Studies the performance of adaptive Beamforming algorithm such as: RLS, DMI and LMS based on angle of separation between the desire and the interferer signal(bore sight, nulling and side lobe level)
- Studies the effect of spacing and number of array for different angle of separation on the performance of smart antenna system.
- Studies the trade of between increasing number of array and spacing on the performance of the adaptive array system in various angle of separation.
- Recommending the adjustment of the available algorithm and selecting array parameters based on angle separation to enhance the system performance

1.8 Organization of the thesis

The remainder of the thesis is organized as follows: In chapter 2 fundamental of antenna and antenna arrays are described and mathematical analysis of the array factor used in the thesis is provided. Chapter 3 presents brief introduction of fundamental of smart antenna system and beam forming along with their system and signal model is described. Similarly, Chapter 4 introduce adaptive Beamforming algorithm used in this thesis.

In Chapter 5 simulation results of the adaptive Beaforming algorithm, effect of array parameter for different angle of separation and the performance the recommended algorithm and array parameters are studied. Most of the simulation results are array factor versus angle of arrival, and bore sight and nulling versus angle of arrival characteristics, which are used to compare performance of different adaptive beam forming algorithm and array parameters. Finally, in Chapter six, conclusions based on the results obtained and recommendations to future works are given.

Chapter 2: Fundamentals of Antenna and Antenna Arrays

2.1 Introduction

In the previous chapter, introduction and literature review of works related to adaptive Beamforming algorithm for smart antenna system were briefly discussed. In this chapter, basics of antenna, antenna array and signal model of uniform linear array are discussed. The chapter is organized as follows.

In section 2.2 fundamentals of antenna and brief discussion of basics of antenna parameters are provided. In section 2.3 antenna arrays and signal model of uniform linear array along with its system model are described. Basics parameters of antenna arrays such as: array factor, beam steering, array geometry and element spacing briefly described in section 2.4. Finally types of antenna based on their purpose discussed in section 2.5.

2.2 Basics of antenna

An antenna is one of the most critical components in wireless communication systems. As stated by Balanis [24] in a review on antennas, an antenna is a transducer that converts guided electromagnetic waves from transmission lines to a free space unbounded wave in its transmission mode and converts free space waves to guided waves in its reception mode. It demonstrates a property known as reciprocity, which means that an antenna will maintain the same characteristics regardless if it is transmitting or receiving.

In addition to receiving or transmitting energy, an antenna in an advanced wireless system is usually required to optimize or accentuate the radiation energy in some directions and suppress it in others. Thus the antenna must also serve as a directional device in addition to a probing device .There are different types of antenna. The isotropic point source radiator, one of the basic theoretical radiators, is useful because it can be considered a reference to other antennas. The isotropic point source radiates equally in all direction in free space. Based on their geometrical arrangement antenna can be classified as: linear, planer and circular. Here some important parameters are defined that are basic and related to every type of antenna.

2.2.1 Radiation pattern

The radiation or antenna pattern describes the relative strength of the radiated field in various directions from the antenna, at a constant distance. The radiation pattern is a reception pattern as well, since it also describes the receiving properties of the antenna. The radiation pattern is three-dimensional, but usually the measured radiation patterns are a two dimensional slice of the three-dimensional pattern, in the horizontal or vertical planes. These pattern measurements are presented in either a rectangular or a polar format. The radiation pattern consists of a main lobe where the intensity is maximum and some side lobes that are pointed at different directions and don't contribute to the antenna performance.

The radiation pattern in the region close to the antenna is not the same as the pattern at large distances. The term near-field refers to the field pattern that exists close to the antenna, while the term far field refers to the field pattern at large distances. The far field is also called the radiation field, and is what is most commonly of interest. Ordinarily, it is the radiated power that is of interest, and so antenna patterns are usually measured in the far-field region. The following figure shows a rectangular plot presentation of a typical linear Antenna.

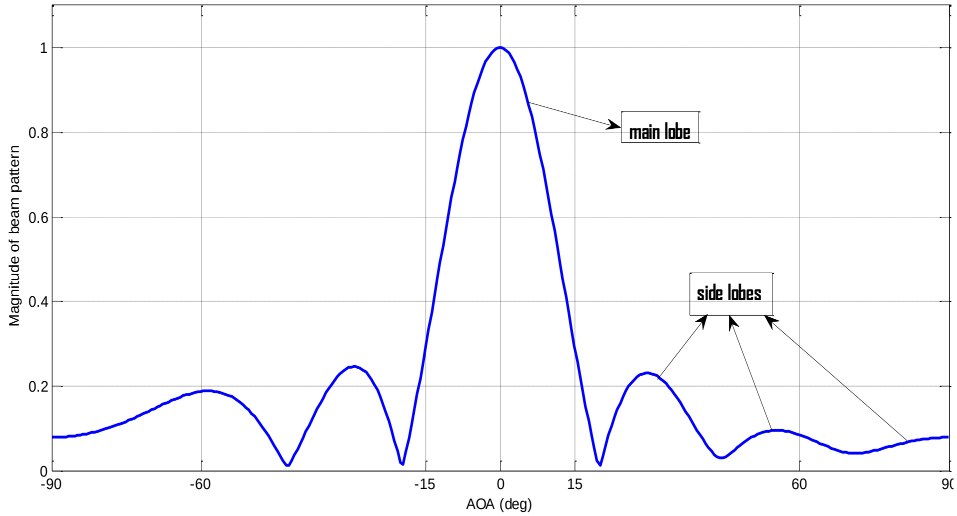

Figure 2.1 Rectangular plot of radiation

2.2.2 Beam width

An antenna's beamwidth is usually understood to mean the half power beamwidth. The peak radiation intensity is found and then the points on either side of the peak which represent half the power of the peak intensity are located. The angular distance between the half power points is defined as the beamwidth. Half the power expressed in decibels is 3dB, so the half power beamwidth is sometimes referred to as the 3dB beamwidth. Both horizontal and vertical beamwidths are usually considered. Assuming that most of the radiated power is not divided into side lobes, and then the directive gain is inversely proportional to the beamwidth: as the beamwidth decreases, the directives gain increases.

2.2.3 Side lobes and nulls

No antenna is able to radiate all the energy in one preferred direction. Some energy is inevitably in other direction with lower levels than the main lobe. The smaller peaks are referred to as side lobes, commonly specified in db down from the main lobe.

In an antenna radiation pattern, a null is a zone in which the effective radiated power is at a minimum. A null often has a narrow directivity angle compared to that of the main beam. Thus, the null is useful for several purposes, such as suppression of interfering signals in a given direction.

2.2.4 Bore sight

The antenna bore sight is the intended physical aiming direction or the location at where the radiation pattern needs to be maximized. In other words, it is the normally intended direction for maximum radiation.

2.2.5 Plane Waves

A plane wave is not an antenna parameter; it is a transverse electromagnetic (TEM) wave having constant amplitude and phase in an infinite plane in space at an instant in time. A TEM wave has the electric and magnetic fields orthogonal to the direction of propagation. The plane wave travels in the direction orthogonal to the plane. Thus, a plane wave is described by a vector or an angle of propagation and magnitude and phase of the field in the plane.

2.2.6 Directivity and Gain

Directivity is the ability of an antenna to focus energy in a particular direction when transmitting, or to receive energy better from a particular direction when receiving. In a static situation, it is possible to use the antenna directivity to concentrate the radiation beam in the wanted direction. However in a dynamic system where the transceiver is not fixed, the antenna should radiate equally in all directions, and this is known as an omni-directional antenna.

Gain is not a quantity which can be defined in terms of a physical quantity such as the Watt or the Ohm, but it is a dimensionless ratio. Gain is given in reference to a standard antenna. The two most common reference antennas are the isotropic antenna and the resonant half-wave dipole antenna. The isotropic antenna radiates equally well in all directions. Real isotropic antennas do not exist, but they provide useful and simple xvi theoretical antenna patterns with which to compare real antennas. Any real antenna will radiate more energy in some directions than in others. Since it cannot create energy, the total power radiated is the same as an isotropic antenna, so in other directions it must radiate less energy.

The gain of an antenna in a given direction is the amount of energy radiated in that direction compared to the energy an isotropic antenna would radiate in the same direction when driven with the same input power. Usually we are only interested in the maximum gain, which is the gain in the direction in which the antenna is radiating most of the power. An antenna gain of 3 dB compared to an isotropic antenna would be written as 3 dBi. The resonant half-wave dipole can be a useful standard for comparing to other antennas at one frequency or over a very narrow band of frequencies

2.2.7 Polarization

Polarization is defined as the orientation of the electric field of an electromagnetic wave. Polarization is in general described by an ellipse. Two special cases of elliptical polarization are linear polarization and circular polarization. The initial polarization of a radio wave is determined by the antenna.

2.3 Antenna arrays

An antenna array is a set of antenna elements arranged in space whose outputs are combined to give an overall antenna pattern that can differ from the pattern of the individual elements [24]. An array can achieve the same directional performance of a larger antenna by trading the electrical problems of combining several antenna outputs for the mechanical problems of supporting and turning a large antenna. By varying the phase and amplitude of the individual element outputs before combining, the overall array pattern can be steered in the desired user's direction without physically moving any of the individual elements. The overall radiation pattern of an array is determined by the radiation pattern of the individual elements, their positions, orientations in space, and the relative phase and amplitudes of the feeding currents to the elements and amplitudes of the feeding currents to the elements.

By the principle of pattern multiplication, the overall radiation pattern form is found as the product of the individual element radiation patterns with the array factor. The array factor is in turn determined by the relative positions of the elements in space as well as the relative phase and amplitude levels of the feeding currents to the elements. An array of antenna performs better compared to the single antenna element. It can steer the beams and put nulls in the desire and interfere point accordingly the need of the user. Arrays of antennas can have any geometric shapes such as: linear, planer and circular. One of the simplest geometries for an array is a linear array in which the centers of the antenna elements are aligned along a straight line as shown the figure below.

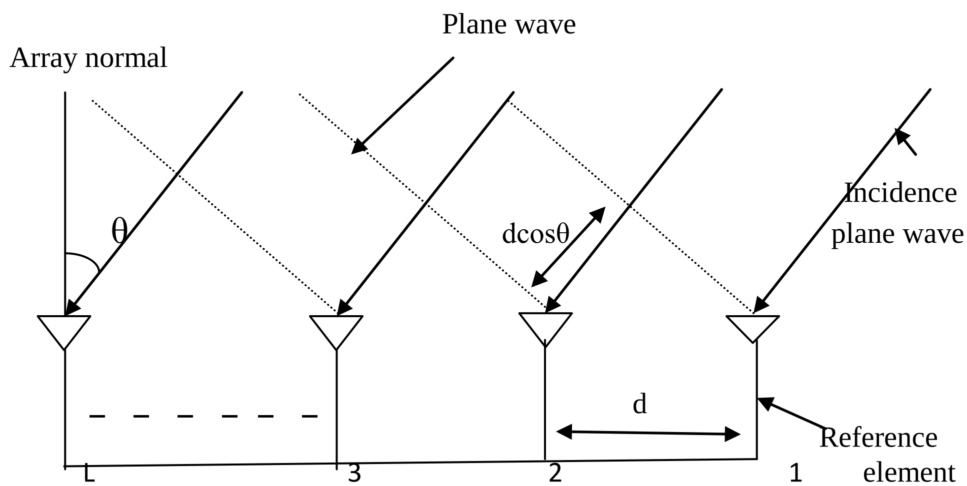

Figure2.2 Uniformly spaced linear antenna

2.3.1 Signal model of uniform linear array

The basic setup of an arbitrary antenna array is shown in the figure above. For this arrangement and if we assume the array is located in the far field of directional sources , the directional signal incident on the array can be considered as a plane wave front. Also assume that the plane wave propagates in a homogeneous media and that the array consists of identical distortion-free Omni-directional elements,

The time taken by a plane wave arriving from the k^{th} source to an element in a direction θ_k and measured from the i^{th}element to the origin is given by [21].

$$\tau\,(\theta_k)\ = \frac{d}{c} * (i-1)\ cos\ \theta_k \qquad \text{……………………. (2.1)}$$

Where d is the spacing between the arrays and c is the speed of light.

And the signal induced on the i^{th} element due to the k^{th} source can be expressed

$$X_i(t) = M_k(t)\, e^{j2\pi f_o\left(t+\tau(\theta_k)\right)} \qquad \text{………………..} \quad (2.2)$$

Where f_o is denotes the carrier frequency and $M_k(t)$ the complex modulating is function and can take different forms, and for narrow band signals assumption $M_k(t)$=$M_k(t+\tau)$.

The signal induced due to all M directional sources and back ground noises on the i^{th} element is given by

$$X_i(t) = \sum_{K=1}^{M} M_k(t) e^{j2\pi f_o\left(t+\tau(\theta_k)\right)} + n_i(t) \;\text{…………………} \quad (2.3)$$

Where n_i(t) is random noise component on the lth element, which includes background noise.
Using vector notation the signal induced on all elements, the weights and noise respectively

$$\boldsymbol{X(t)} = [x_1(t), x_2(t), \dots \dots \dots.., x_L(t)]^{\boldsymbol{T}} \;\text{……………………….} \;(2.4)$$

$$\boldsymbol{W} = [\, w_{1,} w_2, \dots \dots \dots \dots \dots.., w_L] \quad \text{………………………….} \;(2.5)$$

$$\boldsymbol{n}\,(\boldsymbol{t}) = [n_1\ (t), n_2(t), \dots \dots \dots, n_L(t)]^T \;\text{...................................} \;(2.6)$$

Defining the steering vector as L- dimensional complex vector containing response of all elements of the array to a narrow band source denoted by $\boldsymbol{S_k}$ which is associated with the K^{th} source for array of identical element ,

$$\boldsymbol{S_k} = \big[exp\,[2\Pi f_o \tau_1(\theta_k)]\,, exp[\,2\Pi f_o \tau_2(\theta_k)], \dots \dots, exp\,[2\Pi f_o \tau_L(\theta_k)]\,\big] \;\text{…….. } (2.7)$$

By substituting equation (2.3) into (2.4) and using (2.7) the signal vector can expressed compactly as

$$\boldsymbol{X}\,(\boldsymbol{t}) = \sum_{\mathbf{k=1}}^{\mathrm{M}} M_{\boldsymbol{k}}\,(t)\ \boldsymbol{S_k} + \boldsymbol{n}\,(t) \qquad \text{...………………………..} \;(2.8)$$

2.4 Basic parameters of antenna array

2.4.1 Array factor (A.F)

The radiation pattern of antenna array is given by the product of array factor and element factor. If we assume all elements radiates in all direction equally, the radiation pattern is equal to the array factor. Consider figure 2.2 and assuming far field conditions such that *r* >>*d*, we can derive the array factor as follows:

$$A.F=\sum_{l=1}^{L} e^{j2\pi f_o(\tau(\theta_k))} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (2.9)$$

Substituting equation (2.1) into (2.9)

$$A.F= 1+ e^{j2\pi f_o(\frac{d}{c}* \cos\theta_k)} + e^{j2\pi f_o(2\frac{d}{c}* \cos\theta_k)} +\ldots + e^{j2\pi f_o((L-1)\frac{d}{c}* \cos\theta_k)}$$

$$= 1+ e^{j(k\cos\theta_k)}+ e^{j(2k\cos\theta_k)}+\ldots\ldots\ldots\ldots+ e^{j((L-1)k\cos\theta_k)} \quad \ldots\ldots\ldots\ldots\ (2.10)$$

Where K= $\frac{2\Pi f_0}{\lambda}$

The expression is for the array system which all elements fed with the same current and this determine the beam pattern of the given array system.

2.4.2 Beam Steering

For a given array the beam may be pointed in different directions by moving the array mechanically. This is known as mechanical steering. Beam steering can also be accomplished by appropriately delaying the signals before combining. The process is known as electronic steering, and no mechanical movement occurs. For narrowband signals, the phase shifters are used to change the phase of signals before combining. When processing is carried out digitally, the signals from various elements can be sampled, stored, and summed after appropriate delays to form beams. The required delay is provided by selecting samples from different elements such that the selected samples are taken at different times. Each sample is delayed by an integer multiple of the sampling interval; thus, a beam can only be pointed in selected directions when using this technique

2.4.3 Array geometry and element spacing

Spacing between the antenna elements is an important factor in the design of an antenna array. Grating lobes appears in the antenna pattern if the elements are more than $\lambda/2$ apart, where λ is the wavelength of the signal which is given by $3 \times 10^8/fc$, fc is the carrier frequency [1]. Mutual coupling is an effect that limits the inter-element spacing of an array. If the elements are spaced closely, the coupling effects will be larger and generally tends to decrease with increase in the spacing. The mutual coupling effect depends on the array geometry and the radiation pattern of element in the array. For $d < \lambda/2$ the mutual impedance tends to increase considerably, so it is advisable to maintain at least $\lambda/2$ spacing between arrays of dipoles. Therefore the elements have to far enough to avoid mutual coupling and the spacing have to be smaller than $\lambda/2$ to avoid grating lobes.

2.5 Types of antenna elements based on their purpose

2.5.1 Optimal Antenna

An antenna is optimal when the weight of each antenna element is adjusted to achieve optimal performance of an array system in some sense [21]. For example, assume that a communication system is operating in the presence of unwanted interferences. Furthermore, the desired signal and interferences are operating at the same carrier frequency such that these interferences cannot be eliminated by filtering. The optimal performance for a communication system in such a situation may be to maximize the signal-to-noise ratio (SNR) at the output of the system without causing any signal distortion. This would require adjusting the antenna pattern to cancel these interferences with the main beam pointed in the signal direction. Thus, the communication system is said to be employing an optimal antenna when the gain and the phase of the signal induced on each element are adjusted to achieve the maximum output SNR (sometimes also referred to as signal to interference and noise ratio, SINR).

2.5.2 Smart antenna

The term smart antenna incorporates all situations in which a system is using an antenna array and the antenna pattern is dynamically adjusted by the system as required [20]. Thus, a system employing smart antennas processes signals induced on a sensor array. The type of sensors used and the additional information supplied to the processor depend on the application. For example, a communication system uses antennas as sensors and may use some signal characteristics as additional information. The processor uses this information to differentiate the desired signal from unwanted interference.

Chapter 3: Fundamentals of Smart Antenna

3.1 Introduction

Smart antenna is a combination of antenna array elements connected in such a way that when each element is activated the radiation pattern created change accordingly [23]. The term 'smart' refers to the antenna array system that can adapt its radiation pattern according to the need of the user based on the criterion. This is done by multiplying each array output by the complex weight that is present in smart antenna system. The complex weight is obtained in many different ways, but for the case of smart antenna it should be adaptive. This means that the complex weights are not fixed, its value varies based on the specific direction of the signals. The adaptation can be achieved when the array is transmitting and receiving. This chapter briefly reviews some of fundamentals of Beamforming and smart antenna with their mathematical model.

The chapter is organized as follows: in section 3.2 basics and use of smart antenna are discussed in brief. In the sub section of this chapter Beamforming, estimation of direction of arrival, optimal criterion for weight estimation and general system model of smart antenna system along with its mathematical description are presented.

3.2 Smart Antenna

Smart Antenna systems provide numerous major benefits in wireless communications environments. These include reducing multipath fading, increasing system capacity, extending battery life of the terminals and the range of a base station [25]. The smart/adaptive antenna refers to any antenna array that can adjust or adapt its beam pattern toward the desired signal and nulls toward interfering signals with the means of sophisticated signal processing algorithm. Adaptive arrays have the capabilities to steer the beam at any direction of interest and simultaneously steering the pattern nulls toward the interfering signal. If we assume the beam pattern of the adaptive antenna to be an inflated balloon on a child's hand, then the algorithm performs the function of the child's hands squeezing the balloon to any form factor. This means the antenna can form multiple adaptive main lobes as well as multiple adaptive nulls. This flexibility of the beam pattern by the adaptive antenna array is obtained by the complex weight vectors generated from the adaptive Beamformer. The smart antenna concept is opposed to the fixed-beam dumb antenna, which does not attempt its radiation pattern to be adjusted to the ever-changing electromagnetic environment

Smart antennas have two main functions: beam forming and estimation of direction arrival (DOA). Beam forming is the method used to create the radiation pattern of the antenna arrays by adding constructively the phase of the signals in the direction of desired targets and nulling the pattern of undesired targets. In Beamforming, both the amplitude and phase of each antenna elements are controlled. Combined amplitude and phase control can be used to adjust side lobe levels and steer nulls better than can be achieved by phase control alone. Smart antenna system estimates the DOA in many different ways.

3.3 Beamforming

A Beamformer is an array of sensors which can do spatial filtering. The objective is to estimate the signal arriving from the desired direction in the presence of noise and other interfering signals. A Beamformer does spatial filtering in the sense that it separates two signals with overlapping frequency content originating from different directions [13]. Spatially propagating signals encounter the presence of interfering signals and noise signals. If the desired signal and the interferers occupy the same temporal frequency band, then temporal filtering cannot be used to separate the signal from the interferers. The optimum Beamforimng algorithm works if R and r available and the direction of arrival (signal environment) is not changing. However in practice these may not appear always, so the task of adaptive Beamforming is estimating the optimal weight for rapidly changing Chanel state and DOA. Adaptive Beamforming algorithms iteratively approximate these optimum weights

However the desired and the interfering signals generally originate from different spatial locations. This spatial separation can be exploited to separate the signals from the interference using a Beamformer. The output of each sensor is properly filtered and the filtered outputs of all the sensors are added up. Typically a Beamformer linearly combines the spatially sampled waveform from each sensor. Typical uses of Beamforming arise in RADAR, SONAR, communications, imaging, Geophysical exploration, Biomedical and also in acoustic source localization. Beamforming is the process by which the information, obtained from the signals incident on an antenna array, are used to generate an optimum pattern which maximizes the radiated power towards the intended users and minimizes it, in the form of radiation nulls, towards interferers [1]. The objective of Beamforming is to separate the desired signal from interfering signals, given that they have the same frequencies but different spatial locations. Interfering signals can be the delayed version of the desired one. A Beamformer consists of an array of sensors in a particular configuration as shown in figure below.

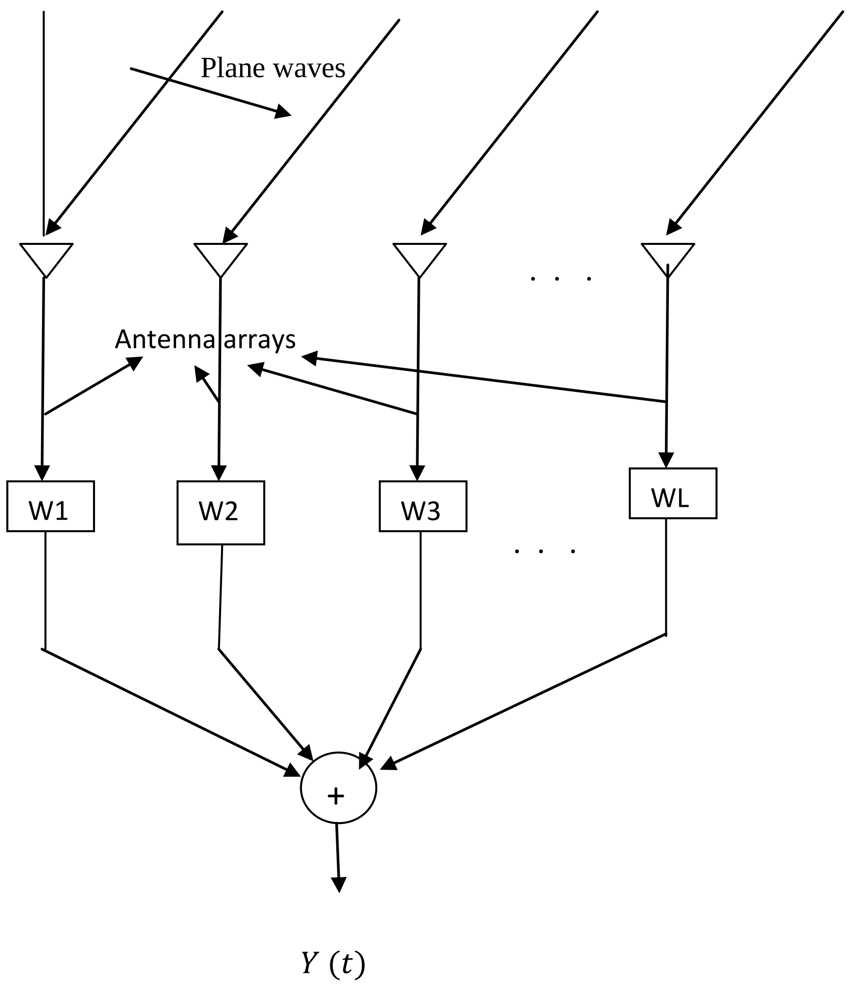

Figure 3.1 A general Beamformer system

The output of the smart antenna system can be given by the following expression

$$Y\ (\boldsymbol{t}) = \boldsymbol{W}^{\boldsymbol{H}}.\boldsymbol{X}\ (t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\quad (3.1)$$

Substituting equation (2.8) into (3.1)

$$Y\ (t)\ =\ \sum_{\boldsymbol{k=1}}^{\boldsymbol{M}} \boldsymbol{M}_{\boldsymbol{k}}\ (t)\ \ \boldsymbol{W}^{\boldsymbol{H}}\boldsymbol{S}_{\boldsymbol{k}}\ \ +\ \boldsymbol{W}^{\boldsymbol{H}}\ \boldsymbol{n}\ (t)\ \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ (3.2)$$

Where $\boldsymbol{W}^{\boldsymbol{H}}$ is the complex weights which adjust the beam pattern.

The first term in equation (3.2) is the contribution from all directional sources and the second term is the random noise contribution to the array output. The weights of the array system determine system performance. The selection process of these weights depends on the application and leads to various types of Beamforming schemes. The weights of the array system determine system performance. The selection process of these weights depends on the application and leads to various types of Beamforming schemes.

3.3.1 Criteria for Optimal Beamforming

An adaptive Beamformer is able to adjust the weight on each antenna element based on the statistics of the array data. In general, it adjusts the weight vector such that it places nulls in the direction of interfering signals in an attempt to maximize the SNR at the Beamformer output. Since the statistics of the array data may not be known and may change over time, adaptive algorithms are typically employed to determine the weights. Most adaptive Beamforming algorithms involve iterative process to adjust the weights until a certain performance criterion is met. The most common performance criteria are the minimum mean-squared error (MMSE) and maximum signal-to-interference-plus-noise ratio (MSINR). An antenna is optimal when the weight of each antenna element is adjusted to achieve optimal performance of an array system in some sense.

3.3.1.1 Minimum Mean-Square Error

The shape of the desired received signal waveform is known by the receiver. Complex weights are adjusted to minimize the mean-square error between the Beamformer output and the expected signal waveform. The antenna elements are spaced a uniform d distance apart. To develop system model we need to consider the following assumption. The signals induced in each array elements are narrow bands, uncorrelated and coupling is neglected A diagram of L element uniform linear antenna array with K impinging wave fronts is shown in Figure below.

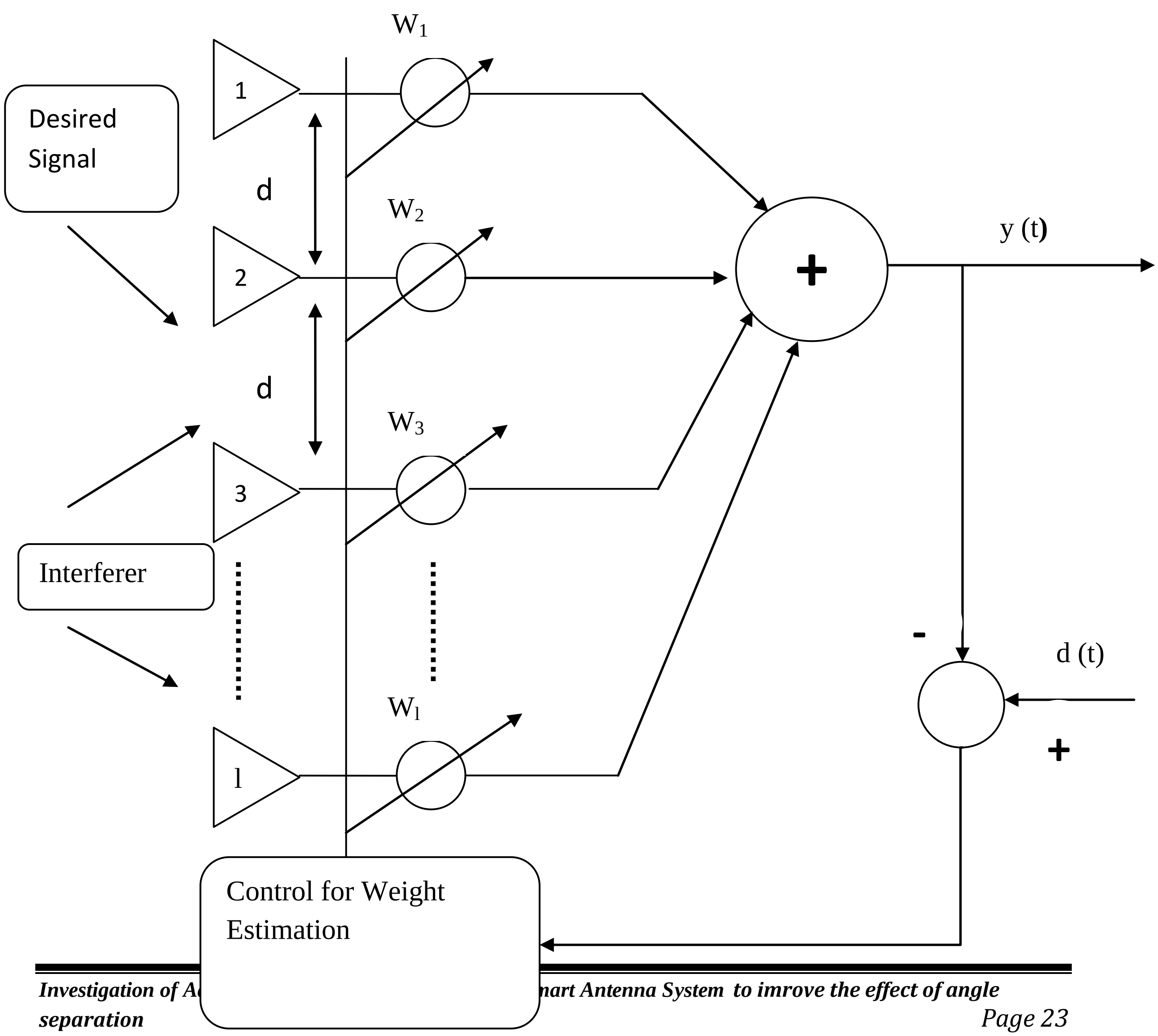

Figure 3.2 Typical Smart Antenna System

.

The error signal is given by [23].

$$E(t) = d(t) - y(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.3)}$$

Substituting equation (3.2) into (3.3)

$$= d(t) - \boldsymbol{W^H}.\boldsymbol{X}(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4)}$$

Then the square error is given by

$$= |\, d(t) - \boldsymbol{W^H}.\boldsymbol{X}(t)\,|^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.5)}$$

By inserting equation (2.8) into (3.5) and squaring we obtain

$$|\,E(t)\,|^2 = |\,d(t)\,|^2 - 2 \times d(t)\,\boldsymbol{W^H}.\boldsymbol{X}(t) + \boldsymbol{W^H}.\boldsymbol{X}(t).\boldsymbol{X}(t)^{\boldsymbol{H}}.\boldsymbol{X}(t) \quad \ldots\ldots \text{(3.6)}$$

Taking the expected value of both sides and simplifying the expression we get

$$\boldsymbol{E}[|\,\boldsymbol{E}(t)\,|^2] = \boldsymbol{E}[\,|\,\boldsymbol{d}(t)\,|^2 - 2 \times \boldsymbol{d}(t)\,\boldsymbol{W^H}.\boldsymbol{X}(\boldsymbol{t}) + \boldsymbol{W^H}.\boldsymbol{X}(t).\boldsymbol{X}(\boldsymbol{t})^{\boldsymbol{H}}.\boldsymbol{X}(t)] \ldots \text{(3.7)}$$

$$\boldsymbol{J}(\boldsymbol{w}) = \boldsymbol{E}[\,|\,\boldsymbol{d}(t)|^2] - 2\boldsymbol{W^H}\boldsymbol{r} + \boldsymbol{W^H}\boldsymbol{R}_{xx} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.8)}$$

Where $\boldsymbol{r} = \boldsymbol{E}[\boldsymbol{d}^*.\boldsymbol{x}]$ is the correlation between the reference and induced signal

$\boldsymbol{R_{xx}} = [\boldsymbol{x}.\boldsymbol{x^H}]$ is the correlation matrix (correlation between the signals induced in each array elements)

Equation (3.8) is sometimes called cost function or performance surface. We can find the minimum value by taking the gradient of the MSE with respect to the weight vectors and equating it to zero. Thus the Wiener-Hopf equation is given as

$$\boldsymbol{W}_{opt} = \boldsymbol{R_{xx}}^{-1}\boldsymbol{r} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.9)}$$

It is interesting to note that all criterion leads similar solution of optimal antenna array weights which are differing in scalar multiplication to MMSE.

3.3.1.2 Maximum Signal-to-Interference-plus-Noise Ratio

In this performance criterion, the weights can be chosen to directly maximize the output signal to Interference-plus noise ratio (SINR) where the receiver can estimate the strengths of the desired signal and of an interfering signal; weights are adjusted to maximize the ratio. Once again consider figure 3.1where signals from each element are multiplied by a complex weight and summed to form the array output. The output power of the array at any time t is given by the magnitude square of the array output, that is

$$P(t) = |y(t)^2|$$

$$P(t) = y(t)y(t)^* \qquad \ldots\ldots\ldots\ldots \quad (3.10)$$

Substituting equation (3.1) into (3.10)

$$P(t) = \boldsymbol{W}^H \boldsymbol{X}(t)\, \boldsymbol{X}^{\mathrm{H}}(t)\, \boldsymbol{W} \qquad \ldots\ldots\ldots\ldots \quad (3.11)$$

And assuming $\boldsymbol{X}(t)$ is a zero mean stationary processes, then a given $\boldsymbol{W}$ the mean output power of the array system is obtained by taking the expectation over $\mathbf{X}(t)$

$$P(w) = E[\,|\boldsymbol{W}^H \boldsymbol{x}(t)|^2]$$

$$= E[\{\boldsymbol{W}^H\boldsymbol{x}(t)\}\{\boldsymbol{W}^H\boldsymbol{x}(t)\}^*]$$

$$= \boldsymbol{W}^H E[\boldsymbol{x}(t)\,\boldsymbol{x}(t)^H]\,\boldsymbol{w}$$

$$= \boldsymbol{W}^H \boldsymbol{R}\,\boldsymbol{w} \qquad \ldots\ldots\ldots\ldots \quad (3.12)$$

Where $\boldsymbol{R} = E[\boldsymbol{x}(t)\,\boldsymbol{x}(t)^H]$ is the array correlation matrix of the induced signal in each array elements. assume that there is a desired signal source in the presence of unwanted interference and random noise. Let $\mathrm{X}_s(t)$, $\mathrm{X}_I(t)$, and $\mathbf{n}$ (t), denote the signal vector due to the desired signal source, unwanted interference, and random noise respectively. The components of signal, interference, and random noise in the output y_s(t), y_I(t), and y_n(t) are then obtained by taking the inner product of the weight vector with Let $X_s(t)$, $X_I(t)$, and **n**(t) . These are given by

$$y_s(t) = \boldsymbol{W}^H X_s(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.13)}$$

$$y_I(t) = \boldsymbol{W}^H X_I(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.14)}$$

$$y_n(t) = \boldsymbol{W}^H \boldsymbol{n}\,(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.15)}$$

Define the array correlation matrices due to the signal source, unwanted interference, and random noise, respectively, as

$$\boldsymbol{R}_S(t)= E[X_S(t)X_S^H(t)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.16)}$$

$$\boldsymbol{R}_I(t)=E[X_I(t)X_I^H(t)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.17)}$$

$$\boldsymbol{R}_n(t) = E[\ n(t)n^H(t)] \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.18)}$$

$\boldsymbol{R}$ is the sum of these three matrices, that is

$$\mathbf{R}=\boldsymbol{R_S} + \boldsymbol{R_I} + \boldsymbol{R_n}$$

Let P_S, P_I and P_n denote the mean output power due to the signal source, unwanted interference, and random noise, respectively.

$$P_S = \boldsymbol{W}^H \boldsymbol{R}_S\ \boldsymbol{W} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.19)}$$

$$P_I = \boldsymbol{W}^H \boldsymbol{R}_I\ \boldsymbol{W} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.20)}$$

$$P_n = \boldsymbol{W}^H \boldsymbol{R}_n\ \boldsymbol{W} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.21)}$$

Let P_N denote the mean power at the output of the array contributed by random noise and unwanted interference, that is,

$$P_N = P_I + P_n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.22)}$$

P_N is also referred to as noise plus interference

Substituting from (3.19) and (3.20) in to (3.22)

$$P_N = \mathbf{W}^H \boldsymbol{R}_I \boldsymbol{W} + \mathbf{W}^H \boldsymbol{R}_n\ \boldsymbol{W}$$

$$P_N = \mathbf{W}^H (R_I + R_n)\, \boldsymbol{w} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.23)$$

Let R_N denote the noise array correlation matrix, that is,

$$R_N = R_I + R_n$$

Then P_N , the mean noise power at the output of the system can be expressed in terms of weight vector and R_N as

$$P_N = \mathbf{W}^H \boldsymbol{R}_N \boldsymbol{w} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.24)$$

Let the output signal to interference plus noise ratio (SINR), be defined as the ratio of the mean output signal power to the mean output noise power at the output of the array system, that is,

$$\text{SINR} = \frac{P_S}{P_N} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.25)$$

Substituting from (3.19) and (3.20) into (3.25)

$$\text{SINR} = \frac{\mathbf{W}^H R_S\, \boldsymbol{w}}{\mathbf{W}^H R_N \boldsymbol{w}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.26)$$

To maximize the output SINR, we take the derivative of equation with respect to $\mathbf{w}$ and set it to zero, which gives the following result:

$$R_S\, \boldsymbol{w} = \frac{\mathbf{W}^H R_S\, \boldsymbol{w}}{\mathbf{W}^H R_N \boldsymbol{w}}\, R_N \boldsymbol{w} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.27)$$

3.4 Estimation of direction of arrival

The smart antenna system estimates the direction of arrival of the signal, using techniques Spectral Estimation Methods and Eigen structure methods. Bartlett Method, Minimum Variance Distortion less Response Estimator, Linear Prediction Method, Maximum

Likelihood Method are some of spectral estimation methods and music methods, sprit method, CLOSEST Method, ESPRIT Method are included in Eigen structure methods.

3.4.1 Spectral Estimation Methods

These methods estimates the DOA of the incoming signal by computing the spatial spectrum *p(θ)* , that is the mean power received by an antenna array , as a function of direction of arrival *(θ)* and then determining the local maxima of this computed spatial spectrum .

3.4.1.1 Bartlett Method

This is the earliest method in which a rectangular window of uniform weighting is applied to the time series data to be analyzed [20]. For bearing estimation problems using an array, this is equivalent to applying equal weighting on each element. Thus, by steering the array in θ direction this method estimates the mean power $p_b(\theta)$, and the expression is given by

$$p_b(\theta) = \frac{S_\theta \ R \, S_\theta^H}{L^2} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.28)}$$

Where S_θ denotes the steering vector associated with the direction θ, L denotes the number of elements in the array, and R is the array correlation matrix. A set of steering vectors S_θ associated with various direction θ is often referred to as the array manifold in DOA estimation. From the array manifold and an estimate of the array correlation matrix, $p_b(\theta)$ is computed using equation (3.28) Peaks in $p_b(\theta)$ are then taken as the directions of the radiating sources.

3.4.1.2 Minimum Variance Distortionless Response Estimator

The minimum variance distortionless response estimator (MVDR) is the maximum likelihood method (MLM) of spectrum estimation which finds the maximum likelihood (ML) estimate of the power arriving from a point source in direction θ assuming that all other sources are interference [21]. For DOA estimation problems, MLM is used to find the ML estimate of the direction rather than the power. This method uses the array weights obtained by minimizing the mean output power and given by

$$P_{MV}(\theta) = \frac{1}{S_\theta^H R^{-1} S_\theta} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.29)$$

3.4.1.3 Linear Prediction Method

The linear prediction (LP) method estimates the output of one sensor using linear combinations of the remaining sensor outputs and minimizes the mean square prediction error, that is, the error between the estimate and the actual output [21]. Thus, it obtains the array weights by minimizing the mean output power of the array subject to the constraint that the weight on the selected sensor is unity.

3.4.1.4 Maximum Likelihood Method

The MLM estimates the DOAs from a given set of array samples by maximizing the log likelihood function .The Likelihood function is the joint probability density function of the sampled data given the DOAs and viewed as a function of the desired variables, which are the DOAs in this case. The method searches for those directions that maximize the log of this function. The ML criterion signifies that plane waves from these directions are most likely to cause the given samples to occur Maximization of the log-likelihood function is a nonlinear optimization problem, and in the absence of a closed-form solution requires iterative schemes.

The MLM provides superior performance [20] compared to other methods particularly when SNR is small, the number of samples is small, or the sources are correlated and thus is of practical interest.

3.4.2 Eigenstructure Methods

These methods rely on the space spanned by its eigenvectors may be partitioned in two subspaces, namely the signal subspace and the noise subspace; and the steering vectors corresponding to the directional sources are orthogonal to the noise subspace. As the noise subspace is orthogonal to the signal subspace, these steering vectors are contained in the signal subspace. It should be noted that the noise subspace is spanned by the eigenvectors associated with the smaller eigenvalues of the correlation matrix, and the signal subspace is spanned by the eigenvectors associated with its larger eigenvalues.

3.4.2.1 MUSIC methods

The multiple signal classification (MUSIC) method is a relatively simple and efficient eigenstructure variant of DOA estimation methods. So far it is the most studied method in its class and has many variations. Spectral MUSIC, Root-MUSIC, Constrained MUSIC and Beam Space MUSIC are some of its class.

Spectral MUSIC

In its standard form, also known as spectral MUSIC, the method estimates the noise subspace from available samples. This can be done either by eigenvalue decomposition of the estimated array correlation matrix or singular value decomposition of the data matrix with its N columns being the N array signal vector samples, also known as snapshots [12]. The latter is preferred for numerical reasons. Once the noise subspace has been estimated, a search for M directions is made by looking for steering vectors that are as orthogonal to the noise subspace as possible. This is normally accomplished by searching for peaks in the MUSIC spectrum given by

$$P_{MV}(\theta) = \frac{1}{/S_\theta^H U_L/^2} \quad \text{……………………………………………… (3.30)}$$

Where U_L denotes an L by $L - M$ dimensional matrix, with $L - M$ columns being the eigenvectors corresponding to the $L - M$ smallest eigenvalues of the array correlation matrix and S_θ denoting the steering vector that corresponds to direction θ.

Root-MUSIC

For a uniformly spaced linear array (ULA), the MUSIC spectra can be expressed such that the search for DOA can be made by finding the roots of a polynomial. In this case, the method is known as root-MUSIC. Thus, root-MUSIC is applicable when a ULA is used and solves the polynomial rooting problem in contrast to spectral MUSIC's identification and localization of spectral peaks. Root-MUSIC has better performance than spectral MUSIC [12].

Constrained MUSIC

This method incorporates the known source to improve estimates of the unknown source direction. The situation arises when some of the source directions are already known. The method removes signal components induced by these known sources from the data matrix and then uses the modified data matrix for DOA estimation. Estimation is achieved by projecting the data matrix onto a space orthogonal complement to a space spanned by the steering vectors associated with known source directions. A matrix operation, the process reduces the signal subspace dimension by a number equal to the known sources and improves estimate quality, particularly when known sources are strong or correlated with unknown sources.

3.4.2.2 Beam Space MUSIC

The MUSIC algorithms discussed so far process the snapshots received from sensor elements without any preprocessing, such as forming beams, and thus may be thought of as element space algorithms, which contrasts with the Beamspace MUSIC algorithm in which the array data are passed through a Beamforming processor before applying MUSIC or any other DOA estimation algorithms. The Beamforming processor output may be thought of as a set of beams; thus, the processing using these data is normally referred to as Beamspace processing. A number of DOA estimation schemes are discussed in where data are obtained by forming multiple beams using an array

3.4.2.3 CLOSEST Method

The CLOSEST method is useful for locating sources in a selected sector. Contrary to Beamspace methods, which work by first forming beams in selected directions, CLOSEST operates in the element space and in that sense it is an alternative to Beamspace MUSIC. In a way, it is a generalization of the minimum-norm method [20]. It searches for array weights in the noise subspace that are close to the steering vectors corresponding to DOAs in the sector under consideration, and thus its name. Depending on the definition of closeness, it leads to various schemes. A method referred to as FINE (First Principal Vector) selects an array weight vector by minimizing the angle between the selected vector and the subspace spanned by the steering vectors corresponding to DOAs in the selected sector.

3.4.2.4 ESPRIT Method

Estimation of signal parameters via rotational invariance techniques is a computationally efficient and robust method of DOA estimation. It uses two identical arrays in the sense that array elements need to form matched pairs with an identical displacement vector, that is, the second element of each pair ought to be displaced by the same distance and in the same direction relative to the first element.

Chapter 4: Adaptive Antenna Algorithms

4.1 Introduction

Adaptive Beamforming is an iterative approximation of optimum Beamforming. In this works adaptive Beamforming algorithms such as LMS, DMA, RLS are studied. In traditional or fixed Beamforming the weights are calculated to satisfy some optimality criterion and do not change these values once they are placed. However, if the signal environment and the direction of arrival change the traditional Beamformers are not optimal. So what adaptive Beamforming algorithms do is that they iteratively estimate the optimal weights over time. As the weights are iteratively adjusted, the performance of Beamformer is closer to the desired criterion after a number of iteration depending on the algorithm. The algorithm is converged when these optimal criterions is achieved. There are a number of adaptive Beamforming algorithms.

Adaptive Beamforming algorithms can be classified into two categories: non-blind adaptive algorithms and blind adaptive algorithms. Non-blind adaptive algorithms rely on statistical knowledge about the transmitted signal in order to converge to a solution. This is typically accomplished through the use of a pilot training sequence sent over the channel to the receiver to help it identifying the desired user. On the other hand, blind adaptive algorithms do not require prior training, and hence they are referred to as "blind" algorithms. These algorithms attempt to extract salient characteristic of the transmitted signal in order to separate it from other users in the surrounding environment. In this section the most common algorithms such as: LMS, DMI, RLS are discussed.

4.2 Classification of adaptive array algorithms

4.2.1 Training based algorithm

Adaptive Beamforming algorithm can be classified as training and blind algorithm [26]. Trained algorithms use training signal to adapt the weights of the array and minimize mean square error. The processor in the adaptive array has a pre-stored training signal and the array adapts its weights when the training signal is transmitted by the transmitter. This technique requires synchronization. These algorithms work very well, but the only cost paid is the excess transmission time or wastage of bandwidth.

The trained algorithms are classified based on their adaptation criteria and they are least-mean squares method (LMS), sample matrix inversion (SMI) or least-squares method (LS) and recursive least-squares method (RLS). All these techniques minimize the squared error. The fundamental assumptions behind these minimization techniques is that the error vector follows a Gaussian probability density function

4.2.2 Blind algorithm

Unlike training algorithm blind algorithm do not require training signals to adapt their weights. Therefore these algorithms save transmission bandwidth. Blind algorithms can be classified as property restoral algorithms, channel estimation algorithms, and dispread and respread algorithms. Property restoral algorithms restore certain properties of the desired signal and hence enhance the SINR. The property that is being restored may be the modulus or the spectral coherence. Blind property restoral algorithms can be classified as Constant Modulus (CM) algorithm, Spectral self-Coherence Restoral (SCORE) algorithms, and decision directed (DD) algorithms.

Channel estimation techniques [26] use the knowledge of the special code properties of the spread spectrum signals to obtain estimates of the channel parameters. These techniques first estimate the channel parameters and then use the channel estimates to form beams in the direction of the desired signals. These techniques are applicable only for CDMA signals.

Despread-respread techniques for CDMA belong to the family of demod-remod techniques, which is common in FM interference rejection. A despread-respread technique works on the principle of despreading the signal at the output of the ith user and then making a bit decision. The error between the respread data and the output of the array is minimized using a least-squares or a steepest descent approach. The assumption behind the despread-respread based adaptation is that the synchronization has been achieved prior to Beamforming, since despreading requires synchronization.

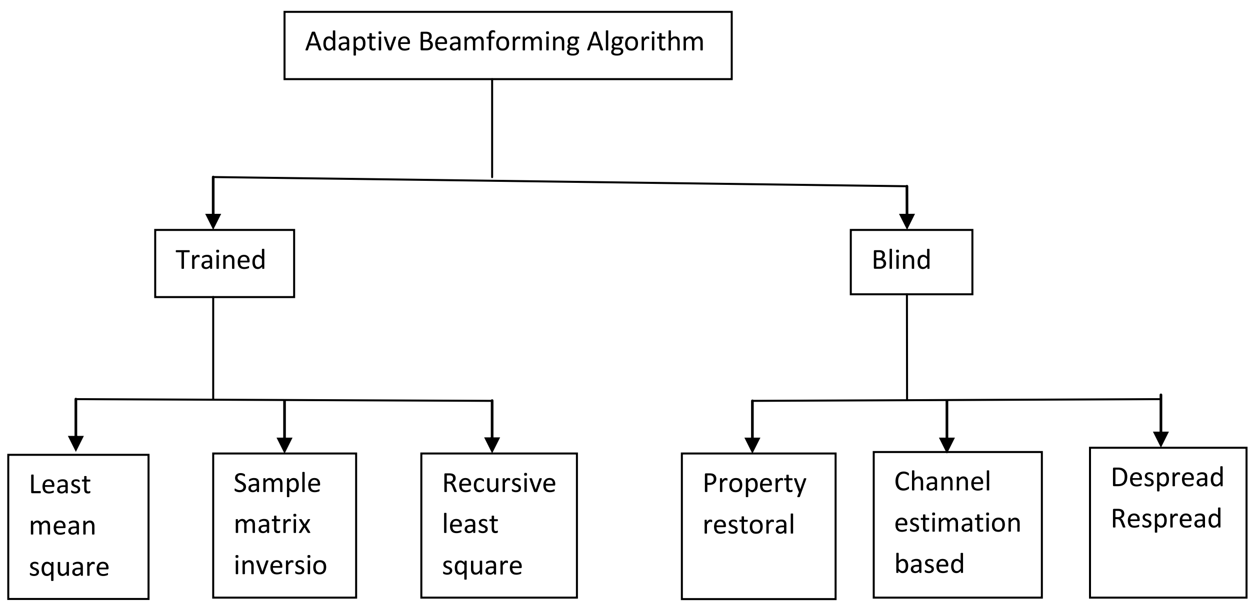

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Figure 4.2 Classification of Adaptive Array Algorithms

4.3 Adaptive Beamforming algorithm used in the thesis

4.3.1 Least-Mean-Square Algorithm

The optimum Wiener solution $\boldsymbol{W_{opt}}$= $\boldsymbol{R_{xx}}^{-1}\mathbf{r}$ requires the calculation of the inverse of the correlation matrix $\boldsymbol{R}$ and this results in a high computational complexity. The Least mean square algorithm is a gradient based quadratic approach. Gradient algorithms assume an established quadratic performance surface which is a function of the array weights, the Performance surface *J (W)* is in the shape of an elliptic parabola having one minimum [28].

One of the best ways to establish the minimum is through gradient method. We can establish the performance surface (cost function) by again finding the MSE. Therefore, the spatial filtering problem involves estimation of signal from received signal (i.e. the array output) by minimizing error between the reference signal *d (t)* (which closely matches or has some extent of correlation with the desired signal estimate) and the beam former output *y (t)* equal to *W x (t).* This is a classical wiener filtering problem for which solution can be iteratively found using the LMS algorithm.

The signal x(t) received by multiple antenna elements is multiplied with the coefficients in a weight vector w (series of amplitude and phase coefficients) which adjusted the phase and the amplitude of the incoming signal accordingly. The weighted signal is summed up, resulted in the array output *y(t)*. An adaptive algorithm is then employed to minimize the error *e(t)* between a desired signal *d(t)* and the array output *y (t)* given by linear combination of the data at the k sensors.

The Least-Mean-Square (LMS) Algorithm avoids matrix inverse operation by using the instantaneous gradient vector ***J (w)*** to update the weight vector .The steepest descent iterative approximation is given as [22]

$$W(k+1) = w(k) - 1/2\mu \nabla_w (J(w(k)) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.1)}$$

Where μ is the convergence factor which controls the speed of convergence and its value is usually between 0 and 1 and ∇_w is the gradient of the performance surface. The direction of steepest descent is in the opposite direction as the gradient vector.

An exact measurement of the instantaneous gradient vector is not possible since this would require a prior knowledge of both the correlation matrix ***R*** and the cross-correlation vector ***r***. Instead, an instantaneous estimate of the gradient vector is used which is given by

$$\nabla_w(J(w(k)) = -2r(k) + 2R(k)\,w(k) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.2)}$$

Where

$$\hat{R}_{xx}(k)=\boldsymbol{x}(k)\,.\,x^H(k) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.3)}$$

$$r(k)=d^*(\text{k}).\text{x}(\text{k}) \qquad \ldots\ldots\ \ldots\ldots\ldots\ldots\ldots\ldots \text{(4.4)}$$

are the instantaneous estimate of the self correlation between the signal induced in each array element and the cross correlation between the reference signal and the induced signal respectively. If these values are substituted in the gradient of performance surface we can get the LMS solution.

$$W(k+1) = w(k) - \mu\,[R_{xx}w - r] \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.5)}$$

$$= W(k) + \mu\, e^*(k).x(k) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.6)}$$

Where

$$e(k)=d(k) - \boldsymbol{w}^H.\boldsymbol{x}(k) \quad = \textit{error signal}$$

The LMS algorithm is a member of stochastic gradient algorithms since the instantaneous estimate of the gradient vector is a random vector that depends on the input vector x (k). The LMS algorithm requires only 2M complex multiplications per iteration, where M is the number of weights used in the adaptive array [27].

If the step-size is too small and the convergence is slow, we will have the over damped case. If the convergence is slower than the changing angles of arrival, it is possible that the adaptive array cannot acquire the signal of interest fast enough to track the changing signal. If the step-size is too large, the LMS algorithm will overshoot the optimum weights of interest. This is called the under damped case. If attempted convergence is too fast, the weights will oscillate about the optimum weights but will not accurately track the solution desired. It is therefore imperative to choose a step-size in a range that insures convergence

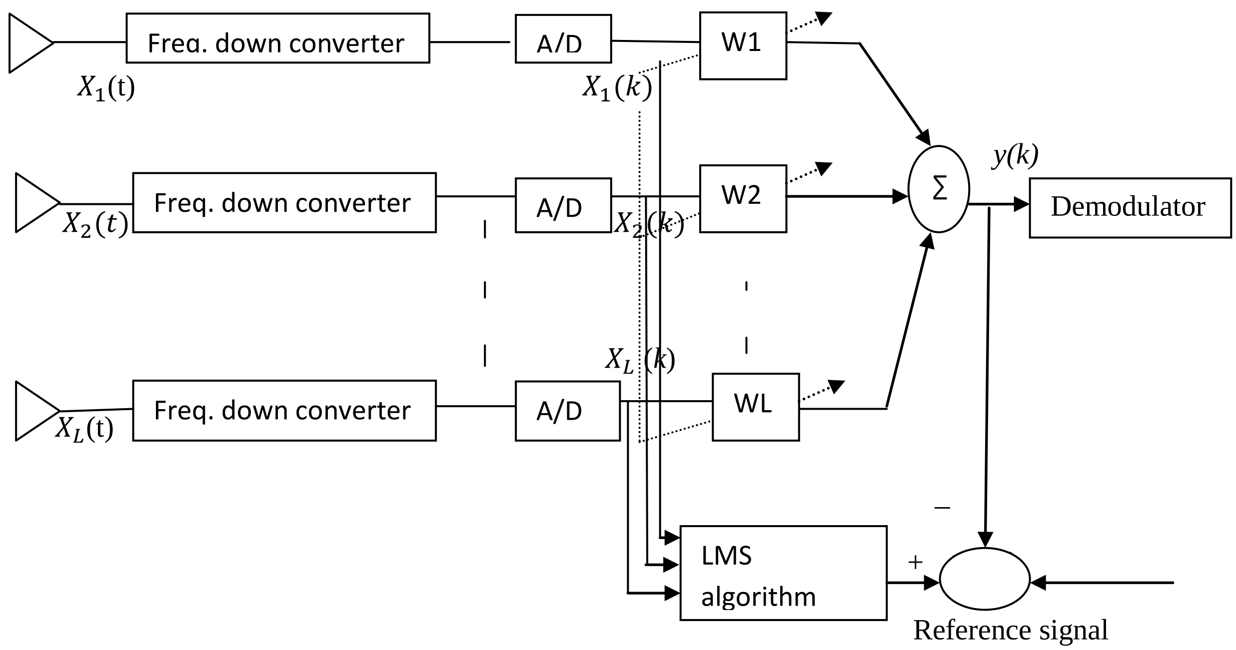

Figure 4.3 Adaptive array antenna using LMS algorithm

Figure 4.4 shows the flow chart of LMS algorithm. For this case the array parameters such as: spacing and number of arrays are set before the estimation of angle of arrival, hence the performance of LMS algorithm (bore sight and nulling) are degraded when separation becomes small and small.

Flow chart of LMS algorithm

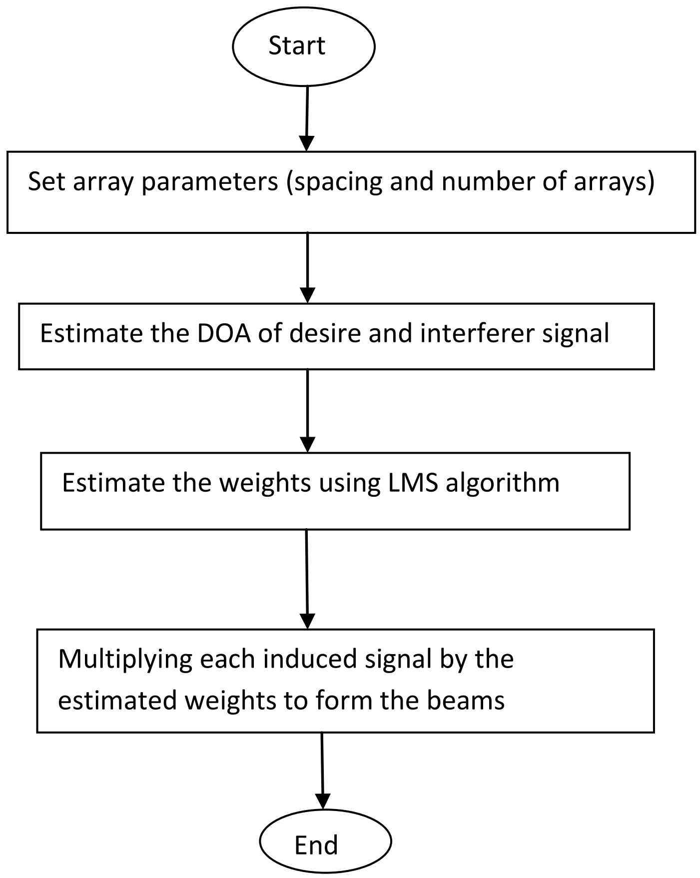

Figure 4.4 Flow chart of LMS adaptive Beamforming algorithm

To reduce the performance degradation due to angle separation, we recommend setting array parameter after estimating angle of arrival of the desired and the interferer signals. So, the system uses these parameters based on angle difference to enhance system performance and reduce computational complexity. The flow chart below shows how we adjust the LMS algorithm to reduce the effect of angle separation between the desired and the interferer signals.

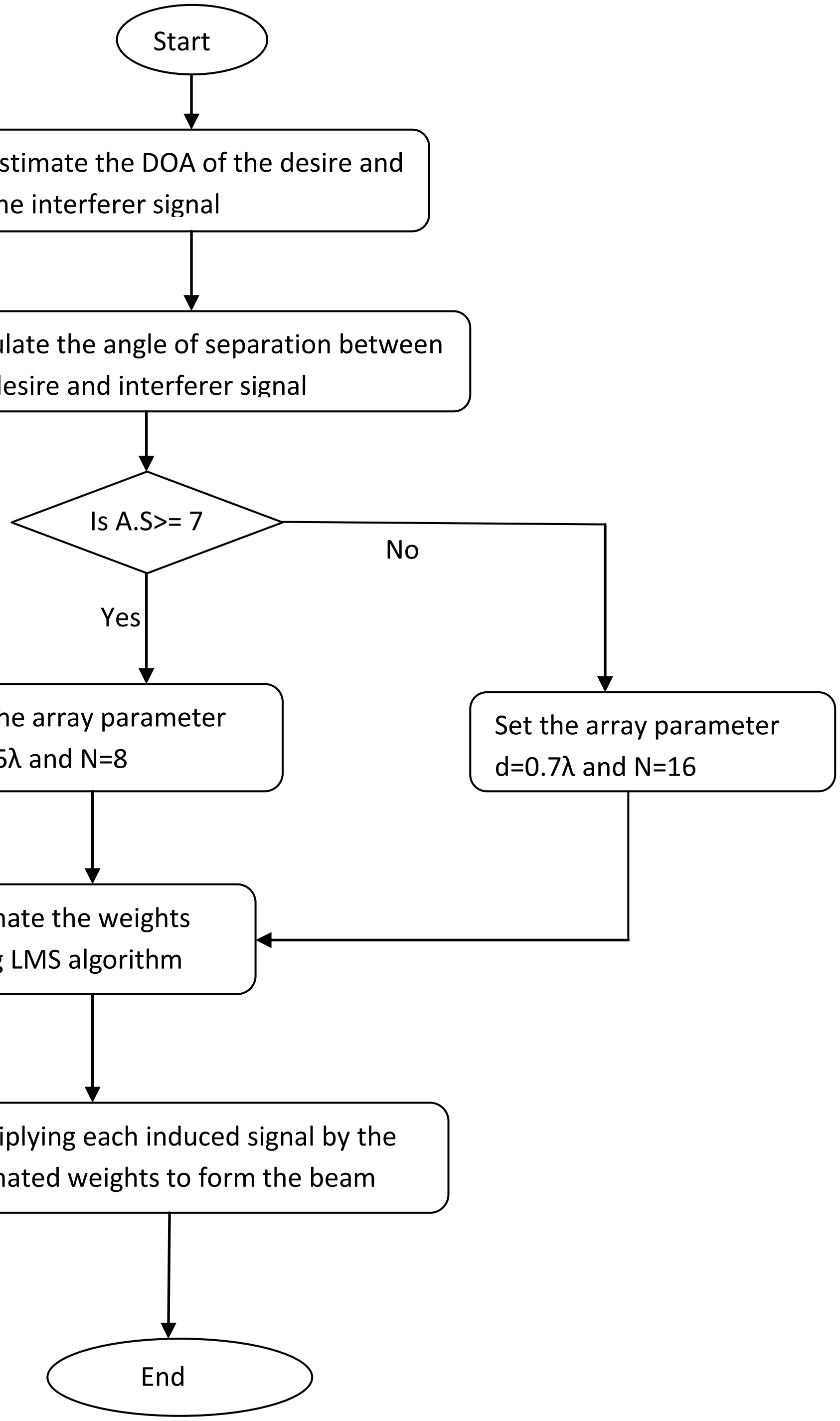

Figure 4.5 Flow chart of Recommended adjusted LMS algorithm and array parameter

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4.3.2 Sample Matrix Inversion Algorithm

LMS adaptive Beamforming algorithm [27] requires much iteration to converge the estimated optimal value. The idea of sample matrix inversion (SMI) algorithm is to estimate the correlation matrix **R** and the cross-correlation vector **r** based on the samples of the array sensor input in an observation interval so that the speed of convergence is improved. This method is also alternatively known as direct matrix inversion

(DMI) The sample matrix is a time average estimate of the array correlation, matrix using *K*-time samples. If the random process is ergodic in the correlation, the time average estimate will equal the actual correlation matrix. Recall from previous equation

$$\boldsymbol{W_{opt}} = \boldsymbol{R_{xx}}^{-1}\mathbf{r}$$

Where

$$\boldsymbol{R_{xx}} = [\mathrm{x}.\boldsymbol{x^H}]$$

$$\mathbf{r} = \mathbf{E}\ [\boldsymbol{d}^*.\mathbf{x}]$$

So we can estimate the correlation matrix by calculating the time average such that

$$R_{xx} = \frac{1}{K}\sum_{k=1}^{K} x(k)\, x(k)^H \quad \ldots\ldots \quad (4.7)$$

Where *K* is the observation interval

The correlation vector **r** can be estimated by

$$\mathbf{r} = \frac{1}{K}\sum_{k=1}^{K} d^*(k)\ \ x(k) \quad \ldots\ldots \quad (4.8)$$

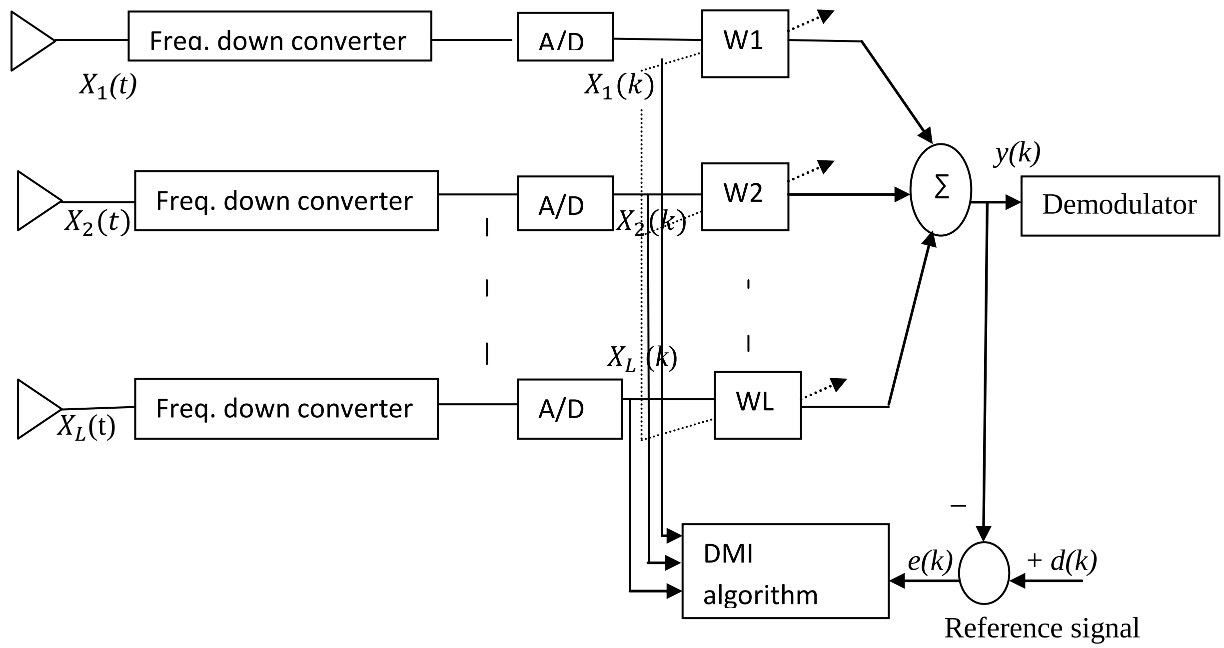


Figure 4.6 Adaptive array antenna using DMI algorithm

In order to allow the array to adapt as the signal environment changes, the correlation sample matrix **R** and the cross-correlation sample vector **r** are re-estimated for each observation interval. Data that are outside the current observation interval do not have any effect on the calculation of the weight vector for the current observation interval, The SMI algorithm using matrix inversion lemma requires 3.5M^2+M complex multiplications per iteration [27], where M is the number of weights used in the adaptive array.

4.3.3 Recursive least square algorithm

Unlike SMI which uses an observation interval to estimate both **R** and **r**, recursive least-squares (RLS) algorithm [27] uses the weighted sum to estimate them:

$$\boldsymbol{R}_{xx}(k) = \sum_{i=1}^{k} \alpha^{k-i}\, x(i).x^H(i) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.9)}$$

$$\boldsymbol{r}_{xx}(k) = \sum_{i=1}^{k} \alpha^{k-i} d^*(i).x(i) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.10)}$$

$0 < \alpha \leq 1$ is the weighting factor or forgetting factor which determines how quickly the previous data are de-emphasized. When $\alpha = 1$, we restore the ordinary least squares algorithm. By breaking the above equation into two parts: the summation for values up to $i = k-1$ and last term for $i = k$.

$$R_{xx}(k) = \alpha \sum_{i=1}^{k} \boldsymbol{\alpha}^{k-1-i}\, x(i).x^H(i) + x(k)x^H(k) \quad \ldots\ldots\ldots\ldots\ldots\ldots(4.11)$$

$$= \alpha\, R_{xx}(k\text{-}1) + x(k)x^H(k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.12)$$

$$r_{xx}(k) = \sum_{i=1}^{k} \boldsymbol{\alpha}^{k-1-i} d^*(i).x(i) + d^*(k).x(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.13)$$

$$= \alpha\, r_{xx}(k-1) + d^*(k).x(k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.14)$$

These are the recursion equation that uses for updating both R_{xx}(k) and $r_{xx}(k)$

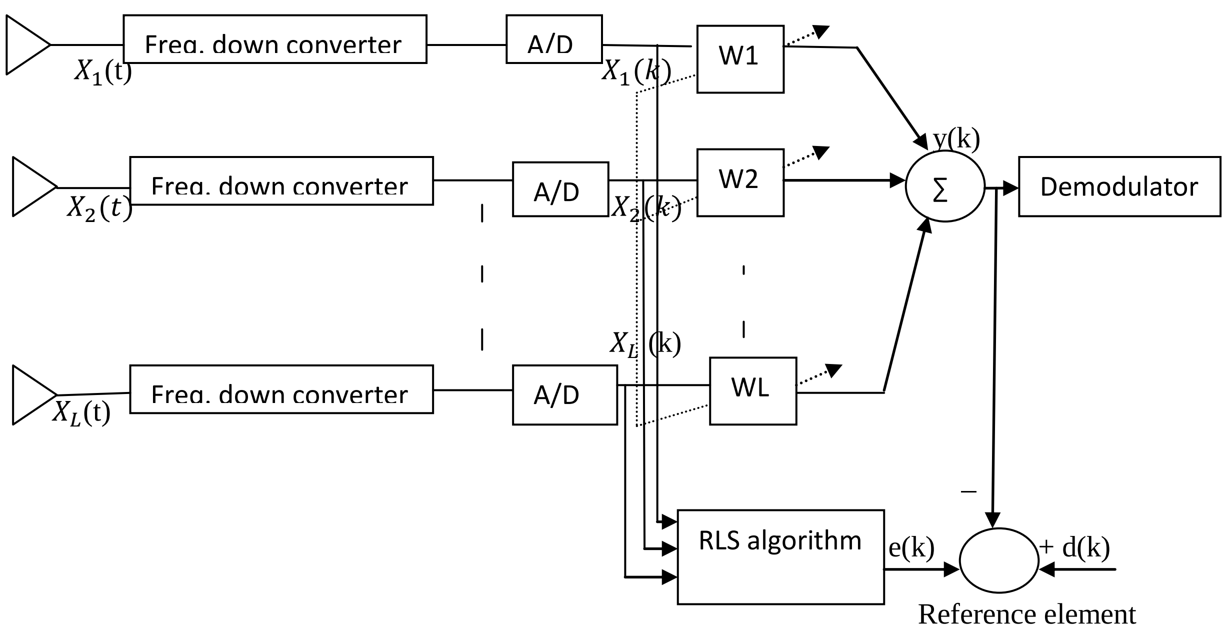


Figure 4.7 Adaptive array antenna using RLS algorithm

The fundamental difference between the RLS algorithm and the LMS algorithm is that the convergence factor μ in the LMS algorithm is replaced by the inverse of the correlation matrix $\boldsymbol{R_{xx}}^{-\mathbf{1}}$. The resulting rate of convergence is typically an order of magnitude faster than the LMS algorithm. However, the computational complexity of the RLS algorithm is much higher than that of the LMS algorithm. It requires $4M^2$ + $4M$ + 2 complex multiplications per iterations [27], where M is the number of weights used in the adaptive array.

Chapter 5: Simulation Results and Discussions

5.1 Introductions

In this chapter, array parameters (spacing between array elements, number of array) and adaptive Beamforming algorithms (LMS, RLS and DMI) which are described in Chapters 3 and 4 are programmed in MATLAB and simulations are performed to obtain array pattern, Boresight and Nulling. These performance characteristics are used to compare the performances of the different adaptive Beamforming algorithms such as: RLS, LMS and DMI. There are also simulations included to compare the side lobe level and speed of convergence. Simulation results of the proposed adjusted algorithm and array parameters also presented.

In this thesis we take non uniform linear array of different number and length of spacing, located at the base station to perform spatial filtering. The weights of the adaptive Beamforming algorithms are adjusted using the training signal (the pilot signal) and the channel is assumed to be flat fading channel. What is required from smart antenna system is that to steer the main beam in the desire direction, minimum power in the jammer location and minimum side lobe level by adjusting the complex weight.

In the simulation the effect of angle separation between the desire and the interferer signal, for different performance criterion, such as beam steering ability, nullifying capability speed of convergence and side lobe levels , relationship between beam width and performance criterion like bore sight and nulling are investigated. In addition the performance of adaptive Beamforming algorithm RLS, LMS and DMI and the recommended algorithm with array parameter are also studied.

The bore sight and nulling are obtained by first calculating an array factor, then multiplying the complex weight with it then taking the value at the respective position of bore sight and nulling for the desire and interferer angle and finally taking the logarithm of these values.

Channel types	AWGN
SNR , INR	20 db
K (number of iteration)	100
μ (convergence factor)	0.02
α (forgotten factor)	0.01
Coupling is neglected Uniform spacing between array elements The signals are Narrow band signals The signals are uncorrelated	

Table 5.1 Simulation parameters and assumptions

5.2 Simulation Results for different DOA of desire and interferer signal.

Figure 5.1 and 5.2 shows that the effect of angle separation between the desire and the interferer signal on the performance of adaptive Beamforming algorithm (LMS) such as: bore sight, nulling, speed of convergence and side lobe level. These figures are plotted using the same array parameters like spacing between arrays, number of array and SNR, but having different DOA of interfering signal. From figures 1, when θ_i=60 degree, one can see that for large angle of separation or when the separation is larger than half of the first null beam width, the side lobe level, the beam steering ability and nullifing capability of the LMS algorithm is satisfactory as shown in figure 5.1. According to figure 5.1 the normalized array pattern at desire direction (θ_d=0) is 0 db and the value in the undesired location is around -46.21 db which is close to zero, and this is required in the smart antenna system for beam steering and interference mitigation. The side lobe level is also about -14.03 db which is much smaller than the main beam.

On the other hand when the interferer angle is in the range of half of the first null beam width specifically θ_i=7 degree the performance of LMS algorithm is degraded. As shown in figure 5.2 the beam pattern at the desire direction is not maximum , the nulling become around -25.20 db and the side lobe level is around -6db which is comparable to the main lobe. These results are undesired in the system and should be minimized as much as possible for reliable communication. The other point which can be observed in figure 5.1 and 5.2 is that the speed of convergence is not affected by angle of separation but the error becomes very large until the weight converges to the optimal value.

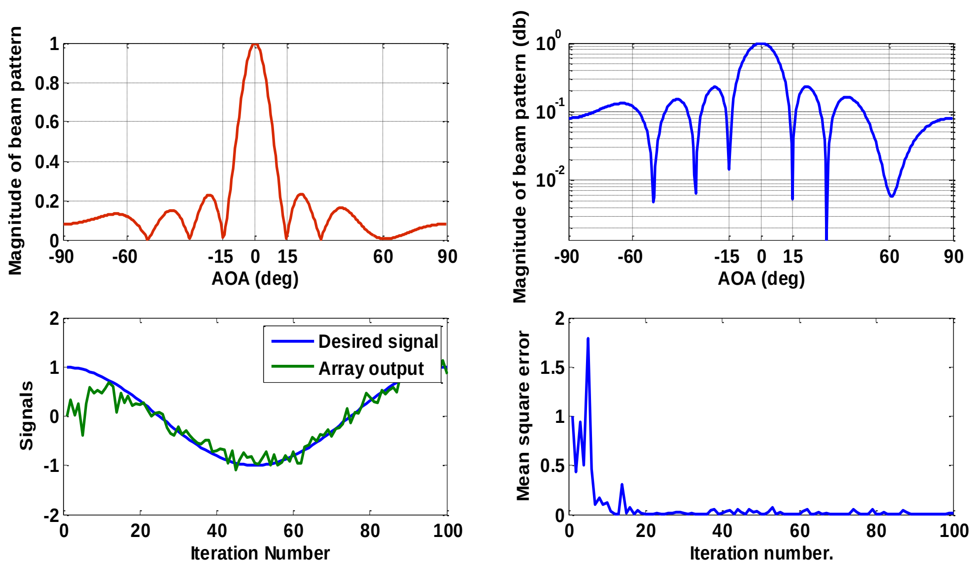


Figure 5.1 Normalized array factor, Array output, weights and Mean square error. ($\boldsymbol{\theta_d}$ =0 and $\boldsymbol{\theta_i}$ =60, N=8, d=.5λ)

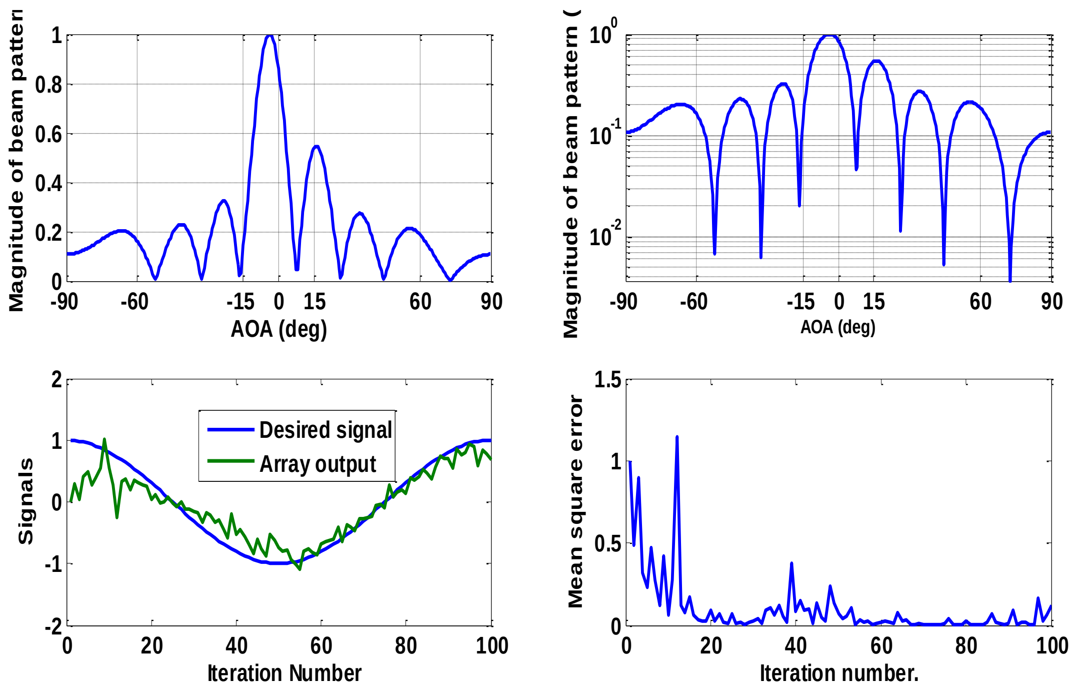


Figure 5.2 Normalized array factor, Array output, weights and Mean square error. (d=0.5λ, $\boldsymbol{\theta_d}$=0 and $\boldsymbol{\theta_i}$=7, N=8)

Figure 5.3 is plotted to show how the Boresight and the Nulling of LMS algorithm is affected by angle of separation. These figures are plotted first taking the respective magnitude of the desire and the interferer signal at the respective location from the beam pattern then normalized these values by the maximum one and taking the logarithm of the results. So in order to get the point which is shown in figure 5.1 and 5.2 first we need to denormalized then again we need to normalized by the respective maximum value for each DOA of desire and interferer signals. From figure 3 one can observed that when the separation become close to zero both the normalized values of Boresight and nulling become unity. This implies that the communication system is not performing well, that means the system is wasting power or causes interference in the other user. So what those figures show is that when the separation become small, side lobe level and nulling is increased and Boresight is reduced or starts to decline.

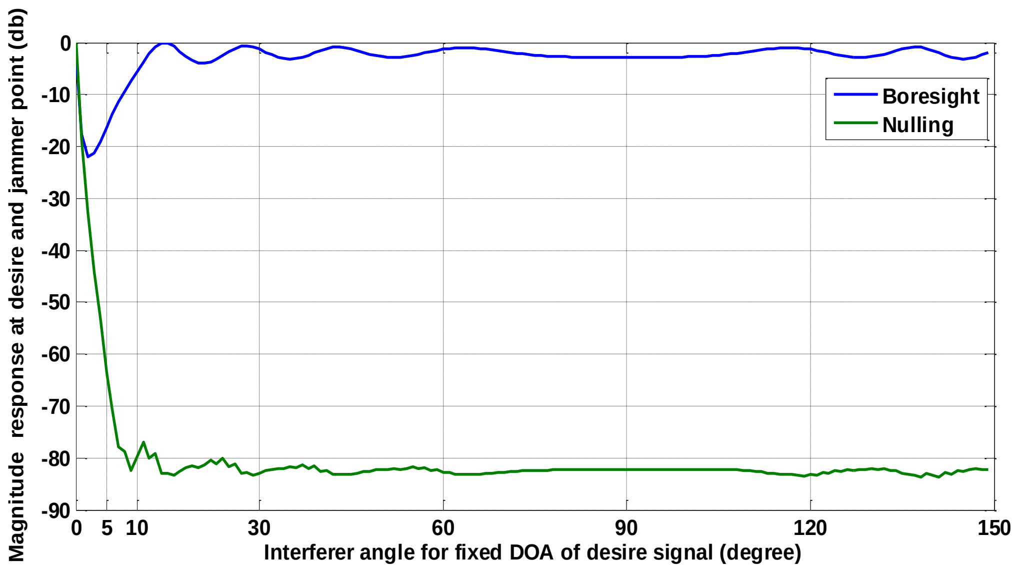


Figure 5.3 Response of array pattern (d=0.5λ, N=8)

Angle of separation(θ_d) (degree) Spacing (d) (λ) Number of array (N)	Bore sight (db)	Nulling (db)	Side lobe level (db)
θ_d=60, d=0.5 λ, N=8	0	-46.21	-14.03
θ_d=7, d=0.5 λ, N=8	-1.72	-25.20	-5.10

Table 5.2 Values of bore sight, nulling and side lobe level at desire and jammer point

5.2.1 Simulation result for different length of spacing and direction of arrival

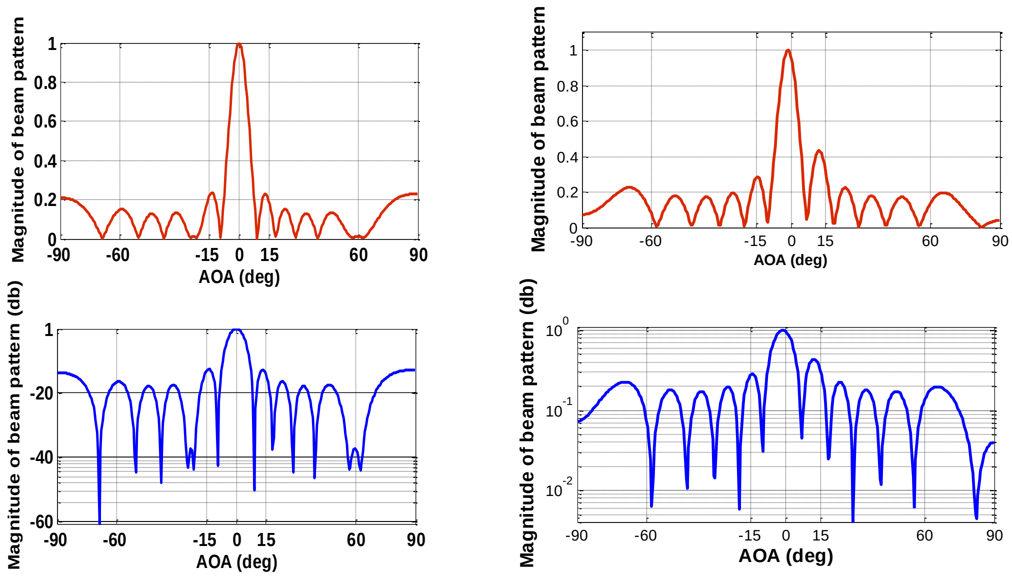
Figure 5.4, 5.5 and 5.6 is plotted to study the effect of spacing on the performance of smart antenna system for different angle of separation especially when the separation become small.

What figure 5.4 makes different from figure 5.1 is that all parameters are the same except that their array spacing. From figure 5.4 one can observes that the number of side lobes is increasing and grating lobe is introducing as a result of increasing the spacing to 0.8λ. The result obtained in this situation is not satisfactory compared to the result obtained using 0.5λ as in figure 1 shown. There is no grating lobe at d=0.5λ and also there are small number of side lobes but the beam width is wider compared to figure 5. 4. The nulling value which is obtained from figure 4 is about -38db. This value is larger than the value obtained from figure 1 by -8 db. So what figure 5.1 and 5.4 show that for large angle of separation (when the separation is greater than half of the first beam width) d=0.5λ gives a better performance as many papers suggests [1], [2], [4] [10][15][16][18].

On the other hand for small angle of separation as in figure 5.2 shown the performance of the system is not satisfactory. However unlike for large angle of separation increasing spacing between array elements gives a better performance for small angle of separation as shown in both figure 5.5 and 5.6.

The parameter of figure 5.5 is similar to figure 5.2 except that they have different array spacing. As in the figure 5.5 shown increasing the spacing to 0.8λ introducing grating lobe but the Boresight, nulling and side level improves significantly compared to figure 5.2. For example the first side lobe level in figure 5.2 which is plotted for d=0.5λ is about -6db whereas the level for d=0.7λ is about -8db.

What an interesting situation is observed in figure 5.6 is that d=0.5λ is optimal only for angle of separation larger than half of the first beam width. For angle of separation around half of the first null beam width the situation starts to reverse as shown in figure 5.6. Increasing the spacing between array enhance the nulling, Boresight as well as the side lobe levels for small angle of separation except at the cost of increasing the number of side lobe level and introducing grating lobe. As in figure 5.6 shown as increasing spacing beyond d=0.5λ the system do not form deep null where as the Boresight almost similar in all case. However when the separation become small, the Boresight start to decline fast and the nulling starts to increase for d=0.5λ.



a)

b)

Figure 5.4 Amplitude pattern in linear and logarithmic scale a, (d= 0.8 λ, $\boldsymbol{\theta_d}$=0 and $\boldsymbol{\theta_i}$=60, N=8) and b, (d= 0.7 λ, N=8, $\boldsymbol{\theta_d}$=0 and $\boldsymbol{\theta_i}$=10)

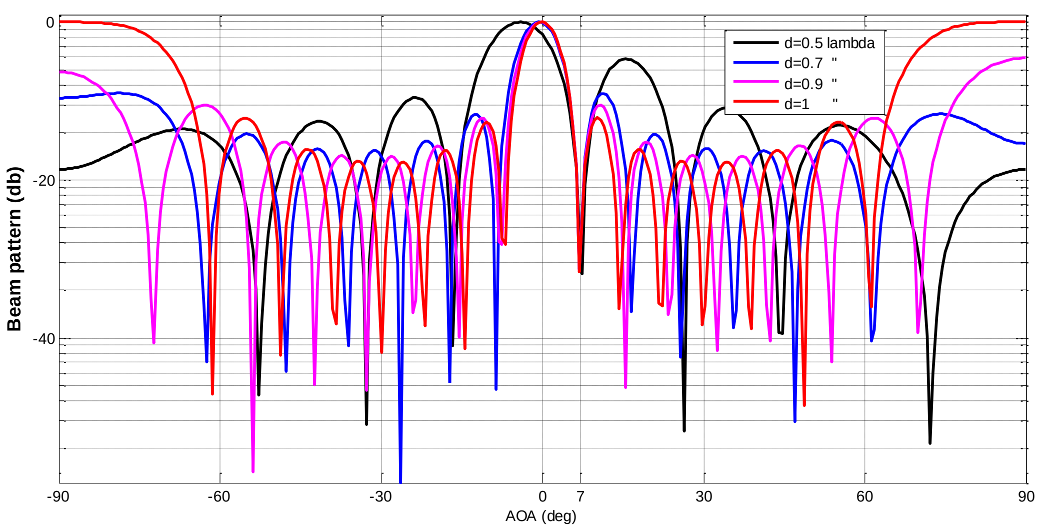


Figure 5.5 Array pattern for (N=8, θ_d =0, = θ_i =7 degree)

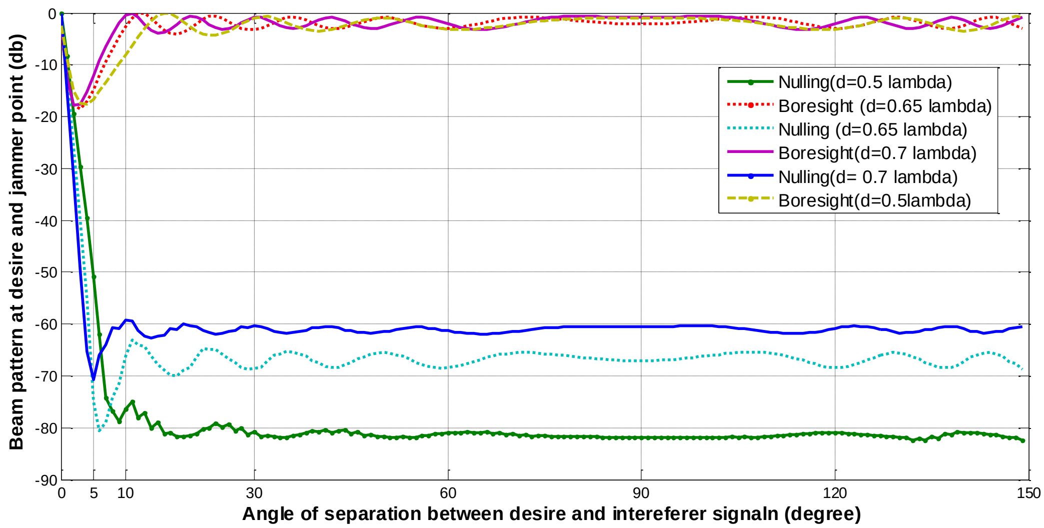


Figure 5.6 Boresight and Nulling (N=8)

Angle of separation(θ_d) (degree) Spacing (d) (λ) Number of array (N)	Bore sight (db)	Nulling (db)	Side lobe level (db)	remark
θ_d=60, d=0.5 λ, N=8	0	-46.21	-14.03	No grating lobe
θ_d=60, d=0.8 λ, N=8	0	-38.01	-13.15	Grating lobe is there.
θ_d=7, d=0.5 λ, N=8	-1.72	-25.20	-5.10	No grating lobe
θ_d=7, d=0. 7λ, N=8	-1.31	-28.31	-9.11	Grating lobe is there
θ_d=7, d=0. 9λ, N=8	-0.20	-30.45	-10.45	Grating lobe is there
θ_d=7, d=λ, N=8	-0.08	-32.04	-12.04	Grating lobe is there

Table 5.3: Values of bore sight, nulling and side lobe level at desire and jammer point

5.2.2 Simulation results for different number of array.

Figure 5.7, 5.8 and 5.9 show that the performance of array system improves as the number of array element increase at a cost of increasing system power and computational complexity. Unlike spacing increasing number of array enhance the system performance for all angle of separation.

What the parameters of figure 5.7 makes different from figure 5.1 is that number of array. As in figure 5.7 shown increasing the number array to 14, the nullifying capability of LMS algorithm is enhance but the number of side lobes increase like the effect of increasing spacing.

As discussed above increasing the spacing to 0.75λ, the beam steering ability , the nullifying capability increase, in addition the side lobe level reduce to – 8db compared to figure 5.2. What figure 5.8 shows that for small angle of separation increasing number of array have similar effect to spacing. For instance the side lobe level reduces to -12 db by increasing the number of array to 14. As states above increasing the number of array results in increasing computational cost, increase system power demand and increase number of side lobes.

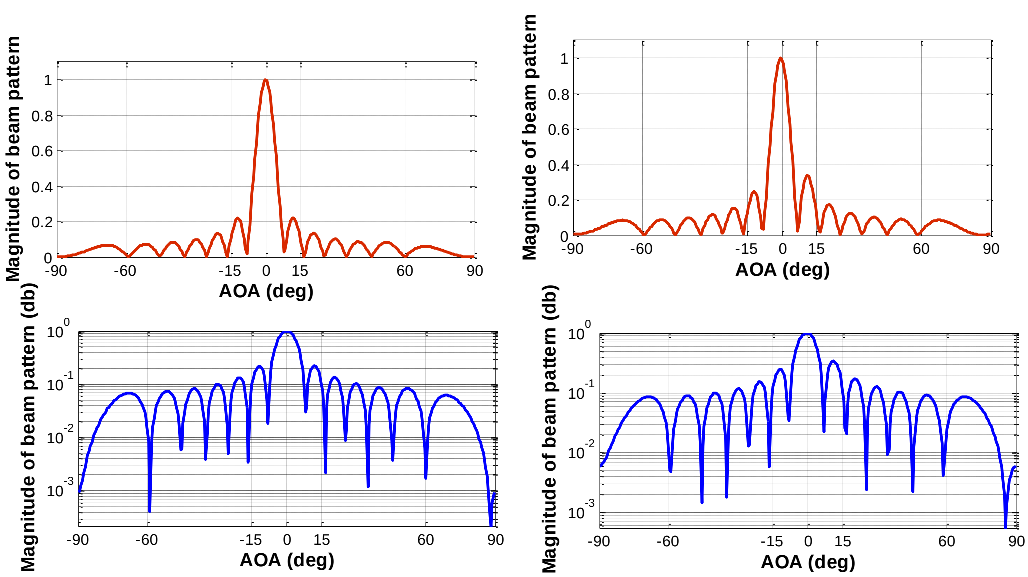


Figure 5.7 Magnitude of array factor (θ_d=0, θ_i =60, d=0.5λ, N=16) and (θ_d=0, θ_i =7, d=0.5λ, N=16)

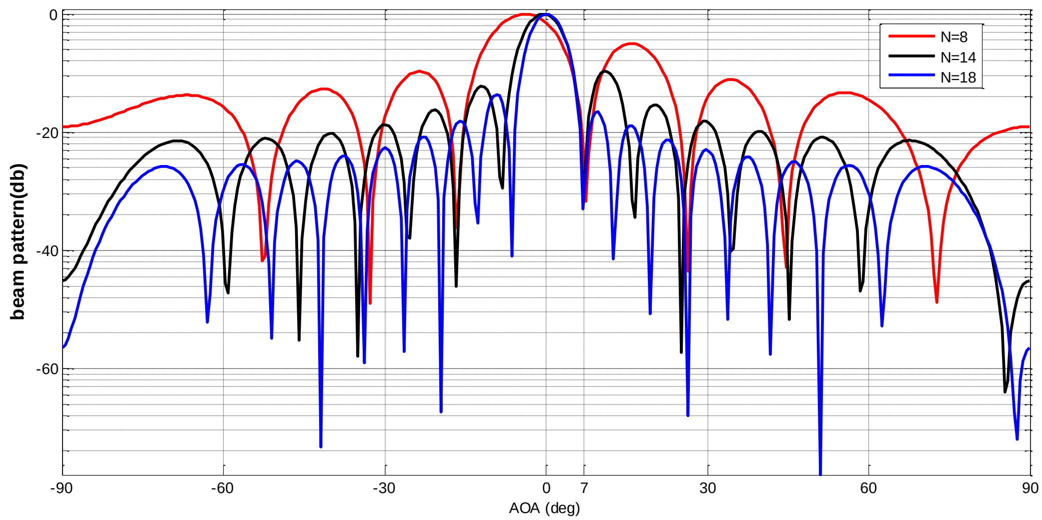


Figure 5.8 Array pattern for (d=0.5, θ_d =0 degree and θ_i=7)

Figure 5.9 shows that how number of array enhance Boresight and Nulling for different angle of separation. As in the figure 5.9 shown the system performance enhance for every angle of separation as the number of array increase unlike spacing. For instance at θ_i=5 degree the nulling values are -100db, -68db and – 40db for array number 25, 14 and 8 respectively.

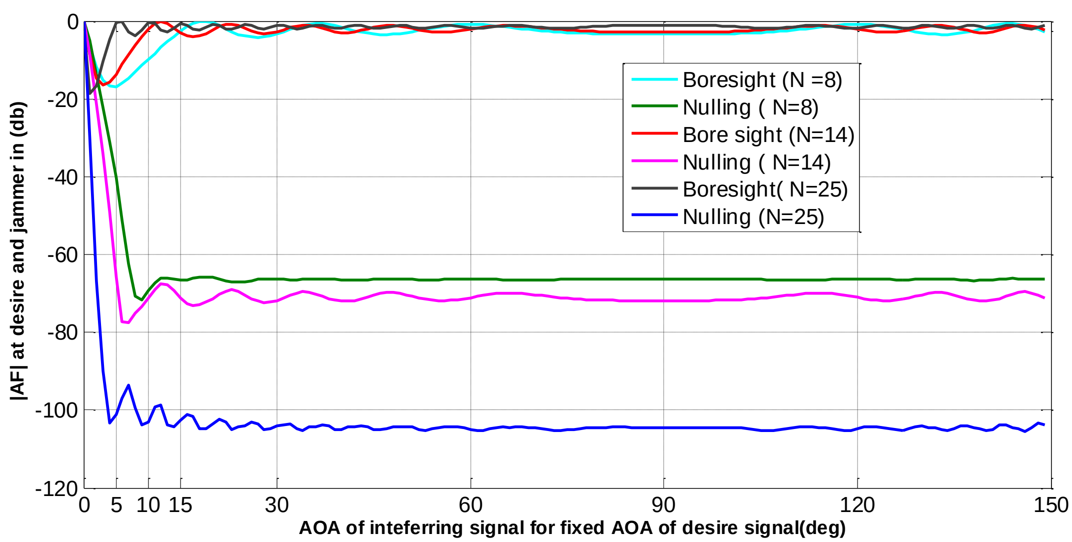


Figure 5.9 Beam pattern at desire and jammer point for different number of array (d=0.5λ)

Angle of separation(θ_d) (degree) Spacing (d) in (λ) Number of array (N)	Bore sight (db)	Nulling (db)	Side lobe level (db)	remark
θ_d=60, d=0.5 λ, N=8	0	-46.21	-14.03	No grating lobe
θ_d=60, d=.5 λ, N=16	0	-57.48	-13.97	>>
θ_d=7, d=0.5 λ, N=8	-1.72	-25.20	-5.10	>>
θ_d=7, d=0. 5λ, N=14	0	-30.31	-10.71	>>
θ_d=7, d=0. 5λ, N=18	0	-33.56	-16.48	>>

Table 5.4 Values of bore sight, nulling and side lobe level at desire and jammer point

5.3 Performance comparison of LMS, DMI and RLS

Figure 5.10, 5.11 and 5.12 shows that how adaptive Beamforming algorithm RLS, DMI and LMS perform based on angle of separation for the same array parameters. As in figure 5.10 shown the performance of LMS and DMI are almost similar but as in literature review discussed the computational complexity of DMI high compared to LMS algorithm. For the case of DMI it requires $3.5w^2+w$ complex multiplications per iteration and LMS require only $2w$ complex multiplication per iteration. However DMI algorithm has high speed of convergence compared to LMS algorithm. Of the three algorithms as in figure shown below RLS algorithm out perform for every angle of separation for both beam steering ability and forming deep null in the location of the jammer. RLS algorithm has high computational cost compared to both LMS and DMI algorithm. It requires $4w^2+4w+2$ complex multiplications per iteration.

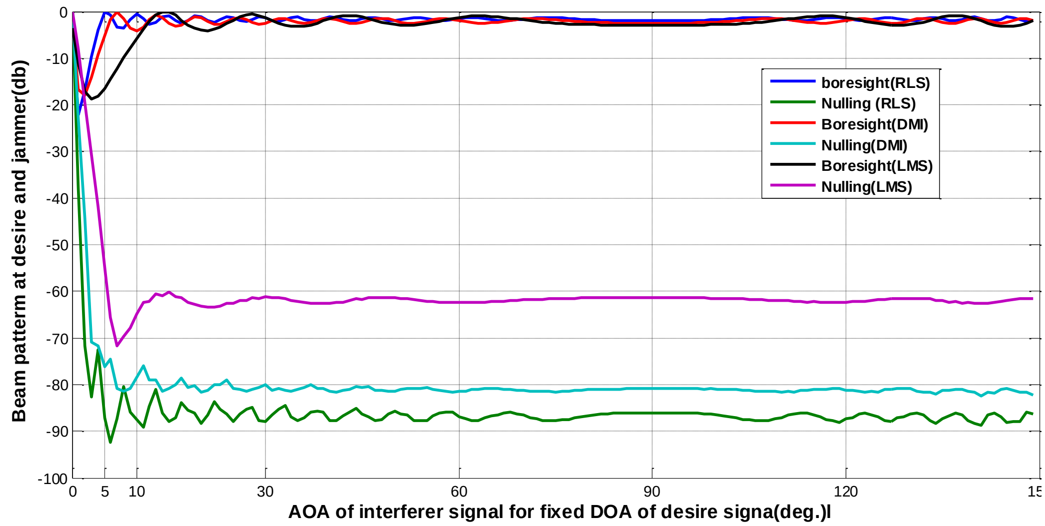


Figure 5.10 Performance of RLS, DMI and LMS beam steering ability and nullifing capability for angle separation vary from 0 deg to 150 degree (d= 0.5 lambda and N= 10)

Figure 5.11 is plotted to study side lobe level of the three adaptive algorithms for small angle of separation. According to the simulation results LMS algorithm has the lowest side lobe level and DMI algorithm has the highest side lobe level.

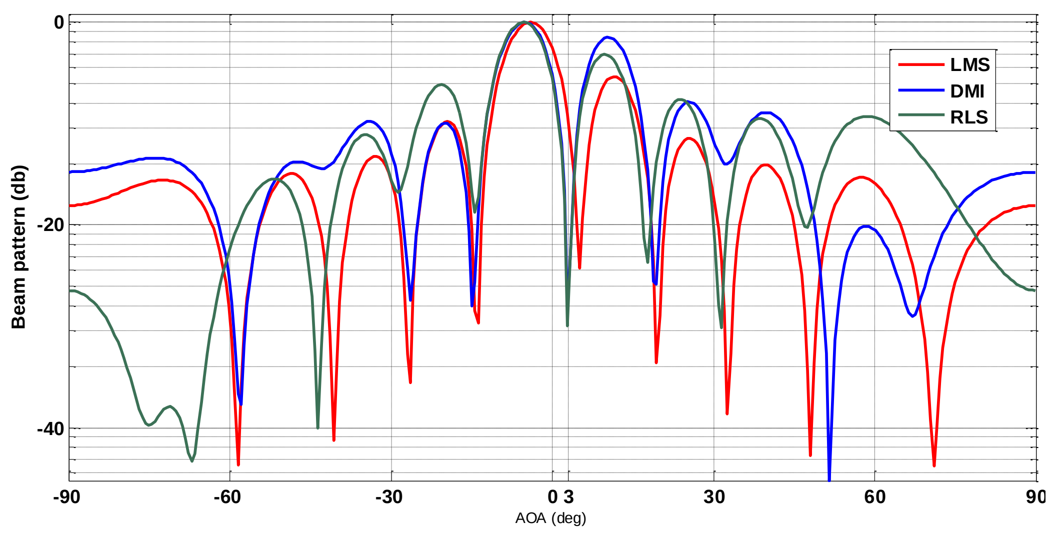


Figure 5.11 Beam pattern of linear array (N=8, d=0.5, $\boldsymbol{\theta_d}$=0 deg. $\boldsymbol{\theta_i}$ =3 degree)

Figure 5.12 and 5.13 are plotted to compare the effect of spacing and number of array for the three adaptive algorithms. The simulation results show that all the three algorithms are changing when these parameters are changing. By increasing the spacing between the array elements to it is possible to increase the boresight of the pattern as shown in the figures.

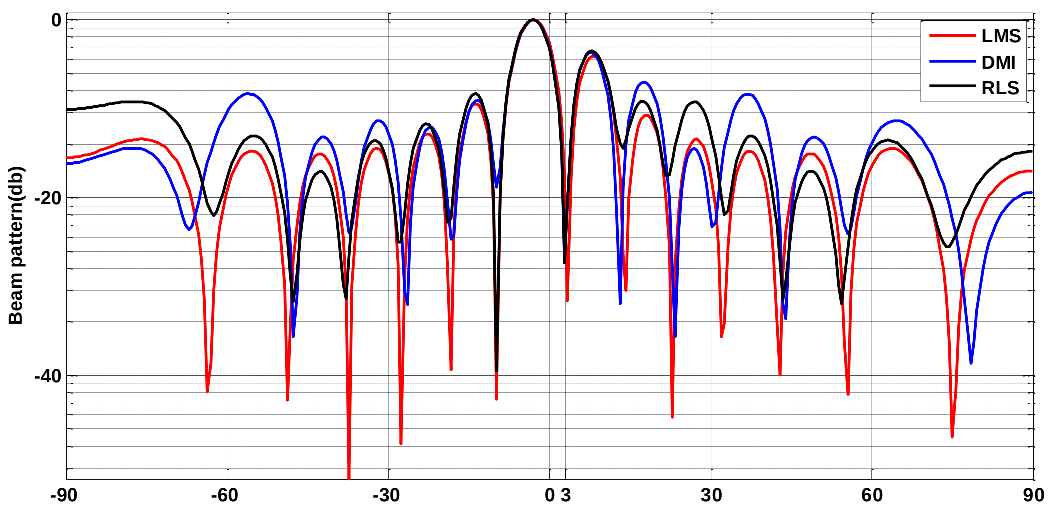


Figure 5.12 Beam pattern of linear uniform array (N=8, d=0.7λ, $\boldsymbol{\theta_d}$ =0 deg. $\boldsymbol{\theta_i}$ =3 degree)

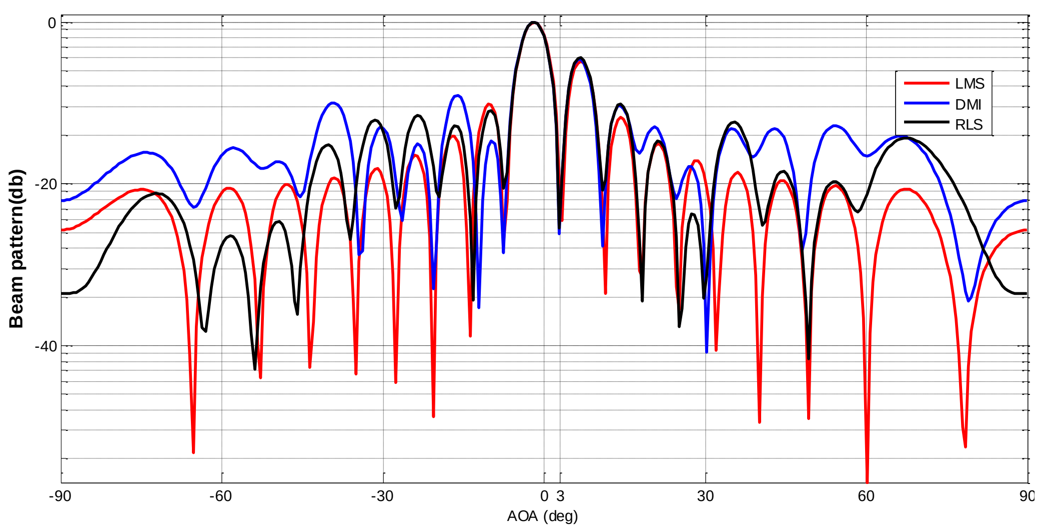


Figure 5.13 Beam pattern of uniform linear array (N=18, d=0.5, θ_d=0 deg. andθ_i =3 degree)

Angle of separation(θ_d) (degree) Spacing (d) (λ) Number of array (N)	Bore sight (db)			Nulling (db)			Side lobe level (db)		
	LMS	DMI	RLS	LMS	DMI	RLS	LMS	DMI	RLS
θ_d=3, d=0.5 λ, N=8	-4	-8.6	-8.4	-18.6	-33	-35.9	-9.5	-4	-6
θ_d=3, d=0.7 λ, N=8	-7	-7.4	-7.8	-34	-34.2	-34.5	-10	-9	-9
θ_d=3, d=0.7 λ, N=18	-0.2	-0.2	-0.2	-30	-32	-33.5	-11.2	-11	-11

Table 5.5 Values of bore sight, nulling and side lobe level at desire and jammer point

5.4 Simulation result of adjusted LMS algorithm

After observing the simulation results of different adaptive algorithm and array parameters we recommend the following array parameters and algorithm due to the following reason. Among the three adaptive algorithm which uses training signal for their weight updating case, we have chosen the LMS algorithm. This is because for small angle of separation all algorithms suffer with performance degradation in spite of performance differences. However increasing number of array or spacing reduces the effect of small angle of separation. On the basis of increasing number of array increases computational cost. So, among the three adaptive algorithms the increment of LMS algorithm is relatively small as described above, hence LMS algorithm with large number of array is preferred. Again for angle of separation larger than half of the first null beam width d=0.5λ gives a better performance, on the other hand for small angle of separation d=0.7λ is preferred. This is because at this point bore sight nulling point and side lobe level improves and the grating lobe is half of the first side lobe level.

According to the simulation result which is shown in figure 5.14 the performance of LMS algorithm such as bore sight and nulling is degrading as the angle of separation between the desire and the interferer angle become small. Particularly the bore sight starts to fall and the nulling starts to rise in the angle of separation around 13 and 8 degree respectively. On the other hand by using the above adjusting LMS algorithm, the performance of smart antenna system improves irrespective of their angle of separation as shown in figure 14. The bore sight of the adjusted LMS algorithm starts to fall and nulling starts to rise in the angle of separation 5 and 3 degree respectively which is better than the normal LMS algorithm.

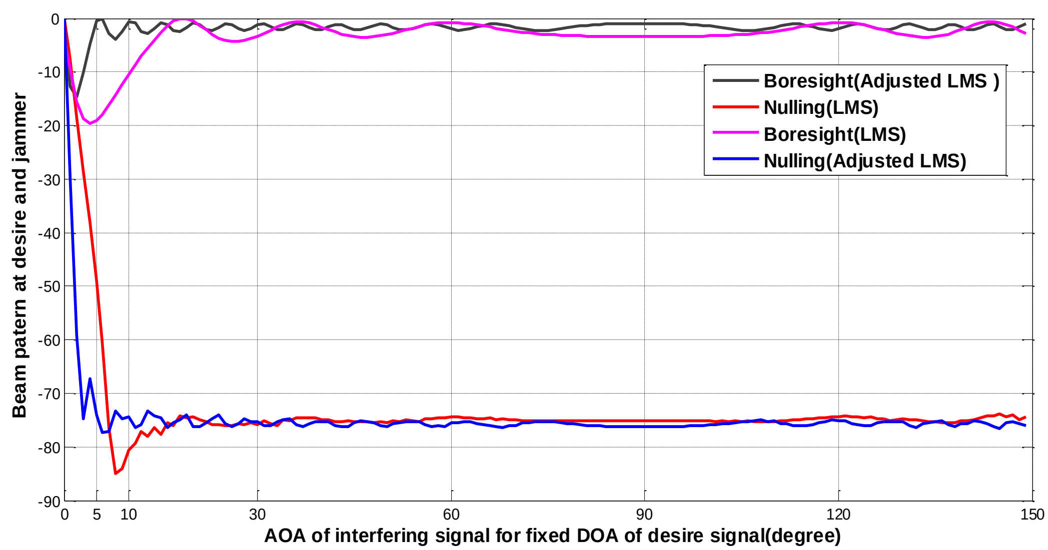


Figure 5.14 Bore sight and nulling of adjusted LMS algorithm (variable number of array and spacing between array elements).

Chapter 6: Conclusion and future work

6.1 Conclusion

Smart antenna is one of the possible candidates of future generation communication system. Although this technology provides a lot of advantages compared to the traditional Beamformer, there are issues that need to investigate. One of the possible issues that need to resolve is the possible performance degradation due to angle separation between the desire and the interferer signals different cases.

In this thesis work, adaptive Beamforming algorithms for smart antenna system are investigated. Particularly the effect of angle separation on the performance of adaptive array system such as: side lobe level, Bore sight and Nulling are presented. In addition, the performance of array parameters (number of array and spacing between array elements) and Adaptive algorithms such as: LMS, DMI, RLS are compared based on angle separation.

There are important observations from our simulation results. First of all, there is performance degradation due to angle of separation between the desire and the interferer signal. As in the results shown when the separation is the range of half of the first null beam width the performance of the smart antenna system is not satisfactory.

The second important observation is that d=0.5λ is not an optimal value for all angle of separation. Increasing spacing between array elements for small angle of separation system performance enhances at the cost of grating lobes. However for large angle of separation the grating lobe is introduced which is unintended in smart antenna system.

The other observation in this simulation is that increasing the number of array increase the system performance for all angle of separation. And also Performances of RLS, DMI and LMS are observed.

So the basic question arises from this observation is that how these observations included in system to enhance the system performance especially for small angle of separation?

So how can we use different number of array and spacing for different angle of separation?

6.2 Future work

Although we have investigated the adaptive array system for different array parameters, performance criterions, adaptive algorithm and the results presented in this work are useful for smart antenna system, there are still some issues that require further research for further improvement. Here are list of recommendations to the possible extensions of the works of this thesis research:

- In this thesis uniform linear arrays are considered. Further work can be extended for other array geometries such as: planar and circular array.
- The self-correlation (correlation between the signals induced in each array element) and the cross correlation (the correlation between the induced signal and the reference signal) is assumed uncorrelated in this work. Assuming the signals to be correlated is another challenge. Thus the work can be extended for uncorrelated signals.
- The coupling effect in this work is not considered. Thus the work can be extended by including coupling effect.
- Narrow band signals and training based algorithms are used in the work. Thus, blind algorithms and wide band signals can be considered for further studies.
- In this work, when the angle difference is 0 degree, it is very challenging to differentiate the desire and the interferer signal. Thus, the work can be extended to alleviate such type of problem either by modify the available algorithm or introduce the new one.

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