Implementation of Smart Antenna System

Using Genetic Algorithm and Artificial Immune System

Defining futures

By

PC Habib Awan
PC Khurrum Abdullah
Capt. Shahid Abbas
Capt. Ali Ahsan

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Abstract

In simple words, smart antenna is such that it can sense its environment and can adjust its gain in different directions accordingly. They provide a smart solution to the problem of communication traffic overload i.e. they increase the traffic capacity. They also improve the QOS.

RF spectrum is a limited resource and is becoming crowded day by day due to the advent of new technologies. The sources of interference are increasing as well and hence interference is becoming the limiting factor for wireless communication.

Smart Antenna adapts its radiation pattern in such a way that it steers its main beam in the DOA (direction of arrival) of the desired user signal and places null along the interference. It refers to a system of antenna arrays with smart signal processing algorithms.

This project aims to implement a complete smart antenna system with an altogether different hybrid biological technique which gives better results than the previous algorithms used in this regard. We have done both pats here i.e. DOA Estimation and Beamforming. We have developed its code using MATLAB. We have also implemented it on DSP-Kit. Instead of using actual signals, we have used dummy signals, which are fed to DSK- C6713 for processing.

Acknowledgement

We wish to thank Almighty Allah who gave us the strength and determination to complete this project. We gratefully acknowledge the continuous guidance and motivation provided to us by our project advisors Lt. Col (R) Syed Javed Hussain and Mr. Muhammad Faryad (Quaid-e-Azam University). Without their personal supervision, advice and help, timely completion of this project would have been impossible. Our very special thanks are extended to Mr. Khalil Ahmed (Shifa Medical College) for helping us for getting the details of our biological algorithms. We would also like to thank Mr. Amir Rasheed and Miss Attiya Obaid for their assistance regarding the implementation on DSK.

We are also deeply indebted to our families for their never ending patience and support for our mental peace and to our parents for the strength that they gave us through their prayers.

List of Publications

[1]. **Habib Awan, Khurrum Abdullah and Muhammad Faryad, *"Implementing Smart Antenna System using Genetic Algorithm"*,** in **third All Pakistan Electrical Engineering Conference, APE^{2}C, Nov 2007, Pakistan.**

[2]. **Habib Awan, Khurrum Abdullah and Muhammad Faryad, *"Implementing Smart Antenna System using Genetic Algorithm and Artificial Immune System"*,** accepted for the **17th International Conference on Microwaves, Radar and Wireless Communications MIKON 2008 - May 19-21, Wroclaw, Poland.**

Chapter 1

Introduction

1.1 Motivation and Objective

The challenge of next generation wireless communication systems comes from the fact that they will have to offer data rates in the hundreds of megabits per second. This requirement translates into the demand for wide frequency bands. The problem of overcoming spectrum limitation while delivering high data rate requirement can be achieved using smart antennas

The adaptive antenna array is capable of automatically forming beams in the directions of the desired signals and steering nulls in the directions of the interfering signals. The dual purpose of a smart antenna system is to augment the signal quality of the radio-based system through more focused transmission of radio signals while enhancing capacity through increased frequency reuse. There exist many adaptive algorithms that have been used in the adaptive antenna array. But to improve the efficiency of adaptive antenna, there is requirement to implement it some more efficient algorithms. So we will be using here a hybridized technique of Genetic Algorithm and Artificial Immune system for its implementation.

The aim of this project is to implement some algorithm for both DOA Estimation and Beamforming and compare the performance of this algorithm with the previous algorithms.

1.2 Outline of Thesis

This thesis is organized as follows.

Chapter 2, Antenna Basics This chapter gives a brief overview of the basic terminologies related to all type of antennas.

Chapter 3, Antenna Arrays This chapter introduces the fundamentals of antenna arrays, the terminology, and the basic concepts related to the antenna arrays.

Chapter 4, Smart Antenna This chapter provides a detailed survey of the Smart Antenna System, its properties and functions.

Chapter 5, Genetic Algorithm This chapter presents an overview of this biological algorithm. Although material is available in detail but it is here briefed for the interested readers.

Chapter 6, Artificial Immune System This chapter presents the basics of this algorithm.

Chapter 7, Our Proposed Technique This chapter explains the implementation of Genetic Algorithm and Artificial Immune System towards Smart Antenna.

Chapter 8, Overview of Previous Techniques This chapter gives a bird eye view of the previous algorithms for the implementation of Smart Antenna and also compares them with our proposed technique.

Chapter 9, DSP Kit This chapter explains the basics of the DSP kit and the implementation of DOA Estimation module on it.

Chapter 10, Conclusion and Future Recommendations A brief summary of future recommendations and conclusions is provided in this chapter.

Chapter 2

Antenna Basics

2.1 Introduction

Antennas are a very important component of communication systems. By definition, it is a device that converts guided electromagnetic waves into unguided ones and vice versa. Antennas demonstrate a property known as *reciprocity*, which means that an antenna will maintain the same characteristics regardless if it is transmitting or receiving. Most antennas are resonant devices, which operate efficiently over a relatively narrow frequency band. An antenna must be tuned to the same frequency band of the radio system to which it is connected; otherwise the reception and the transmission will be impaired. When a signal is fed into an antenna, the antenna will emit radiation distributed in space in a certain way. Here some important parameters are defined that are basic and related to every type of antenna.

Input Impedance

For an efficient transfer of energy, the impedance of the radio, of the antenna and of the transmission cable connecting them must be the same. Transceivers and their transmission lines are typically designed for 50Ω impedance. If the antenna has impedance different from 50Ω, then there is a mismatch and an impedance matching circuit is required.

Return loss

The return loss is another way of expressing mismatch. It is a logarithmic ratio measured in dB that compares the power reflected by the antenna to the power that is fed into the antenna from the transmission line. The relationship between SWR and return loss is the following:

$$\text{Return Loss (in dB)} = 20\log_{10}\frac{\text{SWR}}{\text{SWR}-1}$$

--- 2.1

Bandwidth

The bandwidth of an antenna refers to the range of frequencies over which the antenna can operate correctly. The antenna's bandwidth is the number of Hz for which the antenna will exhibit an SWR less than 2:1. The bandwidth can also be described in terms of percentage of the center frequency of the band.

$$BW = 100 \times \frac{F_H - F_L}{F_C} \qquad \textbf{---2.2}$$

Where FH is the highest frequency in the band, FL is the lowest frequency in the band, and FC is the center frequency in the band.

In this way, bandwidth is constant relative to frequency. If bandwidth was expressed in absolute units of frequency, it would be different depending upon the center frequency. Different types of antennas have different bandwidth limitations.

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 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. To compare the dipole to an antenna over a range of frequencies requires a number of dipoles of different lengths. An antenna gain of 3 dB compared to a dipole antenna would be written as 3 dBd. The method of measuring gain by comparing the antenna under test against a known standard antenna, which has a calibrated gain, is technically known as a gain transfer technique. Another method for measuring gain is the 3 antennas method, where the transmitted and received power at the antenna terminals is measured between three arbitrary antennas at a known fixed distance.

Mathematically the directivity is given by the formula

$$D(\theta, \phi) = \frac{\mathcal{P}(\theta, \phi)}{(1/4\pi r^2) \int_0^{\pi} \int_0^{2\pi} \mathcal{P}(\theta', \phi') r^2 \sin\theta' \, d\theta' \, d\phi'} \quad \text{---2.3}$$

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 following figure shows a rectangular plot presentation of a typical 10 element Yagi. The detail is good but it is difficult to visualize the antenna behavior at different directions.

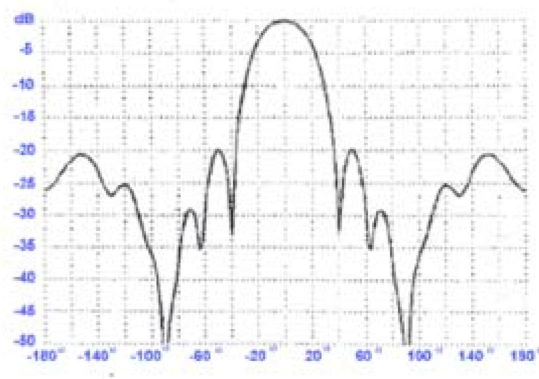

Figure 2.1: Rectangular Plot of the Radiation Pattern

Polar coordinate systems are used almost universally. In the polar coordinate graph, points are located by projection along a rotating axis (radius) to an intersection with one of several concentric circles. Following is a polar plot of the same 10 element Yagi antenna.

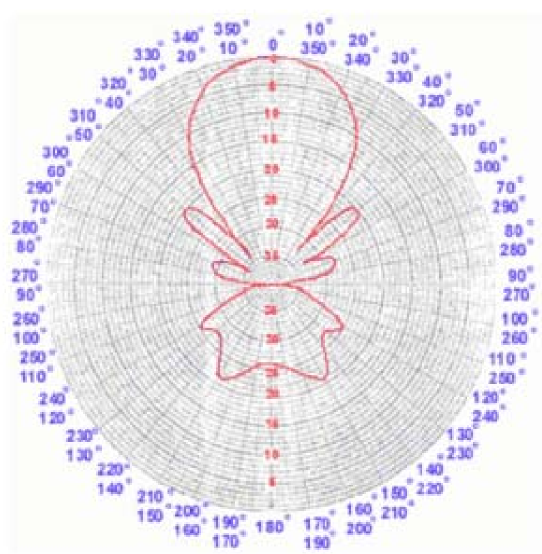

Figure 2.2: Polar Plot of the Radiation Pattern

Polar coordinate systems may be divided generally in two classes: *linear* and *logarithmic*. In the linear coordinate system, the concentric circles are equally spaced, and are graduated. Such a grid may be used to prepare a linear plot of the power contained in the signal. For ease of comparison, the equally spaced concentric circles may be replaced with appropriately placed circles representing the decibel response, referenced to 0 dB at the outer edge of the plot. In this kind of plot the minor lobes are suppressed. Lobes with peaks more than 15 dB or so below the main lobe disappear because of their small size. This grid enhances plots in which the antenna has a high directivity and small minor lobes. The voltage of the signal, rather than the power, can also be plotted on a linear coordinate system. In this case, too, the directivity is enhanced and the minor lobes suppressed, but not in the same degree as in the linear power grid.

In the logarithmic polar coordinate system the concentric grid lines are spaced periodically according to the logarithm of the voltage in the signal. Different values may be used for the logarithmic constant of periodicity, and this choice will have an effect on the appearance of the plotted patterns. Generally the 0 dB reference for the outer edge of the chart is used. With this type of grid, lobes that are 30 or 40 dB below the main lobe are still distinguishable. The spacing between points at 0 dB and at -3 dB is greater than the spacing between -20 dB and -23 dB, which is greater than the spacing between -50 dB and -53 dB. The spacing thus corresponds to the relative significance of such changes in antenna performance.

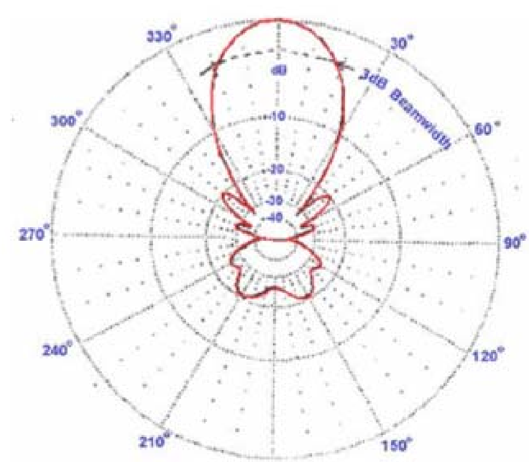

Figure 2.3: Power Pattern in logarithmic polar coordinates

A modified logarithmic scale emphasizes the shape of the major beam while compressing very low-level (>30 dB) side lobes towards the center of the pattern. There are two kinds of radiation pattern: absolute and relative. Absolute radiation patterns are presented in absolute units of field strength or power. Relative radiation patterns are referenced in relative units of field strength or power. Most radiation pattern measurements are relative to the isotropic antenna, and then the gain transfer method is then used to establish the absolute gain of the antenna.

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. For pattern measurement it is important to choose a distance sufficiently large to be in the far-field, well out of the near-field. The minimum permissible distance depends on the dimensions of the antenna in relation to the wavelength. The accepted formula for this distance is:

$$r_{min} = \frac{2d^2}{\lambda}$$

--- 2.4

Where r_{min} is the minimum distance from the antenna, d is the largest dimension of the antenna, and λ is the wavelength.

Beamwidth

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 sidelobes, then the directive gain is inversely proportional to the beamwidth: as the beamwidth decreases, the directive gain increases.

Sidelobes

No antenna is able to radiate all the energy in one preferred direction.
Some is inevitably radiated in other directions. The peaks are referred to as sidelobes, commonly specified in dB down from the main lobe.

Nulls

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.

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.

With linear polarization the electric field vector stays in the same plane all the time. Vertically polarized radiation is somewhat less affected by reflections over the transmission path. Omni directional antennas always have vertical polarization. With horizontal polarization, such reflections cause variations in received signal strength. Horizontal antennas are less likely to pick up man-made interference, which ordinarily is vertically polarized. In circular polarization the electric field vector appears to be rotating with circular motion about the direction of propagation, making one full turn for each RF cycle. This rotation may be righthand or lefthand. Choice of polarization is one of the design choices available to the RF system designer.

Polarization Mismatch

In order to transfer maximum power between a transmit and a receive antenna, both antennas must have the same spatial orientation, the same polarization sense and the same axial ratio. When the antennas are not aligned or do not have the same polarization, there will be a reduction in power transfer between the two antennas. This reduction in power transfer will reduce the overall system efficiency and performance. When the transmit and receive antennas are both linearly polarized, physical antenna misalignment will result in a polarization mismatch loss which can be determined using the following formula:

$$\text{Polarization Mismatch Loss (dB)} = 20 \log (\cos \vartheta) \qquad \textbf{---2.5}$$

Where θ is the misalignment angle between the two antennas. For 15° we have a loss of 0.3 dB, for 30° we have 1.25 dB, for 45° we have 3 dB and for 90° we have an infinite loss. The actual mismatch loss between a circularly polarized antenna and a linearly polarized antenna will vary depending upon the axial ratio of the circularly polarized antenna. If polarizations are coincident no attenuation occurs due to coupling mismatch between field and antenna, while if they are not, then the communication can't even take place.

Front-to-back ratio

It is useful to know the *front-to-back ratio* that is the ratio of the maximum directivity of an antenna to its directivity in the rearward direction. For example, when the principal plane pattern is plotted on a relative dB scale, the front-to-back ratio is the difference in dB between the level of the maximum radiation, and the level of radiation in a direction 180 degree.

2.2 Types of Antennas

A classification of antennas can be based on:

Frequency and size

Antennas used for HF are different from the ones used for VHF, which in turn are different from antennas for microwave. The wavelength is different at different frequencies, so the antennas must be different in size to radiate signals at the correct wavelength. We are particularly interested in antennas working in the microwave range, especially in the 2.4 GHz and 5 GHz frequencies. At 2.4 GHz the wavelength is 12.5 cm, while at 5 Ghz it is 6 cm.

Directivity

Antennas can be omni directional, sectorial or directive. Omni directional antennas radiate the same pattern all around the antenna in a complete 360 degrees pattern. The most popular types of omni directional antennas are the Dipole-Type and the Ground Plane. Sectorial antennas radiate primarily in a specific area. The beam can be as wide as 180 degrees, or as narrow as 60 degrees. Directive antennas are antennas in which the beamwidth is much narrower than in sectorial antennas. They have the highest gain and are therefore used for long distance links. Types of directive antennas are the Yagi, the biquad, the horn, the helicoidal, the patch antenna, the Parabolic Dish and many others.

Physical construction

Antennas can be constructed in many different ways, ranging from simple wires to parabolic dishes, up to coffee cans. When considering antennas suitable for 2.4 GHz WLAN use, another classification can be used:

Application

We identify two application categories which are Base Station and Point-to-Point. Each of these suggests different types of antennas for their purpose. Base Stations are used for multipoint access. Two choices are Omni antennas which radiate equally in all directions, or Sectorial antennas,

1/4 Wavelength Ground Plane

The 1⁄4 Wavelength Ground Plane antenna is very simple in its construction and is useful for communications when size, cost and ease of construction are important. This antenna is designed to transmit a vertically polarized signal. It consists of a 1⁄4 wave element as half-dipole and three or four 1⁄4 wavelength ground elements bent 30 to 45 degrees down. This set of elements, called *radials*, is known as a *ground plane*. This is a simple and effective antenna that can capture a signal equally from all directions. To increase the gain, however, the signal can be flattened out to take away focus from directly above and below, and providing more focus on the horizon. The vertical beamwidth represents the degree of flatness in the focus. This is useful in a Point-to-Multipoint situation, if all the other antennas are also at the same height. The gain of this antenna is in the order of 2 - 4 dBi.

Yagi antenna

A basic Yagi consists of a certain number of straight elements, each measuring approximately half wavelength. The driven or active element of a Yagi is the equivalent of a center-fed, half-wave dipole antenna. Parallel to the driven element, and approximately 0.2 to 0.5 wavelength on either side of it, are straight rods or wires called reflectors and directors, or passive elements altogether. A reflector is placed behind the driven element and is slightly longer than half wavelength; a director is placed in front of the driven element and is slightly shorter than half wavelength. A typical Yagi has one reflector and one or more directors. The antenna propagates electromagnetic field energy in the direction running from the driven element toward the directors, and is most sensitive to incoming electromagnetic field energy in this same direction. The more directors a Yagi has, the greater the gain. As more directors are added to a Yagi, however, it becomes longer. Following is the photo of a Yagi antenna with 6 directors and one reflector.

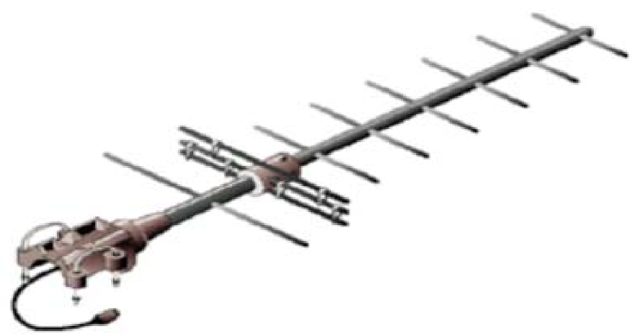

Figure 2.4: A Yagi Uda TV antenna

Horn

The horn antenna derives its name from the characteristic flared appearance. The flared portion can be square, rectangular, cylindrical or conical. The direction of maximum radiation corresponds with the axis of the horn. It is easily fed with a waveguide, but can be fed with a coaxial cable and a proper transition. Horn antennas are commonly used as the active element in a dish antenna. The horn is pointed toward the center of the dish reflector. The use of a horn, rather than a dipole antenna or any other type of antenna, at the focal point of the dish minimizes loss of energy around the edges of the dish reflector. At 2.4 GHz, a simple horn antenna made with a tin can has a gain in the order of 10 - 15 dBi.

Figure 2.5: A Horn Antenna made out of can

Parabolic Dish

Antennas based on parabolic reflectors are the most common type of directive antennas when a high gain is required. The main advantage is that they can be made to have gain and directivity as large as required. The main disadvantage is that big dishes are difficult to mount and are likely to have a large windage. The basic property of a perfect parabolic reflector is that it converts a spherical wave irradiating from a point source placed at the focus into a plane wave. Conversely, all the energy received by the dish from a distant source is reflected to a single point at the focus of the dish. The position of the focus, or focal length, is given by:

$$f = \frac{D^2}{16 \times c}$$

---2.6

Where D is the dish diameter and c is the depth of the parabola at its center. The size of the dish is the most important factor since it determines the maximum gain that can be achieved at the given frequency and the resulting beamwidth. The gain and beamwidth obtained are given by:

$$G = \frac{(\pi \times D)^2}{\lambda^2} \times n$$

---2.7

$$BW = \frac{70\lambda}{D}$$

---2.8

Where D is the dish diameter and n is the efficiency. The efficiency is determined mainly by the effectiveness of illumination of the dish by the feed, but also by other factors. Each time the diameter of a dish is doubled, the gain is four times, or 6 dB, greater. If both stations double the size of their dishes, signal strength can be increased of 12 dB, a very substantial gain. An efficiency of 50% can be assumed when hand-building the antenna.

The ratio f/D (focal length/diameter of the dish) is the fundamental factor governing the design of the feed for a dish. The ratio is directly related to the beamwidth of the feed necessary to illuminate the dish effectively. Two dishes of the same diameter but different focal lengths require different design of feed if both are to be illuminated efficiently. The value of 0.25 corresponds to the common focal-plane dish in which the focus is in the same plane as the rim of the dish.

Dishes up to one meter are usually made from solid material. Aluminum is frequently used for its weight advantage, its durability and good electrical characteristics. Windage increases rapidly with dish size and soon becomes a severe problem. Dishes which have a reflecting surface that uses an open mesh are frequently used. These have a poorer front-to-back ratio, but are safer to use and easier to build. Copper, aluminum, brass, galvanized steel and iron are suitable mesh materials.

Figure 2.6: A 3.2 GHz Parabolic Dish Antenna

Other Antennas

Many other types of antennas exist and new ones are created following the advances in technology.

Sector or Sectorial antennas:

They are widely used in cellular telephony infrastructure and are usually built adding a reflective plate to one or more phased dipoles. Their horizontal beamwidth can be as wide as 180 degrees, or as narrow as 60 degrees, while the vertical is usually much narrower. Composite antennas can be built with many Sectors to cover a wider horizontal range (*multisectorial antenna*).

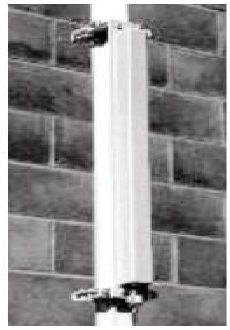

Figure 2.7: A Wifi Sector Antenna

Panel or Patch antennas: they are solid flat panels used for indoor coverage, with a gain up to 20 dB.

Figure 2.8: A Simple Patch Antenna

Chapter 3

Antenna Arrays

3.1 Introduction:

There's a huge family of antennas and monopole, dipole, patch, slot, wave guide, loop, and helix etc. are all cousins. All of them have their specific radiation patterns. Instead of using these antennas individually, they can also be used collectively, such symmetry is called antenna array. An array consists of two or more antenna elements that are spatially arranged and electrically interconnected to produce a directional radiation pattern. The interconnection between elements, called the feed network, can provide fixed phase to each element or can form a phased array. As Smart antenna is a special application of antenna array, therefore in chapter we have explained the basic parameters related to an antenna array, which must be familiarized before going to Smart antennas.

3.2 Radiation Pattern

Radiation pattern is the variation of the field intensity of an antenna as an angular function. [1] It is graphical representation of the distribution of radiation from an antenna as a function of angle. It's always the same for receiving as for transmitting. This property is known as *reciprocity.* [2]

An electromagnetic wave measured at a point far from the antenna is the sum of the radiation from all parts of the antenna. Each small part of the antenna is radiating waves of a different amplitude and phase, and each of these waves travels a different distance to the point where a receiver is located. In some directions, these waves add constructively to give a gain. In some directions they add destructively to give a loss. For e.g. the practical center-fed dipole usually consists of a pair of tubular conductors of diameter d aligned in tandem so that there is a small feeding gap at the center. The total length is 21 >> d. A voltage is applied across the gap, often by means of a two-wire transmission line. The resulting current distribution on the pair of tubular conductors gives rise to a radiating field. The following figure shows its radiation pattern.

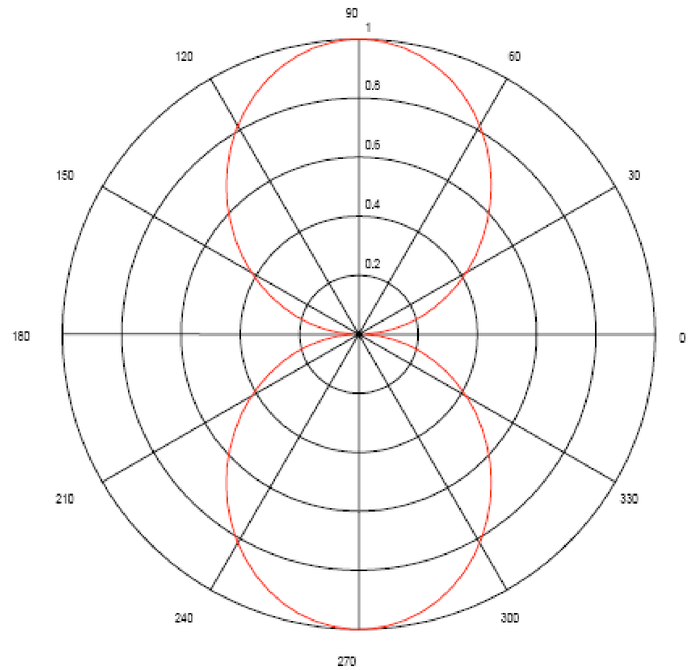

Figure3.1: Half wave dipole antenna, length ½ Lambda [6]

If a circular wire loop of radius a small compared to a wavelength is fed by a two wire-line, as shown in Figure3.2.

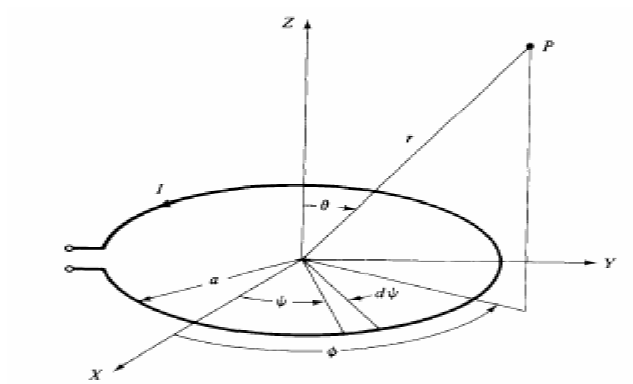

Figure3.2: Small Current loop [3]

Its radiation pattern is given by Figure3.3.

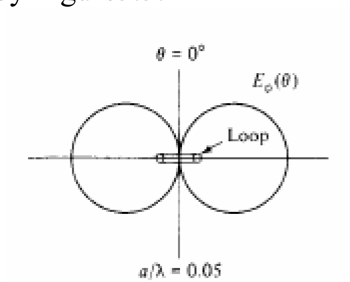

Figure3.3: Normalized E-field pattern of a small loop [3]

3.3 Linear Arrays

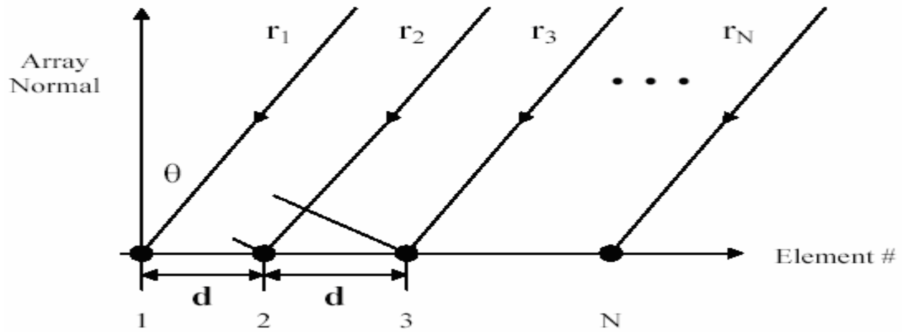

Figure3.4: Linear Array of N elements

On the basis of symmetry there are three types of arrays i.e. Linear Arrays, Planar Arrays and 3-D Arrays. But here we will focus only on linear arrays. A simple directional antenna consists of a linear array of small radiating antenna elements, each fed with identical signals (the same amplitude and phase) from one transmitter. As the total width of the array increases, the central beam becomes narrower. As the number of elements increases, the side lobes become smaller.

The following figure is the radiation pattern for a linear array of 4 elements spaced 1/2 wavelength apart.

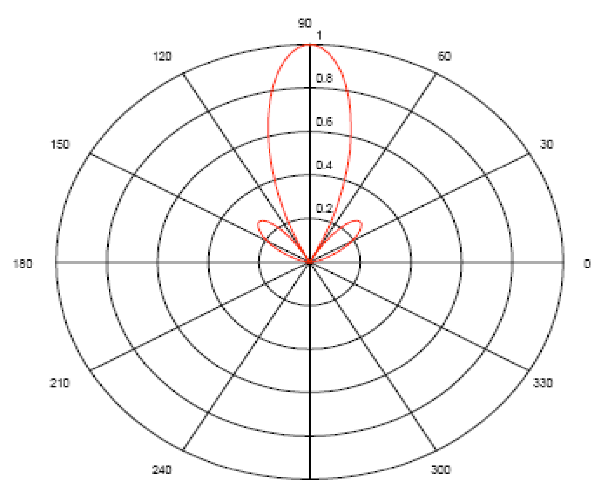

Figure3.5: 3- 4-Element 1.5 lambdą Linear Array 4 Identical Omni directional Antennas

If the spacing is increased to more than 1/2 wavelength, large side lobes begin to appear in the radiation pattern. However, the central beam gets narrower because the overall length of the antenna has increased. The following radiation pattern, for 4 elements spaced 1 wavelength apart, illustrates this.

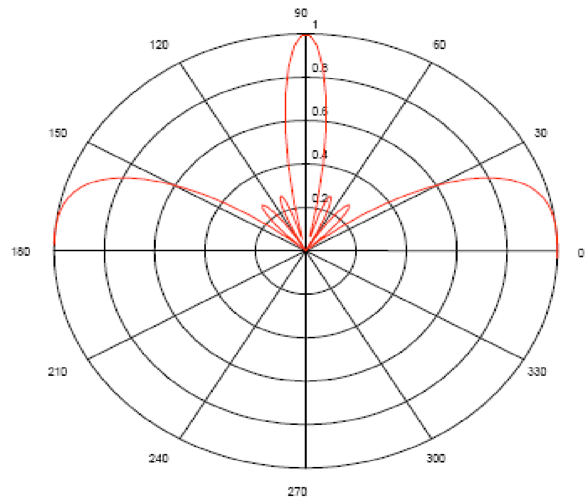

Figure3.6: 4-Element Linear Array, Spacing lambda

By keeping the overall length the same, and adding elements to reduce the spacing back to 1/2 wavelength, the side lobes are reduced. Following is the radiation pattern if 3 more elements are added to the linear array above to reduce the element spacing.

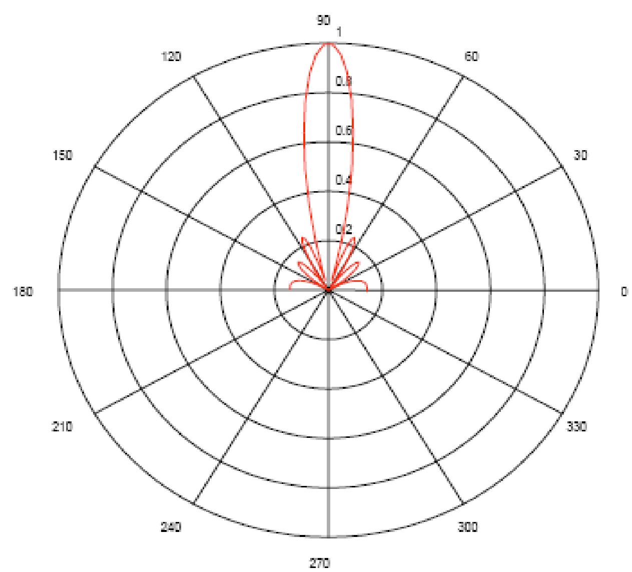

Figure3.7: 7-Element 3 λ Linear Array

Hence we can conclude that the radiation pattern of an antenna array is affected by following parameters

1. Difference in amplitude of currents fed to different array elements
2. Difference in phase of current fed to different array elements
3. Distances between individual antenna elements i.e. inter element spacing.
4. No. of elements
5. Radiation pattern of individual elements.

3.4 Array Factor (AF)

The radiation pattern of antenna array is given by

$$a = \underbrace{a_a(\theta, \phi)}_{\textbf{Array factor}} \times \underbrace{a_{\theta,e}(\theta, \phi)}_{\textbf{Element Factor}} \qquad \textbf{---3.1}$$

In this array factor is more dominative due to its sharp transitions. Therefore to simplify the analysis we have based our study on the array factor, which is given by

$$\mathrm{a}_a(\theta,\phi) \;=\; \sum_{n=0}^{N} \frac{I_n}{I_0} \exp\{jkr_n(\cos\alpha\sin\theta\cos\phi + \cos\beta\sin\theta\sin\phi + \cos\gamma\cos\theta)\} \qquad \textbf{---3.2}$$

Where N is the total number of elements, r_n is the distance of the nth element from the origin. Angles α, β and γ are shown in Figure 3.8. θ and φ are the spherical coordinates.

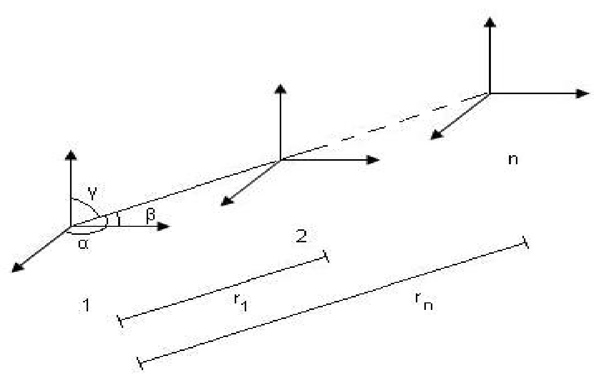

Figure3.8: Geometry of Array

Assuming this array to be equispaced and laid out along z-axis, (3.2) simplifies to

$$\mathfrak{a}_a(\theta) = \sum_{n=-N}^{N} \frac{I_n}{I_0} e^{jnkd\cos\theta} \qquad \textbf{---3.3}$$

The derivation of this equation can be found in [3]. In this equation total no. of elements are 2N+1, I_n are the element currents, I_o is the reference current, n is the iteration/element no., k is the wave no., d is the inter – element spacing and θ corresponds to the spherical coordinate.

If all the elements are fed with the same current, then the expression reduces to

$$\mathfrak{a}_a(\theta) = \sum_{n=-N}^{N} e^{jnkd\cos\theta} \qquad \textbf{---3.4}$$

Eq. 3.4 corresponds to broadside array, but our equation of interest would be eq.3.3.

3.5 Summary

In this chapter, we have given the basic introduction of the arrays; linear arrays in particular as we have used a linear array for smart antenna. Array factor is also discussed, upon which all further concentration will be focused.

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Chapter 4

Smart Antennas

4.1 INTRODUCTION

Many refer to smart antenna systems as smart antennas, but in reality antennas by themselves are not smart. It is the digital signal processing capability, along with the antennas, which make the system smart. Although it may seem that smart antenna systems are a new technology, the fundamental principles upon which they are based are not new. In fact, in the 1970s and 1980s two special issues of the *IEEE Transactions on Antennas and Propagation* were devoted to adaptive antenna arrays and associated signal processing techniques. The use of adaptive antennas in communication systems initially attracted interest in military applications. Particularly, the techniques have been used for many years in electronic warfare (EWF) as countermeasures to electronic jamming. In military radar systems, similar techniques were already used during World War II. However, it is only because of today's advancement in powerful low-cost digital signal processors, general-purpose processors and ASICs (Application Specific Integrated Circuits), as well as innovative software-based signal processing techniques (algorithms), that smart antenna systems are gradually becoming commercially available.

4.2 NEED FOR SMART ANTENNAS

Wireless communication systems, as opposed to their wire line counterparts, pose some unique challenges [7]:

- the limited allocated spectrum results in a limit on capacity
- the radio propagation environment and the mobility of users give rise to signal fading and spreading in time, space and frequency
- the limited battery life at the mobile device poses power constraints

In addition, cellular wireless communication systems have to cope with interference due to frequency reuse. Research efforts investigating effective technologies to mitigate such effects have been going on for the past twenty five years, as wireless communications are experiencing rapid growth [7]. Among these methods are multiple access schemes, channel coding and equalization and smart antenna employment. Fig below summarizes the wireless communication systems impairments that smart antennas are challenged to combat.

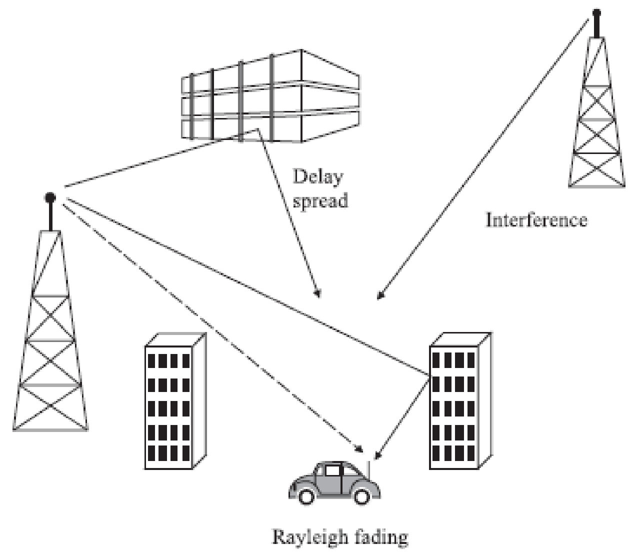

Figure 4.1: Wireless systems impairments

An antenna in a telecommunications system is the port through which radio frequency (RF) energy is coupled from the transmitter to the outside world for transmission purposes, and in reverse, to the receiver from the outside world for reception purposes. To date, antennas have been the most neglected of all the components in personal communications systems. Yet, the manner in which radio frequency energy is distributed into and collected from space has a profound influence upon the efficient use of spectrum, the cost of establishing new personal communications networks and the service quality provided by those networks. The commercial adoption of smart antenna techniques is a great promise to the solution of the aforementioned wireless communications' impairments.

4.3 Overview

The basic idea on which smart antenna systems were developed is most often introduced with a simple intuitive example that correlates their operation with that of the human auditory system. A person is able to determine the Direction of Arrival (DoA) of a sound by utilizing a three-stage process:

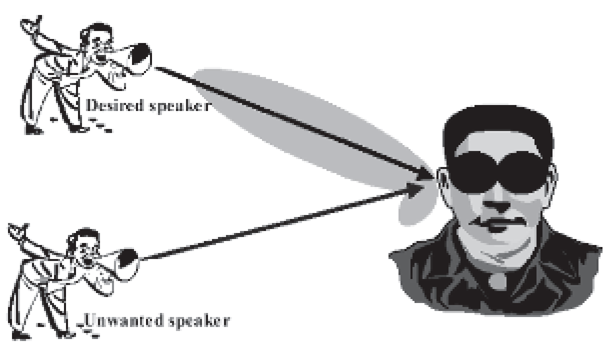

Figure 4.2: Human auditory function

- One's ears act as acoustic sensors and receive the signal.
- Because of the separation between the ears, each ear receives the signal with a different time delay.
- The human brain, a specialized signal processor, does a large number of calculations to correlate information and compute the location of the received sound.

To better provide an insight of how a smart antenna system works, let us imagine two persons carrying on a conversation inside an isolated room as illustrated in Fig. above The listener among the two persons is capable of determining the location of the speaker as he moves about the room because the voice of the speaker arrives at each acoustic sensor, the ear, at a different time. The human "signal processor," the brain, computes the direction of the speaker from the time differences or delays received by the two ears. Afterward, the brain adds the strength of the signals from each ear so as to focus on the sound of the computed direction. Utilizing a similar process, the human brain is capable of distinguishing between multiple signals that have different directions of arrival. Thus, if additional speakers join the conversation, the brain is able to enhance the received signal from the speaker of interest and tune out unwanted interferers. Therefore, the listener has the ability to distinguish one person's voice, from among many people talking simultaneously, and concentrate on one conversation at a time. In this way, any unwanted interference is attenuated. Conversely, the listener can respond back to the same direction of the desired speaker by orienting his/her transmitter, his/her mouth, toward the speaker. Electrical smart antenna systems work the same way using two antennas instead of two ears, and a digital signal processor instead of the brain as seen in Fig.4.3. Thus, based on the

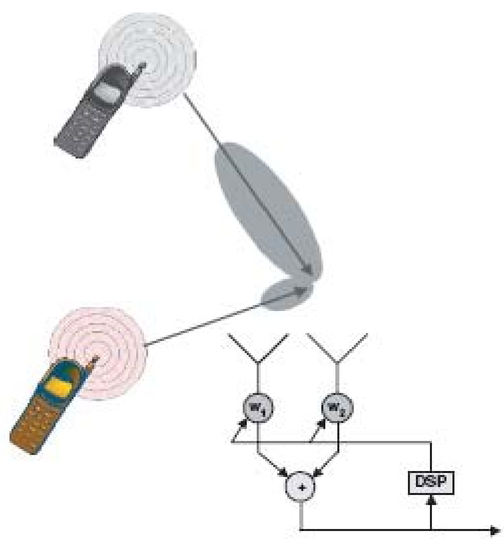

Figure 4.3: A two-element electrical smart antenna

Thus, based on the time delays due to the impinging signals onto the antenna elements, the digital signal processor computes the direction-of-arrival (DOA) of the signal-of-interest (SOI), and then it adjusts the excitations (gains and phases of the signals) to produce a radiation pattern that focuses on the SOI while tuning out any interferers or signals-not-of-interest (SNOI). Transferring the same idea to mobile communication systems, the base station plays the role of the listener, and the active cellular telephones simulate the role of the several sounds heard by human ears. The principle of a smart antenna system is illustrated in Fig. below. A digital signal processor located at the base station works in conjunction with the antenna array and is responsible for adjusting various system parameters to filter out any interferers or signals-not-of-interest (SNOI) while enhancing desired communication or signals-of-interest (SOI). Thus, the system forms the radiation pattern in an adaptive manner, responding dynamically to the signal environment and its alterations. The principle of beamforming is essentially to weight the transmit signals in such a way that the receiver obtains a constructive superposition of different signal parts. Note that some knowledge of the transmission channel at the transmitter is necessary in order for beamforming to be feasible.

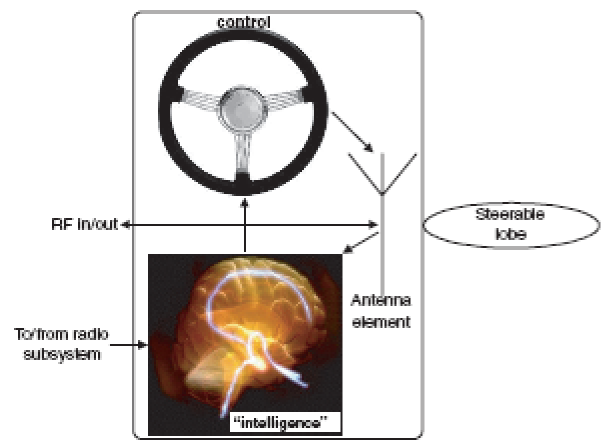

Figure 4.4: Principle of a smart antenna system [14].

4.4 SMART ANTENNA CONFIGURATIONS

Basically, there are two major configurations of smart antennas:

- Switched-Beam: A finite number of fixed, predefined patterns or combining strategies (sectors).
- Adaptive Array: A theoretically infinite number of patterns (scenario-based) that are adjusted in real time according to the spatial changes of SOIs and SNOIs.

In the presence of a low level interference, both types of smart antennas provide significant gains over the conventional sectorized systems. However, when a high level interference is present, the interference rejection capability of the adaptive systems provides significantly more coverage than either the conventional or switched beam system [4]. Fig. below illustrates the relative coverage area for conventional sectorized, switched-beam, and adaptive antenna systems. Both types of smart antenna systems provide significant gains over conventional sectorized systems. The low level of interference environment on the left represents a new wireless system with lower penetration levels. However the environment with a significant level of interference on the right represents either a wireless system with more users or one using more aggressive frequency reuse patterns. In this scenario, the interference rejection capability of the adaptive system provides significantly more coverage than either the conventional or switched beam systems [4].

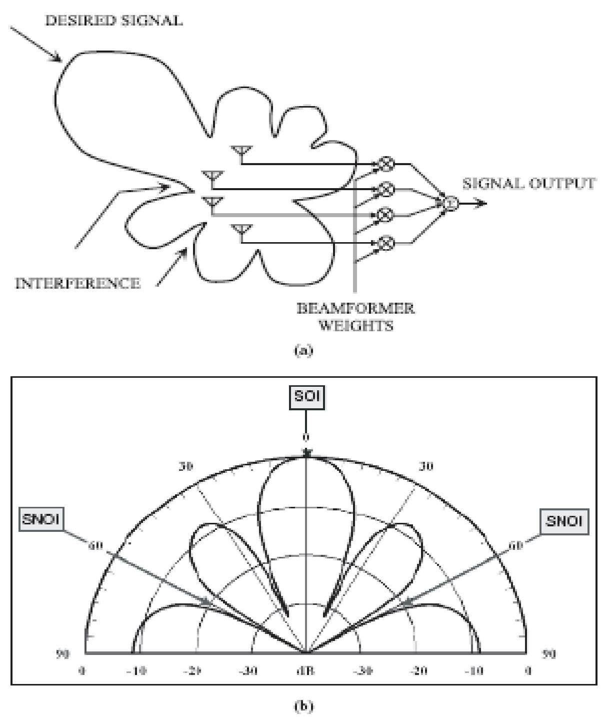

Figure 4.5 Adaptation procedures: (a) Calculation of the beamformer weights [2]
(b) Beamformed antenna amplitude pattern to enhance SOI and suppress SNOIs.

Now, let us assume that a signal of interest and two co-channel interferers arrive at the base station of a communications system employing smart antennas. Fig. below illustrates the beam patterns that each configuration may form to adapt to this scenario.

The switched-beam system is shown on the left while the adaptive system is shown on the right. The light lines indicate the signal of interest while the dark lines display the direction of the co-channel interfering signals. Both systems direct the lobe with the greatest intensity in the general direction of the signal of interest. However, switched fixed beams achieve coarser pattern

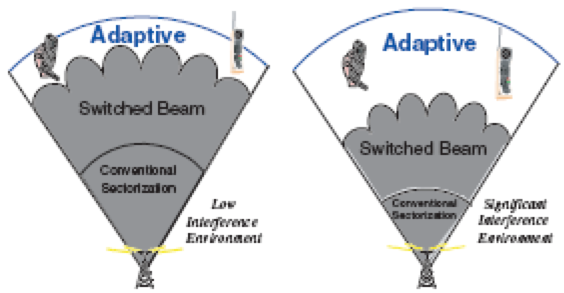

Figure 4.6: Coverage patterns for switched beam and adaptive array antennas [2]

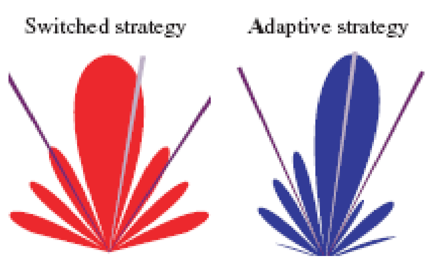

Figure 4.7: Beamforming lobes and nulls that Switched-Beam (left) and Adaptive Array (right) systems might choose for identical user signals (light line) and co-channel interferers (dark lines) [2]. control than adaptive arrays [15].

The adaptive system chooses a more accurate placement, thus providing greater signal enhancement. Similarly, the interfering signals arrive at places of lower intensity outside the main lobe, but again the adaptive system places these signals at the lowest possible gain points. The adaptive array concept ideally ensures that the main signal receives maximum enhancement while the interfering signals receive maximum suppression.

Switched-Beam Antennas

A switched-beam system is the simplest smart antenna technique. It forms multiple fixed beams with heightened sensitivity in particular directions. Such an antenna system detects signal strength, chooses from one of several predetermined fixed beams, and switches from one beam to another as the cellular phone moves throughout the sector, as illustrated in Fig. 4.8.

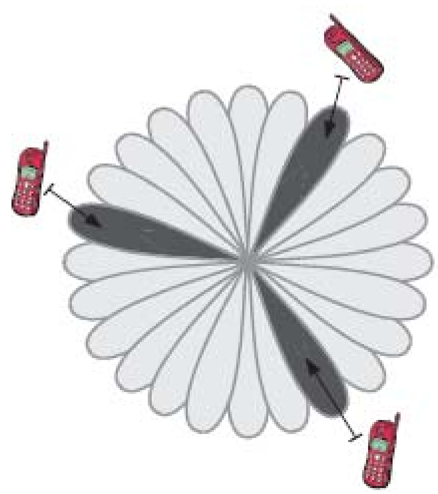

FIGURE 4.8: Switched-beam coverage pattern [16].

The switched-beam, which is based on a basic switching function, can select the beam that gives the strongest received signal. By changing the phase differences of the signals used to feed the antenna elements or received from them, the main beam can be driven in different directions throughout space. Instead of shaping the directional antenna pattern, the switched-beam systems combine the outputs of multiple antennas in such a way as to form narrow sectorized (directional) beams with more spatial selectivity that can be achieved with conventional, single-element approaches. Other sources in the literature [17] define this concept as phased array or multibeam *antenna*. Such a configuration consists of either a number of fixed beams with one beam turned in toward the desired signal or a single beam (formed by phase adjustment only) that is steered toward the desired signal. A more generalized to the Switched-Lobe concept is the Dynamical Phased Array (DPA). In this concept, a direction of arrival (DOA) algorithm is embedded in the system [2]. The DOA is first estimated and then different parameters in the system are adjusted in accordance with the desired steering angle. In this way the received power is maximized but with the trade-off of more complicated antenna designs. The elements used in these arrays must be connected to the sources and/or receivers by feed networks. One of the most widely-known multiple beamforming networks is the Butler matrix [18, 19].

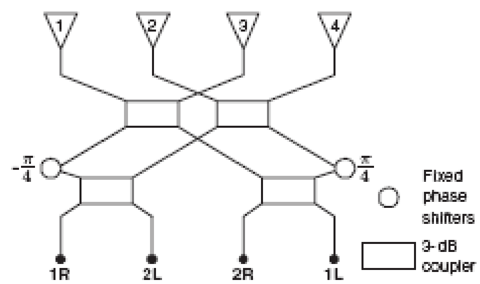

Figure 4.9 a schematic diagram of a 4 × 4 Butler matrix [21]

It is a linear, passive feeding, N × N network with beam steering capabilities for phased array antennas with *N* outputs connected to antenna elements and *N* inputs or beam ports. The Butler matrix performs a spatial fast Fourier transform and provides *N* orthogonal beams, where *N* should be an integer power of 2 [20]. These beams are linear independent combinations of the array element patterns. A Butler matrix-fed array can cover a sector of up to 360◦ depending on element patterns and spacing. Each beam can be used by a dedicated transmitter and/or receiver and the appropriate beam can be selected using an RF switch. A Butler matrix can also be used to steer the beam of a circular array by exciting the Butler matrix beam ports with amplitude and phase weighted inputs followed by a variable uniform phase taper [20]. The only required transmit/receive chain combines alternate rows of hybrid junctions (or directional couplers) and fixed phase shifters [21]. Fig. above shows a schematic diagram of a 4 × 4 Butler matrix.

Adaptive Antenna Approach

The adaptive antenna systems approach communication between a user and a base station in different way by adding the dimension of space. By adjusting to the RF environment as it changes (or the spatial origin of signals), adaptive antenna technology can dynamically alter the signal patterns to optimize the performance of the wireless system. Adaptive array systems [12] provide more degrees of freedom since they have the ability to adapt in real time the radiation pattern to the RF signal environment; in other words, they can direct the main beam toward the pilot signal or SOI while suppressing the antenna pattern in the direction of the interferers or SNOIs. To put it simply, adaptive array systems can customize an appropriate radiation pattern for each individual user. Fig. below illustrates the general idea of an adaptive antenna system. The adaptive concept is far superior to the performance of a switched-beam system, as it is shown in Fig. above. Also, it shows that switched-beam system not only may not be able to place the desired signal at the maximum of the main lobe, but also it exhibits inability to fully reject the interferers. Because of the ability to control the overall radiation pattern in a greater coverage area for each cell site, as illustrated in Fig. above adaptive array systems can provide great increase in capacity. Adaptive array systems can locate and track signals (users and interferers) and dynamically adjust the antenna pattern to enhance reception while minimizing interference using signal processing algorithms. A functional block diagram of the digital signal processing part of an adaptive array antenna system is shown in Fig. below.

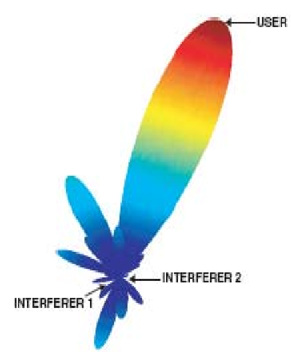

Figure 4.10 Adaptive array coverage: A representative depiction of a main lobe extending toward a user with nulls directed toward two co-channel interferers.

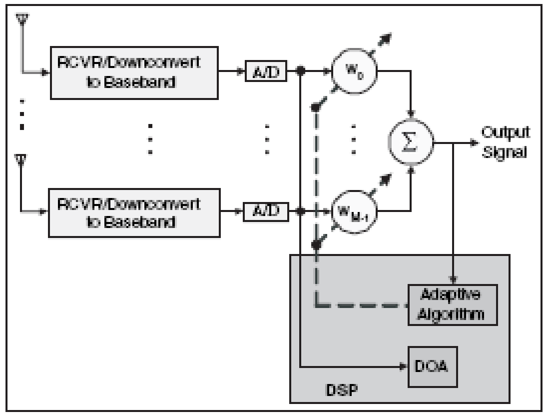

Figure 4.11 Functional block diagram of an adaptive array system

After the system down converts the received signals to base band and digitizes them, it locates the SOI using the direction-of-arrival (DOA) algorithm, and it continuously tracks the SOI and SNOIs by dynamically changing the complex weights (amplitudes and phases of the antenna elements). Basically, the DOA computes the direction-of-arrival of all the signals by computing the time delays between the antenna elements, and afterward, the adaptive algorithm, using a cost function, computes the appropriate weights that result in an optimum radiation pattern. Because adaptive arrays are generally more digital processing intensive and require a complete RF portion of the transceiver behind each antenna element, they tend to be more expensive than switched-beam systems.

Adaptive arrays utilize sophisticated signal-processing algorithms to continuously distinguish between desired signals, multi path, and interfering signals, as well as calculate their Directions of Arrival (DOA). This approach updates its transmit strategy continuously based on changes in both the desired and interfering signal locations. A number of well-documented algorithms exist for estimating the DOA; for example, MUSIC, ESPRIT, or SAGE. These algorithms, which are discussed in Chapter 5, make use of a data matrix with the array snapshots collected within the coherence time of the channel. In essence, spatial processing dynamically creates a different sector for each user and conducts a frequency/channel allocation in an ongoing manner in real time. Fig. 4.12 illustrates the beams of a fully adaptive antenna system supporting two users.

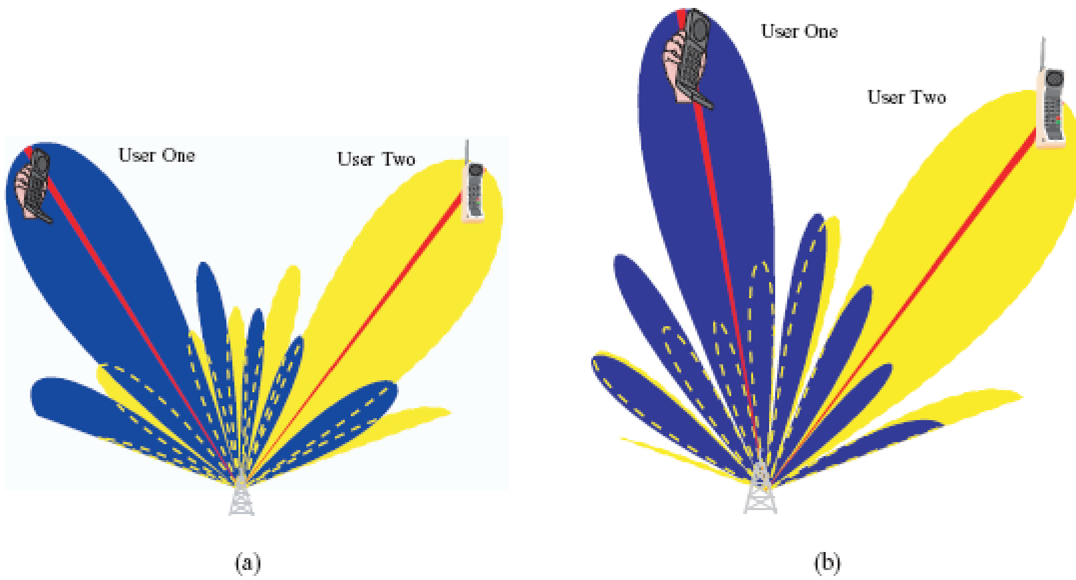

Figure 4.12: Fully adaptive spatial processing supporting two users on the same conventional channel simultaneously in the same cell [2].

In adaptive beamforming techniques, two main strategies are distinguished. The first one is based on the assumption that part of the desired signal is already known through the use of a training sequence. This known signal is then compared with what is received, and the weights are then adjusted to minimize the Mean Square Error (MSE) between the known and the received signals. In this way, the beampattern can be adjusted to null the interferers. This approach optimizes the signal-to-interference ratio (SIR), and is applicable to non-line-of-sight (NLOS) environments [24]. Since the weights are updated according to the incoming signals, not only the interference is reduced but the multipart fading is also mitigated. In the second one, the directions of arrivals from all sources transmitting signals to the array antenna are first identified. The complex weights are then adjusted to produce a maximum toward the desired angle and null toward interfering signals. This strategy may turn out to be deficient in practical scenarios where there are too many DOAs due to multi paths, and the algorithms are more likely to fail in properly detecting them. This is more likely to occur in NLOS environments where there are many local scatterers close to the users and the base station, thus resulting in a wider spread of the angle of arrival [24]. Another significant advantage of the adaptive antenna systems is the ability to share spectrum. Because of the accurate tracking and robust interference rejection capabilities, multiple users can share the same conventional channel within the same cell. System capacity increases through lower inter-cell frequency reuse patterns as well as intra-cell frequency reuse. Fig. above shows how adaptive antenna approach can be used to support simultaneously two users in the same cell on the same conventional channel.

In each of the two plots, the pattern on the left is used to communicate with the user on the left while the pattern on the right is used to talk with the user on the right. The drawn lines delineate the actual direction of each signal. Notice that as the signals travel down the indicated line toward the base station, the signal from the right user arrives at a null of the left pattern or minimum gain point and vice versa. As the users move, beam patterns are constantly updated to insure these positions. The plot at the bottom of the figure shows how the beam patterns have dynamically changed to insure maximum signal quality as one user moves toward the other. Fig. below summarizes the different smart antenna concepts and the functions of each one.

4.5 SPACE DIVISION MULTIPLE ACCESS (SDMA)

A concept completely different from the previously described multiple access schemes, is the spatial division multiple access (SDMA) scheme. SDMA systems utilize techniques by which signals are distinguished at the BS based on their origin in space. They are usually used in conjunction with FDMA, TDMA, or CDMA in order to provide the latter with the additional ability to explore the spatial properties of the signals [16]. SDMA is among the most sophisticated utilizations of smart antenna technology; its advanced spatial processing

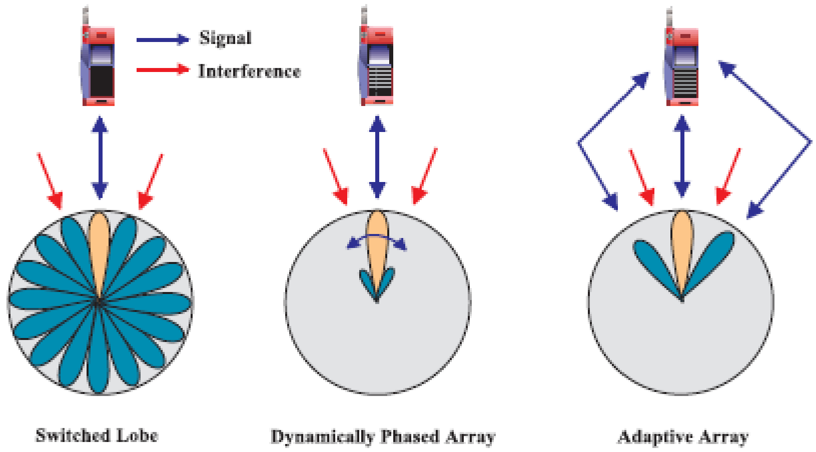

Figure 4.13 Different smart antenna concepts [2].

capability enables it to locate many users, creating different beams for each user, as shown in Fig. below The SDMA scheme is based upon the concept that a signal arriving from a distant source reaches different antennas in an array at different times due to their spatial distribution. This delay is utilized to differentiate one or more users in one area from those in another area. The scheme allows an effective transmission to take

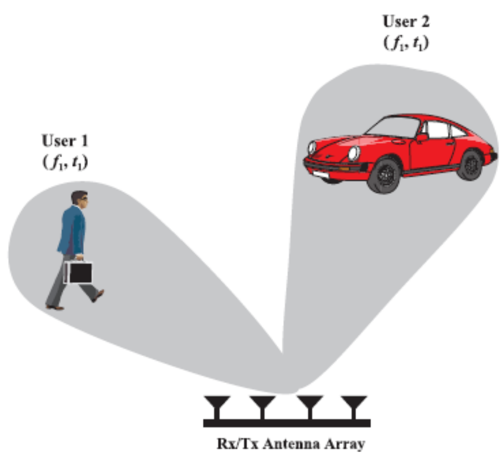

Figure 4.14: SDMA concept [2].

place in one cell without disturbing a simultaneous transmission in another cell. For example, conventional GSM/GPRS allows one user at a time to transmit or receive in a frequency band to the base station, where GSM/GPRS with SDMA allows multiple simultaneous transmissions in that same frequency band, multiplying the capacity of the system. CDMA system capacity is limited by its SIR; hence, with SDMA boosting the SIR in the system, more users will be allowed access by the network [25].

Filtering in the space domain can separate spectrally and temporally overlapping signals from multiple mobile units and it enables multiple users within the same radio cell to be accommodated on the same frequency and time slot [2], as illustrated in Fig. above. This means that more than one user can be allocated to the same physical communication channel in the same cell simultaneously, with only separation in angle. This is accomplished by having N parallel beamformers at the base station operating independently, where each beamformer has its own adaptive beamforming algorithm to control its own set of weights and its own direction-of arrival algorithm (DOA) to determine the time delay of each user's signal [26, 27]

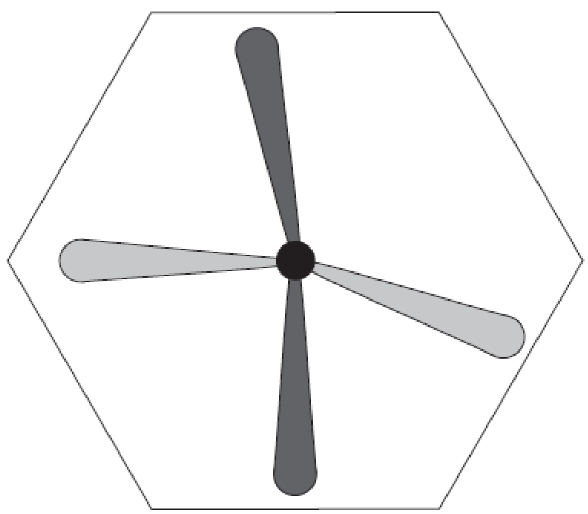

Figure 4.15: Channel reuse via angular separation .

Each beamformer creates a maximum toward its desired user while nulling or attenuating the other users. This technology dramatically improves the interference suppression capability while greatly increases frequency reuse resulting in increased capacity and reduced infrastructure cost.

With SDMA, several mobiles can share the same frequency within a cell. Multiple signals arriving at the base station can be separated by the base station receiver as long as their angular separation is larger than the transmit/receive beamwidths. This is shown in Fig. above. The beams that have the same shading use the same frequency band. This technique is called channel reuse via angular separation.

Methods acting against fading are required for high data rate and highly reliable mobile communication systems [28]. A SDMA system is an effective measure to cope with fading, since it distinguishes radio signals in space or angular domain by using antenna directivity or beamforming according to the direction of arrival (DOA) of signals [9, 29].

4.6 ARCHITECTURE OF A SMART ANTENNA SYSTEM

Any wireless system can be separated to its reception and transmission parts. Because of the advanced functions in a smart antennas system, there is a greater need for better co-operation between its reception and transmission parts.

Receiver

Fig. below shows schematically the block diagram of the reception part of a wireless system employing a smart antenna with M elements. In addition to the antenna itself, it contains a radio unit, a beam forming unit, and a signal processing unit [14]. The number of elements in the array should be relatively low (the minimum required), in order to avoid unnecessarily high complexity in the signal processing unit. Array antennas can be one, two, and three-dimensional, depending on the dimension of space one wants to access. The first fig shows different array geometries that can be applied in adaptive antennas implementations [14]. The first structure is used primarily for beamforming in the horizontal plane (azimuth) only. This will normally be sufficient for outdoor environments, at least in large cells. The example shows a one-dimensional linear array with uniform element spacing of x. Such a structure can perform beamforming in one plane within an angular sector. This is the most common structure due to its low complexity [2].

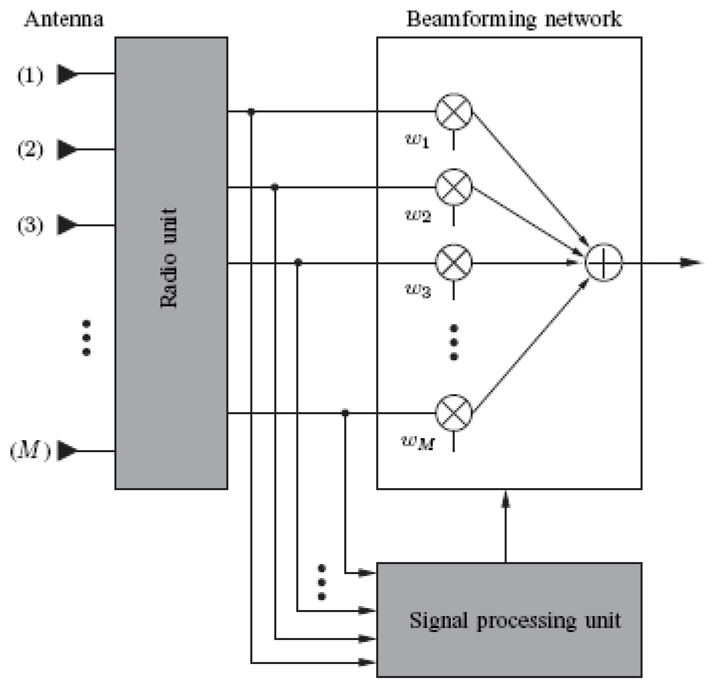

Figure 4.16: Reception part of a smart antenna [2].

The estimate of the weights can be optimized using one of the two main criteria depending on the application and complexity:

- Maximization of the power of the received signal from the desired user (e.g., switched beam or phased array), or
- Maximization of the SIR by suppressing the signal received from the interference sources (adaptive array).

In theory, with *M* antenna elements *M*− 1 sources of interference can be "nulled out", but this number will normally be lower due to the multipath propagation environment. The method for calculating the weights differs depending on the type of optimization criterion. When the switched-beam (SB) is used, the receiver will test all the predefined weight vectors corresponding to the beam set) and choose the best one giving the strongest received signal level. If the phased array approach (PA) is used, which consists of directing a maximum gain beam toward the strongest signal component, the weights are calculated after the direction-of-arrival (DOA) is first estimated.

Transmitter

Normally the adaptive process is applied to the uplink/reception only (from the mobile to the base station). In that case the mobile unit consumes less transmission power, and the operational time of the battery is extended. However, the benefits of adaptation are very limited, if no beamforming is applied in the downlink transmission (from the base station to the mobile). In principle, the methods used in the uplink can be carried over the downlink .The transmission part of a smart antenna system is schematically similar to its reception part as shown in Fig. below. The signal is split into *N* branches, which are weighted by the complex weights *w*1*, w2. . . wN* in the lobe-forming unit. The signal-processing unit calculates suitably the weights, which form the radiation pattern in the downlink direction. The radio unit consists of D/A converters and the up-converter chains. In practice, some components, such as the antennas themselves and the DSP, will be the same as in reception. The principal difference between uplink and downlink is that since there are no smart antennas applied to the user terminals (mobile stations), there is only limited knowledge of the *Channel State Information* (CSI) available. Therefore, the optimum beamforming in downlink is difficult and the same performance as the uplink cannot be achieved.

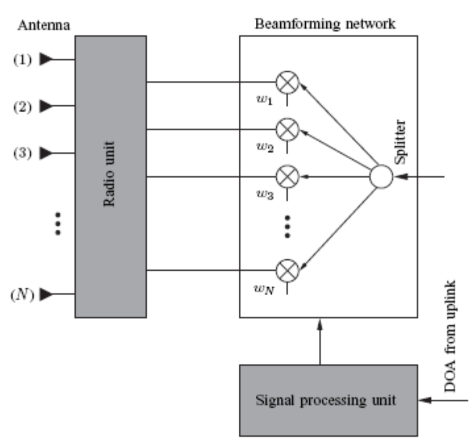

Figure 4.17: Transmission part of a smart antenna [2].

Typically there exist two approaches to overcome this impairment. The first one is to devise methods that do not require any CSI, but with somewhat limited performance gain. The second one is the assumption of directional reciprocity, i.e., the direction from which the signal is arrived on the uplink is closely related to the downlink CSI. This assumption has been strengthened by recent experimental results. Physically an adaptive antenna looks very much like an ordinary antenna but has built-in electronics and control software. It cooperates with the receiver's adaptive control system in real time. It may also communicate interactively with the cellular radio network control system. Smart antenna techniques have only recently been considered for implementation in land mobile stations and vehicle installed units because of their high system complexity and large power consumption [30]. A number of smart antenna arrays for base station applications have already been proposed in [12, 13, 6]. However, only limited efforts have been yet considered for developing adaptive antenna array receivers suitable for handsets [31–33]. In fact, there exist several practical difficulties with the implementation of such a solution at the handset level [34]. These are:

- The space on the handset device is limited and does not allow the implementation of an antenna array with number of elements necessary enough for efficient spatial signal processing. In addition, two (or multiple) antennas in proximity may reduce the effectiveness of the antenna system due to coupling.
- The problem related to the movement of the mobile that provides an omni directional scenario.
- The cost and the complexity of the implementation at every mobile is much greater than the implementation at each base radio station.

Besides these difficulties, the adaptive algorithm for signal processing at the handset must be fast; however it needs only a few simple calculations, and requires a simple hardware implementation [34]. To justify further research efforts in employing multiple antennas at handsets, the gain in performance should be large enough to offset the additional cost and power consumption. Finally, it can be stressed that the use of digital beamforming antennas, both in satellites and in land-fixed and mobile units, remains a challenge for future satellite communication systems.

4.7 Summary

The introduction of smart antennas is expected to have a large impact on the performance of cellular communications networks. It will also affect many aspects of both the planning and deployment of mobile systems. The great interest in smart antennas is the increase in capacity and range. In densely populated areas the main source of noise is the interference from other users. The deployment of adaptive arrays is to simultaneously increase the useful received signal level and lower the interference level, thus providing significant improvement in the Signal to Interference Ratio (SIR). An immediate impact to the increase of the SIR is the possibility for reduced frequency reuse distance. This will lead to a large capacity increase since more carriers can be allocated per cell. An immediate advantage will be noticed in TDMA systems (GSM) which are more concerned about increased SIR. An example is shown in Fig. 4.21, where the traditional seven-cell cluster has been reduced to a three-cell cluster. This will lead to a capacity increase of 7/3. Using smart antennas, an increase of the range of coverage by a base station is possible since they are able to focus their energy toward the intended users instead of directing and wasting it in other unnecessary directions. In other words, smart antennas are more directive than traditional sectorized or omnidirectional antennas. Thus, base stations can be placed further apart, potentially leading to more cost-efficient deployment [2]. Therefore, in rural and sparsely populated areas, where radio coverage rather than capacity is more important, smart antenna systems are also well-suited [13].

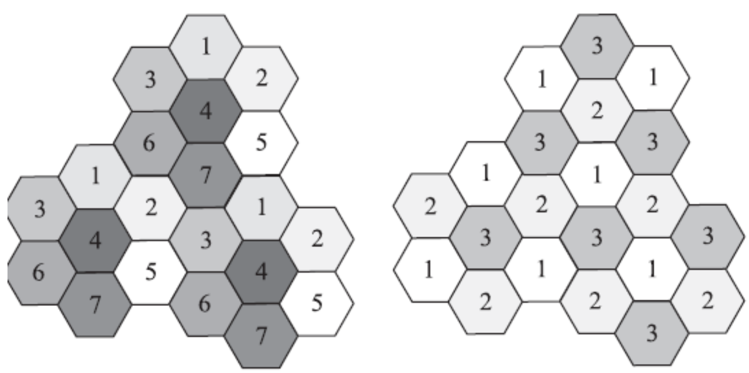

Figure 4.18: (a) Traditional 7-cell cluster
(b) possible 3-cell cluster enabled by interference
reduction like when employing smart antennas [2].

Moreover, using transmit and receive beams that are directed toward the mobile user of interest, the multipath [35] and the inter-symbol-interference, due tomultipath propagation present in mobile radio environments, are mitigated. Another added advantage of smart antenna systems is security. In a society that becomes more dependent on conducting business and distributing personal information, security is an important issue. Smart antennas make it more difficult to tap a connection because the intruder must be positioned in the same direction as the user as “seen” from the base station to successfully tap a connection [13].

Finally, due to the spatial detection nature of smart antenna systems, the network will have access to spatial information about users [2]. This information may be exploited in estimating the positions of the users much more accurately than in existing networks. Consequently, exact positioning can be used in services to locate humans in case of emergency calls or for any other location-specific service [2].

Although the benefits of using smart antennas are considered many, there also exist some important drawbacks. A smart antenna transceiver is much more complicated than a traditional base station transceiver [14]. Separate transceiver chains are needed for each of the array antenna elements and accurate real-time calibration of each of them is required. Moreover, adaptive beamforming is a computationally intensive process; thus the smart antenna base station must include very powerful numeric processors and control systems.

Figure 4.19: Picture of an eight-element array antenna at 1.8 GHz. (Antenna property of Telia Research AB, Sweden) [14].

Smart antenna base stations will no doubt be much more expensive than conventional base stations. Even though smart antennas are mainly a radio technology, it will unavoidably put new demands on network functions such as resource and mobility management. SDMA involves different users using the same physical communication channel in the same cell, separated only by angle. When angular collisions between these users occur, one of them must quickly switch
to another channel so that the connection is not broken.

For the smart antenna to obtain a reasonable gain, an antenna array with several elements is necessary. Typically arrays consisting of six to ten horizontally separated elements have been suggested for outdoor mobile environments. The necessary element spacing is 0.4–0.5 wavelengths. An eight-element antenna, for example, would be approximately 1.2 meters wide at a frequency of 900 MHz and 60 cm at 2 GHz. With a growing public demand for less visible base stations, geometries with size of several wavelengths (corresponding to current carrier frequencies used), although not excessive, could provide a problem. Fig. above, showing a picture of an eight- element antenna array operating at 1.8 GHz, reinforces the argument.

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Chapter 5

Genetic Algorithm

5.1 Introduction

A genetic algorithm is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are a particular class of evolutionary algorithms (also known as evolutionary computation) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination). Genetic algorithms are search algorithms based on mechanics of natural selection and natural genetics. In every generation, a new set of artificial creatures or strings is created using bits and pieces of the fittest of the old.

In this chapter genetic algorithms are introduced by highlighting their brief history, how they are different from traditional methods of optimization, how they work, their related techniques, and their vast areas of applications.

5.2 Brief History

Computer simulations of evolution started as early as in 1954 with the work of Nils Aall Barricelli, who was using the computer at the Institute for Advanced Study in Princeton, New Jersey. His 1954 publication was not widely noticed. Starting in 1957, the Australian quantitative geneticist Alex Fraser published a series of papers on simulation of artificial selection of organisms with multiple loci controlling a measurable trait. From these beginnings, computer simulation of evolution by biologists became more common in the early 1960s, and the methods were described in books by Fraser and Burnell (1970) and Crosby (1973). Fraser's simulations included all of the essential elements of modern genetic algorithms. In addition, Hans Bremermann published (a series of papers in the 1960s that also adopted a population of solution to optimization problems, undergoing recombination, mutation, and selection. Bremermann's research also included the elements of modern genetic algorithms. Other noteworthy early pioneers include Richard Friedberg, George Friedman, and Michael Conrad. Many early papers are reprinted by Fogel (1998).

Although Barricelli, in his work he reported in 1963, had simulated the evolution of ability to play a simple game, artificial evolution became a widely recognized optimization method as a result of the work of Ingo Rechenberg and Hans-Paul Schwefel in the 1960s and early 1970s - his group was able to solve complex engineering problems through evolution strategies (1971 PhD thesis and resulting 1973 book). Another approach was the evolutionary programming technique of Lawrence J. Fogel, which was proposed for generating artificial intelligence. Evolutionary programming originally used finite state machines for predicting environments, and used variation and selection to optimize the predictive logics. Genetic algorithms in particular became popular through the work of John Holland in the early 1970s, and particularly his 1975 book. His work originated with studies of cellular automata, conducted by Holland and his students at the University of Michigan.

Research in Genetic algorithms remained largely theoretical until the mid-1980s, when The First International Conference on Genetic Algorithms was held in Pittsburgh, Pennsylvania. As academic interest grew, the dramatic increase in desktop computational power allowed for practical application of the new technique. In 1989, The New York Times writer John Markoff wrote about Evolver, the first commercially available desktop genetic algorithm. Custom computer applications began to emerge in a wide variety of fields, and these algorithms are now used by a majority of Fortune 500 companies to solve difficult scheduling, data fitting, trend spotting and budgeting problems, and virtually any other type of combinatorial optimization problem. Most applications do not use traditional genetic algorithms but a broader set of evolutionary algorithms that incorporate facets of evolution strategies, evolutionary programming, and genetic algorithms. [1]

5.3 How Genetic Algorithms are Different from Traditional Methods

Genetic algorithms are different from more normal optimization and search procedures, like direct and indirect calculus-based methods, enumerative schemes, random search algorithms etc, in four ways: [2]

a. It works on coding of the parameter set, not the parameters themselves.

b. It searches from a population of points, not a single point.

c. It uses objective function information, not the derivative or other auxiliary knowledge.

d. It uses probabilistic transition rules, not deterministic rules.

Genetic algorithms require the natural parameter set of the optimization problem to be coded as a finite-length string over some finite alphabet. In many optimization methods, we move gingerly from a single point in the decision space to the next using some transitional rule to determine the next point. The point-to-point method is dangerous because it is perfect prescription for locating false peak in multi-modal search spaces. By contrast, genetic algorithm works from a rich database of points simultaneously, climbing many peaks in parallel; thus, probability of finding a false peak is reduced over that go point-to-point.

Many search techniques require much auxiliary information in order to work properly. In contrast, genetic algorithm requires only objective function values associated with individual string. Unlike other methods, genetic algorithms use random choice as a tool to guide a search toward regions of the search space with likely improvement. These four differences contributes towards genetic algorithm's robustness and resulting advantage over other more commonly used techniques.

5.4 How Genetic Algorithms Work

Genetic algorithms are implemented as a computer simulation in which a population of abstract representations (called chromosomes or the genotype or the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encoding are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. A typical genetic algorithm requires two things to be defined:

a. a genetic representation of the solution domain.

b. a fitness function to evaluate the solution domain.

A standard representation of the solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size that facilitates simple crossover operation. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in Genetic programming and graph-form representations are explored in Evolutionary programming.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. For instance, in the knapsack problem we want to maximize the total value of objects that we can put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The fitness of the solution is the sum of values of all objects in the knapsack if the representation is valid, or 0 otherwise. In some problems, it is hard or even impossible to define the fitness expression; in these cases, interactive genetic algorithms are used.

Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover and selection operators.

A genetic algorithm is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are a particular class of evolutionary algorithms (also known as evolutionary computation) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination). Genetic algorithms are search algorithms based on mechanics of natural selection and natural genetics. In every generation, a new set of artificial creatures or strings is created using bits and pieces of the fittest of the old.

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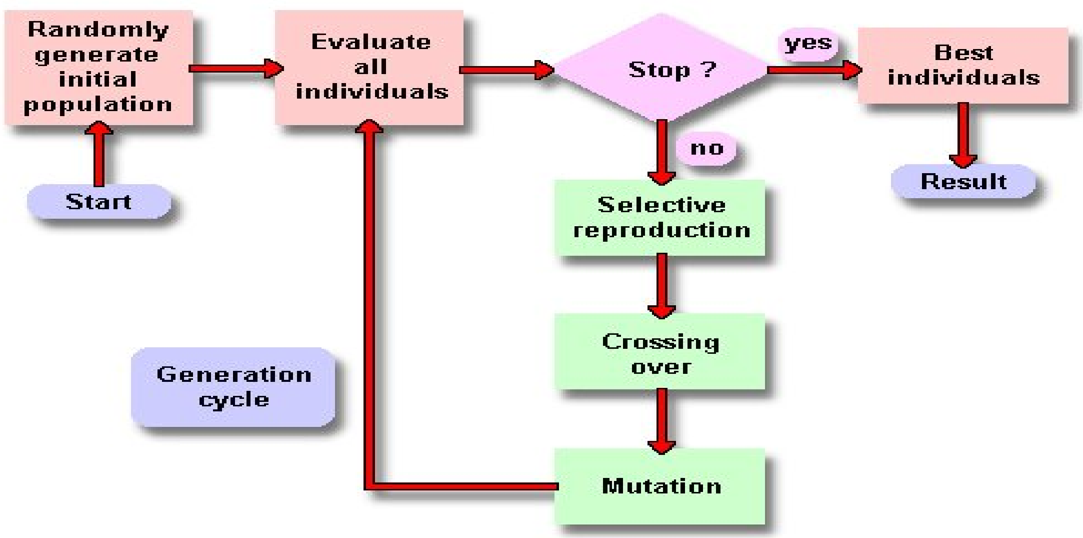

FIGURE 5.1: Flow Diagram of Genetic Algorithm [1]

a. **Initialization**

Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

b. **Selection**

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming.

Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.

c. **crossover and mutation**

The next step is to generate a second generation population of solutions from those selected through genetic operators: crossover (also called recombination), and/or mutation. For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each child, and the process continues until a new population of solutions of appropriate size is generated.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions, for reasons already mentioned above.

d. **Termination**

This generational process is repeated until a termination condition has been reached. Common terminating conditions are

(1). A solution is found that satisfies minimum criteria

(2). Fixed number of generations reached

(3). Allocated budget (computation time/money) reached

(4). The highest ranking solution's fitness is reaching or has reached a plateau. [3]

5.5 Related Techniques

Ant Colony Optimization (ACO) uses many ants (or agents) to traverse the solution space and find locally productive areas. While usually inferior to genetic algorithms and other forms of local search, it is able to produce results in problems where no global or up-to-date perspective can be obtained, and thus the other methods cannot be applied.

Bacteriologic Algorithms (BA) inspired by evolutionary ecology and, more particularly, bacteriologic adaptation. Evolutionary ecology is the study of living organisms in the context of their environment, with the aim of discovering how they adapt. Its basic concept is that in a heterogeneous environment, you can't find one individual that fits the whole environment. So, you need to reason at the population level. BAs have shown better results than Genetic algorithms on problems such as complex positioning problems (antennas for cell phones, urban planning, and so on) or data mining.

Cross-Entropy (CE) method generates candidates solutions via a parameterized probability distribution. The parameters are updated via cross-entropy minimization, so as to generate better samples in the next iteration.

Evolution Strategies (ES) evolve individuals by means of mutation and intermediate and discrete recombination. ES algorithms are designed particularly to solve problems in the real-value domain. They use self-adaptation to adjust control parameters of the search.

Evolutionary Programming (EP) involves populations of solutions with primarily mutation and selection and arbitrary representations. They use self-adaptation to adjust parameters, and can include other variation operations such as combining information from multiple parents.

Extremal Optimization (EO) Unlike Genetic algorithms, which works with a population of candidate solutions, EO evolves a single solution and makes local modifications to the worst components. This requires that a suitable representation be selected which permits individual solution components to be assigned a quality measure ("fitness"). The governing principle behind this algorithm is that of emergent improvement through selectively removing low-quality components and replacing them with a randomly selected component. This is decidedly at odds with a GA that selects good solutions in an attempt to make better solutions.

Gaussian Adaptation (normal or natural adaptation, abbreviated NA to avoid confusion with GA) is intended for the maximization of manufacturing yield of signal processing systems. It may also be used for ordinary parametric optimization. It relies on a certain theorem valid for all regions of acceptability and all Gaussian distributions. The efficiency of NA relies on information theory and a certain theorem of efficiency. Its efficiency is defined as information divided by the work needed to get the information. Because NA maximizes mean fitness rather than the fitness of the individual, the landscape is smoothed such that valleys between peaks may disappear. Therefore it has a certain "ambition" to avoid local peaks in the fitness landscape. NA is also good at climbing sharp crests by adaptation of the moment matrix, because NA may maximize the disorder (average information) of the Gaussian simultaneously keeping the mean fitness constant.

Genetic Programming (GP) is a related technique popularized by John Koza in which computer programs, rather than function parameters, are optimized. Genetic programming often uses tree-based internal data structures to represent the computer programs for adaptation instead of the list structures typical of genetic algorithms.

Grouping Genetic Algorithm (GGA) is an evolution of the GA where the focus is shifted from individual items, like in classical Genetic algorithms, to groups or subset of items. The idea behind this GA evolution proposed by Emanuel Falkenauer is that solving some complex problems, a.k.a. clustering or partitioning problems where a set of items must be split into disjoint group of items in an optimal way, would better be achieved by making characteristics of the groups of items equivalent to genes. These kind of problems include Bin Packing, Line Balancing, Clustering w.r.t. a distance measure, Equal Piles, etc., on which classic Genetic algorithms proved to perform poorly. Making genes equivalent to groups implies chromosomes that are in general of variable length, and special genetic operators that manipulate whole groups of items. For Bin Packing in particular, a GGA hybridized with the Dominance Criterion of Martello and Toth, is arguably the best technique to date.

Harmony Search (HS) is an algorithm mimicking musicians behaviors in improvisation process.

Interactive Evolutionary Algorithms are evolutionary algorithms that use human evaluation. They are usually applied to domains where it is hard to design a computational fitness function, for example, evolving images, music, artistic designs and forms to fit users' aesthetic preference.

Mimetic Algorithm (MA), also called hybrid genetic algorithm among others, is a relatively new evolutionary method where local search is applied during the evolutionary cycle. The idea of mimetic algorithms comes from memes, which–unlike genes–can adapt themselves. In some problem areas they are shown to be more efficient than traditional evolutionary algorithms.

Simulated Annealing (SA) is a related global optimization technique that traverses the search space by testing random mutations on an individual solution. A mutation that increases fitness is always accepted. A mutation that lowers fitness is accepted probabilistically based on the difference in fitness and a decreasing temperature parameter. In SA parlance, one speaks of seeking the lowest energy instead of the maximum fitness. SA can also be used within a standard GA algorithm by starting with a relatively high rate of mutation and decreasing it over time along a given schedule.

Stochastic Optimization is an umbrella set of methods that includes Genetic algorithms and numerous other approaches.

Tabu Search (TS) is similar to Simulated Annealing in that both traverse the solution space by testing mutations of an individual solution. While simulated annealing generates only one mutated solution, tabu search generates many mutated solutions and moves to the solution with the lowest energy of those generated. In order to prevent cycling and encourage greater movement through the solution space, a tabu list is maintained of partial or complete solutions. It is forbidden to move to a solution that contains elements of the tabu list, which is updated as the solution traverses the solution space. [4]

5.6 Applications

Some out of the large no. of applications of genetic algorithm are listed down here:

a. Artificial Creativity

b. Automated design, including research on composite material design and multi-objective design of automotive components for crashworthiness, weight savings, and other characteristics.

c. Automated design of mechatronic systems using bond graphs and genetic programming (NSF).

d. Automated design of industrial equipment using catalogs of exemplar lever patterns.

e. Calculation of Bound states and Local-density approximations.

f. Chemical kinetics (genetic algorithms and solid phases)

g. Configuration applications, particularly physics applications of optimal molecule configurations for particular systems like C60 (buckyballs).

h. Container loading optimization.

i. Code-breaking, using the GA to search large solution spaces of ciphers for the one correct decryption.

j. Design of water distribution systems.

k. Distributed computer network topologies.

l. Electronic circuit design, known as Evolvable hardware.

m. File allocation for a distributed system.

n. Parallelization of Genetic algorithms/GPs including use of hierarchical decomposition of problem domains and design spaces nesting of irregular shapes using feature matching and Genetic algorithms.

o. Game Theory Equilibrium Resolution.

p. Learning Robot behavior using Genetic Algorithms.

q. Learning fuzzy rule base using genetic algorithms.

r. Linguistic analysis, including Grammar Induction and other aspects of Natural Language Processing (NLP) such as word sense disambiguation.

s. Mobile communications infrastructure optimization.

t. Molecular Structure Optimization (Chemistry).

u. Multiple population topologies and interchange methodologies.

v. Optimisation of data compression systems, for example using wavelets.

w. Protein folding and protein/ligand docking.

x. Selection of optimal mathematical model to describe biological systems.

y. Solving the machine-component grouping problem required for cellular manufacturing systems.

z. Training artificial neural networks when pre-classified training examples are not readily obtainable (neuroevolution).

5.7 Summary

Genetic algorithms find application in biogenetics, computer science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields. Here we have laid foundation for understanding genetic algorithms, their mechanisms and their power. We are led to these methods by our search for robustness, as natural systems are robust-efficient and efficacious-as they adapt to a wide variety of environments. Often, genetic algorithms can rapidly locate good solutions, even for difficult search spaces. The same is of course also true for evolution strategies and evolutionary programming.

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Chapter 6

Artificial Immune System

6.1 Introduction

Biological studies have always constituted a large pool of inspiration for the design of systems. In the last decades, two biological systems have provided a remarkable source of inspiration for the development of new types of algorithms: neural networks and evolutionary algorithms. In recent years, another biological inspired system has attracted the attention of researchers, the immune system and its powerful information processing capabilities. In particular, it performs many complex computations in a highly parallel and distributed fashion. The key features of the immune system are: pattern recognition, feature extraction, diversity, learning, memory, self-regulation, distributed detection, probabilistic detection, adaptability, specificity, etc. The mechanisms of the immune system are remarkably complex and poorly understood, even by immunologists. Several theories and mathematical models have been proposed to explain the immunological phenomena. There is also a growing number of computer models to simulate various components of the immune system and the overall behavior from the biological point of view. Those approaches include differential equation models, stochastic differential equation models, cellular-automata models, shape-space models, etc. The models based on the immune system principles, such as the Clonal Selection Theory [5, 6], the immune network model [9, 7], or the negative selection algorithm [8], have been finding increasing applications in science and engineering [10]: computer security, virus detection, process monitoring, fault diagnosis, pattern recognition, etc. Although the number of specific applications confirms the interest and the capabilities of these principles, the lack of a general purpose algorithm for solving problems based on them contrasts with the major achievements with other biologically inspired models.

6.2 Artificial Immune System (AIS)

Different aspects of the immune system (IS) have been modeled for solving different problems including anomaly detection, clustering, and function optimization.

Since the interest is on the computational model, the use of biological terms is limited and simplified in the following.

Anomaly Detection

The obvious feature of the IS is its ability to protect an organism from harmful agents known as pathogens, such as bacteria and vira. The concept is simple: Find the pathogen, identify it as harmful, and destroy it. The cell responsible for this is the lymphocyte1. Assuming the pathogen has already been found, the distinguishing between harmful and harmless is the focus of our attention, and the destruction of harmful pathogens is replaced in an implementation by a context-appropriate response. The objective of AIS in anomaly detection is to minimize damage while maximizing usability. But being completely usable, the system would have no protection, being completely safe the system would not be usable. Once again it is a matter of balancing requirements.

Self, Non-self

Although the optimal classification of pathogens is either as harmful or harmless, the IS works slightly different. Normally the lymphocytes do not know what a harmful pathogen looks like, because this information is not encoded into the organism, it only knows what itself looks like. So the organism trains the lymphocytes to look for pathogens that do not look like anything it knows, i.e. non-self.

Negative Selection

When a new lymphocyte is created, this training is achieved by a process known as negative selection. The lymphocyte is exposed for a certain amount of time to self, if it recognizes any of these it is destroyed. This ensures that a lymphocyte will only recognize non-self, and this is a quality that is desired in many protection systems since it avoids the explicit definition of abnormal behavior.

Co stimulation

In the IS it is possible for lymphocytes to bind to self. Such suicidal behavior is of course unwanted, and the solution is known as co stimulation in which the lymphocyte will die if it does not receive a second signal. When tissue is damaged this second signal will be chemical, but in the AIS co stimulation is not always easy to model, as damage to a hardware or software system may be hard to assess. If co stimulation is required then the matching of lymphocytes and pathogens can be even less rigid as co stimulation provides the ultimate gate before a response is launched.

Lymphocyte

When a lymphocyte has survived negative selection, it is said to be mature. The life of a mature lymphocyte is relatively short though, and it is necessary for it to bind with a pathogen a number of times to get activated. If co stimulation is required but is absent, the lymphocyte will also die.

Such a hard life serves a number of purposes. First off if the lymphocyte makes it all the way, it will become a memory cell and will be rewarded with longevity (possibly indefinite), and it will only require one binding with a pathogen to become activated in the future. This corresponds to primary and secondary response of the IS, in which the primary response is not as effective until the IS catches up, but the secondary is almost immediate. The second purpose is to create diversity. A lymphocyte recognizes a limited number of different pathogens. Continuously replacing useless lymphocytes with mutated (or random) ones increases the number of recognizable pathogens over time.

Pathogen Binding

The binding of a lymphocyte to a pathogen in the IS is done by protein matching. Because there are so many lymphocytes, this matching can be rather strict, whereas it makes sense to use a less rigid match in the AIS with its (comparatively) small amount of lymphocytes.

Implementation-wise the AIS can use binary strings for the matching (binding) of lymphocytes and pathogens, with the matching criterion being a number of equal contiguous bits, Hamming distance, etc. It is however useful to abstract from this and consider any object that can be compared for similarity and is capable of mutation or random generation, as a possible representation.

Mutation

When a lymphocyte dies, it is replaced with either a randomly generated or a mutation of one of the best lymphocytes (as measured by their success in matching pathogens). Different schemes are possible for the mutation, but it is necessary to choose the scheme and its parameters depending on the need for convergence, and adjust the life span of a matured lymphocyte accordingly. If the matching function is expensive to compute for less rigid matching, fast mutation can in some cases be used as a cheap alternative. The mutation scheme can be selected so that AIS resembles genetic algorithms (GA) without crossover, so the lymphocytes perform optimization when converging on their betters.

Self-adaptation

A number of parameters and topologies are possible for different parts of the AIS. Making these self-adaptive will push the empirical decision-making one or more levels, but may cause less transparent cause-effect relationships that could ultimately lead to erroneous - instead of improved - classification of pathogens. It is noted that some of these empirical problems are known from other aspects of computer science, for example the choice of what memory-lymphocyte to throw away when a new one is created (e.g. least-recently-used), is very similar to the problem of cache policies that try to limit thrashing.

6.3 Anomaly Detection Applications

Network Intrusion Detection

Using AIS for detecting intrusion attempts in a network is described in [1]. Their implementation uses information from TCP packets, including the addresses and ports of source and destination. Their system relies on human interaction for co stimulation and response, but was able to detect simulated intrusion attempts (mainly probing) based on real occurrences.

Surface Defect Inspection

Surface defects in textures are recognized quite successfully in [4] by the use of AIS to optimize parameters in so-called Gabor filters. An iterative training algorithm is used before the filters are applied to the textures, resulting in selection of the best fit lymphocytes (filter parameters).

Hardware Failure

A finite state machine (FSM) is monitored by an AIS for invalid transitions and states in [3]. A greedy generation of lymphocytes is used to create optimal diversity, enabling good coverage of the non-self space when using shorter match lengths. Although the basic idea is intriguing for important real-time applications such as medical equipment, the article notes that the AIS is seemingly more complicated than the FSM that it monitors.

Copy Protection

A potentially powerful usage of AIS is for copy protection of commercial software. It is however rather different from the other applications depicted here, in that they are of a monitory nature, in which the lymphocytes are more or less isolated from the pathogens. In copy protection, the malicious user has access to the inner workings of the lymphocytes themselves. The expected power arises from the fact that the copy protection is then complex and adapts to the behavior of the malicious user, who will (perhaps) find this feedback akin to a Gordian knot. Technically yet another interesting problem arises, because a database of normal behavior (self) should be compiled into the program, and is therefore again subject to manipulation.

Spectrum Analysis

A chicken-farmer who has a problem with foxes could train his AIS while guarding the chickens himself. The AIS would be specialized to monitor the frequency spectrum of a real-time sound recording. The matching of lymphocyte with pathogen would then recognize abnormal sounds such as a fox causing turmoil. Perhaps a more plausible use would be in automated chemical analysis for industrial and medical applications.

Target Identification

Friend or foe, self or non-self. Negative selection seems tailored to military purposes: First it is able to recognize the enemy without having seen it before (unless of course the enemy looks and behaves just like friends), and once recognized as a foe it will be memorized as such, furthermore friendly fire could be limited because of the classification. Co stimulation could be a network of sensors signaling whether damage has been sustained - for an entire nation this is similar to the triggering mechanism of the doomsday-device in Dr. Strangelove.

Thoughts on Soft Computing

The viability of soft computing stems from its ability to solve hard problems quickly, and by providing simple, generalized algorithmic frameworks for complex decision making, or from extracting meaning from noisy data, etc. The success however,

seems to depend on tricks and empirical magic. Eventually, it will be useful to identify the weakness precisely and improve upon
it in a scientific way. A soft computing algorithm is strictly better than its deterministic counterpart if:

- The deterministic algorithm can solve the problem optimally in t time units, then so must the soft computing algorithm.
- The probability of the soft computing algorithm failing to find the optimal solution must rival the probability of hardware failure.
- The probability that an optimal solution will be found by the soft computing algorithm in less than t time units is greater than 0

Perhaps the dire P = NP question becomes less interesting the more soft computing bridges these probabilistic gaps.

Thoughts on Evolution

What defines evolution? Is it strictly biological, chemical, divine or primal? What is the threshold when some object can be said to be evolved? If such things as language, fashion in clothing, tools, machinery, and computers are not considered part of evolution, are they then part of an isolated and parallel evolution? If this parallel evolution is boot-strapped by humans, would it then not be plausible that our evolved gadgets eventually will evolve their own sub gadgets? And considering the effect our own inventions have on our lives and indeed the entire globe, this tendency of back propagation or feedback would surely also emerge from the sub-sub-layers of evolutions. It is then hard to distinguish whether computers (or whatever the stepping stone to the next evolutionary twist will be) are part of the same evolution as we are. One could curiously ask: If evolution had an immune system, would it characterize computers as self or non-self? Harmless or harmful?

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Chapter 7

Our Proposed Technique

7.1 Introduction

In this chapter, we have described the technique which we have proposed. This is basically a hybridized technique of Genetic Algorithm and Artificial Immune system. This hybridization makes the system more robust and efficient. This chapter explains how we have used these algorithms in implementing smart antenna systems.

7.2 Signal Creation

In actual hardware implementation where RF end is designed actual signals are received from the environment and further processing is done on them. But we have not implemented the RF end and therefore instead of actual signals we have created dummy signals which imitate the actual signals.

Before going to the details of how we have created these signals, we must know the effect of the impinging signals on the antenna. So simply when a signal impinges on the antenna array, it induces some phase in its elements. We suppose that the phase induced in the first element is α_z given by

$$\alpha_z = kd\cos\theta \qquad \text{--- 7.1}$$

Where k is the wave no. and is given by

$$K = 2\pi/\lambda \qquad \text{--- 7.2}$$

d is the inter-element spacing and θ is the direction of the incoming signal. It is important to note that our algorithm does not know about this direction but phase is physically induced on its elements.

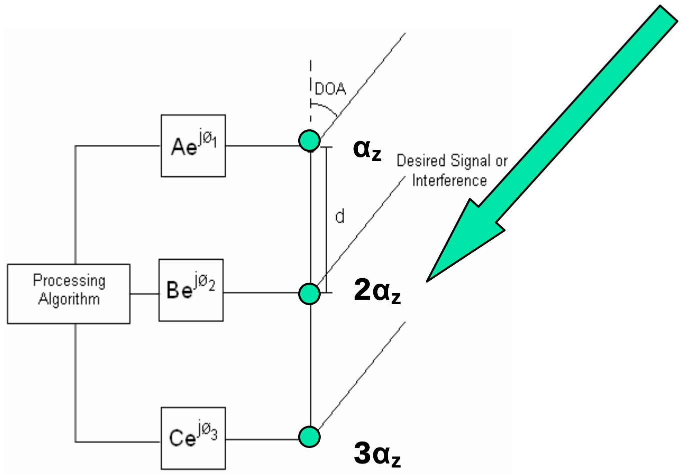


Figure7.1: Phase induced on three elements Smart Antenna

The phases that are induced on the next elements are the integral multiple of phase induced on the 1st element, as shown in figure.

So what we have done is we have catered for these phases that correspond to the incoming signals.

7.3 Direction of Arrival Estimation

7.3.1 Single User Environment

In Genetic Algorithm, chromosomes correspond to weights of the array elements as already explained. Now considering the effect of induced signal, induced phases generate some currents. These currents are multiplied by the corresponding weights and then added together to calculate the received current. Now if we look at the function of this received current, there will be one maximum that corresponds to the direction of arrival of the incoming signal. Now we have to reach to this maxima using Genetic Algorithm. This is done using the same steps already explained. One thing to be noted here is that here the cost function is the received current, on the basis of which survival of the fittest is performed. Once the algorithm is converged, then we take the best chromosome of the converged population and check the direction of maximum due to this chromosome (chromosome corresponds to array weights and have a specific radiation pattern). This direction is the direction of arrival of the incoming signal.

7.3.2 Multi-user Environment

Here all the procedure is same. Only the difference is that instead of one incoming signal there is more than one signal. Each incoming signal induces its own phase. Now the received current will be the addition of currents due to all the phases induced by the incoming signals. When the received current is processed by Genetic Algorithm to find the DOA, it will converge randomly to any one of the directions of arrival. After that we intentionally subtract the current due to that direction of arrival i.e.

$$\textbf{Received current} = \textbf{Received current} - e^{jDOA} \qquad \text{---7.3}$$

Now this changed received current is again fed to the processor and it randomly finds some other direction of arrival. This process is repeated until direction of arrivals of all the users are calculated.

7.4 Beamforming

Once the current phases and magnitudes are calculated, radiation pattern is calculated by

$$\mathfrak{a}_a(\theta) = \sum_{n=-N}^{N} \frac{I_n}{I_0} e^{jnkd\cos\theta} \qquad \text{---7.4}$$

In this equation I_n is the element current, I_o is the refernce current, n is the iteration no., d is the inter-element spacing, k is the wave no. and theta corresponds to the spherical coordinate. Here In is calculated by

$$I_n = mag_n * e^{j\ phasen} \qquad \text{---7.5}$$

Now each chromosome in the population is tested to form this radiation pattern. Once the radiation pattern is calculated, direction of main beam is found. Difference is then taken between calculated DOA and direction of main beam due to each chromosome. This is graphically shown in figure, In this figure actual DOA is 20^0 but due to one chromosome beam is formed at 60^0. Here the difference is 40^0.

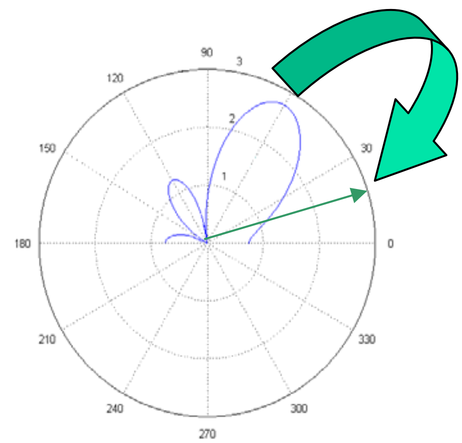


Figure7.2: Cost Function in Beamforming

Now this difference is calculated for all chromosomes in the population. This difference becomes the cost function for this population. In this case there are two cost functions; the other cost function is the magnitude of the radiation pattern at the interference, which should be as low as possible.

This population is now converged using multi-objective optimization.

$$\textbf{Optimization function} = (\textbf{cost func 1})^2 + (\textbf{cost func 2})^2 \qquad \textbf{---7.5}$$

Now the convergence criterion will be such that the value of this optimization function should be less than a certain value. This is multi-objective optimization, we can simultaneously optimize many parameters, but again we have trade-off between processing power and convergence criterion.

7.5 Proposed Technique

In our proposed technique, first of all antenna senses its environment and receives the signal. Then it calculates its direction of arrival. Once its direction has been calculated, it matches its characteristics to that stored in memory, if a match is found then it immediately produces the stored response. If a match is not found it runs the algorithm in the routine manner as shown in Figure 7.3.

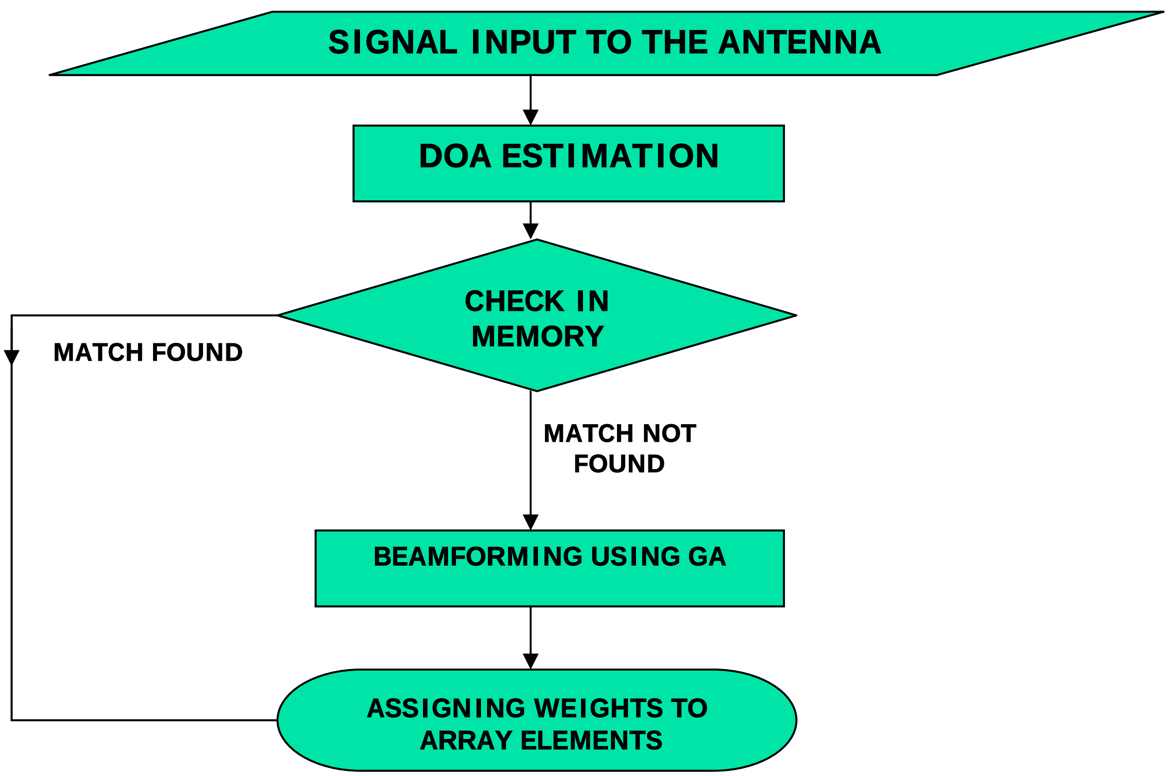


Figure7.3: Our Proposed Technique

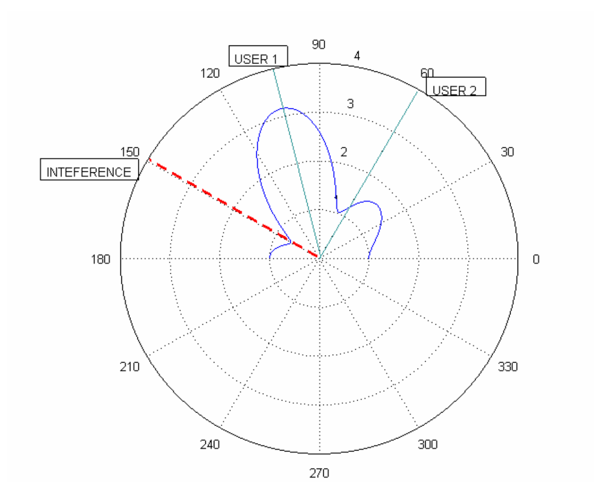
7.5.1 DOA Estimation.

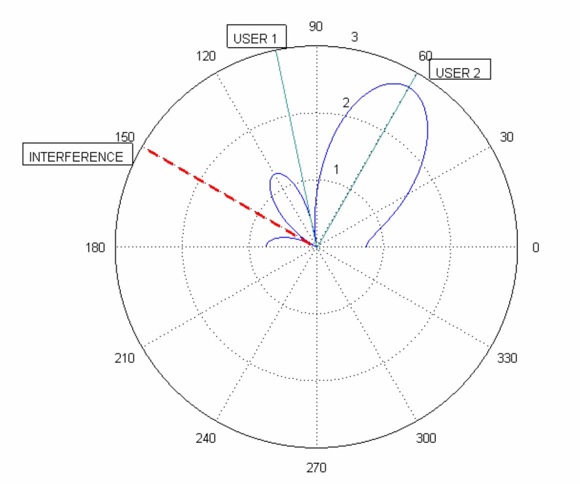
It is done in the same manner i.e. Artificial Immune System is not incorporated here. A signal that impinges on the array elements induces current in them. The magnitude of induced currents in the array elements will be same, but with a successive phase difference. We now multiply the induced currents with the weights (randomly assigned through GA) of the array elements and add them. This becomes the cost function which is to be maximized. This is done using the same steps of Genetic algorithm i.e. natural selection, cross over and mutation. The new population thus formed is treated in the same manner. This process goes on until the algorithm is converged. Once it is converged, we select the best chromosome of the last population that gives us the optimized complex weights, giving us the direction of arrival of the user.

7.5.2 AIS Scanning

Now AIS scanning is performed i.e. match is found in the stored response in the memory. If the DOA is within 50 of the stored DOA and magnitude at the interference is within a Specific margin then we can directly provide the stored weights to the array elements instead of running the entire algorithm again. In case a match is not found, then beamforming is done using GA as explained earlier.

7.6 Simulations





These two simulations show the case of two user signals environment. First their direction of arrival is calculated and the beams are formed accordingly. Note that user 1 is interference for user 2 and vice versa.

7.7 Summary

In this chapter we explained our technique for the implementation of smart antenna system. This technique gives better results in terms of accuracy, efficiency and no. of operations. A detailed comparison is given in the next chapter. We have also shown some simulations here for the proper understanding of the user.

Chapter 8

<u>Overview of Previous Techniques</u>

8.1 Introduction

In this chapter, a brief overview of previous algorithms used to implement smart antenna is provided. At the end a comparison is made between the previous algorithms and the technique which we have developed.

In beamforming, both the amplitude and phase of each antenna element 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. The combined relative amplitude and phase shift for each antenna is called a "***complex weight***". These weights are calculated using different algorithms.

Beamforming is the term used to describe the application of weights to the inputs of an array of antennas to focus the reception of the antenna array in a certain direction, called the look direction or the main lobe. These effects are all achieved electronically and no physical movement of the receiving antennas is necessary.

In Beamforming, we discriminate between signals according to their direction of arrival (DOA). Beam pattern is controlled by the complex weights.

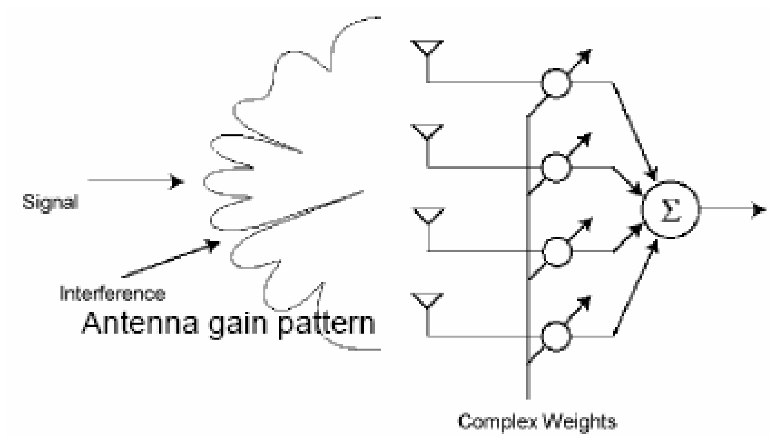


Figure8.1: Beamforming [1]

A beam pattern describes the gain versus DOA of the beamformer. The beam pattern is dependent on array geometry (number of antennas, physical extent of the array), carrier frequency, gain pattern of each individual antenna and antenna weights.

8.2 Least-Mean-Squares Algorithm

The LMS algorithm can be considered to be the most common adaptive algorithm for continues adaptation. It uses the steepest-descent method and recursively computes and updates the weight vector.

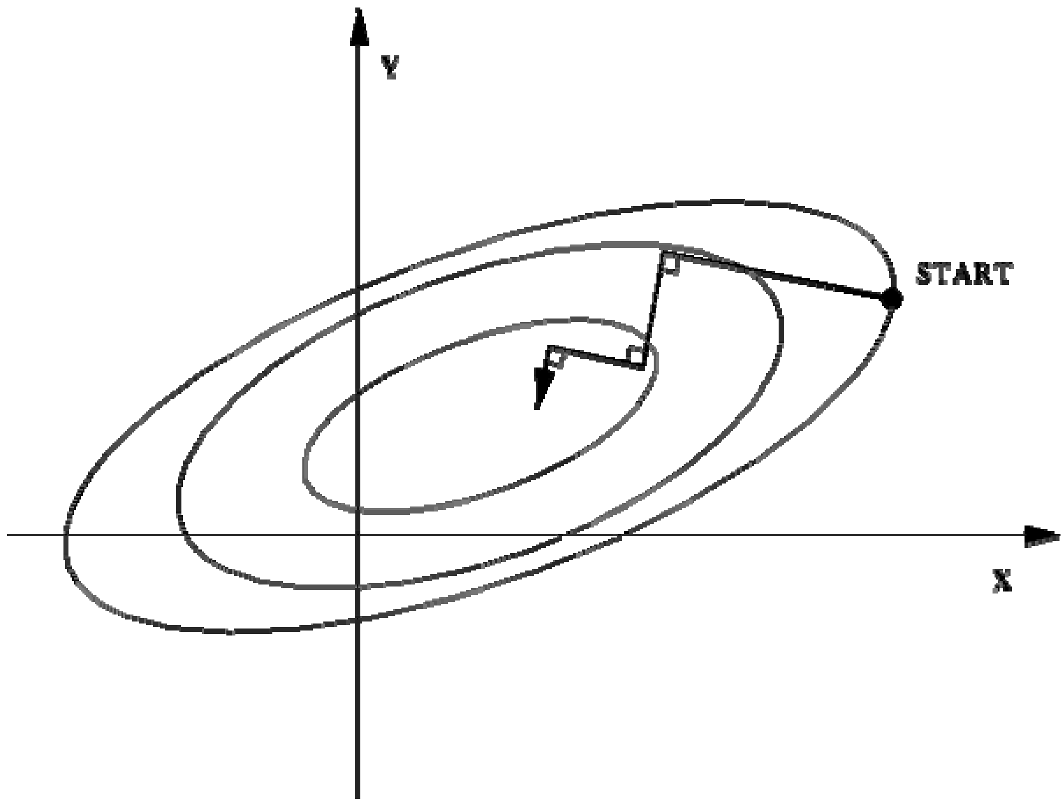


Figure 8.2: The method of Steepest Descent approaches the minimum in a zigzag manner, where the new search direction is orthogonal to the previous.

The method of *Steepest Descent* is the simplest of the gradient methods. The choice of direction is where *f* decreases most quickly. The search starts at an arbitrary point and then slide down the gradient, until we are close enough to the solution. [1]

8.3 RLS Algorithm

The RLS (recursive least squares) algorithm is another algorithm for continues adaptation. In contrast to the LMS algorithm, the RLS algorithm uses information from all past input samples (and not only from the current tap-input samples) to estimate the weight vectors. To decrease the influence of input samples from the far past, a weighting factor for the influence of each sample is used. This algorithm has fast convergence rate and ability to process the input signal especially when the environment is changing rapidly. [2]

8.4 Constant Modulus Algorithm

The CM algorithm is used for blind equalization of signals that have a constant modulus. The algorithm that updates the weight coefficients is exactly the same as for the LMS algorithm. The constant modulus algorithm tries to drive the output signal to one having constant amplitude. [3]

8.5 MUSIC Algorithm

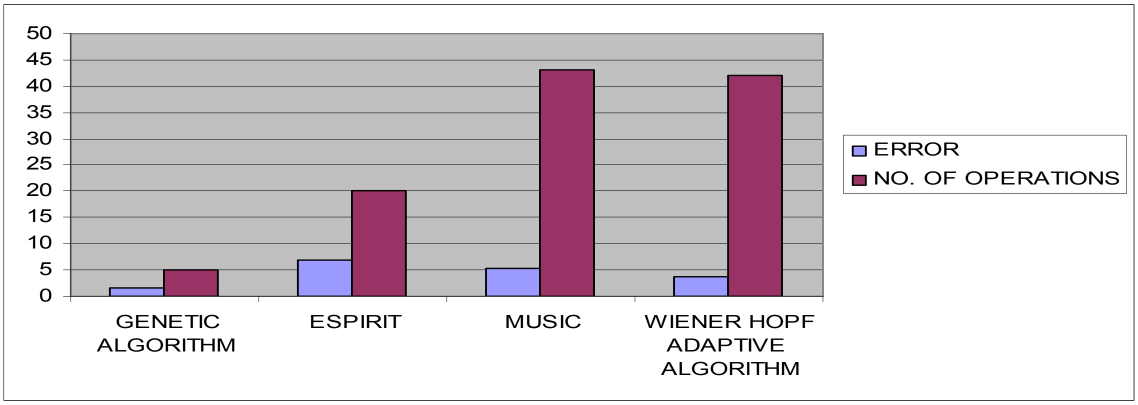
Multiple signal classification (MUSIC) algorithm provides asymptotically unbiased estimates of 1) number of incident wave fronts present; 2) directions of arrival (DOA); 3) strengths and cross correlations among the incident waveforms; 4) noise/interference strength. It was developed by Schmitt in 1979.

8.6 ESPRIT Algorithm

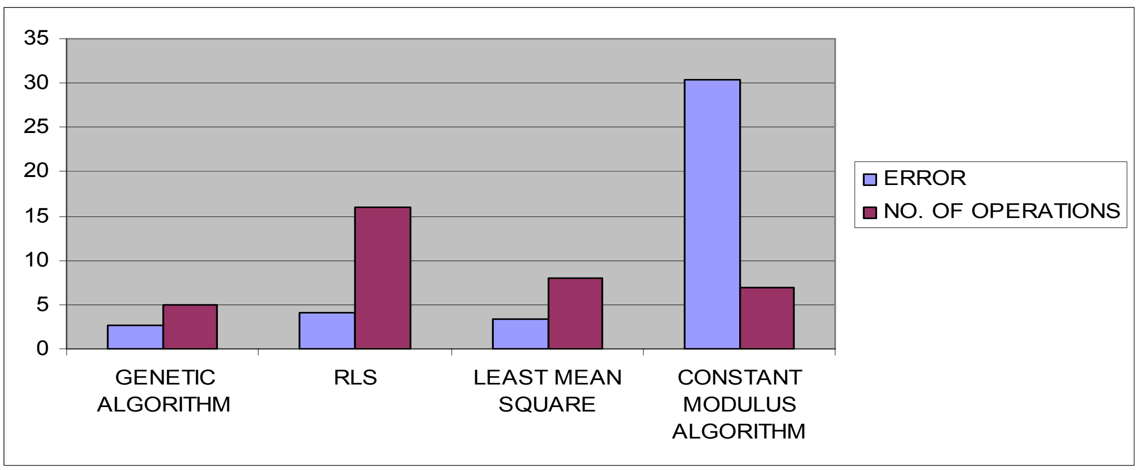
In the ESPRIT (estimation of signal parameters via rotational invariance techniques) algorithm direction of arrival is based on a modification of the generalized singular value decomposition (GSVD) of two data matrices and requires only unitary transformations.

8.7 Comparison with Existing Techniques

We have carried out the comparison of our proposed technique with already existing techniques, in terms of accuracy and no. of operations involved. The graphical representation is given below:-



(a)



(b)

Figure 8.3: Comparison with existing techniques used for (a) DOA estimation (b) Beamforming

8.8 Summary

In this chapter, we have given a brief overview of the existing techniques and carried out a comparison with our developed technique. From the results, it is evident that our technique has upper edge on the existing techniques in terms of accuracy and no. of operations.

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[3] portal.aem.org

Chapter 9

DSP Kit

9.1 Introduction

Digital signal processors such as the TMS320C6x (C6x) family of processors are like fast special-purpose microprocessors with a specialized type of architecture and an instruction set appropriate for signal processing. The C6x notation is used to designate a member of Texas Instruments' (TI) TMS320C6000 family of digital signal processors. The architecture of the C6x digital signal processor is very well suited for numerically intensive calculations. Based on a very-long-instruction-word (VLIW) architecture, the C6x is considered to be TI's most powerful processor. Digital signal processors are used for a wide range of applications, from communications and controls to speech and image processing.

This chapter introduces DSP kit by highlighting it's features, supporting tools, code composer studio, useful types of files and it's integration with Matlab.

9.2 Key Features

Main features associated with the subject kit are following:-

a. C6713 DSP Starter Kit (DSK) is a low cost standalone development platform using TI C6713 DSP.
b. A TI C6713 DSP operating at 225MHz
c. An AIC23 stereo codec
d. 8 MB synchronous DRAM (SDRAM)
e. 512 KB flash memory
f. 4 user accessible LEDs and DIP switches
g. Both fixed- and floating- point processing
h. VLIW architecture (8 32-bit instructions/cycle)
i. 225MHz clock rate
k. 264kB of internal memory
l. 8kB as L1P and L1D Cache
m. 256kB as L2 memory
n. 8 functional or execution units
o. 6 arithmetic-logic units (ALUs)
p. 2 multiplier units

q. 32-bit address bus

r. 2 sets of 32-bit general-purpose registers

9.3 DSK Support Tools

To perform the experiments applications, the following tools are used:

a. TI's DSP starter kit (DSK). The DSK package includes:

(1) Code Composer Studio (CCS), which provides the necessary software support tools. CCS provides an integrated development environment (IDE), bringing together the C compiler, assembler, linker, debugger, and so on.

(2) A board that contains the TMS320C6713 (C6713)
Floating- point digital signal processor as well as a 32-bit stereo codec for input and output (I/O) support.

(3) A universal synchronous bus (USB) cable that connects the DSK board to a PC.

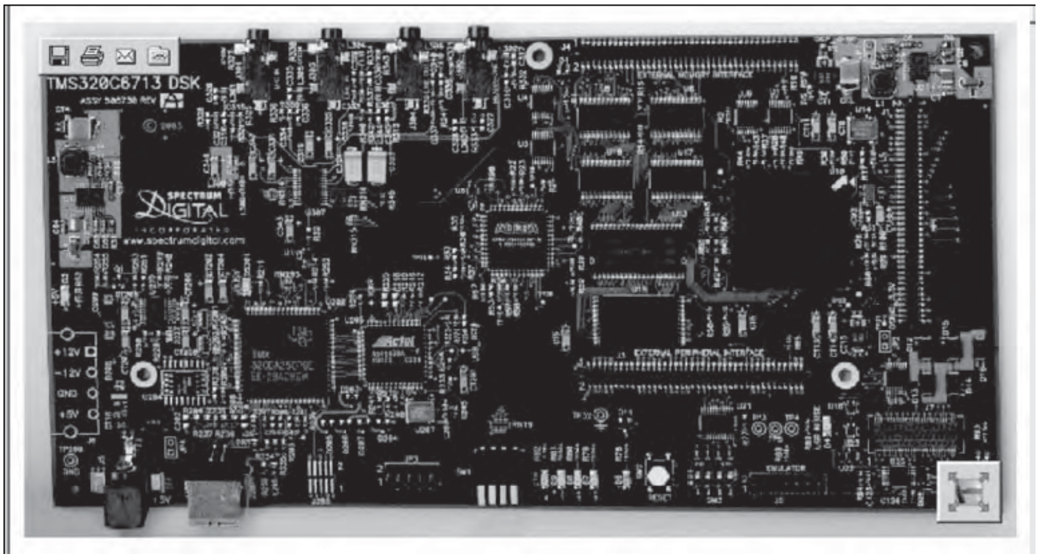
(4) 5V power supply for the DSK board.

b. The DSK board connects to the USB port of the PC through the USB cable included with the DSK package.

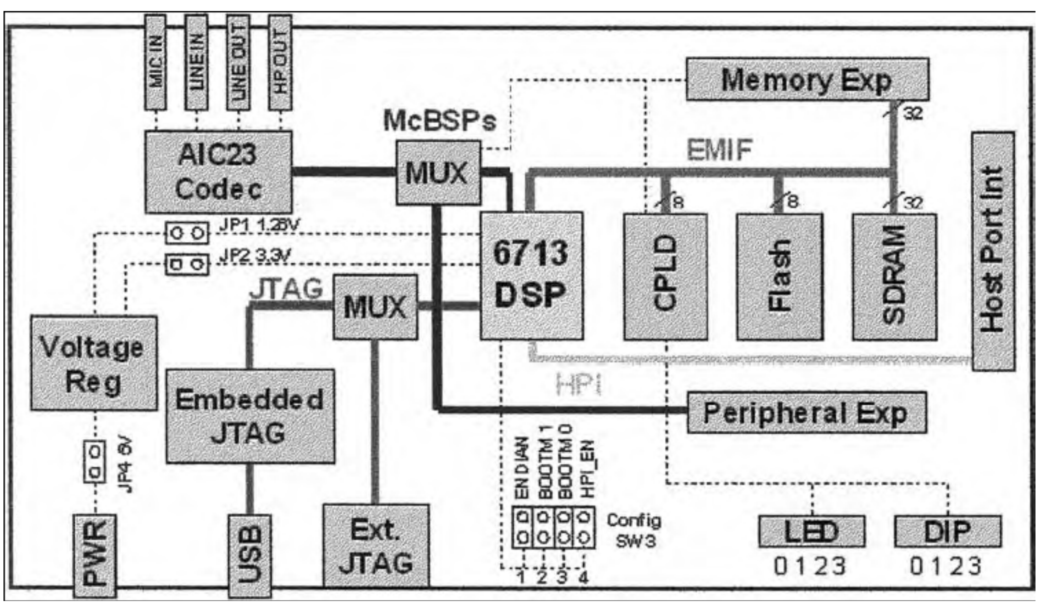
c. An oscilloscope, signal generator, and speakers. A signal/spectrum analyzer is optional. Shareware utilities are available that utilize the PC and a sound card to create a virtual instrument such as an oscilloscope, a function generator, or a spectrum analyzer. [1]

9.4 DSK Board

The DSK package is with the necessary hardware and software support tools for real-time signal processing. It is a complete DSP system. The DSK board includes the C6713 floating-point digital signal processor and a 32-bit stereo codec TLV320AIC23 (AIC23) for input and output.



(a)



(b)

FIGURE 1 TMS320C6713-based DSK board: (a) board; (b) diagram. [2]

The onboard codec AIC23 uses a sigma–delta technology that provides ADC and DAC. It connects to a 12-MHz system clock. Variable sampling rates from 8 to 96 kHz can be set readily. A daughter card expansion is also provided on the DSK board. Two 80-pin connectors provide for external peripheral and external memory interfaces. The DSK board includes 16MB (megabytes) of synchronous dynamic random access memory (SDRAM) and 256kB (kilobytes) of flash memory. Four connectors on the board provide input and output: MIC IN for microphone input, LINE IN for line input, LINE OUT for line output, and HEADPHONE for a headphone output (multiplexed with line output). The status of the four user dip switches on the DSK board can be read from a program and provides the user with a feedback control interface. The DSK operates at 225MHz. Also onboard the DSK are voltage regulators that provide 1.26 V for the C6713 core and 3.3 V for its memory and peripherals.

9.5 Code Composer Studio

CCS provides an IDE to incorporate the software tools. CCS includes tools for code generation, such as a C compiler, an assembler, and a linker. It has graphical capabilities and supports real-time debugging. It provides an easy-to-use software tool to build and debug programs. The C compiler compiles a C source program with extension .c to produce an assembly source file with extension .asm. The assembler assembles an .asm source file to produce a machine language object file with extension .obj. The linker combines object files and object libraries as input to produce an executable file with extension .out.

This executable file represents a linked common object file format(COFF), popular in Unix-based systems and adopted by several makers of digital signal processors. This executable file can be loaded and run directly on the C6713 processor. A linear optimizer optimizes this source file to create an assembly file with extension .asm (similar to the task of the C compiler). To create an application project, one can “add” the appropriate files to the project. Compiler/linker options can readily be specified. A number of debugging features are available, including setting breakpoints and watching variables; viewing memory, registers, and mixed C and assembly code; graphing results; and monitor. [3]

9.6 Useful Types of Files

A user would be working with a number of files with different extensions. They include:

a. file.pjt: to create and build a project named file

b. file.c: C source program

c. file.asm: assembly source program created by the user, by the C compiler, or by the linear optimizer

d. file.sa: linear assembly source program. The linear optimizer uses file as input to produce an assembly program file.asm

e. file.h: header support file

f. file.lib: library file, such as the run-time support library file rts6700.lib

g. file.cmd: linker command file that maps sections to memory

h. file.obj: object file created by the assembler

i. file.out: executable file created by the linker to be loaded and run on the C6713 processor

j. file.cdb: configuration file when using DSP/BIOS

9.7 Integration of Matlab Tools for DSP Code Generation

The Embedded Target for TI C6000 DSP platform integrates Simulink and Matlab with Texas Instrument express DSP(tm) tools. The software suite allows a user to develop DSP designs from concept through code and automates rapid prototyping on the C6713 DSP starter kit. The Build process builds a Code Composer Studio (CCS) project from the C code generated by Real-Time Workshop. The CCS project is automatically compiled and linked, and the executable is loaded onto your board, and run on the C6713 DSP.

9.8 Summary

The general-purpose digital signal processor is dominated by applications in communications (cellular). Applications embedded digital signal processors are dominated by consumer products. They are found in cellular phones, fax/modems, disk drives, radio, printers, hearing aids, MP3 players, high-definition television (HDTV), digital cameras, and so on. These processors have become the products of choice for a number of consumer applications, since they have become very cost-effective. They can handle different tasks, since they can be reprogrammed readily for a different application. DSP techniques have been very successful because of the development of low-cost software and hardware support. For example, modems and speech recognition can be less expensive using DSP techniques.

References

[1] User Manual C6713, Texas Instruments, Dallas, TX.

[2] Code Composer Studio Getting Started Guide, SPRU509, Texas Instruments, Dallas, TX, 2001.

[3] Rulph Chassaing, Digital Signal Processing with Applications with the C6713 and C6416 DSK, Wiley

Chapter 10

Conclusion and Future Recommendations

Conclusion

In the recent years, advancement in telecommunication technologies and the increasing demand of data rate has motivated the optimized use of frequency spectrum. One technique for the efficient usage of frequency is Smart Antenna system. Smart Antennas are though developed using different algorithms, but the urge was felt for improving the technique to increase their efficiency. Therefore we humbly tried to present a new technique which tried to fulfill all the issues of smart antenna.

Future Recommendations

We would definitely like someone to extend this project for the case of planar arrays and also doing RF end designing. This technique may also be incorporated in Radar scanning.

Appendix A

MATLAB Code

Note: The GUI files are not provided here, though they are given in the disk provided and the website.

%%%%%%%%AIS Scanninguni%%%%%%%%

```
function [s]= aisscanninguni(doa,m,current,doi)
load ais.mat
if m==1
            for i=1:2000
            if (abs(ang(i)-doa)<=5)&&abs((doid(i)-doi)<=5)
              s=distrib(i);
            break
            else
                s=0;
        end
    end

else

    tempdist=distrib;
    tempang=ang;
    tempdoid=doid;
    tempdist(2000)=current;
    tempang(2000)=doa;
    tempdoid(2000)=doi;
    doid=circshift(tempdoid,1);
    ang=circshift(tempang,1);
    distrib=circshift(tempdist,1);

s=0;
save ('ais','ang','distrib','doid')
end
```

%%%%%%%%Main Program single user %%%%%%%%

```
function [solution]= geneticalgophase()
clc
y=2;%for controllng the no. of iterations
Element=input('plz enter the no. of elements in the array ');
gene=input('enter da no.bits in a gene ');
d=input('plz enter the inter-element spacing of the array elements in
terms of lambda ');
DOA=inducedsignal(Element,d,gene);
doi=input('plz enter the doi');
doi=deg2rad(doi);


[binrnd,decrnd]=rndgen(Element,gene);%gen 1
    iter=0;
```

```
while y~=1
        dec2bin(decrnd,2*Element*gene);
    current=seperate(decrnd,gene,Element);%chromosomes being
transformed into complex currents
    mbdir=direction(current,Element,d);%direction of main beam
    magdoi=mgdoi(current,Element,d,doi);%magnitude at the interference
    magdoa2=mgdoi(current,Element,d,DOA(2));%magnitude at the doa2
    for t=1:12
      difference(t,1)=2*(mbdir(t,1)-DOA(1));%abs
      magdiff(t,1)=(10*log(magdoi(t,1)))-5;
      magdiffdoa2(t,1)=(10*log(magdoa2(t,1)));

vector(t,1)=((difference(t,1))^2)+(magdiff(t,1)^2)+(magdiffdoa2(t,1)^2)
;
    end
     y=testconvergence(vector);
  if y==1
    break
  end
  [surpopb,surpopd]=survival(decrnd,vector);
  crossedpop=crossover(surpopd,gene,Element);%gen 2
  decrnd=crossedpop;
  iter=iter+1;
  if iter>20
      [binrnd,decrnd]=rndgen(Element,gene);
      iter=1;
  end
end

[phase,mag]=result(decrnd,vector,gene,Element);
draw(phase,mag,Element,d);
```

%%%%%%%%%Main Program multiuser %%%%%%%%%

```
function [solution]= geneticalgophasecheck()
clc
Element=input('plz enter the no. of elements in the array ');
gene=input('enter da no.bits in a gene ');
d=input('plz enter the inter-element spacing of the array elements in
terms of lambda ');
DOA=inducedsignal(Element,d,gene)
doi=input('plz enter the doi');
doi=deg2rad(doi);

[gen,res,int]=multiuser(DOA,doi,Element,d,gene);
gen
subplot(2,1,1)
polar(transpose(0:int:pi),res(:,1));

DOA=DOA(end:-1:1);
[gen,res,int]=multiuser(DOA,doi,Element,d,gene);
gen
subplot(2,1,2)
polar(transpose(0:int:pi),res(:,1));
```

%%%%%%%%multiuser %%%%%%%%

```
function [gen,res,int]= multiuser(DOA,doi,Element,d,gene)
iter=0;
   [binrnd,decrnd]=rndgen(Element,gene);%gen 1
y=2;%for controllng the no. of iterations
while y~=1
    dec2bin(decrnd,2*Element*gene);
    current=seperate(decrnd,gene,Element);%chromosomes being
transformed into complex currents
    %current{:,:}
    mbdir=direction(current,Element,d);%direction of main beam
    magdoi=mgdoi(current,Element,d,doi);%magnitude at the interference

        DOA(2)=deg2rad(DOA(2));
        magdoa2=mgdoi(current,Element,d,DOA(2));%magnitude at the doa2

    for t=1:12
      difference(t,1)=2*(mbdir(t,1)-DOA(1));%abs
      magdiff(t,1)=(10*log(magdoi(t,1)))-5;
      magdiffdoa2(t,1)=(10*log(magdoa2(t,1)))-5;

vector(t,1)=((difference(t,1))^2)+(magdiff(t,1)^2)+(magdiffdoa2(t,1)^2)
;
    end
  % y=testconvergence(difference,magdiff);
   y=testconvergence(vector);
  if y==1
    break
  end
  [surpopb,surpopd]=survival(decrnd,vector);
  crossedpop=crossover(surpopd,gene,Element);%gen 2
  decrnd=crossedpop;
  iter=iter+1;
  if iter>20
      [binrnd,decrnd]=rndgen(Element,gene);
      iter=1;
  end
end
[phase,mag]=result(decrnd,vector,gene,Element);
[gen,res,int]=drawcheck(phase,mag,Element,d);
```

%%%%%%%%induced signal %%%%%%%%

```
function [DOA,theeta1,theeta2]= inducedsignal(Element,d,gene,nl,mut)
clc
ll=-2*pi*d*.866;%lower limit
ul=2*pi*d*.866; %upper limit
alpha_z=.54533;
while (alpha_z>=-.54553)&&(alpha_z<=.54553);
alpha_z=(ul-ll).*rand([1,1]) + ll;
end
theeta1=rad2deg(acos(alpha_z/pi))
```

```
a=((50-20).*rand([1,1]) + 20);
theeta2=theeta1+a;
if theeta2>150
    theeta2=theeta1-a;
end

theeta2
alpha_z2=2*pi*d*cos(deg2rad(theeta2));

[binrnd,decrnd]=rndgendoa(Element,gene);

DOA(1)=0;
noise = wgn(Element,1,nl,'complex');
for z=1:2
for y=1:60

current2=seperateinduceddoa(decrnd,gene,Element,alpha_z,alpha_z2,noise,
z,DOA(1));
[surpopb,surpopd]=survivaldoa(decrnd,current2);
if y==60
     decrnd=surpopd;%do padding in evry iteration
   break
end
crossedpop1=crossoverdoa(surpopd,gene,Element);
crossedpop=mutation(crossedpop1,gene,Element,mut);
decrnd=crossedpop;

dec2bin(decrnd);%CHECK
end
decrnd;%check
solution=resultdoa(decrnd(1),gene,Element);
DOA(z)=drawdoa(solution,Element,d);
end
```

%%%%%%%%Crossoveruni%%%%%%%%

```
%MATING OR CROSSOVER
function [B]= crossoveruni(rnds,genebit,ele)
a=2*genebit*ele;
for j=1:12
A{j,1}=dec2binvec(rnds(j,1),a);
%cell array been formed here so that individual elements can accessed
for further crossover.
%8 is placed in the input arguments of abuv func 2 make all chromosomes
of
%equal size
A{j,1}=A{j,1}(end:-1:1);
%for reversing the arrays as dec2binvec func places the LSB in the
first
%columnand MSB in the last.
 end

 for k=7:2:11% first loop is for crossover between first two
chromosomes
random1=round((a-1).*rand + 1);
```

```
random2=round((a-1).*rand + 1);

 temp(1,1)=A{k,1}(random1);
 A{k,1}(random1)=A{k+1,1}(random2);
 A{k+1,1}(random2)=temp(1,1);
end

 for l=1:12
A{l,1}=A{l,1}(end:-1:1);
%for reversing the arrays as binvec2dec func places the LSB in the
first
%columnand MSB in the last.
B(l,1)=binvec2dec(A{l,1});
 end
```

%%%%%%%% Crossoverdoauni %%%%%%%%%

```
%MATING OR CROSSOVER
function [B]= crossoverdoauni(rnds,genebit,ele)
a=genebit*ele;
for j=1:12
A{j}=dec2binvec(rnds(j),a);
%cell array been formed here so that individual elements can accessed
for further crossover.
%8 is placed in the input arguments of abuv func 2 make all chromosomes
of
%equal size
A{j}=A{j}(end:-1:1);
%for reversing the arrays as dec2binvec func places the LSB in the
first
%columnand MSB in the last.
 end

 for k=7:2:11% first loop is for crossover between first two
chromosomes
random1=round((a-1).*rand + 1);
random2=round((a-1).*rand + 1);

 temp(1)=A{k}(random1);
 A{k}(random1)=A{k+1}(random2);
 A{k+1}(random2)=temp(1);
end

 for l=1:12
A{l}=A{l}(end:-1:1);
%for reversing the arrays as binvec2dec func places the LSB in the
first
%columnand MSB in the last.
B(l)=binvec2dec(A{l});
 end
```

%%%%%%%%% Survival of the fittest%%%%%%%%%

```
%SURVIVAL OF THE FITTEST
%this function sorts the chromosomes in ascending order according to
the
%value of difference from DOA
function [rns,rnd]= survivaldoauni(rnd,differ)

a=max(size(differ));
for j=1:a-1
     for i=1:a-1
       if differ(i)<differ(i+1)
        tempor(i,1)=differ(i);
        tempor(i,2)=rnd(i);
        differ(i)=differ(i+1);
        rnd(i)=rnd(i+1);
        differ(i+1)=tempor(i,1);
        rnd(i+1)=tempor(i,2);
       end
     end
 end
for i=1:a/2
rnd(i+(a/2))=rnd(i);
end
rns=dec2bin(rnd);
```

%%%%%%%%% Test Convergence%%%%%%%%%

```
%this function tests the convergence of the algorithm
function [w] = testconvergence(vector)

if min(vector)<40

    w=1;
else
    w=2;
end
```

%%%%%%%%% Mutation%%%%%%%%%

```
function [crpopn]=mutation(cpop,g,E,perc)
for j=1:12
crpop{j,1}=dec2binvec(cpop(j),g*E);
crpop{j,1}=crpop{j,1}(end:-1:1);
end
Nt=ceil((perc/100)*12);%no. of mutations
rnd= round(transpose((12-1).*rand([1,Nt]) + 1));

for k=1:Nt
    x=0;
 a=round(((g*E)-1).*rand([1,1]) + 1);
if crpop{rnd(k),1}(1,a)==0
    crpop{rnd(k),1}(1,a)=1;
    x=x+1;
```

```
end
if  crpop{rnd(k),1}(1,a)==1&&x==0
    crpop{rnd(k),1}(1,a)=0;
end
end
for j=1:12
    crpop{j,1}=crpop{j,1}(end:-1:1);
    crpop{j,1}=binvec2dec(crpop{j,1});
end
for j=1:12
crpopn(j,1)=crpop{j,1};
end
```

%%%%%%%% Magnitude at the interference%%%%%%%%

```
%this function takes complex currents as input and gives the magnitude
in  the direction of
%the interference as output.
function [gen]=mgdoi(I,E,d,doi)

N=(E-(rem(E,2)))/2;%N is the index of the array elements
sum=0;
int=.001;

if (rem(E,2))==1
   for s=1:12
      ent=0;
      theeta=doi;
         p=1;
         for n=-N:1:N % implementing the basic array factor equation
here

sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*n*d*cos(theeta)))));
              p=p+1;
         end
         gen(s,1)=abs(sum);
   end
end

if (rem(E,2))==0
    for s=1:12
      ent=0;
     theeta=doi;
         p=(E/2)+1;
         for n=1:1:N % implementing the basic array factor equation
here
             sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*(((2*n)-
1)/2)*d*cos(theeta)))));
              p=p+1;
         end
         p=1;
         for n=-N:1:-1 % implementing the basic array factor equation
here
```

```
sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*(((2*n)+1)/2)*d*cos(the
eta)))));
              p=p+1;
         end
         gen(s,1)=abs(sum);
   end
end
```

%%%%%%%%% Separate uni%%%%%%%%%

```
%this function separtes the chromosome bits on the basis of no. of bits
in
%a gene and transforms them into complex cuurents.Magnitudes of these
%currents are unity and phases are equal to value given by gen value.
function [current]=seperateuni(b,g,E)

for j=1:12
A{j,1}=dec2binvec(b(j,1),2*g*E);
%cell array been formed here so that individual elements can be
accessed.
%g*E is placed in the input arguments of abuv func 2 make all
chromosomes of
%equal size
end
for k=1:12
m=1;
for l=1:2*g:2*g*E
tempo{k,1}(1,m)=binvec2dec(A{k,1}(1,l:l+g-1));
phase{k,1}(1,m)=0.01745*((tempo{k,1}(1,m))*(360/(2^g)));
m=m+1;
end
end


for k=1:12
m=1;
for l=g+1:2*g:2*g*E
tempo{k,1}(1,m)=binvec2dec(A{k,1}(1,l:l+g-1));
if tempo{k,1}(1,m)==0
    tempo{k,1}(1,m)=1;
end
mag{k,1}(1,m)=10*(tempo{k,1}(1,m));
current{k,1}(1,m)=(mag{k,1}(1,m))*(complex(cos(-
1*phase{k,1}(1,m)),sin(-1*phase{k,1}(1,m))));
m=m+1;
end
end
```

%%%%%%%%% seperateinduceddoa%%%%%%%%%

```
%this function separtes the chromosome bits on the basis of no. of bits
in
%a gene and transforms them into complex cuurents.Magnitudes of these
%currents are unity and phases are equal to value given by gen value.
function
[rxcurrent]=seperateinduceddoa(b,g,E,alpha,alpha2,noise,time,doa)
for j=1:12
A{j,1}=dec2binvec(b(j,1),g*E);
%cell array been formed here so that individual elements can be
accessed.
%g*E is placed in the input arguments of abuv func 2 make all
chromosomes of
%equal size
end
doa=deg2rad(doa);

for k=1:12
    z=0;
    m=1;
    sum=0;
  for l=1:g:g*E
     tempo{k,1}(1,m)=binvec2dec(A{k,1}(1,l:l+g-1));

phase1{k,1}(1,m)=(0.01745*(tempo{k,1}(1,m))*(360/(2^g)))+(z*alpha);

phase1{k,1}(1,m+1)=(0.01745*(tempo{k,1}(1,m))*(360/(2^g)))+(z*alpha2);
  if time==1
       sum=noise(m)+sum+(exp(i*phase1{k,1}(1,m)));
  else
       sum=noise(m)+sum+(exp(i*phase1{k,1}(1,m+1)))-(exp(i*doa));
  end

   m=m+1;
   z=z+1;
   end
rxcurrent(k)=abs(sum);
end
```

%%%%%%%% Random Generator%%%%%%%%

```
function [rn,rnd]= rndgendoauni(elements,gene)%function generating 12
random chromosomes in binary as well as decimal version
 ll=0;%lower limit
ul=(2^(gene*elements))-1;%upper limit, gene*elements will specify the
no. of bits in a chromosome
rnd= transpose((ul-ll).*rand([1,12]) + ll);%decimal version
rn= dec2bin(rnd);%binary version
```

%%%%%%%% direction finding%%%%%%%%

```
%this function takes complex currents as input and gives the direction
of
%the main beam as output.
function [gen]=direction(I,E,d)

N=(E-(rem(E,2)))/2;%N is the index of the array elements
sum=0;
int=.001;

if (rem(E,2))==1
   for s=1:12
      ent=0;
      for theeta=0:int:pi
         p=1;
         for n=-N:1:N % implementing the basic array factor equation
here

sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*n*d*cos(theeta)))));
              p=p+1;
         end
         result(ent+1,1)=abs(sum);
         sum=0;
         ent=ent+1;
      end
      [q,r]=max(result);
       gen(s,1)=(((r(1,1)*int)-int)*57.29578);
   end
end

if (rem(E,2))==0
    for s=1:12
      ent=0;
      for theeta=0:int:pi
         p=(E/2)+1;
         for n=1:1:N % implementing the basic array factor equation
here
             sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*(((2*n)-
1)/2)*d*cos(theeta)))));
              p=p+1;
         end
         p=1;
         for n=-N:1:-1 % implementing the basic array factor equation
here

sum=sum+((I{s,1}(1,p)/I{s,1}(1,1))*(exp(i*(2*pi*(((2*n)+1)/2)*d*cos(the
eta)))));
              p=p+1;
         end
         result(ent+1,1)=abs(sum);
         sum=0;
         ent=ent+1;
      end
      [q,r]=max(result);
       gen(s,1)=(((r(1,1)*int)-int)*57.29578);
   end
end
```

%%%%%%%% directivity%%%%%%%%

```
function[dir]=directivity(result,int)

  pattm=max(result);
      int1=0;
      k=1;
      for theeta=0:int:pi
        int1=int1+result(k);
          k=k+1;
      end
     a=size(result);
      denom=int1/a(1);
      dir=pattm/denom;
```

%%%%%%%%% drawing the radiation pattern%%%%%%%%%

```
function[]=draw(solution,mag,E,d)

N=(E-(rem(E,2)))/2;%N is the index of the array elements
solution=deg2rad(solution);
a=size(solution);
a=a(2);
for k=1:a
I(k)=mag(k)*(cos(-1*solution(k))+1i*sin(-1*solution(k)));
end
sum=0;
ent=0;
result=[];
int=.001;

if (rem(E,2))==1
   for theeta=0:int:pi

      p=1;
      for n=-N:1:N
          sum=sum+((I(p)/I(1))*(exp(i*(2*pi*n*d*cos(theeta)))));
          p=p+1;
      end
      result(ent+1,1)=abs(sum);
      sum=0;
      ent=ent+1;
   end
   [q,r]=max(result);
    r(1,1);
    gen=(((r(1,1)*int)-int)*57.29578)

    while (max(result)>3)
          result=result/3;
    end
```

```
    polar(transpose(0:int:pi),result(:,1));

if (rem(E,2))==0
   for theeta=0:int:pi

       p=(E/2)+1;
      for n=1:1:N
          sum=sum+((I(p)/I(1))*(exp(i*(2*pi*(((2*n)-
1)/2)*d*cos(theeta)))));
          p=p+1;
      end
      p=1;
      for n=-N:1:-1

sum=sum+((I(p)/I(1))*(exp(i*(2*pi*(((2*n)+1)/2)*d*cos(theeta)))));
          p=p+1;
      end
      result(ent+1,1)=abs(sum);
      sum=0;
      ent=ent+1;
   end
   [q,r]=max(result);
    r(1,1);
    gen=(((r(1,1)*int)-int)*57.29578)

    while (max(result)>3)
    result=result/3;
    end

    polar(transpose(0:int:pi),result(:,1));
```