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**MODE SEPARATION-DIRECTION OF  
ARRIVAL ANGLE ESTIMATION USING  
GENETIC SEARCH ALGORITHM**

**OZAN KOROGLU**

Hacettepe University  
Department of Electrical and Electronics Engineering  
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Instructor: Prof.DR. Feza ARIKAN

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## ABSTRACT

Array signal processing has a great field of applications in communication. **Direction Of Arrival (DOA)** is the defined as the direction which the signal arrives to the sensor. Direction finding is one of challenging areas in array processing. There are several direction finding algorithms such as **MU**ltiple **SI**gnal **C**lassification (**MUSIC**), **D**elay and **S**um Beamforming (**DAS**). This project covers a novel approach to direction finding process called **Mode Separation Direction Of Arrival** angle estimation (**MS – DOA**). This algorithm has some upper properties on others. Such as the error performance is better or it can gives solutions with high accuracy. A new search routine for MS-DOA is developed by using Genetic Algorithms. By using genetic algorithm search routine the convergence of the algorithm is improved when the parameters has to be determined increases. In this project the response of the algorithm scenarios are investigated.

# TABLE OF CONTENTS

ABSTRACT.....	ii
TABLE OF CONTENTS .....	iii
LIST OF FIGURES .....	iii
1. INTRODUCTION .....	1
2. DIRECTION FINDING ALGORITHM .....	2
2.1 Signal Model .....	2
2.2 Direction of Arrival Estimation .....	3
2.3 Singular Value Decomposition .....	3
2.4 The Least Squares Solution .....	4
3. GENETIC ALGORITHM SEARCH.....	6
3.1 Genetic Algorithms .....	6
3.2 Proposed Genetic Search Routine for MS-DOA .....	7
3.3 Representation of Chromosomes .....	7
3.4 Initialization Of Population .....	7
3.5 Mating Scheme and Selection Method .....	8
3.6 Crossover Operation .....	8
3.7 Mutation Operation .....	9
3.8 Elitism property .....	9
3.9 Termination Criteria .....	9
4. TESTS AND RESULTS .....	11
4.1 General Settlements and Explanation .....	11
4.2 Optimization of Genetic Algorithm Parameters .....	11
4.3 Scenario A: 1 signal to be estimated .....	12
4.4 Scenario B: 2 signals to be estimated .....	16
4.5 Scenario C: 2 signals to be estimated close to each other.....	24
4.6 Real data Tests .....	32
5. CONCLUSION .....	33
6. REFERENCES .....	34
7. APPENDIX .....	35

## LIST OF FIGURES

Figure	Page
2.1 Incoming electric field and coordinate system for receiver array .....	2
3.2 Emperor Selection Scheme Block Diagram .....	8
3.3 Genetic Algorithm Search flowchart .....	10
4.4 RMSE Error of azimuth for one signal for good Ionosphere .....	12
4.5 RMSE Error of elevation for one signal for good Ionosphere .....	12
4.6 Normalized Standard Deviation of azimuth error for one signal for good Ionosphere .....	13
4.7 Normalized Standard Deviation of elevation error for one signal for good Ionosphere .....	13
4.8 RMSE Error of azimuth for one signal for poor Ionosphere .....	14
4.9 RMSE Error of elevation for one signal for poor Ionosphere .....	14
4.10 Normalized Standard Deviation of azimuth error for one signal for poor Ionosphere .....	15
4.11 Normalized Standard Deviation of elevation error for one signal for poor Ionosphere .....	15
4.12 RMSE Error of azimuth-1 for two signals for good Ionosphere .....	16
4.13 RMSE Error of azimuth-2 for two signals for good Ionosphere .....	16
4.14 RMSE Error of elevation-1 for two signals for good Ionosphere .....	17
4.15 RMSE Error of elevation-2 for two signals for good Ionosphere .....	17
4.16 Normalized Standard Deviation of azimuth-1 error for two signals for good Ionosphere .....	18
4.17 Normalized Standard Deviation of azimuth-2 error for two signals for good Ionosphere .....	18
4.18 Normalized Standard Deviation of elevation-1 error for two signals for good Ionosphere .....	19
4.19 Normalized Standard Deviation of elevation-2 error for two signals for good Ionosphere .....	19
4.20 RMSE Error of azimuth-1 for two signals for poor Ionosphere .....	20
4.21 RMSE Error of azimuth-2 for two signals for poor Ionosphere .....	20
4.22 RMSE Error of elevation-1 for two signals for poor Ionosphere .....	21
4.23 RMSE Error of elevation-2 for two signals for poor Ionosphere .....	21
4.24 Normalized Standard Deviation of azimuth-1 error for two signals for poor Ionosphere .....	22
4.25 Normalized Standard Deviation of azimuth-2 error for two signals for poor Ionosphere .....	22
4.26 Normalized Standard Deviation of elevation-1 error for two signals for poor Ionosphere .....	23
4.27 Normalized Standard Deviation of elevation-2 error for two signals for poor Ionosphere .....	23
4.28 RMSE Error of azimuth-1 for two close signals for good Ionosphere .....	24
4.29 RMSE Error of azimuth-2 for two close signals for good Ionosphere .....	24
4.30 RMSE Error of elevation-1 for two close signals for good Ionosphere .....	25
4.31 RMSE Error of elevation-2 for two close signals for good Ionosphere .....	25

4.32 Normalized Standard Deviation of azimuth-1 error for two close signals for good Ionosphere .....	26
4.33 Normalized Standard Deviation of azimuth-2 error for two close signals for good Ionosphere .....	26
4.34 Normalized Standard Deviation of elevation-1 error for two close signals for good Ionosphere .....	27
4.35 Normalized Standard Deviation of elevation-2 error for two close signals for good Ionosphere .....	27
4.36 RMSE Error of azimuth-1 for two close signals for poor Ionosphere .....	28
4.37 RMSE Error of azimuth-2 for two close signals for poor Ionosphere .....	28
4.38 RMSE Error of elevation-1 for two close signals for poor Ionosphere .....	29
4.39 RMSE Error of elevation-2 for two close signals for poor Ionosphere .....	29
4.40 Normalized Standard Deviation of azimuth-1 error for two close signals for poor Ionosphere .....	30
4.41 Normalized Standard Deviation of azimuth-2 error for two close signals for poor Ionosphere .....	30
4.42 Normalized Standard Deviation of elevation-1 error for two close signals for poor Ionosphere .....	31
4.43 Normalized Standard Deviation of elevation-2 error for two close signals for poor Ionosphere .....	31
4.44 RMSE of combined error for good and poor ionosphere conditions .....	33
4.45 Normalized Standard Deviation of error for good ionosphere conditions .....	34
4.46 Normalized Standard Deviation of error for poor ionosphere conditions .....	34
4.47 RMSE of combined error for good and poor ionosphere conditions .....	35
4.48 Normalized Standard Deviation of error for good ionosphere conditions .....	36
4.49 Normalized Standard Deviation of error for poor ionosphere conditions .....	36
4.50 RMSE of combined error for good and poor ionosphere conditions .....	37
4.51 Normalized Standard Deviation of error for good ionosphere conditions .....	38
4.52 Normalized Standard Deviation of error for poor ionosphere conditions .....	38
4.53 Results for real data .....	39

## 1. INTRODUCTION

Information can be delivered via electrical signals or electromagnetic waves in wireless environment. Wireless systems are being used in most application areas. The detection and recognition of objects is provided by receiving and processing signals which emitted from them in military applications. The applications become more complicated and need to receive, transmit and process more signals and data. The requirement of processing more data and robustness needs to use of multiple sensors. Multiple sensor systems can have better SNR, robustness and accuracy. One of the most known applications of these systems is direction finding and source localization. **Direction Of Arrival (DOA)** is one of the most important parameters that needs to be estimated for whole processes. There are several direction finding algorithms. **MU**ltiple **SI**gnal **C**lassification(**MUSIC**), **E**stimation of **S**ignal **P**arameters via **R**otational **I**nvariance **T**echnique (**ESPRIT**) are some of direction finding algorithms. In this project **Mode Separation Direction Of Arrival** angle estimation (**MS – DOA**) which is a novel approach to direction finding algorithms is investigated. MS-DOA consists of two main parts the DOA process and a search routine. A new search routine is proposed by using genetic algorithm. The proposed search routine is investigated for the ionosphere simulations and the real data.

## 2. DIRECTION FINDING ALGORITHM

This chapter describes the theoretical background of MS-DOA algorithm.

### 2.1 SIGNAL MODEL

Consider an array of  $L$  element omnidirectional sensors immersed in a homogenous media in the far field of  $K$  source signals are impinging on the array which have frequency  $f_0$ . [2] As depicted in the figure 2.1 below  $\mathbf{r}_1$  is the reference sensor at the origin. The time taken by a plane wave to arrive each sensor is different. This time difference depends on the array geometry, departure angles of the signals. Since the array geometry is known so that the time delay introduced by  $\gamma_l(\theta_k, \phi_k)$ .

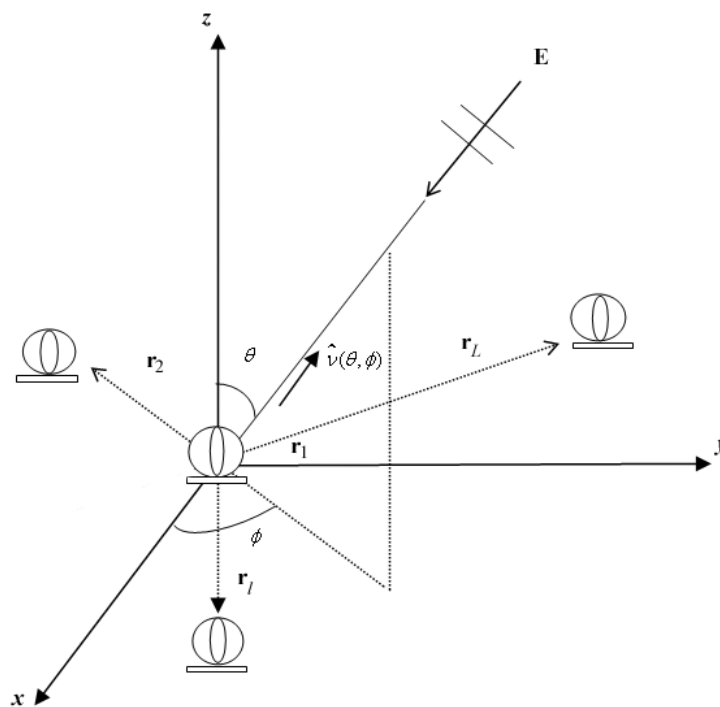


Figure 2.1: Incoming electric field and coordinate system for the receiving array

$$\gamma_l(\theta_k, \phi_k) = \frac{\mathbf{r}_l}{c} \cdot \hat{\mathbf{v}}(\theta_k, \phi_k) \quad (2.1)$$

where  $\mathbf{r}_l$  is position vector of  $l$ th sensor;  $\hat{\mathbf{v}}$  is the unit vector in the direction of  $k$ th signal and  $c$  is velocity of light in vacuum. The demodulated baseband output of reference sensor which is sampled at Nyquist rate is given by  $y_k(l)$  and  $x_l(t)$  which is the output signal of  $l$ th sensor defined by

$$x_l(t) = \sum_{k=1}^K y_k(t) e^{j\omega_0 \gamma_l(\theta_k, \phi_k)} \quad (2.2)$$

The two adjacent sensors have the time delayed versions of same signals. By using equation(2.2) all sensor outputs are combined to have an array output matrix.

## 2.2 DIRECTION OF ARRIVAL ESTIMATION

MS-DOA is a novel approach to direction finding algorithms. The algorithm is based on subspace manipulation. It uses the time delays of individual sensors. The sensor outputs are all linear combinations of each other. System is defined as linear system of equations and the measurement model of the signals is written in matrix-vector form.

$$\mathbf{X} = \mathbf{Y}\mathbf{A}^T \quad (2.3)$$

where

$$\mathbf{X} = [\mathbf{x}_1 \dots \mathbf{x}_l \dots \mathbf{x}_L] \quad (2.4)$$

$$\mathbf{Y} = [\mathbf{y}_1 \dots \mathbf{y}_k \dots \mathbf{y}_K] \quad (2.5)$$

$$\mathbf{A} = \begin{bmatrix} A_1(\mathbf{a}_1) & \dots & A_1(\mathbf{a}_K) \\ \vdots & \dots & \vdots \\ A_L(\mathbf{a}_1) & \dots & A_L(\mathbf{a}_K) \end{bmatrix} \quad (2.6)$$

where  $A_l(\mathbf{a}_k) = e^{jw_0\gamma_l(\theta_k, \phi_k)}$  and  $\mathbf{a}_k = [\theta_k, \phi_k]^T$ . Since  $x_l$ 's are linear combinations of  $y_k$ 's, the rank of  $\mathbf{X}$  can be at most K.[1] This implies that K basis vectors can be necessary and enough to represent the measurement vector. There are several methods to find subspace and basis functions. In this project as a subspace finding method singular value decomposition is used.

## 2.3 SINGULAR VALUE DECOMPOSITION

The **Singular Value Decomposition (SVD)** is one of the most elegant algorithms in linear algebra for providing quantitative information about the structure of the system of linear equations.[?] There are two ways of interest to singular value decomposition in this project. First by using the singular values the number of impinging waves can be determined. Also the basis functions which spans the subspace of  $x_l$ 's. Applying singular value decomposition on the sensor array output matrix in equation(2.3). The sensor array output matrix can be decomposed to three orthogonal matrices each other

$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H \quad (2.7)$$

$$\mathbf{U} = [\mathbf{u}_1 \dots \mathbf{u}_l \dots \mathbf{u}_L] \quad (2.8)$$

$$\mathbf{V} = [\mathbf{v}_1 \dots \mathbf{v}_k \dots \mathbf{v}_L] \quad (2.9)$$

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_L \end{bmatrix} \quad (2.10)$$

$\mathbf{\Sigma}$  have L singular values on its diagonal but only some of them has significance on others. Number of these significant singular values have the information of the number of signals impinging on the array and also the information about subspace. The basis vectors can be chosen as the effective part of these three orthogonal matrices according to the significant singular values.



$$\mathbf{U}_{\text{eff}} = [\mathbf{u}_1 \dots \mathbf{u}_l \dots \mathbf{u}_K] \quad (2.11)$$

$$\mathbf{V}_{\text{eff}} = [\mathbf{v}_1 \dots \mathbf{v}_k \dots \mathbf{v}_K] \quad (2.12)$$

Then  $\mathbf{X}$  can be written as

$$\mathbf{X} = [\mathbf{u}_1 \dots \mathbf{u}_l \dots \mathbf{u}_K][\mathbf{X}_1 \dots \mathbf{X}_k \dots \mathbf{X}_K]^T \quad (2.13)$$

and

$$[\mathbf{X}_1 \dots \mathbf{X}_k \dots \mathbf{X}_K]^T = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_K \end{bmatrix} \mathbf{V}_{\text{eff}}^H \quad (2.14)$$

By using above derivations the linear system of equations can be defined as

$$\begin{bmatrix} \mathbf{A} & 0 & \dots & 0 \\ 0 & \mathbf{A} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{A} \end{bmatrix} \begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \\ \vdots \\ \mathbf{Y}_K \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{Y}_2 \\ \vdots \\ \mathbf{X}_K \end{bmatrix} \quad (2.15)$$

The above matrix equation defines the system and by using it the arrival angles can be determined. Where  $Y_k$ 's are  $\mathbf{y}_g$  which has to be determined and  $X_k$ 's vector is  $\mathbf{x}_g$  which is the measurement data and  $\mathbf{A}$ 's are produces  $\mathbf{A}_g$

## 2.4 THE LEAST SQUARES SOLUTION

The matrix in equation (2.15) has the solutions of the arrival angles but measurement vector  $\mathbf{X}$  has some noise components which are not belong to the subspace. Because of this reason the exact solution can not be found. The optimum solution can be found with some error tolerance. In order to find the optimum solution the least squares approximation can be used. The following cost function which minimizes the difference between the matrices given in equation(2.15)

$$J(\mathbf{a}_1; \dots \mathbf{a}_K; \mathbf{y}_g) = \|\mathbf{A}_g \mathbf{y}_g - \mathbf{x}_g\|^2 \quad (2.16)$$

where  $\|\cdot\|$  denotes the  $L_2$  norm.[1] By using this cost function and writing for all components as a summation

$$J(\mathbf{a}_1; \dots \mathbf{a}_K; \mathbf{y}_g) = \sum_{k=1}^K \|\mathbf{A} \mathbf{Y}_k - \mathbf{X}_k\|^2 \quad (2.17)$$

Principle of orthogonality states that when a filter operates in its optimum condition the estimate of desired response and corresponding estimation error are orthogonal to each other.[3] By keeping this in mind the values of  $\mathbf{a}_k$  and  $\mathbf{y}_g$  which are minimizes the corresponding cost function. Also maximizes the projection of  $\mathbf{X}_k$ 's onto the range space of  $\mathbf{A}$ . The projections are defined by

$$\mathbf{P}_k(\mathbf{a}_k) = \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{X}_k \quad (2.18)$$

Calculating the above projection and adding its magnitude square for all signals the following maximizer can be obtained

$$M(\mathbf{a}_1; \dots \mathbf{a}_K) = \sum_{k=1}^K \|\mathbf{P}_k\|^2 \quad (2.19)$$

The values which are the maximizers of the above equation(2.18) are the desired solutions of the system. Once the optimum angles are found the original message signals can be obtained by further processing.

### 3. THE SEARCHING ROUTINE

#### 3.1 GENETIC ALGORITHMS

**Genetic Algorithms (GA)** are search algorithms based on the mechanics of natural selection and natural genetics. They have some different properties from traditional searching methods.[5]

1. GAs work with coding the parameter set, not the parameters themselves.
2. GAs search from a population of points, not a single point.
3. GAs use an objective function information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rules, not deterministic rules.

GA has the ability of solving multiple parameter problems. The parameters of the GA is converted to binary form according to provided translation procedure which is called chromosome. The combination of one set of parameters is gene. Thus, the algorithm uses these genes in the operation. Every gene has a fitness values according to the objective function.[5]

The operating steps of standard genetic algorithm as follows:

1. (a) There should be a restriction of the range of it.  
(b) Initial population should be appropriate for the objective.
2. Production of next generation by using parents
  - (a) Fitness function gives the information about the member if the member can be suitable member.
  - (b) GA has crossover operator to exchange some parts of parents each other; the selection of parents and which parts should be exchanged can be both deterministic or stochastic. This operator results a new member. Parents produces offsprings by using crossover.
  - (c) Mutation operator is the change of some parts of members randomly with a mutation probability. Mutation provides not to stay around the artifacts.
  - (d) Selection operation is the decision of which member should survive and which should extinct according to fitness of the member.
3. Formation of new population by using survived and produced new members.
4. Turning back and evaluating previous steps.
  - (a) The evaluation loop of whole genetic algorithm must be end.
  - (b) The decision procedure that which situations the solution can be accepted as optimum.

### 3.2 The Proposed Genetic Search Routine For MS-DOA.

There are several applications of genetic algorithms on array signal processing of direction of arrival estimation. The method employed by this project is based on minimization of the cost function defined by equation (2-17). The cost function which has to be minimized actually a multi parameter problem. Genetic algorithms give powerful and accurate solutions for multi parameter problems. GA's can be classified as member of stochastic optimization techniques. By this reason searching the space will be done by stochastically. GA is inspired by the mechanism of natural selection where stronger individuals would like to be the winners in a competing environment.[4] The proposed GA based search routine also uses the direct analogy of human genetic properties. The steps of the search routine can be given as follows:

### 3.3 Representation of the Chromosomes

Binary representation of the chromosomes are widely used in genetic algorithms. In this type of representation all individuals are encoded by a technique to form a chromosome. The algorithm operates on these generated chromosomes not the parameters itself. Some application areas there may not be need of representing the individuals as binary form. In DOA applications the operation is done on the real values of individuals, they are defined as real parameter problems. By this reason making the computations on binary form causes extra computational complexity. To avoid this situation another representation of chromosomes can be used. This is called floating point representation. In floating point representation the chromosomes are not converted in binary; they are represented by their own values. In this project the chromosomes are represented in floating point structure.

### 3.4 Initialization of Population

Initial population could be generated by various methods. It could be generated by randomly or some restrictions could be made. Such as taking the bounds of which the desired angles lies in. This requires a pre-estimation of DOA which is called intelligent initialization. Intelligent initialization is based on some rough DOA estimates, which are computed by a pre-estimator.[4] As pre-estimator various DF methods can be used. In this project the standard MUSIC algorithm is used for initialization of population intelligently. MUSIC roughly estimates where the desired angles could be lied in. There is no need to find very accurate solutions from MUSIC. It only narrows the search space by giving the approximate bounds. Initial population individuals are generated only in the bounds which comes from MUSIC. By making this pre-estimation there is no need to search all space and the computation speed increases.

Each solution set is defined by column vectors of containing the real valued floating point representation of angles. Each member of this column vectors represented by  $\mathbf{P}_n$  vectors. Initial population  $\mathbf{P}$  is composed of this column vectors, where  $N$  denotes the population size.

$$\mathbf{P}_n = [\theta_{1n}\phi_{1n} \cdots \theta_{kn}\phi_{kn}]^T \quad (3.20)$$

$$\mathbf{P} = \begin{bmatrix} \theta_{11} & \theta_{12} & \dots & \theta_{1N} \\ \phi_{11} & \phi_{12} & \dots & \phi_{mN} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{k1} & \theta_{k2} & \dots & \theta_{kN} \\ \phi_{k1} & \phi_{k2} & \dots & \phi_{kN} \end{bmatrix} \quad (3.21)$$

### 3.5 Mating Scheme; Selection Method

The quality of an offspring is almost proportional to its parents. Because of this reason selection of parents gets more important. In genetic algorithm literature there are several selection methods Such as roulette wheel selection and emperor selective scheme. The selection is the process of which parents will mate with which of them. Ranking is also an important parameter which defines the quality of the algorithm. In the project all members of the population is sorted according to their fitness values. The fittest solution sets have higher rank and more closer to the desired solutions. Emperor Selective Scheme **EMS** is used in this project to select the parents which will get mate with each other. In emperor selective scheme the best parents have the chance of getting mate with other parents. The mechanism is explained in the figure. In this problem emperor selective scheme is chose according to its high efficiency in these type of applications.

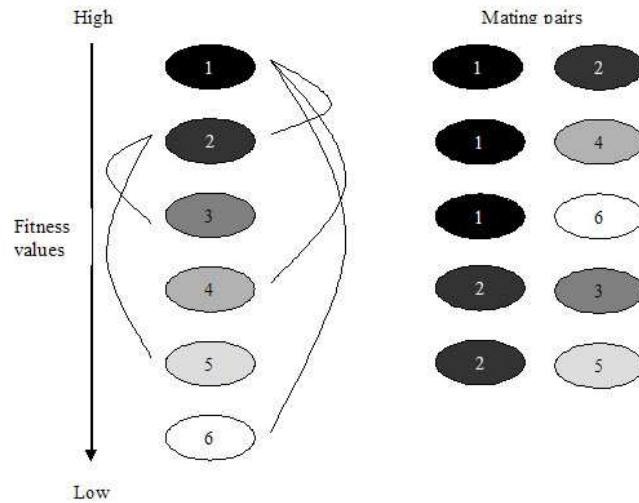


Figure 3.2: Emperor Selective Scheme Block Diagram

### 3.6 Crossover Operation

Crossover operation is one of the most important and basic operators in genetic algorithms. Crossover operation is generating new offsprings from their parents. By making this operation the variation of the population is provided. Crossover is usually carried out on the binary coded chromosomes but this problem the chromosomes are defined by floating point representation. So that the crossover operation could be done either on the real values or some encoding needed to convert the chromosomes to binary form and reverse. In stead of this extra computational load. Extrapolation Crossover **EPX**

Technique is used on the real valued chromosomes. Extrapolation crossover technique is based on generation of new offsprings which are lies in the range defined by two parents. **EPX** takes two parents, P1 and P2, to produce two offsprings, C1 and C2, that lie outside the range, a, of the two parents. The offsprings have equal probability to lie within the range a, extended in both directions from P1 and P2. C1 will then lie on the same side as P1 and C2 on the same side as P2. The range ,a, of the parents is defined by

$$\delta = (P2, P1), \text{ where } P2 > P1 \quad (3.22)$$

$$C1 = P1 + a.\delta \quad (3.23)$$

$$C2 = P2 + a.\delta \quad (3.24)$$

where  $\delta$  is a randomly chosen number between 1 and 2. In this project  $\delta$  is set to 1.5 to have the maximum extrapolation.[6]

### 3.7 Mutation Operation

Mutation is also the important operator of the genetic algorithms. This operator is used to guarantee the variation of the populations. By using this operator the algorithms are avoided from approaching the local maximums instead of the global maximums. As in crossover operators; mutation operation is done on binary coded forms of chromosomes. In this project the chromosomes are represented by floating point structure. Because of this reason the mutation could be carried out on real valued chromosomes due to avoiding the computational complexity. In this project mutation is held by inserting a new solution set into the population.

### 3.7 Elitism Property

Genetic algorithms are already powerful optimization techniques; but their convergence property could be improved by keeping some of previous population to next generation. Keeping some of fittest parents of previous population and inserting them into the new generation is called elitism property. In this type of applications keeping some percentage of the fittest or elite population helps the convergency. In this project 0.1 percent of elite population is said to be elite population and kept for next generation.

### 3.8 Termination Criteria

Termination criteria is the exact definition of where the algorithm must stop and how the solutions that found could be accepted. In some applications especially the algorithms that are designed for approaching specific values of solutions; termination criteria could be defined by using the probability of being close to the desired value. In DOA applications the desired solutions can not be known just they must be estimated. Termination criteria of this type of searching routines are defined by observation of the response of the algorithm. Because the routine does not know how it get close to the exact solutions.

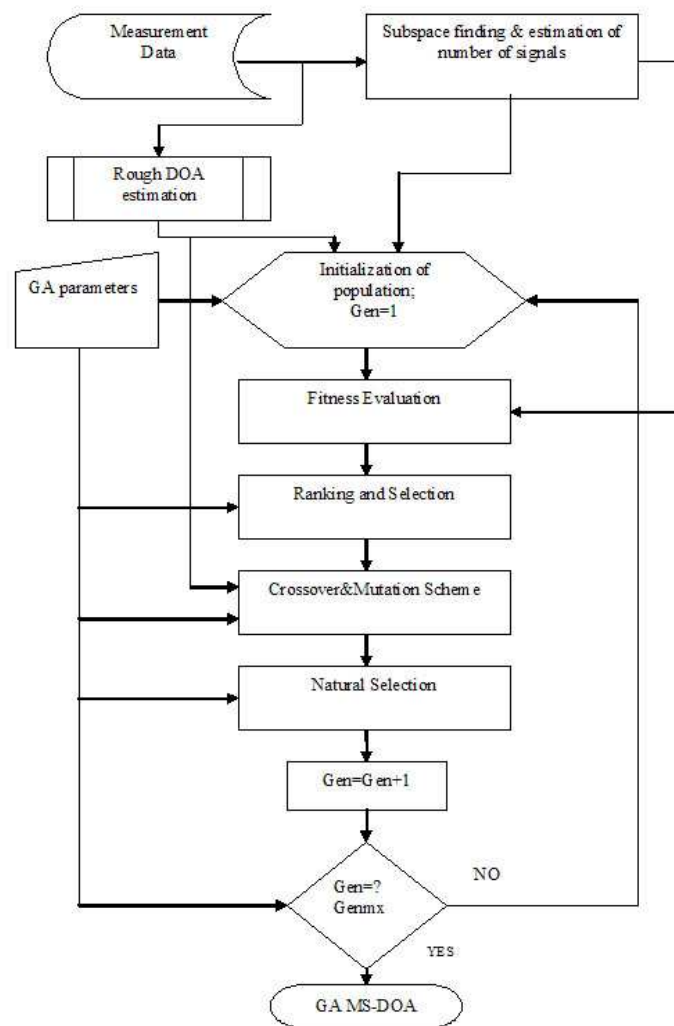


Figure 3.3: Genetic Algorithm Search Flowchart

## 4. TESTS AND RESULTS

### 4.1 General Settlements and Explanation

The Ionosphere channel output is generated by using a computer simulation program in matlab environment. The receiver array is 2x2 planar array which is placed on the xy-plane. There are three different sensor types are used. These are crossed-loop, vertical dipole, tripole antennas. The Ionosphere conditions are set as good and poor Ionosphere. The open circuit antenna outputs are processed by using MS-DOA and the developed search routine. The simulations are carried out for each case by 50 trials. The time required for getting the result for one trial is 120 seconds by mean. The error figures are both given in root mean square and normalized standard deviation forms.

The real data is collected from a circular receiver array. The source point of the real data is in Uppsala, Sweeden. The receiver array is in Kiruna, Sweeden. The open circuit antenna outputs are processed after normalizing each. Some cases investigated for real data case[8]

### 4.2 Optimization Of The Genetic Algorithm Parameters

The developed genetic algorithm search routine has some parameters which should be set to optimum values. The parameters are population size, crossover and mutation probability, elite population percentage and the termination criteria. First of all by keeping all parameters constant; the response of the search routine to the population size variation is investigated. The large population helps the convergence but also it causes extra computational load. On the other hand small population sizes have very little computational load but they might have some convergence problems. The results of them are given at the appendix.



## HF band simulations

### 4.3 SCENARIO A

In this scenario there is one signal impinging on the receiver array. The good and poor ionosphere conditions are investigated separately and the root mean square and normalized standard deviations of the errors are calculated according to various SNR values.

#### Good Ionosphere Condition

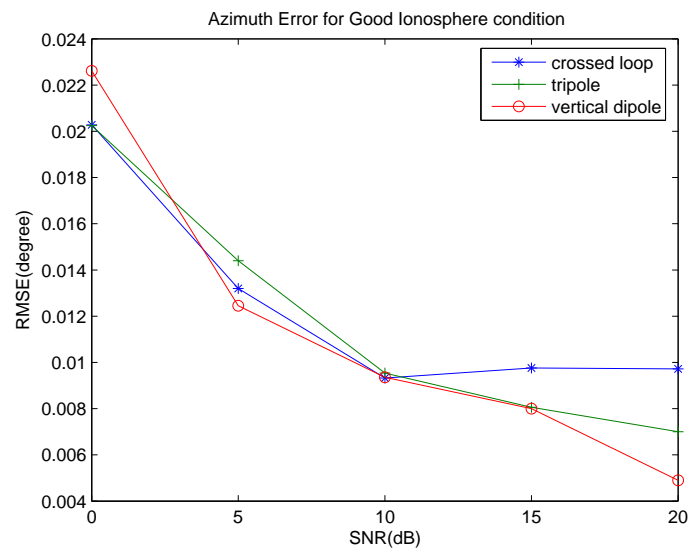


Figure 4.4: RMSE error of  $\phi$  for one signal

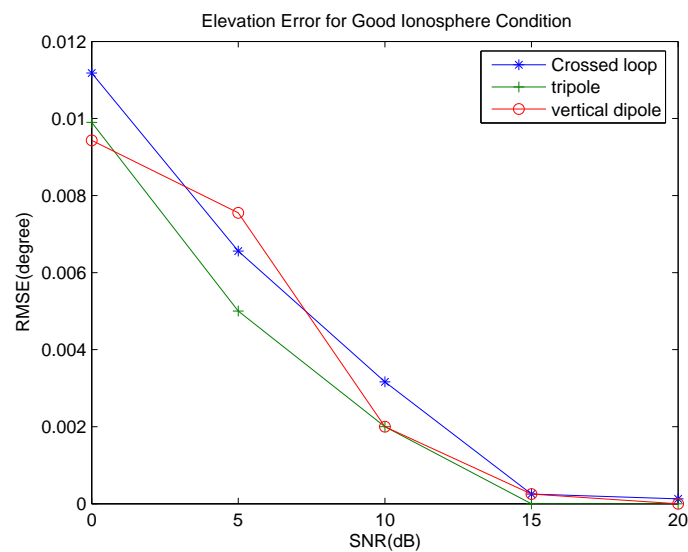


Figure 4.5: RMSE error of  $\phi$  for one signal

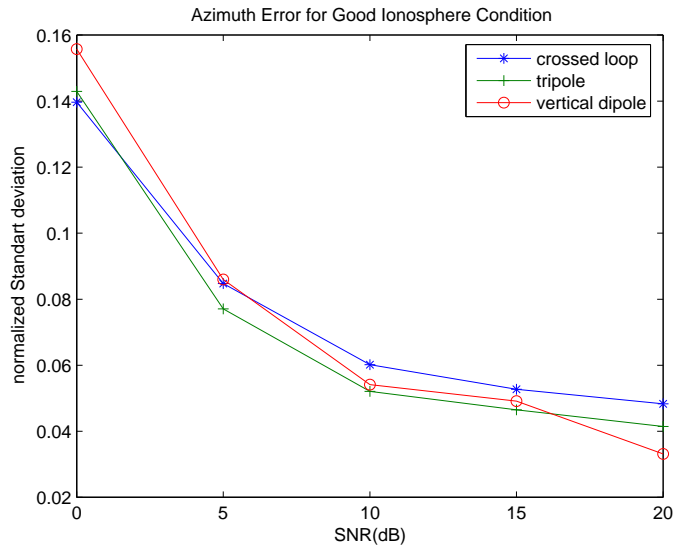


Figure 4.6: Normalized Standard Deviation of  $\phi$  error for one signal

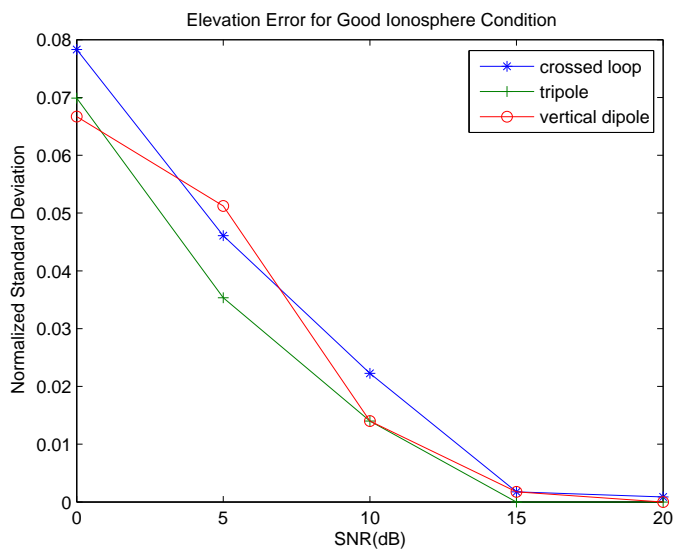


Figure 4.7: Normalized Standard Deviation of  $\theta$  error for one signal

## Poor Ionosphere Condition

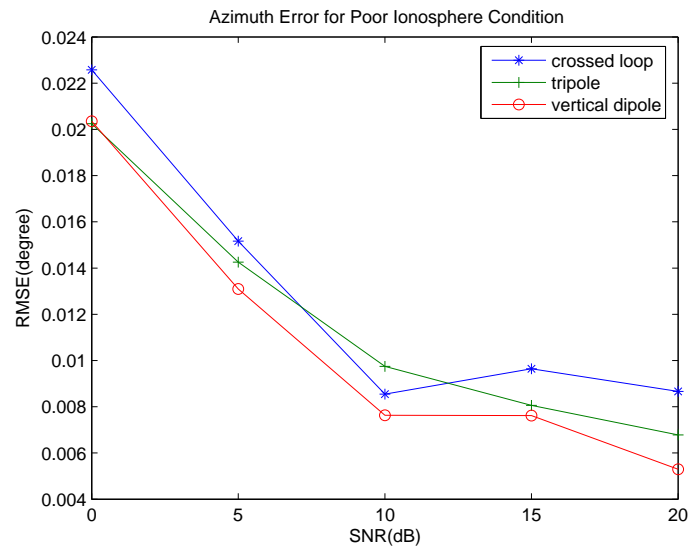


Figure 4.8: RMSE error of  $\phi$  for one signal

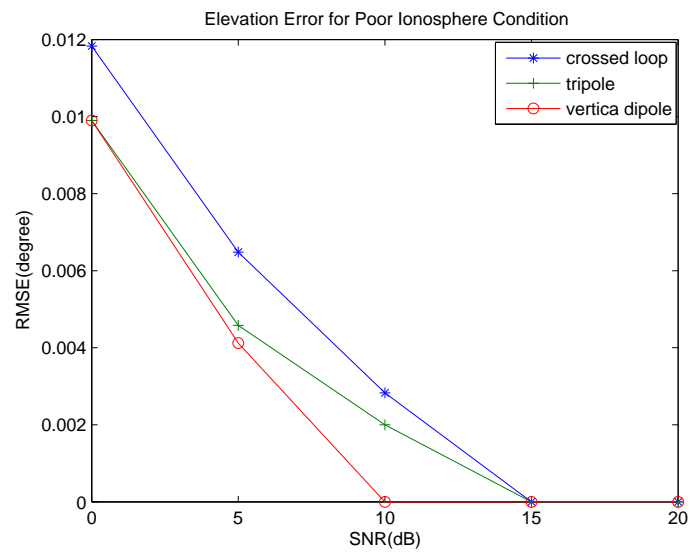


Figure 4.9: RMSE error of  $\theta$  for one signal

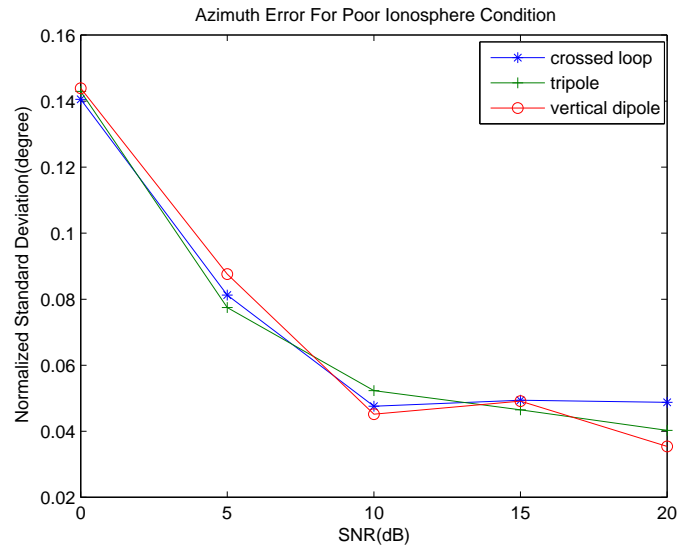


Figure 4.10: Normalized Standard Deviation of  $\phi$  error for one signal

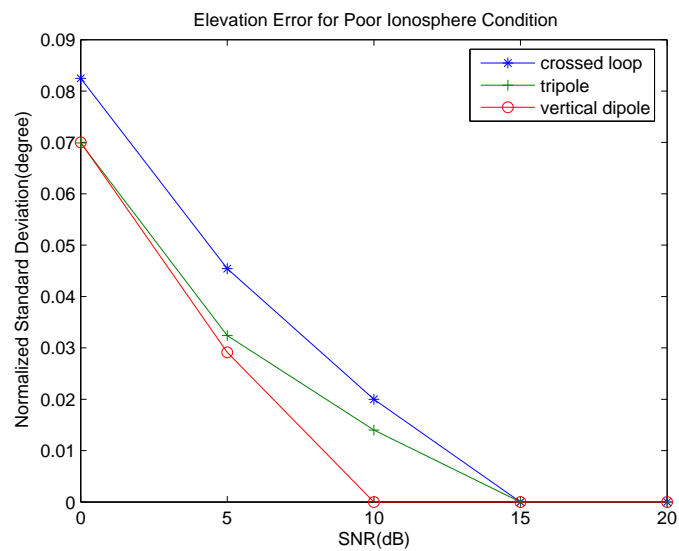


Figure 4.11: Normalized Standard Deviation of  $\theta$  error for one signal

## SCENARIO B

In this scenario there is two signals impinging on the receiver array. They have much distance with each other. The good and poor ionosphere conditions are investigated separately and the root mean square and normalized standard deviations of the errors are calculated according to various SNR values.

### Good Ionosphere Condition

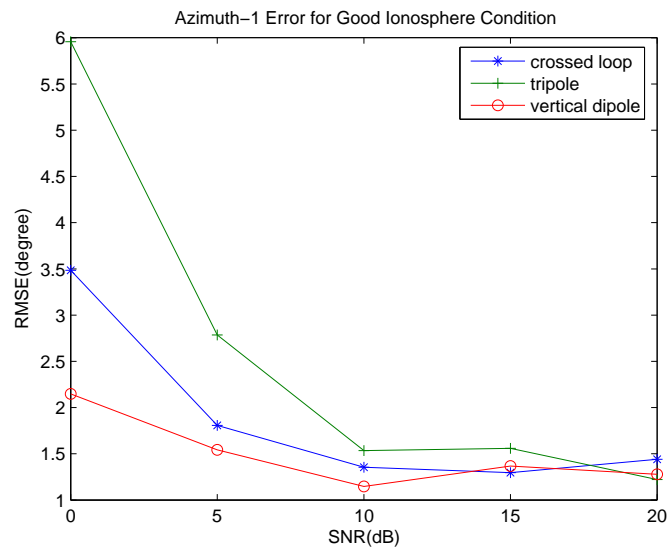


Figure 4.12: RMSE error of  $\phi_1$  for two signals

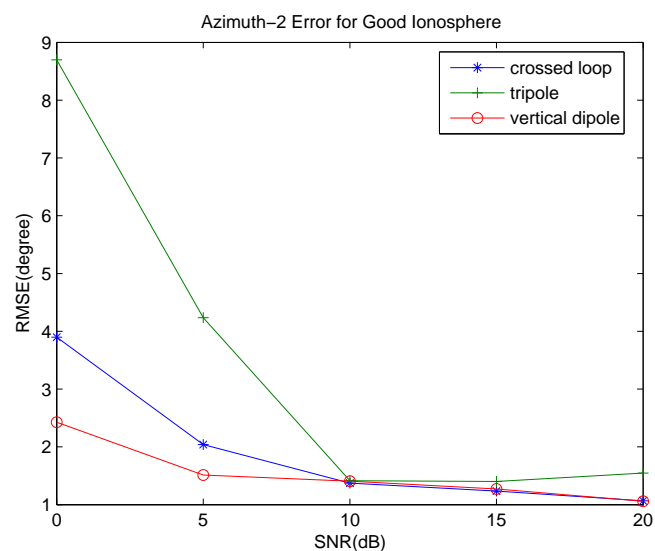


Figure 4.13: RMSE error of  $\phi_2$  for two signals

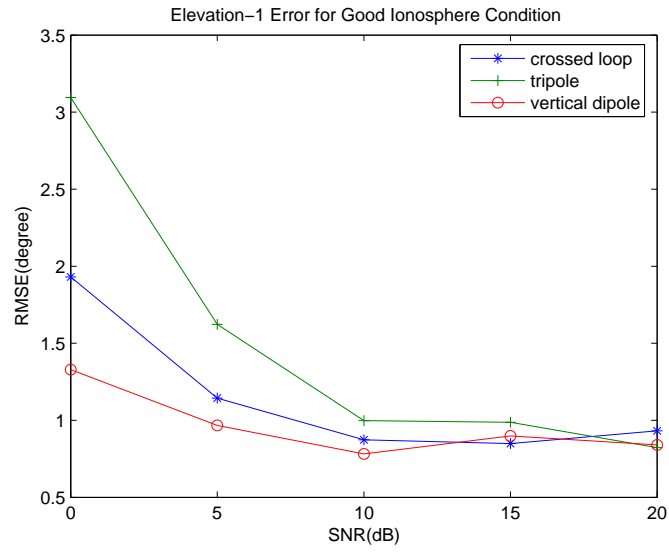


Figure 4.14: RMSE error of  $\theta_1$  for two signals

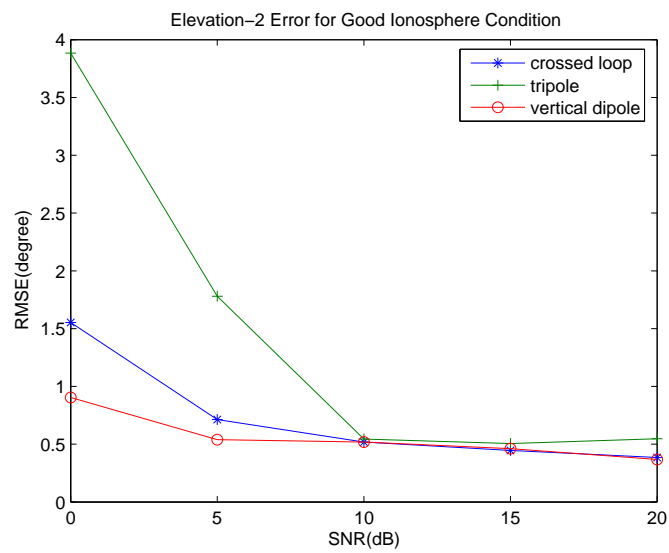


Figure 4.15: RMSE error of  $\theta_2$  for two signals

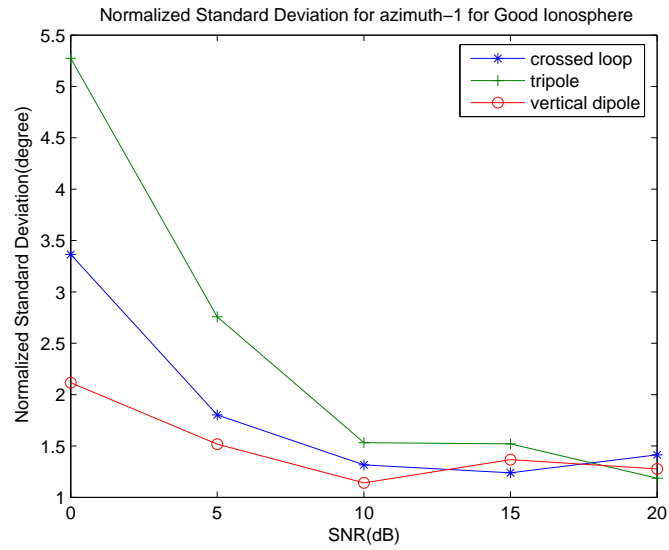


Figure 4.16: Normalized Standard Deviation of  $\phi_1$  for two signals

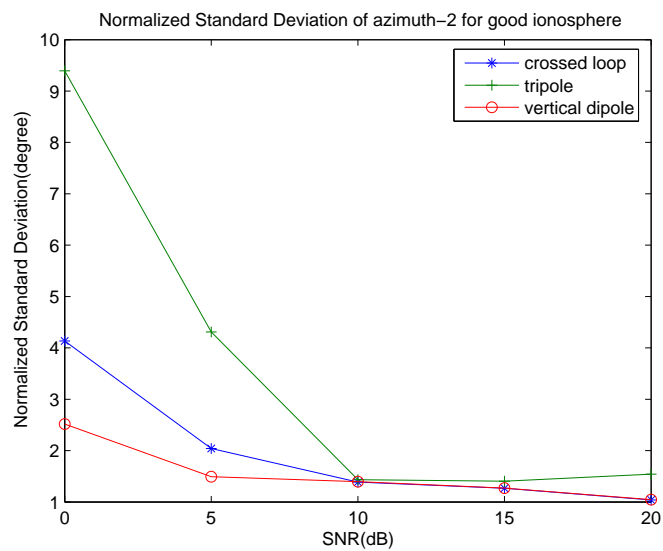


Figure 4.17: Normalized Standard Deviation of  $\phi_2$  for two signals

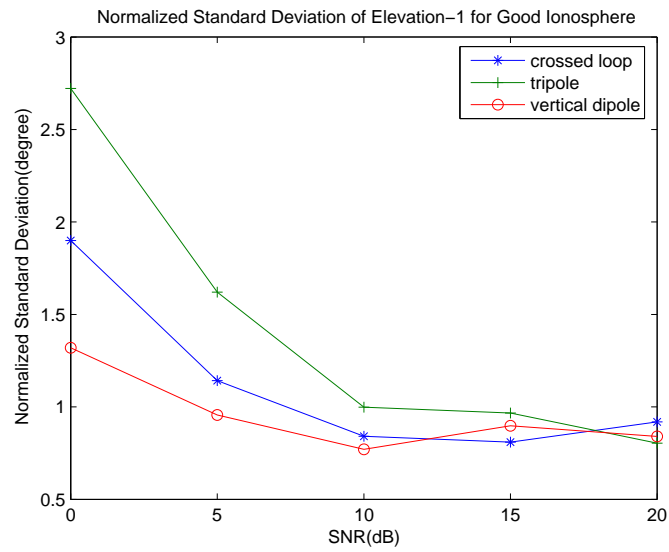


Figure 4.18: Normalized Standard Deviation of  $\theta_1$  for two signals

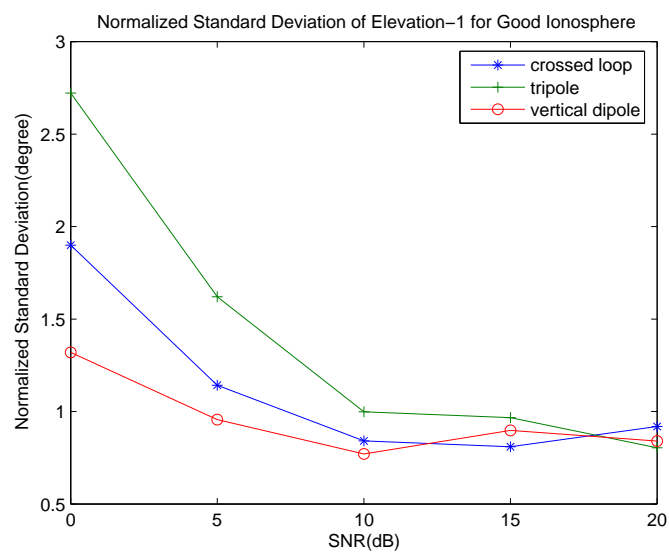


Figure 4.19: Normalized Standard Deviation of  $\theta_2$  for two signals



## POOR Ionosphere Condition

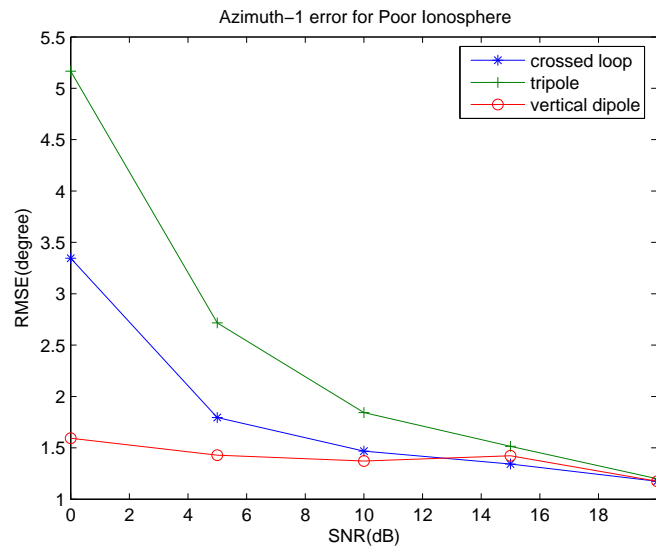


Figure 4.20: RMSE error of  $\phi_1$  for two signals

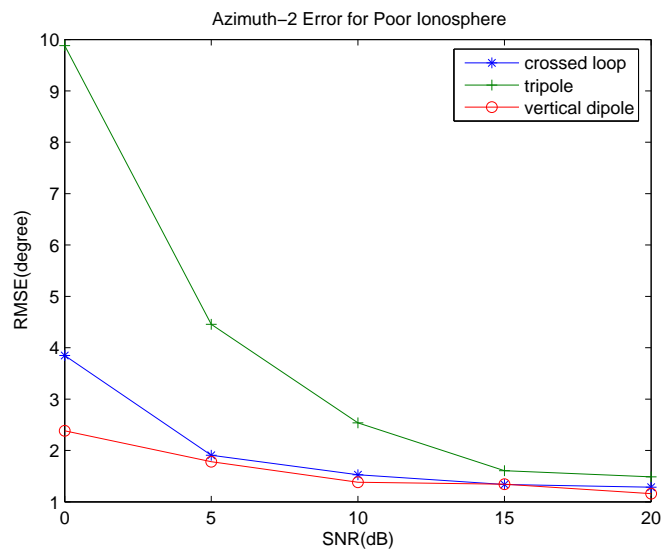


Figure 4.21: RMSE error of  $\phi_2$  for two signals

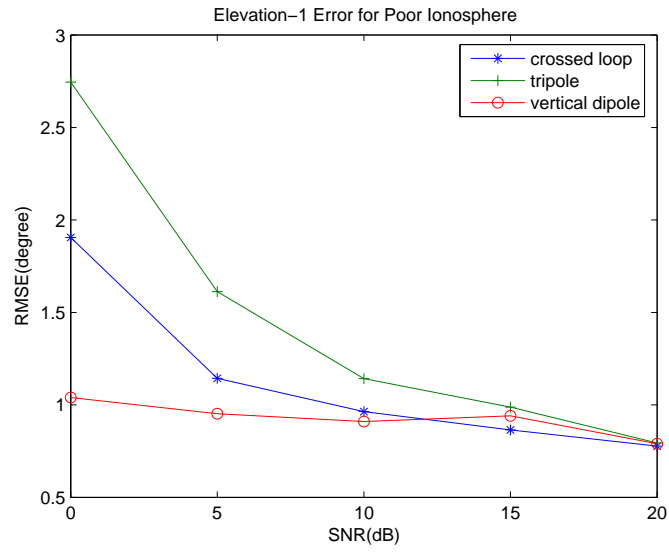


Figure 4.22: RMSE error of  $\theta - 1$  for two signals

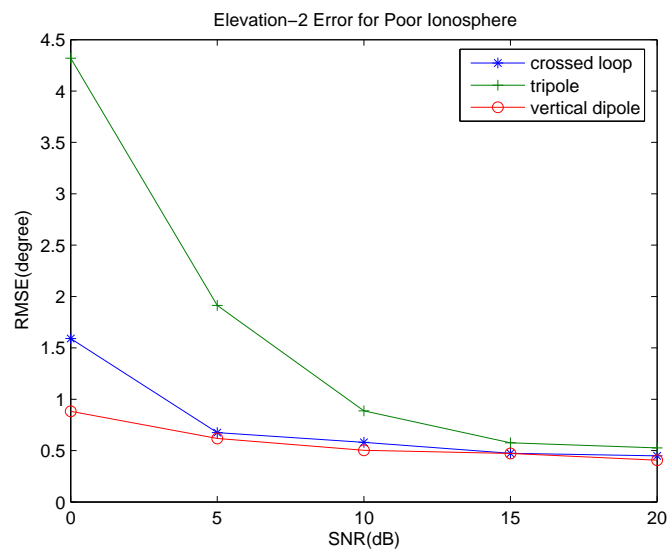


Figure 4.23: RMSE error of  $\theta_2$  for two signals

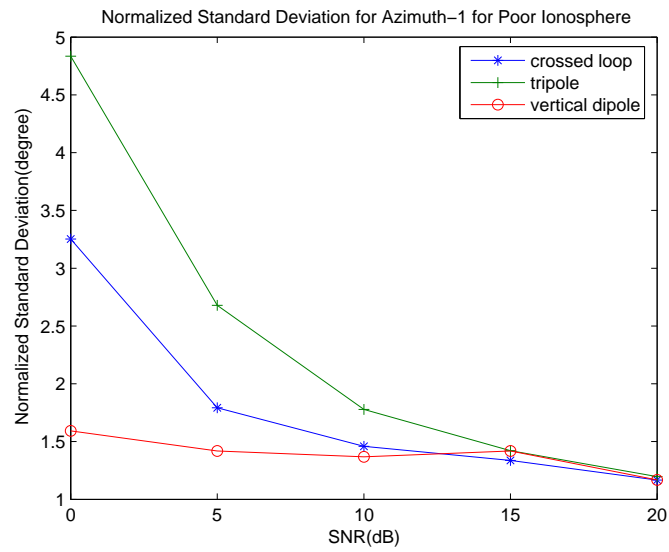


Figure 4.24: Normalized Standard Deviation of  $\phi_1$  for two signals

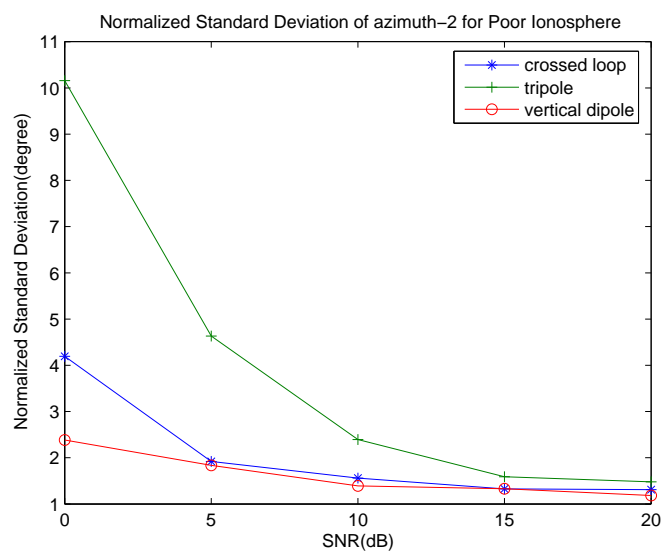


Figure 4.25: Normalized Standard Deviation of  $\phi_2$  for two signals

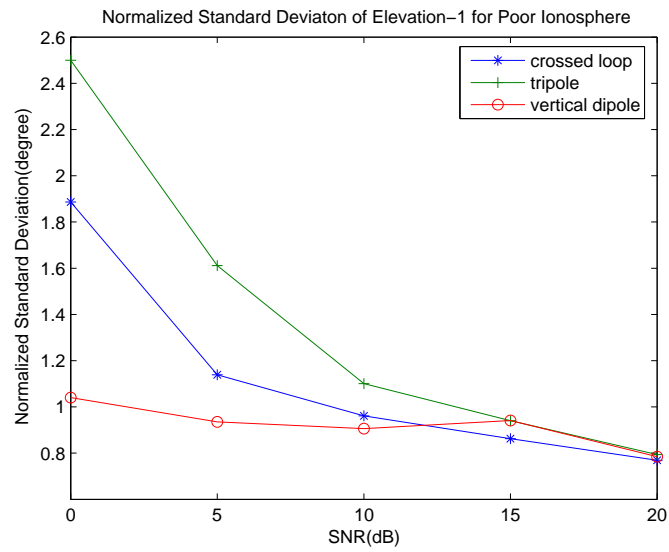


Figure 4.26: Normalized Standard Deviation of  $\theta_1$  for two signals

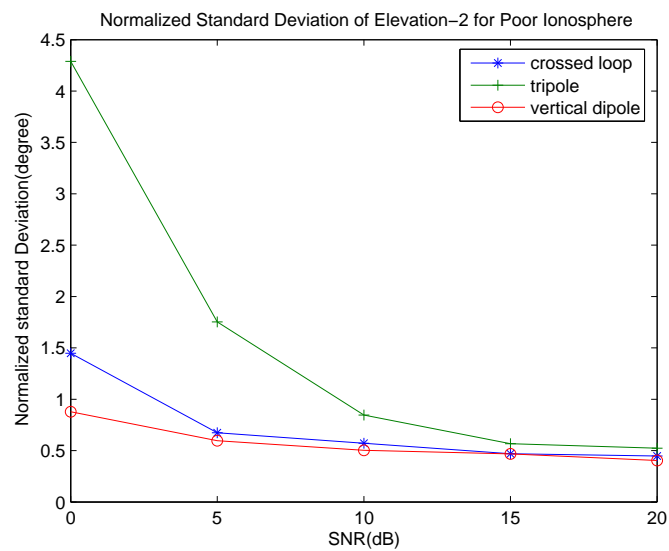


Figure 4.27: Normalized Standard Deviation of  $\theta_2$  for two signals

## SCENARIO C

In this scenario there are two close signals impinging on the receiver array. The good and poor ionosphere conditions are investigated separately and the root mean square and normalized standard deviations of the errors are calculated according to various SNR values.

### Good Ionosphere Condition

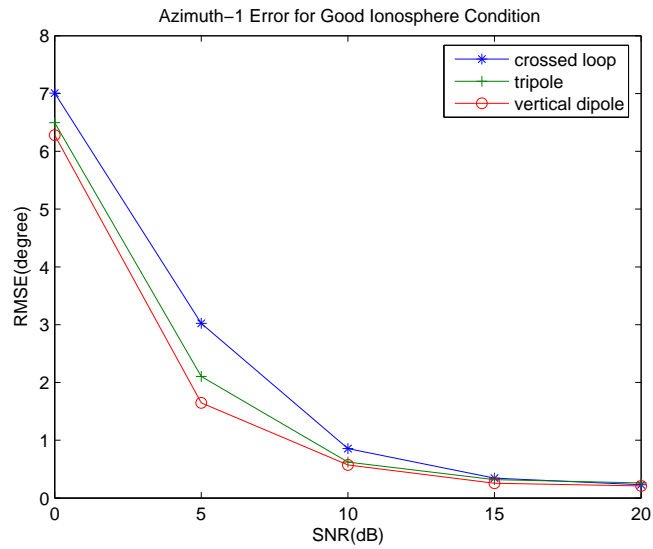


Figure 4.28: RMSE error of  $\phi_1$  for two close signals

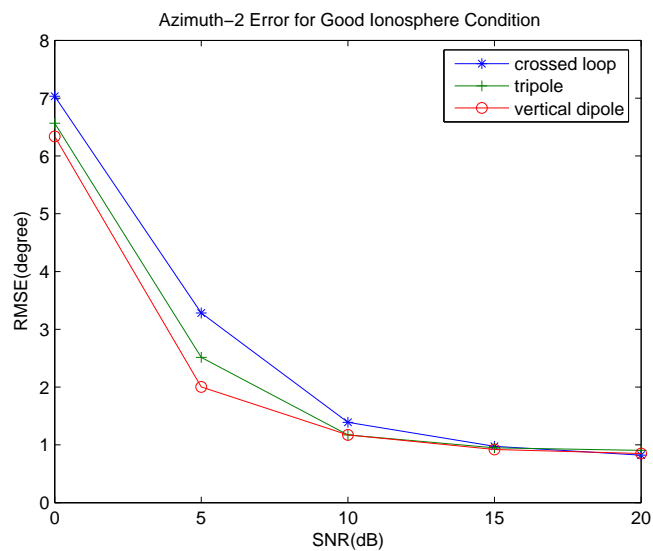


Figure 4.29: RMSE error of  $\phi_2$  for two close signals

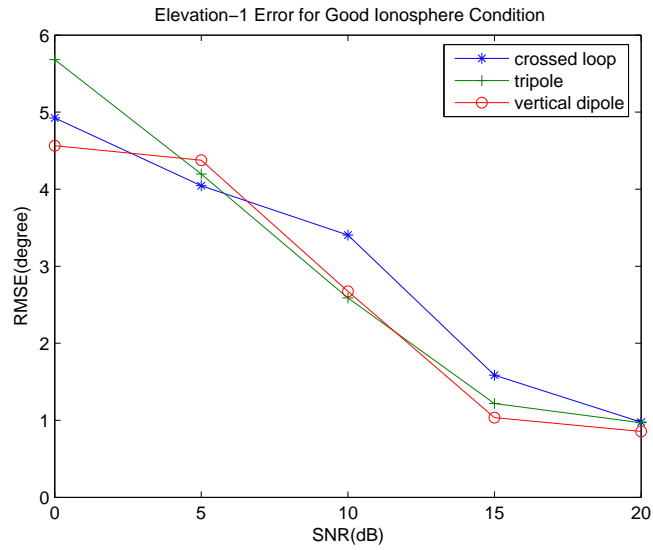


Figure 4.30: RMSE error of  $\theta_1$  for two close signals

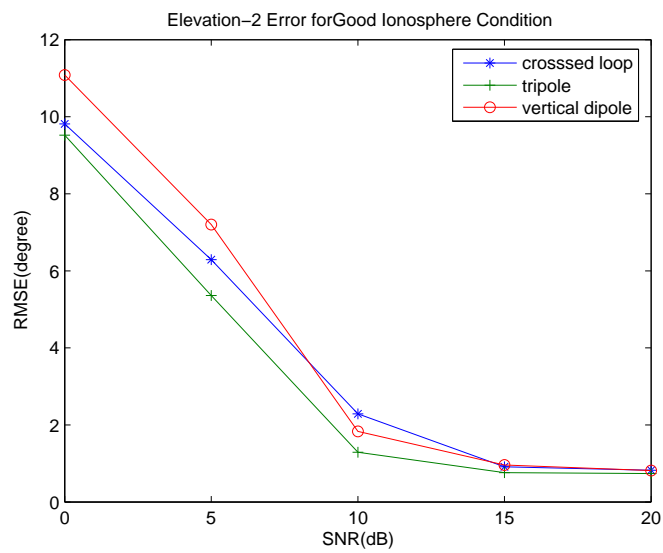


Figure 4.31: RMSE error of  $\theta_2$  for two close signals

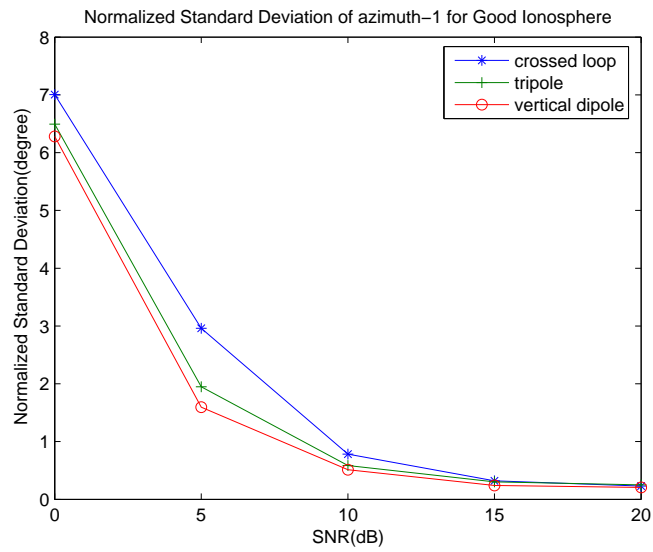


Figure 4.32: Normalized Standard Deviation of  $\phi_1$  for two close signals

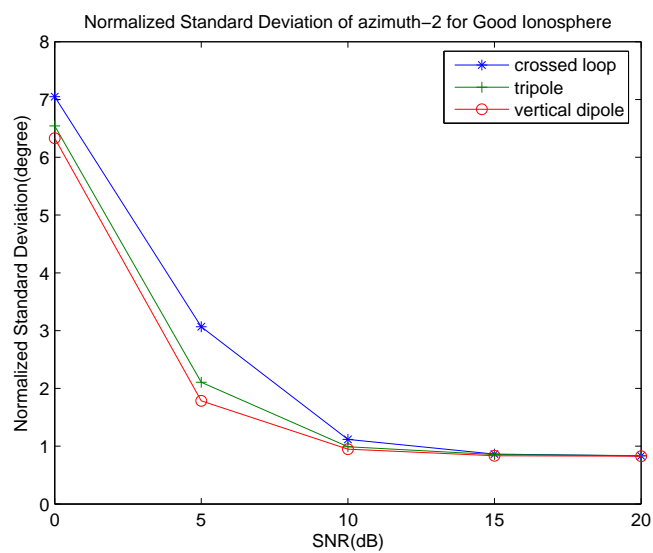


Figure 4.33: Normalized Standard Deviation of  $\phi_2$  for two close signals

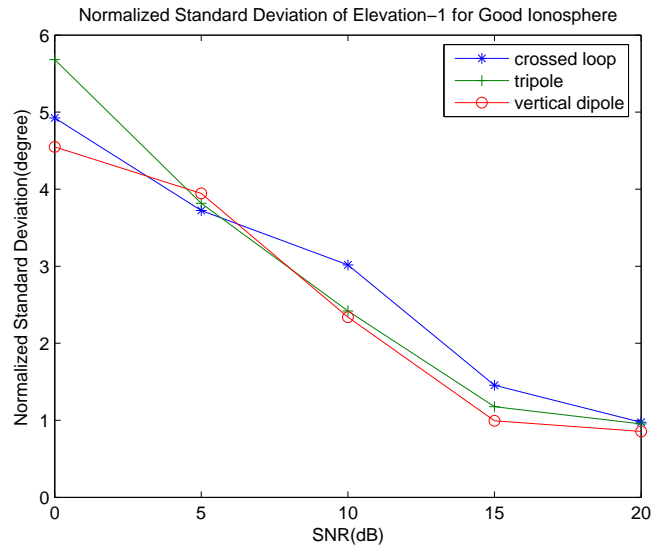


Figure 4.34: Normalized Standard Deviation of  $\theta_1$  for two close signals

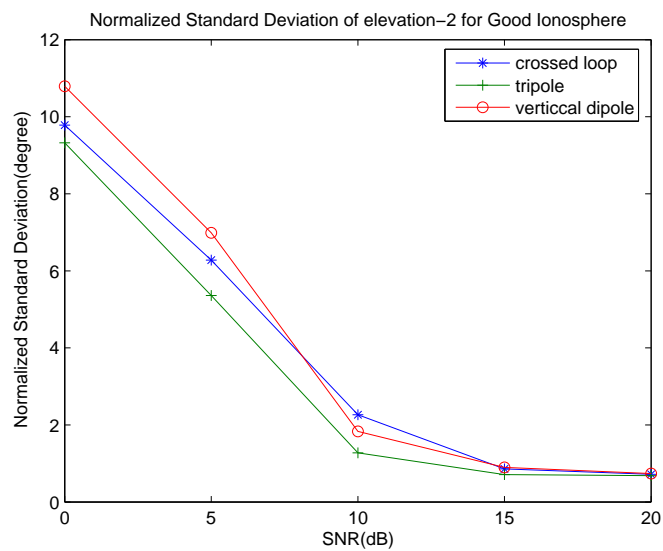


Figure 4.35: Normalized Standard Deviation of  $\theta_2$  for two close signals



## POOR Ionosphere Condition

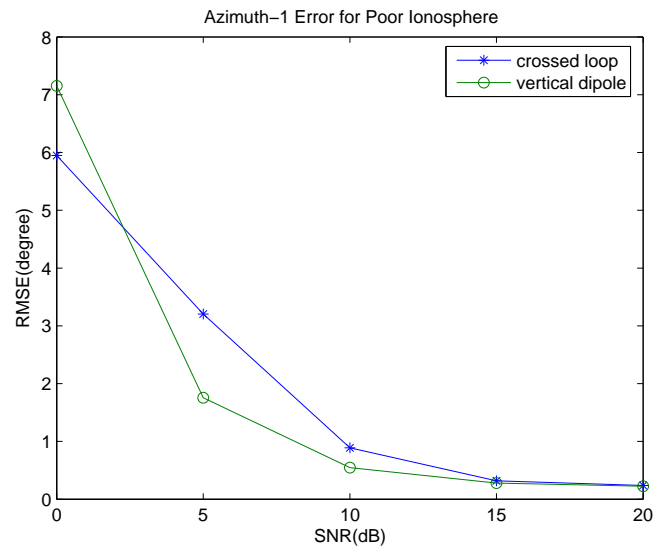


Figure 4.36: RMSE error of  $\phi_1$  for two close signals

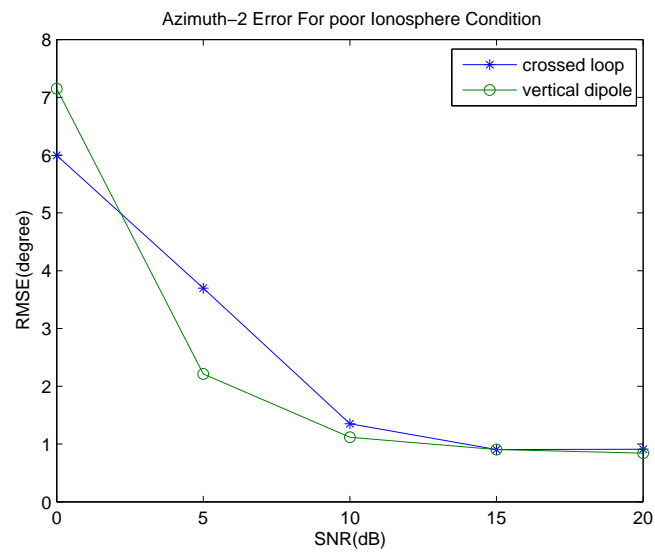


Figure 4.37: RMSE error of  $\phi_2$  for two close signals

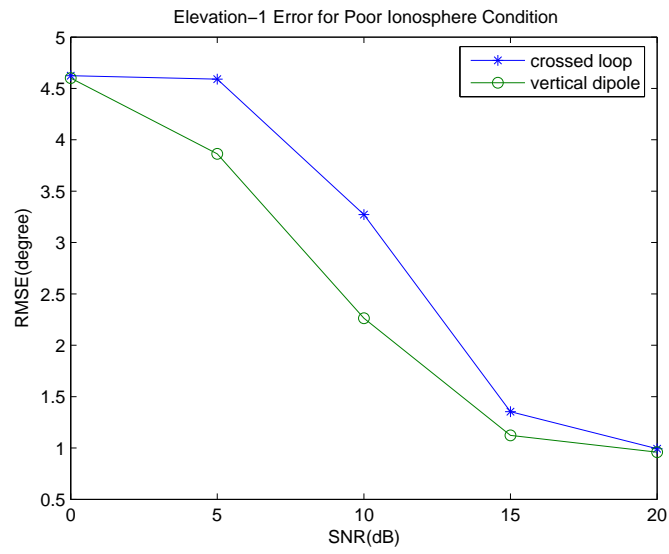


Figure 4.38: RMSE error of  $\theta_1$  for two close signals

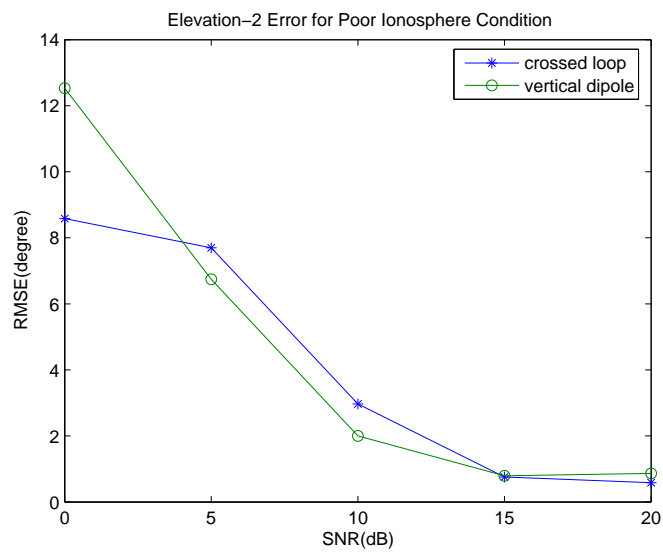


Figure 4.39: RMSE error of  $\theta_2$  for two close signals

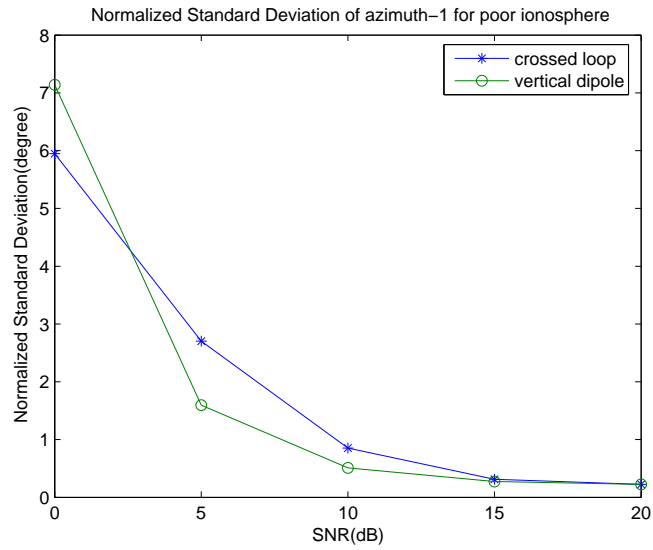


Figure 4.40: Normalized Standard Deviation of  $\phi_1$  for two close signals

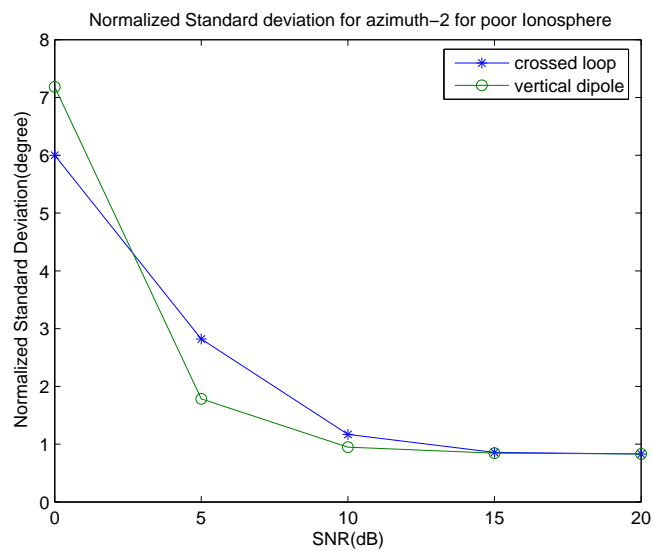


Figure 4.41: Normalized Standard Deviation of  $\phi_2$  for two close signals

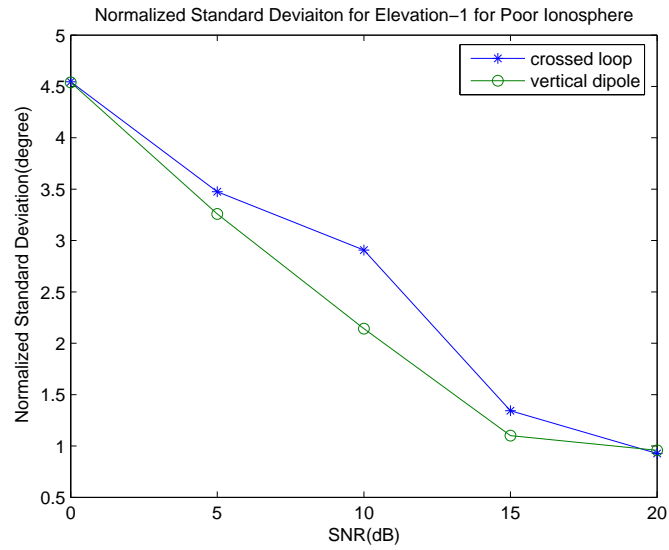


Figure 4.42: Normalized Standard Deviation of  $\theta_1$  for two close signals

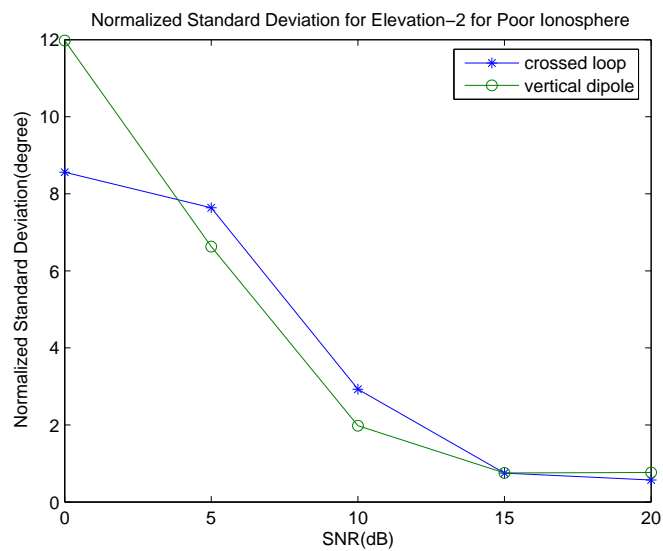


Figure 4.43: Normalized Standard Deviation of  $\theta_2$  for two close signals

## Real Data Tests

The signals processed in the simulations were radiated by a **Doppler and Multipath SOunding Network (DAMSON)** transmitter which is the result of a collaboration between the UK Defence Evaluation and Research Agency, the Canadian Communications Research Center, the Norwegian Defence Research Establishment and the Swedish Defence Research Establishment. This system characterizes the propagation path using a number of sounding signals which can be freely scheduled.

## The Changes on the Genetic Search Method and the Genetic Algorithm Parameters

In the real data considerations there was a need to update the genetic search method and its parameters. Some changes made in the selection and rankings and also the logical flow of the method. The initial population generation is same as the method used in the simulated scenarios. The major change in the search method is the fitness evaluation points. Before fitness evaluation is done just after the initial population generation. This is true for the first generation but for the other generations this scheme had some convergence problems. To guarantee the convergence of the search routine the fitness evaluation point is taken out of the generation loop and the fitness evaluation is done after the new offsprings are generated. This change provided for selection of both more powerful parents and offsprings. The selection is made according to the total of maximums of each signal path. On the other hand next generation the selection is made according to individual maximums. This logic helped the routine to get the global maximum as fast as possible for this problem. The updated new search routine is given at the appendix.

The updated new routine is again tested by the simulations and after by the real data. The parameters of the genetic search routine is set as the population size is consists of 50 individual solution sets. The mutation probability is set as 0.1. Elit parents percentage is set as 0.1. The EMS mating scheme is used for generating the mating pairs and the sets are sorted in descending order according to their whole and individual fitness values for eliminating the weaker solution sets.

## Simulation Tests

There are three conditions are tested. First there are two close signals both elevation and azimuth. Second two signals with same azimuth angle and the last case two signals with same elevation angles.

## Test Case 1

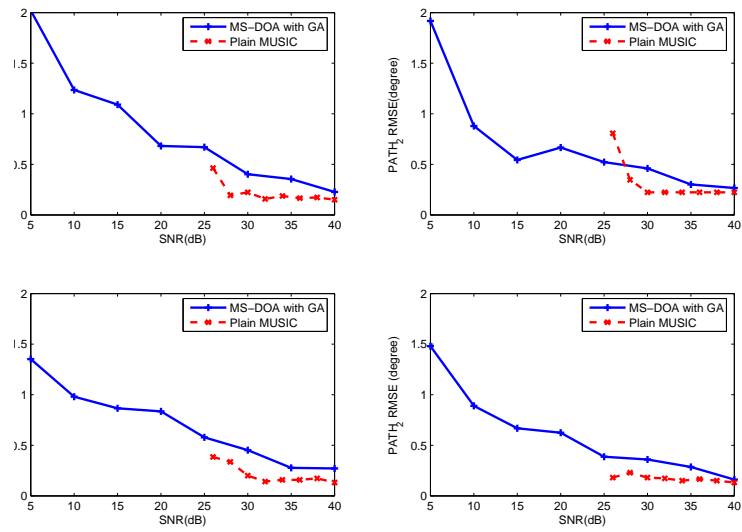


Figure 4.44: RMSE of combined error for good and poor ionosphere conditions

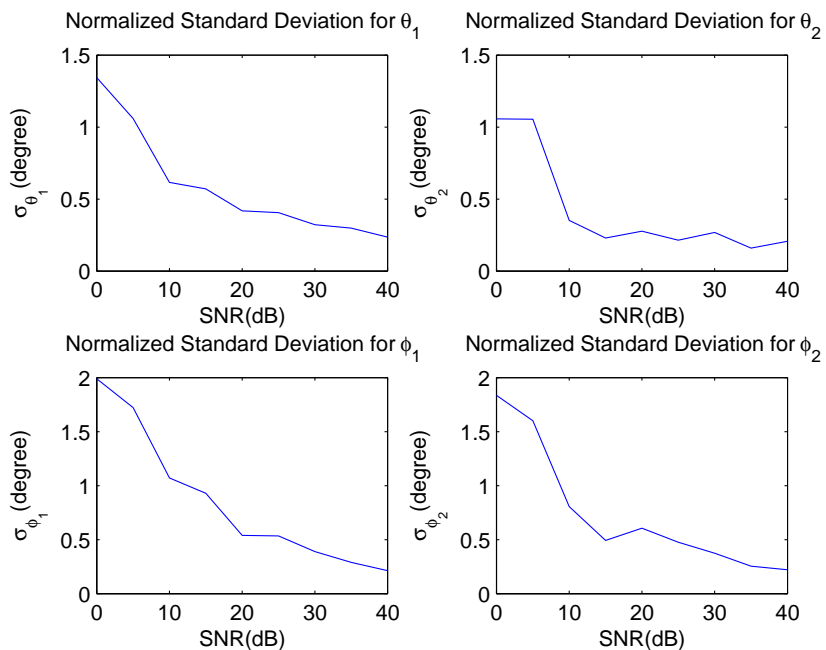


Figure 4.45: Normalized Standard deviation of error for good ionosphere conditions

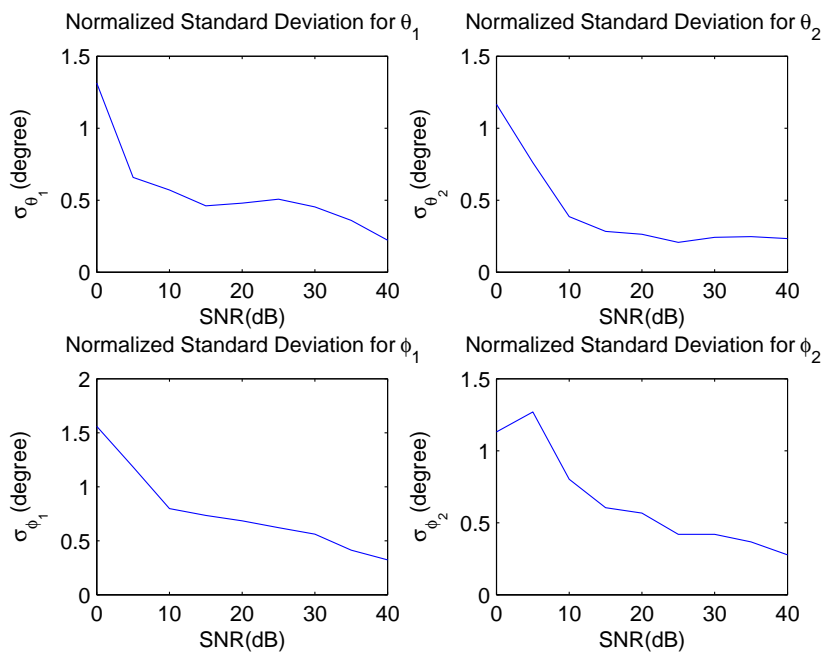


Figure 4.46: Normalized Standard deviation of error for poor ionosphere conditions

## Test Case 2

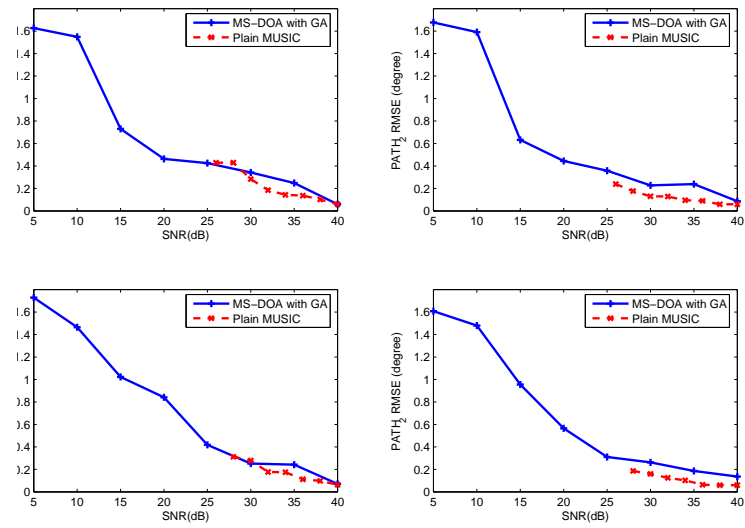


Figure 4.47: RMSE of combined error for good and poor ionosphere conditions



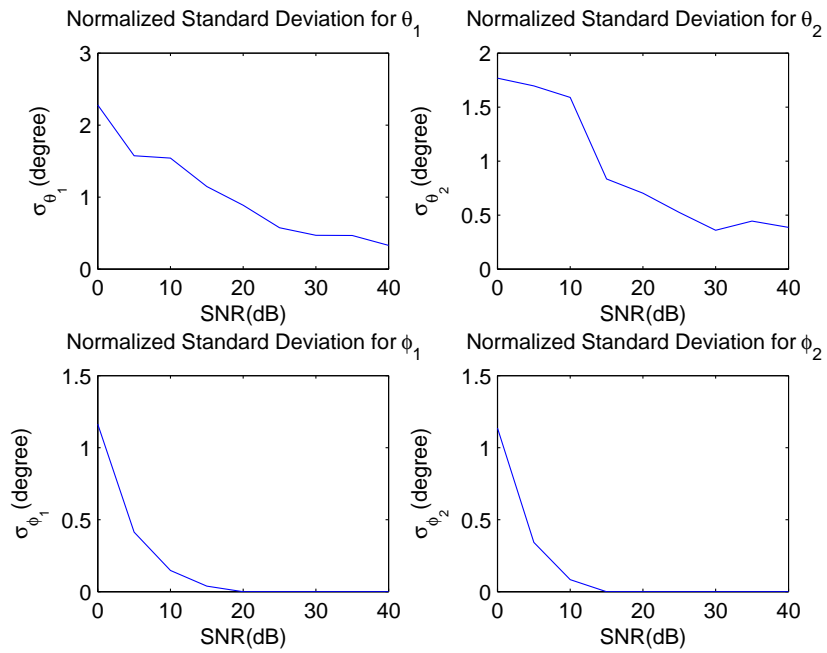


Figure 4.48: Normalized Standard deviation of error for good ionosphere conditions

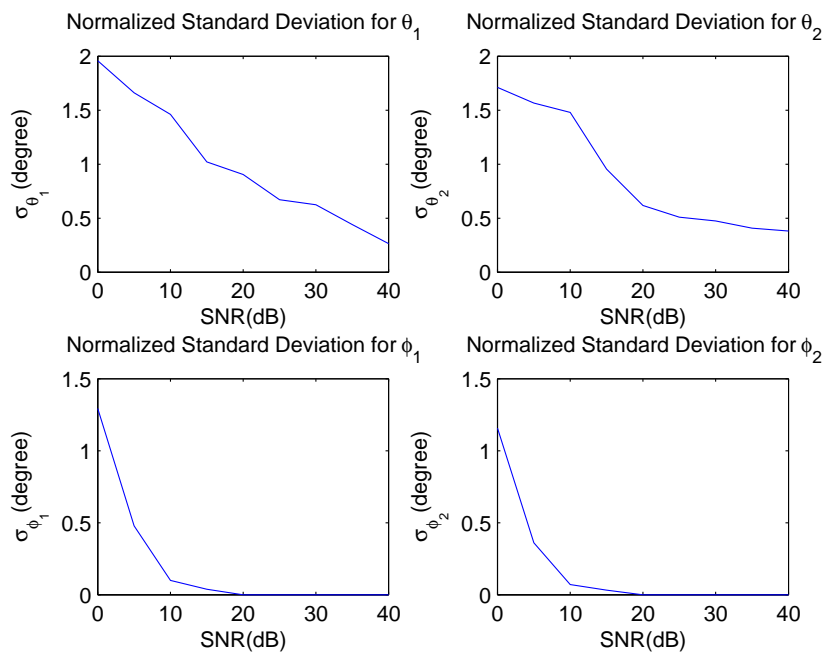


Figure 4.49: Normalized Standard deviation of error for poor ionosphere conditions

## Test Case 3

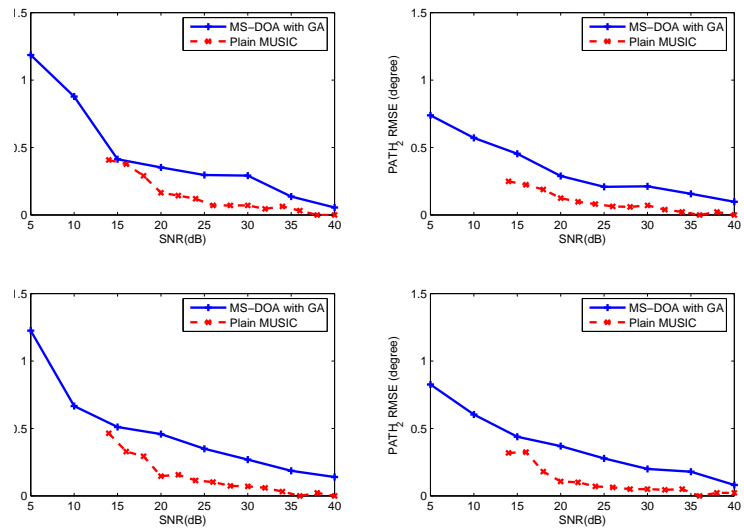


Figure 4.50: RMSE of combined error for good and poor ionosphere conditions

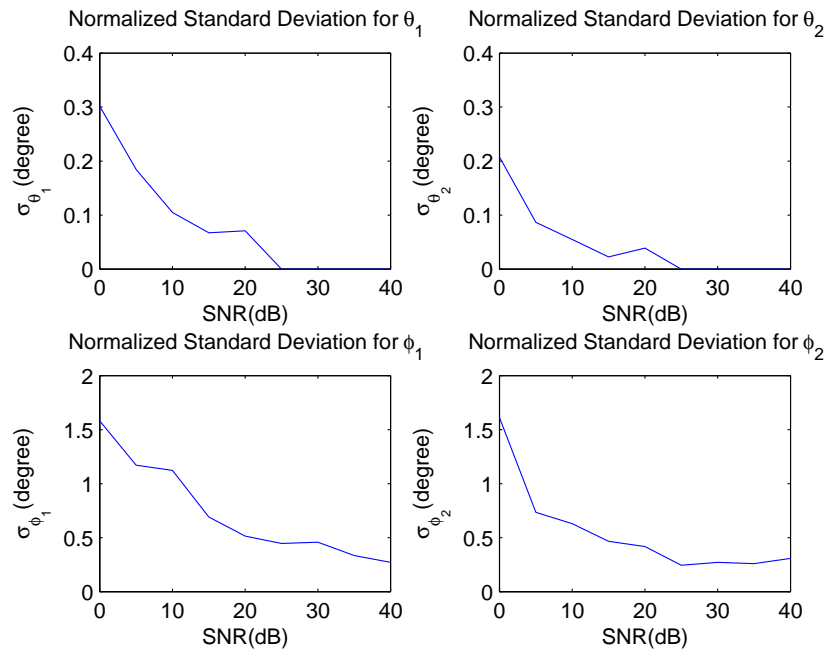


Figure 4.51: Normalized Standard deviation of error for good ionosphere conditions

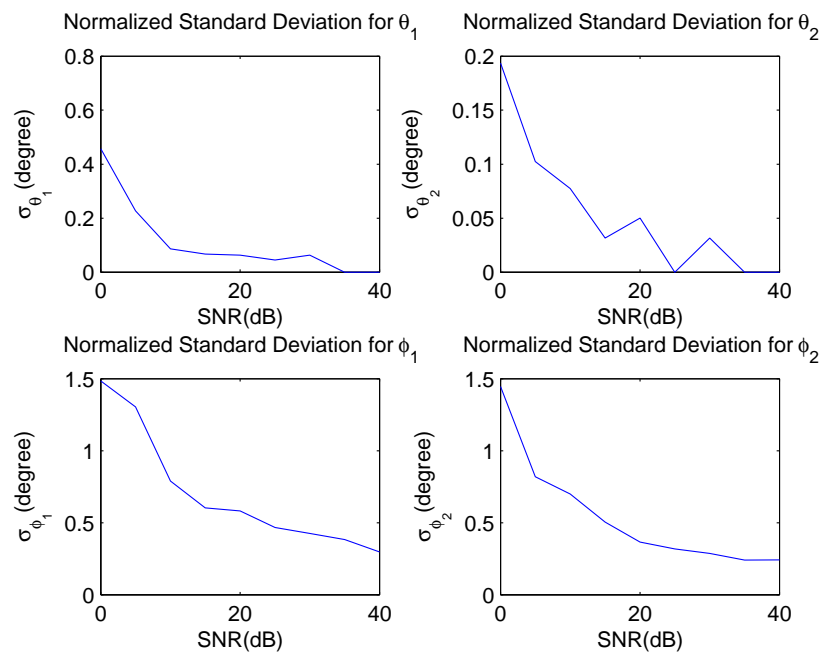


Figure 4.52: Normalized Standard deviation of error for poor ionosphere conditions

### Real Data Test Results

The real data is radiated in two frequencies 4.636 MHz and 6.953 MHz. The data is collected for every 3 minutes. Found angles are given in the figure below and the tabular data is given at the appendix. MUSIC can resolve only one path while MS-DOA can resolve two paths with high accuracy. The search times are also quite short when the genetic search routine is used. MS-DOA with genetic search method can give solutions about 20 seconds meanwhile the brute force search method takes about 15 minutes.

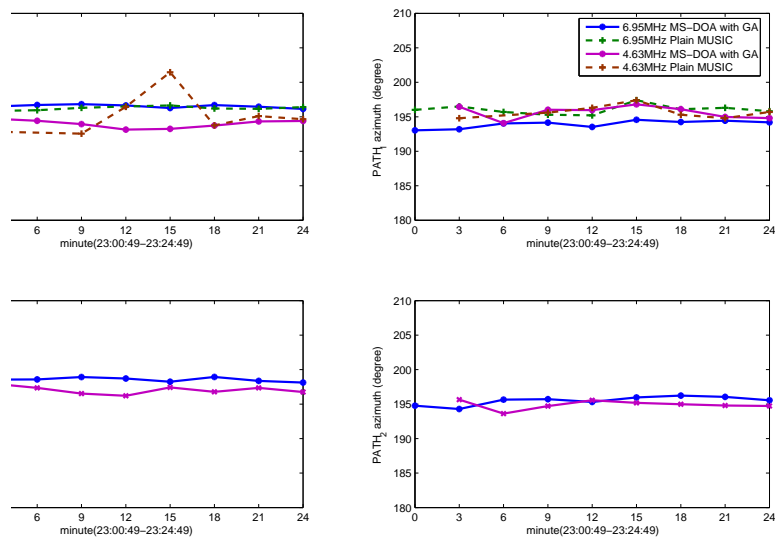


Figure 4.53: Results for real data

## 5. CONCLUSION

Direction Of Arrival (**DOA**) is a very attractive application area in array signal processing. There are several direction finding algorithms in literature. In this project Mode Separation Direction Of Arrival angle estimation(**MS – DOA**) algorithm is investigated. It uses a sensor array and uses the time delay of each array element when a signal impinging on the array. The baseband output of each sensor is sampled with nyquist rate. These sampled data is converted into linear system of equations. Then the measurement matrix is separated into two subspaces according to the number information of incoming signals by singular value decomposition. The signal subspace have the information of signals but can not represent all components of noise in terms subspace coefficients. By the result of this situation the solution can not be estimated directly. The least squares approximation is used for finding the optimum solution. The principle of orthogonality of the least squares algorithm states that when the error gets minimum the projection of coefficients of subspace onto the range space of array manifold gets maximum. As a searching algorithm the brute force is used although it gives the solutions with very high accuracy. It is very slow according to the other search routines. Because of this reason genetic algorithm based new search routine is proposed. The new search routine the time required for getting the solutions are decreased rapidly. Especially when the signal number increases the algorithm could give acceptable solutions again. Genetic search method introduces some error due to stochastic search but the search times gets quite low. In this project the MS-DOA algorithm is improved by adding genetic search method. By making this improvement direction finding capability of MS-DOA is improved by reduced search times. The algorithm resolves the angle of arrivals better than Plain MUSIC and gives more accurate solutions.

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