World Applied Sciences Journal 27 (12): 1695-1705, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.27.12.188

Performance Analysis of Spectral Estimation for Smart Antenna System

Umar Mujahid, Jameel Ahmed, Abdur Rehman, Umair Shahid, Abbass and Mudassir

Department of Electrical Engineering, HITEC University, Taxila Cantt., Pakistan

Abstract: Smart antenna is among the fastest emerging technologies employed in wireless communication. An antenna array and a Digital Signal Processor using an Adaptive Algorithm, make a smart antenna which can precisely locate user position in diverse environments. In this paper spectral estimation algorithms have been analyzed such as Bartlett, Capon, Linear Prediction etc. A systematic overview and comparison of the performance parameters of each spectral estimation algorithms through simulations has also been shown in this paper. Results reveal that the MUSIC AOA Estimate has the finest results in terms of resolution but it requires complex mathematical calculations and its not cost effective.

Key words: Smart Antenna Systems (SAS) . Angle of Arrival (AOA) . spectral estimation . array signal processing . spatial spectrum (pseudo-spectrum) . beam forming . multipath fading

INTRODUCTION

In recent years, a substantial ever-changing demand in broadband wireless networks and cellular systems has been observed. Because of them, a steady growth in the number of users, their ubiquitous demands and capacity-intensive data applications has questioned both manufacturers and operators to provide sufficient capacity in the networks. The deployment of smart antenna systems for wireless communications has emerged as one of the leading technologies for achieving high efficiency networks that maximize capacity and improve quality and coverage [2]. Smart Antennas are not smart by themselves; it is the adaptive algorithms that make SAS intelligent [2]. Smart Antennas have two main features to attain maximum spectral efficiency:

- Direction of Arrival (DOA) estimation
- Beam forming

In propagation environment there exist certain negative factors that contribute to limit capacity and degrade system performance. The radiations exhibit the properties of co-channel interferences, angular spread, delay spread, reflection, refraction, diffraction and multipath fading. As a result, many multiple components may arrive at the receiver following different paths. It is important for the receiving antenna to correctly estimate the Angle of Arrival that locates the exact position of user. Unlike omnidirectional antennas, Smart antenna is capable of extracting useful information not only from desired signal but also from multipath signal effect and suppresses SNOI with higher fidelity.

This paper will be presented in this way; Section II concentrates on signal array processing and its modelling. Section III gives a description on several DOA algorithms and their power spectrum expressions as well. Section IV discusses the comparative summary of these algorithms with their limitations too. Section V provides the simulation and results of the different algorithms being implemented along with conclusion. Graphical results are compared with other methods. Section VI focuses on the future work and perturbations and effects of errors in the array models used for DOA.

BASIC PRINCIPLES

Array Signal Processing is capable of manipulating signals, forming nulls and steering beams in the desired look direction. Prior to implement DOA algorithms we have to perform some assumptions and formulation to carry out simulations and deduction of results.

Modelling of array antennas: For high Antenna gain and to meet requirements for long haul communication, Smart Antenna works on multiple antenna elements having spatial electrical and geometrical arrangement called an "array". The following Fig. 1 depicts the D signals impinging from D phases (θ_1, θ_2... θ_D) on the receiver antennas having M elements and varying potential weights associated with each array elements. Then, the received array signal is given by [1-3, 5];

Corresponding Author: Umar Mujahid, Department of Electrical Engineering, HITEC University, Taxila Cantt., Pakistan

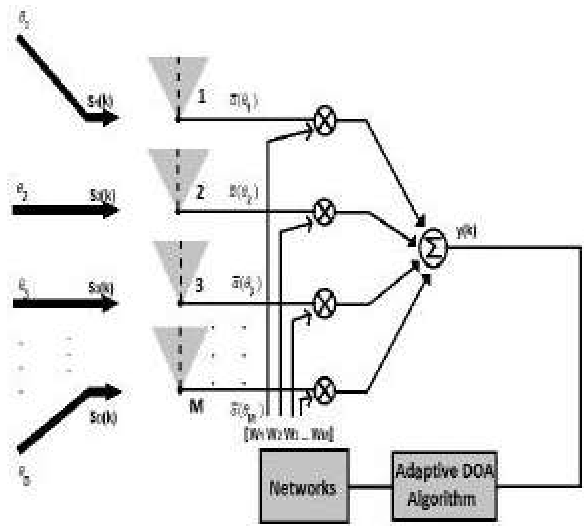

Fig. 1: M-array elements smart antenna system

$$\bar{x}(k) = A\bar{s}(k) + \bar{n}(k)$$

where A=[a(θ_1),a(θ_2)... a(θ_D)] known as steering vector or array response vector representing the set of phase delays the incident sources experiences, caused by each antenna array elements.

$$a(\theta) = [1\ e^{jkd\sin(\theta+d)} \ldots e^{j(M-1)(kd\sin(\theta+d))}]^T$$

$\bar{s}(k) = [\ \bar{s}_1(k)\ \bar{s}_2(k) \ldots \bar{s}_D(k)]^T$ be the vector of incident complex monochromatic signals at time k.
$\bar{n}(k)$ = noise vector consider zero mean spatially white Gaussian noise.

If the complex weights associated with each antenna elements is;

$$\bar{w} = [\bar{w}_1\ \bar{w}_2 \ldots \bar{w}_M]^T$$

We can define Array factor(AF) in the form of steering vector as the total output response to be;

$$AF = y(t) = \bar{w}^T . \bar{x}(k)$$

Spatial covariance matrix: All the methods implemented consider that D<M. Each weight associated with array elements have their own magnitude and phase respectively. As, the arrays are capable of performing D signals spatial filtering based on their AOA and the steering vector differs the direction of radiation by changing the corresponding weights [1, 2, 5, 9]. Assuming the signals are non-coherent. The M×M array correlation matrix can be defined as follows:

$$\bar{R}_{xx} = E[\bar{x} . \bar{x}^H]$$

$$\bar{R}_{xx} = A\,\bar{R}_{xx}\,A^H + \bar{R}_{nn}$$

where,
$\bar{R}_{ss}$ = D×D source correlation matrix.
$\bar{R}_{nn} = s^2_n\,\bar{I}$ = M×M noise correlation matrix.
$\bar{I}$ = N×N identity matrix.

Thus providing information about the array correlation matrix and steered array [5, 8].

DOA ESTIMATION METHODS

DOA estimation is important for locating the user's position in the right direction so that useful information can be extracted using adaptive algorithms at the receiver end. The DOA estimate uses spatial spectrum denoted by P(θ) also known as pseudo-spectrum provides an indication of AOA of mobile user by computing peak value of the spatial spectrum.DOA Algorithms, compared in this paper are grouped as;

1) Spectral estimation based
   a) Bartlett AOA estimate
   b) Capon Minimum Variance Method
   c) Linear prediction Method
   d) Maximum Entropy Method
2) Sup-space or Eigen structure based
   e) Pisarenko Harmonic Decomposition Method
   f) Min-Norm AOA estimation
   g) MUSIC AOA estimation
   h) Root-MUSIC (Extension of MUSIC)
   i) ESPRIT AOA estimate

Spectral estimation based: A critical assumption of the most DOA estimate algorithms is that the number of incident signals should be strictly less than the number of antenna elements. This requirement can be relaxed if the properties of incident signals are exploited [1, 3, 6].

Bartlett AOA estimate: It is non-parametric approach for finding AOA [6], also known as conventional beam former method or Fourier method. If an array is uniformly distributed (ULA) then we can define power spectrum as;

$$P_{BART}(\theta) = a(\theta)\,\bar{R}_{xx}\,a^H(\theta)$$

Bartlett AOA steers its beam by using all directions (θ) of interests including Signal of Interest plus Signals not of interest and compute the spatial spectrum in the direction of maximum array output. In Uniform linear arrays the electrical separation between the array elements is kdcos(θ) [2]. The pseudo-spectrum is equal to the spatial finite Fourier transform of all arriving sources [1].

Capon minimum variance method: Capon Minimum Variance Distortionless Response (MVDR) is also a non-parametric estimate for DOA's and known as Maximum likelihood method because it minimizes the MVDR i-e $\min_{\bar{w}} \{|y(k)|^2\} = \min_{\bar{w}} \bar{w} \bar{R}_{xx} \bar{w}^H$ by minimizing the average power of the output, hence minimizing SNOI while passing SOI undistorted. This technique maintains the gain $\bar{w}^H a(\theta)$ to be unity in the desired direction θ of signals [2, 5, 6, 12].

All the signals are un-interrelated; the pseudo-spectrum can be expressed as;

$$P_{CAP}(\theta) = 1/ a(\theta) \bar{R}^{-1}_{xx} a^H(\theta)$$

Linear prediction AOA estimate: Linear prediction spectral estimation is also known as autoregressive method used to approximate the output of one array element with the outputs of linear combination of M array elements. It minimizes the mean-squared error between the m^{th} array element and the actual output so that optimized weights are selected [1, 7, 9]. These weights are dependent on $\bar{R}_{xx}$. The optimum weights can be expressed as;

$$\bar{w} = \bar{R}^{-1}_{xx} \bar{u}_m / \bar{u}^H_m \bar{R}^{-1}_{xx} \bar{u}_m$$

where, $\bar{u}_m$ is the Cartesian basis vector which is the m^{th} column of the M×M identity matrix. The pseudo-spectrum can be formulated as;

$$P_{LPM}(\theta) = \bar{u}^T_m \bar{R}^{-1}_{xx} \bar{u}_m / \bar{u}^T_m \bar{R}^{-1}_{xx} \bar{u}_m$$

The choice for m^{th} sensor output for prediction is ergodic.

Maximum entropy AOA estimate: In 1972, Burg attributed the Maximum entropy spectral estimation [1, 9]. Entropy is a measure of uncertainty in a system. This method finds a pseudo-spectrum that manipulates maximum entropy function to impose limitations on the values that different array parameters can take and information is applied by using constraint equation in the spatial estimation.
The pseudo-spectrum is expressed by;

$$P_{MEM\,j}(\theta) = 1 / a^H(\theta) \bar{c}_j \bar{c}^H_j a(\theta)$$

where, $\bar{c}_j$ is the j^{th} column of the inverse array correlation matrix $\bar{R}^{-1}_{xx}$.

Eigen structure biased methods: Eigen value decomposition methods for array correlation matrix are useful in evaluating better DOA algorithms. $\bar{R}_{xx}$ contain M eigenvalues($\lambda_1, \lambda_2 ... \lambda_M$) and M eigenvectors ($e_1, e_2 ... e_M$) associated with it. The received signal space is divided into two subspaces. If the subspace spanned by the columns of steering vector representing larger eigenvalues, then it is known as Signal subspace (composed of D arriving signals eigenvectors). If the sub-space spanned is orthogonal to the steering vector representing smaller eigenvalues, then it is called Noise-subspace (composed of M-D noise eigenvectors). Subspace based AOA estimates utilize the prior statistical knowledge of data and received signal vector subspace [1, 2, 7, 9].

Pisarenko harmonic decomposition method: It is also termed as subspace based AOA estimate and involve EVD of array correlation matrix. It minimizes mean squared error which is the error between the desired estimated output and the actual output. In this method smallest eigenvalue of the associated eigenvector is selected so as to minimize the error by fulfilling the constraint that norm of the weight vector to be unity [9].
The pseudo-spectrum can be given by;

$$P_{PHD}(\theta) = 1/ |a^H(\theta) \bar{e}_1|^2$$

Min-norm AOA estimate: Minimum-norm AOA estimate only deals with Uniform Linear Arrays. This method optimizes the weight vector so that is of minimum-norm and checks the orthogonality between the weight vector and signal subspace eigenvectors. The normalized power spectrum is provided as;

$$P_{MNM}(\theta) = 1/|a^H(\theta) \bar{E}_N \bar{E}^H_N \bar{u}_1|^2$$

where, $\bar{E}_N$ is a noise subspace of M-D eigenvectors and $\bar{u}_1$ is Cartesian basis vector and usually uses first column of identity matrix.

Music AOA estimate: MUSIC can be abbreviated as MUltiple SIgnal Classification. It is a high resolution signal parameter estimate and provides information about AOA, incident signals, cross correlation, noise power of the point sources [5]. Assuming noise to be un-correlated makes the noise correlation matrix, diagonal and if signals are somewhat correlated, makes signal correlation matrix, non-diagonal. Basically, MUSIC exploits the orthogonality of the noise subspace with the steering vectors of array correlation matrix at D phases [1, 3, 7, 11]. Array correlation matrix is interpreted as;

$$\bar{R}_{xx} = A \bar{R}_{xx} A^H + s^2_n \bar{I}$$

MUSIC DOA consists of following steps.

- Estimate input signal arrival and compute estimated input covariance matrix.
- Compute Eigen structure of $\bar{R}_{xx}$ (Eigenvectors and Eigenvalues).
- Choose smallest eigenvalues so that variance is equal to D eigenvalues.
- Calculate spectral peaks of P_{MUSIC}

The pseudo-spectrum can be evaluated by;

$$P_{MUSIC}(\theta)= 1/|\, a^{H}(\theta)\, \bar{E}_N\, \bar{E}^{H}_N\, a(\theta)|$$

We can estimate correlation matrices by the definition of time averaging of correlated matrices. In this technique we collect K samples from the received signal vector.

$$\bar{R}_{xx} = A\,\bar{R}_{ss}\,A^{H} + A\,\bar{R}_{sn} + \bar{R}_{ns}\,A^{H} + \bar{R}_{nn}$$

As

$$R_{ss} = \frac{1}{K}\sum_{k=1}^{K} \bar{s}(k)\bar{s}^{H}(k)$$

$$R_{ns} = \frac{1}{K}\sum_{k=1}^{K} \bar{n}(k)\bar{s}^{H}(k)$$

$$R_{sn} = \frac{1}{K}\sum_{k=1}^{K} \bar{s}(k)\bar{n}^{H}(k)$$

$$R_{nn} = \frac{1}{K}\sum_{k=1}^{K} \bar{n}(k)\bar{n}^{H}(k)$$

Root-MUSIC AOA estimate: Root-Music is another extension of MUSIC AOA algorithm but applicable only to ULA. This method is known as Root-MUSIC because DOA can be pointed by finding roots of a polynomial. It solves a polynomial rooting problem in contrast to the identification and localization of spectral peaks using Spectral MUSIC [1, 5, 9, 11].

$$P_{MUSIC}(\theta)= 1/|\, a^{H}(\theta)\, \bar{E}_N\, \bar{E}^{H}_N\, a(\theta)|$$

$$\text{But if } \bar{C} = \bar{E}_N\, \bar{E}^{H}_N$$

$$P_{Root}(\theta)=1 / |a^{H}(\theta)\, \bar{C}\; a(\theta)|$$

Where, $\bar{C}$ is the Hermitian M x M Matrix

Esprit AOA estimate: ESPRIT, an acronym of Estimation of Signal Parameters via Rotational Invariance Technique is a robust and computationally efficient in estimating DOA. It imply the rotational invariance in the signal subspace which considered the two arrays to be matched pairs if the translational displacement between the two elements be equal. ESPRIT assumes sources to be narrowband, have sufficient array, ergodicity in noise with zero-mean [5, 9, 10]. The complete received signal considering the contributions of both sub-arrays is given as;

$$\bar{x}(k) = \begin{bmatrix} \bar{x}_1(k) \\ \bar{x}_2(k) \end{bmatrix} = \begin{bmatrix} \bar{A}_1 \\ \bar{A}_1 . \Phi \end{bmatrix} . \bar{s}(k) + \begin{bmatrix} \bar{n}_1(k) \\ \bar{n}_2(k) \end{bmatrix}$$

$\bar{\Phi}$ = diag $[e^{jkd\sin\theta_1}\, e^{jkd\sin\theta_2} \ldots e^{jkd\sin\theta_D}]$ is a D x D diagonal unitary matrix with phases shifts between the doublets of each AOA. The procedure for the ESPRIT algorithm is followed as;

- Estimating the array correlation matrices from finite samples.
- Calculate the signal subspaces based upon the signal eigenvectors.
- Form a 2D x 2D matrix using the signal subspaces such that

$$\bar{C} = \begin{bmatrix} E_1^{H} \\ E_2^{H} \end{bmatrix} \begin{bmatrix} E_1 & E_2 \end{bmatrix} = \bar{E}\ \bar{\Lambda}\ \bar{E}^{H}_C$$

where $\bar{E}_C$ is the EVD of $\bar{C}$ such that $\lambda_1 = \lambda_2 \ldots = \lambda_{2D}$ and $\bar{\Lambda}$ = diag $\{\lambda_1, \lambda_2 \ldots \lambda_{2D}\}$.

- Partition E_C into D x D sub-matrices such that

$$E_C = \begin{bmatrix} E_{11} & E_{12} \\ E_{21} & E_{22} \end{bmatrix}$$

- Estimate the rotation operator as given by;

$$\bar{\psi} = - E_{12}\, E_{22}^{-1}$$

- Calculate the eigenvalues of $\bar{\psi}$, $\lambda_1, \lambda_2 \ldots \lambda_D$
- Estimate the angle of arrival such that;

$$\Theta_i = \sin^{-1}\left(\frac{\arg(\lambda i)}{hd}\right)$$

COMPARATIVE ANALYSIS

Comparative summary of each implemented AOA methods are discussed. There advantages and limitations are also verified.

Table 1: Comparative summary for smart antenna DOA algorithms

Sr. No	Spectral estimation methods	Advantages	Limitations
1.	Bartlett	Non-Parametric approach for beam forming and null-steering. Resolution can be improved by increasing the length of array elements. Scans for DOA in all phase directions to form spectral peaks.	Poor resolution. Only be suitable for a single source because it is unable to differentiate between two sources. Due to its omnidirectional scan for DOA of sources, array output may contain peaks for undesired signals as well. Heights of side lobes increases. Increasing M arrays will increase the storage capacity.
2.	Capon	Non-parametric approach. Best resolution than Bartlett. It can differentiate the pair of angles of sources efficiently. Scans for DOA in all directions but simultaneously null the SNOI.	Only works when sources are un-correlated with SNOI. Maintain the gain in the desired look direction to be constant. When length of arrays increases, inverse of correlation matrix, may cause computational complexity.
3.	Linear prediction	Known as autoregressive method. Linear prediction estimate is not only responsible for providing information about spectral peaks but also the relative signal strengths of signals. Suitable for low SNR environment. Better resolution than capon and Bartlett approximations.	Odd arrays length can better perform than even length arrays. Mean squared error can only be minimized when the selected array weight will be unity.
4.	Maximum Entropy	Selection of j^{th} column of the inverse correlation matrix can affect the resolution. Better estimate for lower SNR than Bartlett.	It imposes constraints on the values that different array parameters can take to minimize entropy.
5.	Pisarenko Harmonic Decomposition	Based on Eigen structure analysis, has the best resolution as compared to Capon, linear prediction and maximum-entropy methods. Spectral peaks are not an identification of the signals amplitude.	It imply small eigenvalues associated with eigenvectors to minimize the error. Norm of the weight vector must be unity.
6.	Min-Norm	Spectrum is almost same for PHD algorithm. It utilizes all noise eigenvectors as compared to PHD.	Calculating an array weight which should have minimum norm. Applicable for ULA's.
7.	Music AOA	Eigen Value Decomposition is implied in this. It is a high resolution AOA method. Provides unbiased parameter estimates and strength of signals. Sensitive to array phases and array gains.	Input covariance matrix becomes singular under highly correlated sources, computational complexity increases. Requires precise and accurate array calibration.
8.	Root-Music	Decreases computational complexity of MUSIC. Based on polynomial rooting and provides higher resolution at low SNR conditions.	Applicable for Uniform Linear Arrays.
9.	ESPIRIT	Improves the requirement for precise and accurate array calibration as compared to MUSIC. Computationally not intensive than MUSIC. Compute the DOA's directly. Vulnerable with different array geometries.	Imposes constraints on the structure of arrays to have a translational invariance. Sensitive to only array phases.

SIMULATION AND RESULTS

While simulating on MATLAB, assumptions are made and signal properties are exploited. We have assumed M = 4 and M = 6 array element having individual elements spaced at $\lambda/2$ with a pair of arrival angles at $\pm 10^0$. Simulation is based on two cases;

- With M=4, 6 array elements and zero-mean Gaussian Noise Variance s^2_n =0.1.
- With noise variance s^2_n=0.1, 0.5 and M=4 array elements.

Considering the above two cases the normalized spatial spectrums are plotted for each DOA algorithm

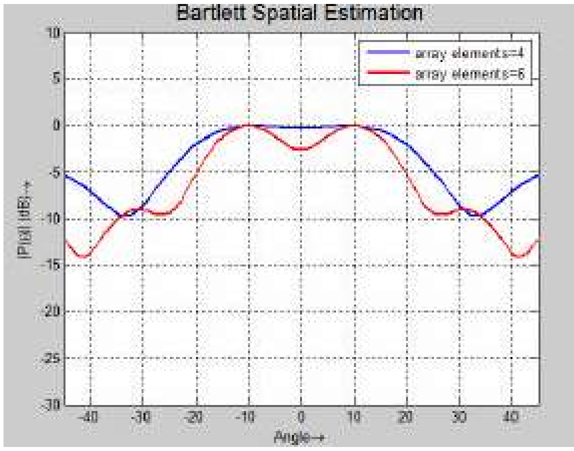

Fig. 2(a): Bartlett Spatial Estimation for array elements M=4 and M=6

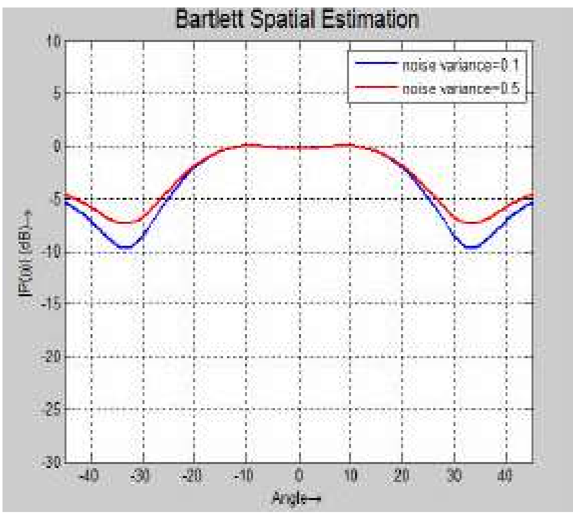

Fig. 2(b): Bartlett Spatial Estimation for noise variance s^2_{n}=0.1 and s^2_{n}=0.5

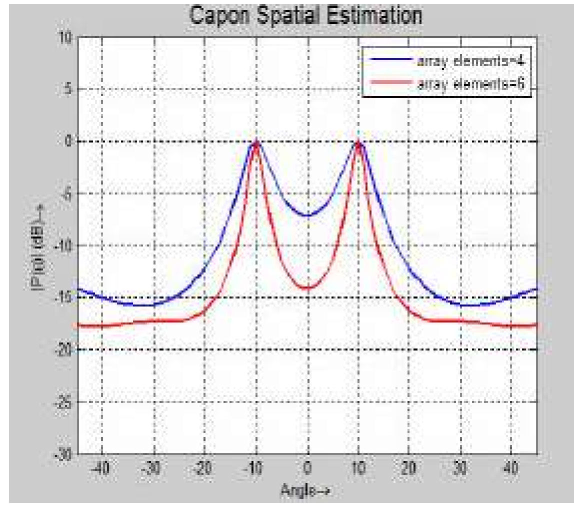

Fig. 3(a): Capon Spatial Estimation for array elements M=4 and M=6

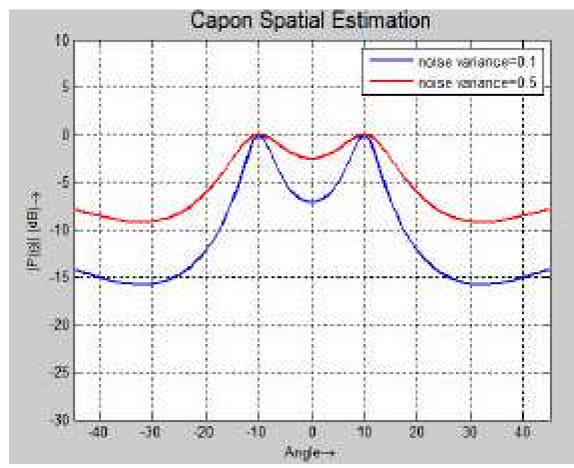

Fig. 3(b): Capon Spatial Estimation for noise variance s^2_{n}=0.1and s^2_{n}=0.5

expressing the indication for angle of arrival of D=2 signals based on spectral peaks and angle of arrival. Spectral Estimation based normalized spectrums are compared for Bartlett method, Capon Method, Linear Prediction Method, Maximum Entropy as well as Eigen Structure based methods i-e Min-Norm Method, Pisarenko Harmonic Decomposition Method, MUSIC Method, Root-MUSIC and ESPRIT methods.

The Fig. 2(a) depicts that Bartlett AOA estimate resolution increases if the length of array elements increases and Fig. 2(b) shows selecting minimum noise variance will have less height of side lobes. Figure 3(a) shows that Capon method is unbiased and with M=6 it shows better result. Figure 3(b) in case of minimum noise variance performance will be high. Figure 4(a) represents that Linear Prediction Method estimates odd arrays well because of precisely centred phase array. Figure 4(b) shows under s^2_n =0.1 it predicts the arrival signals well near $\pm10^0$ as compared to s^2_n =0.5. Figure 5(a) Maximum entropy estimate is immune to noise. Pisarenko Harmonic Decomposition method in Fig. 6(a) and 6(b) provides slightly higher resolution as compared to Min-norm method in both cases as shown in Fig. 7(a) and 7(b). Music Signal Classification Method gives unbiased estimates of the arrival sources as shown in Fig. 8(a). Whereas, in Fig. 8(b) the variation in noise variance will decrease the resolution. Figure 9(a) represents the Time averaging MUSIC AOA estimate. In this, instead of using M = 4 and 6 elements, increasing antenna aperture will work well for MUSIC. Figure 9(b) shows that varying noise variance will diminish the arrival resolution. Root-MUSIC AOA method in Fig. 10(a) it gives the AOA

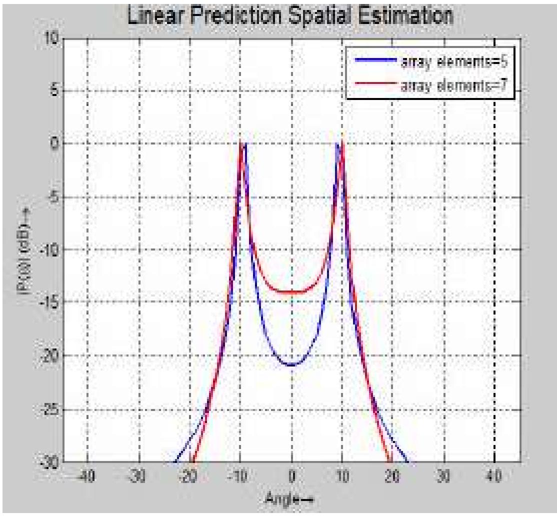

Fig. 4(a): Linear Prediction Spatial Estimation for array elements M=4 and M=6

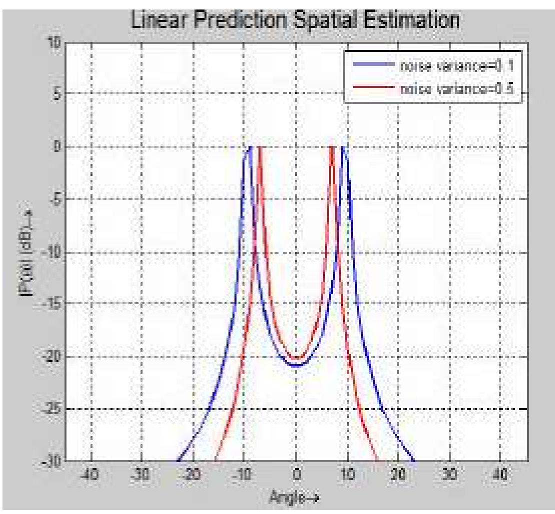

Fig. 4(b): Linear Prediction Spatial Estimation for noise variance s^2_{n}=0.1 and s^2_{n}=0.5

result by finding roots of the polynomial. With M=6 elements arrays as compared with M=4 elements, the expected AOA is very close enough to estimate; hence increasing resolution. Figure 10(b) and 10(c) illustrates that with M=6 array elements the AOA expected values are more accurate than M=4 array elements. Figure 10(d), (e) and (f) shows that with s^2_n = 0.5 the two roots are not lying on the unit circle, but can be expected to be on unit circle. Whereas with s^2_n = 0.1 these roots are providing better estimate of the angle of arrival. The ESPRIT Method in Fig. 11, it shows that by increasing the number of overlapping array elements will provide best resolution as compared with M=4 array elements. The comparison of above discussed DOA are shown below;

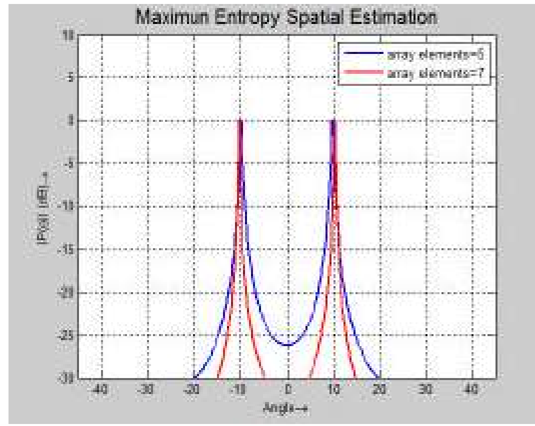

Fig. 5(a): Maximum Entropy Spatial Estimation for array elements M=4 and M=6

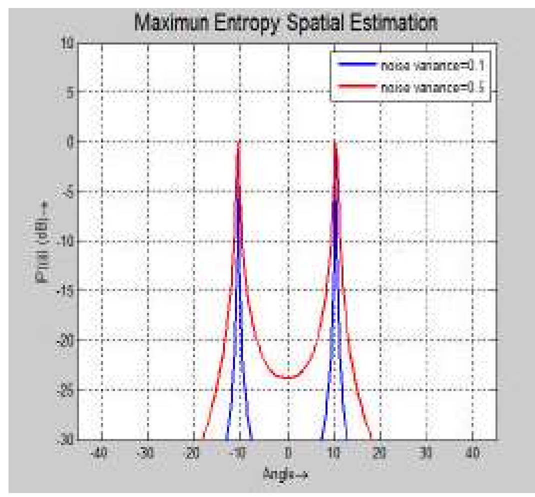

Fig. 5(b): Maximum Entropy Spatial Estimation for noise variance s^2_{n}=0.1and s^2_{n}=0.5

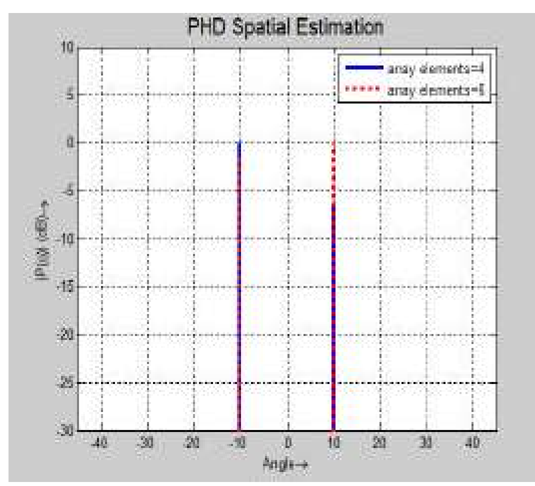

Fig. 6(a): Pisarenko Harmonic Decomposition Spatial Estimation for array elements M=4 and M=6

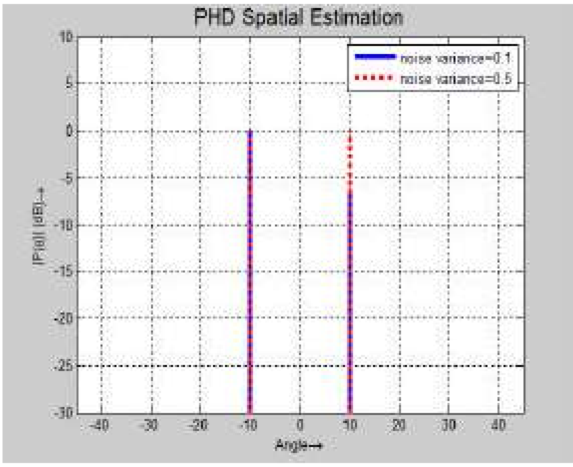

Fig. 6(b): Pisarenko Harmonic Decomposition Spatial Estimation for noise variance $s^{2}_{n=}0.1$and $s^{2}_{n=}0.5$

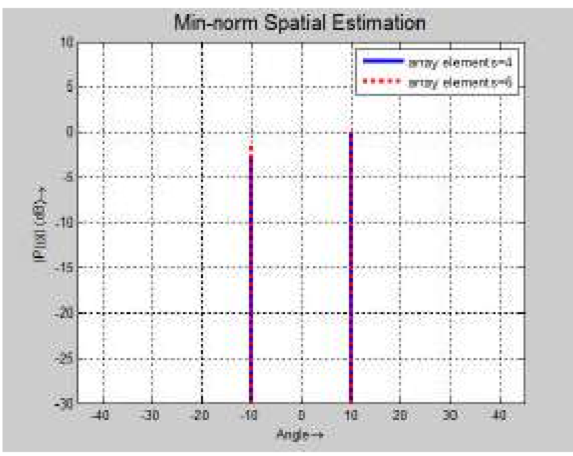

Fig. 7(a): Min-norm Spatial Estimation for array elements M=4 and M=6

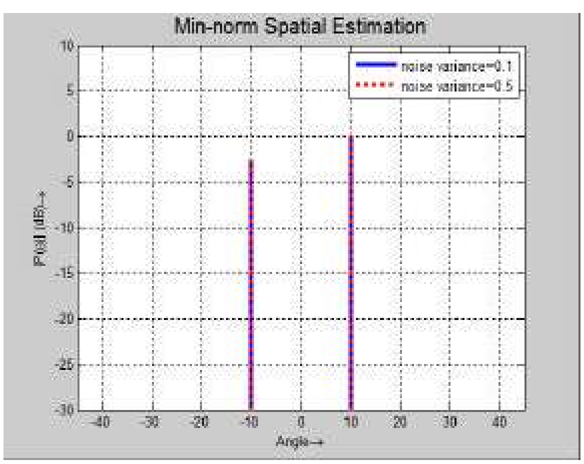

Fig. 7(b): Min-norm Spatial Estimation for noise variance $s^{2}_{n=}0.1$ and $s^{2}_{n=}0.5$

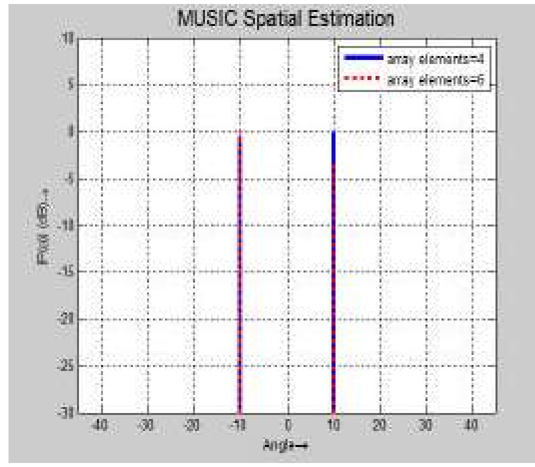

Fig. 8(a): MUSIC Spatial Estimation for array elements M=4 and M=6

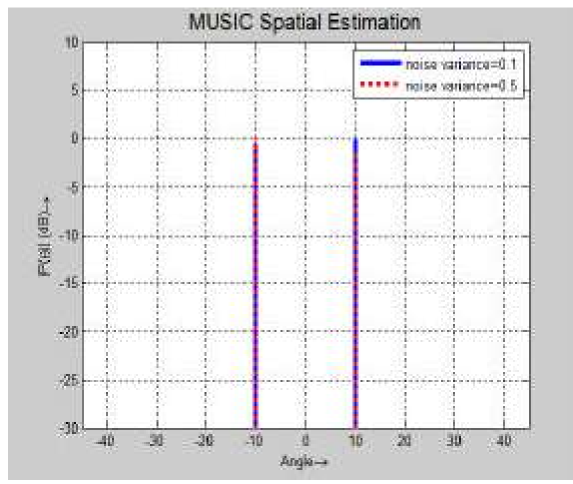

Fig. 8(a): MUSIC Spatial Estimation for noise variance $s^{2}_{n=}0.1$and $s^{2}_{n=}0.5$

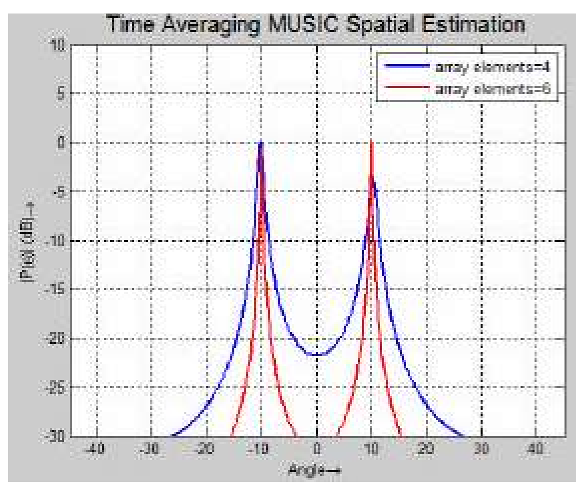

Fig. 9(a): Time Averaging MUSIC Spatial Estimation for Array elements M=4 and M=6

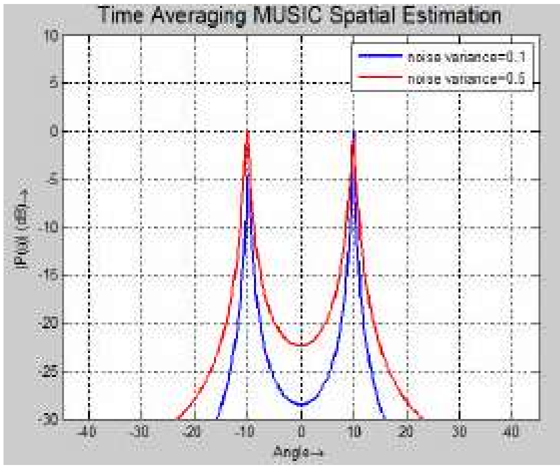

Fig. 9(b): Time Averaging MUSIC Spatial Estimation for noise variance $s^2_n=0.1$ and $s^2_n=0.5$

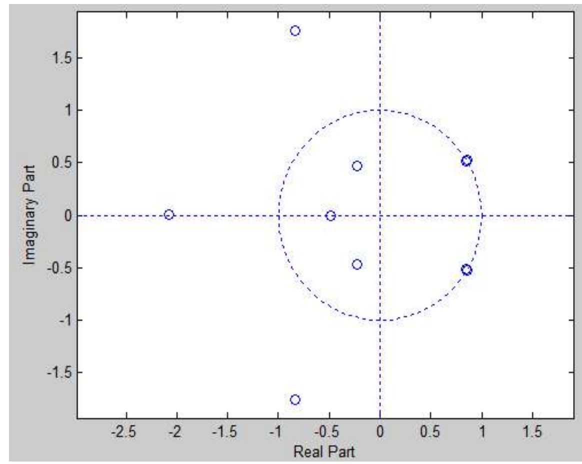

Fig. 10(c): Root Found with root-music for $\theta = \pm 10^0$ and array elements= 6

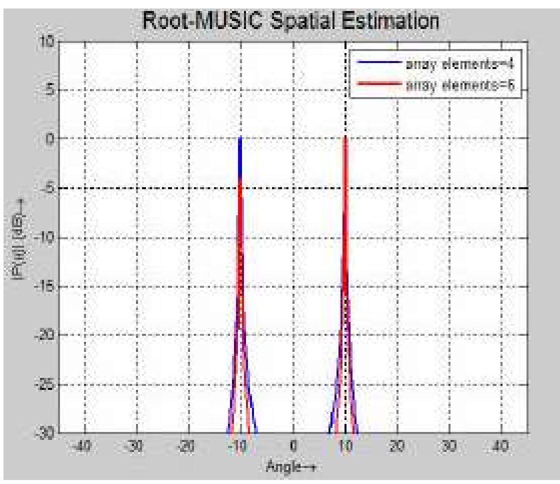

Fig. 10(a): Root MUSIC Spatial Estimation for array elements M=4 and M=6

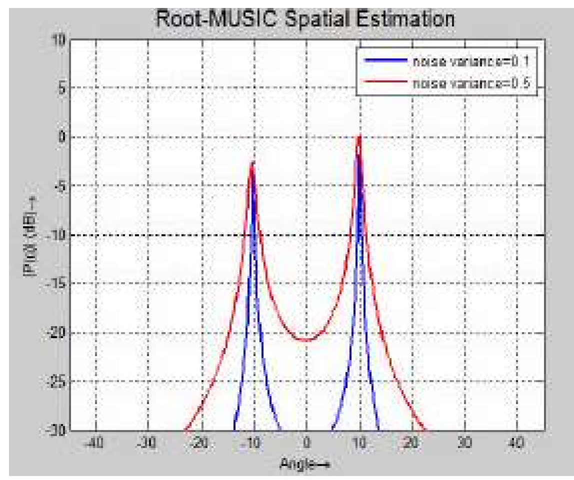

Fig. 10(d): Root MUSIC Spatial Estimation for noise variance $s^2_n=0.1$ and $s^2_n=0.5$

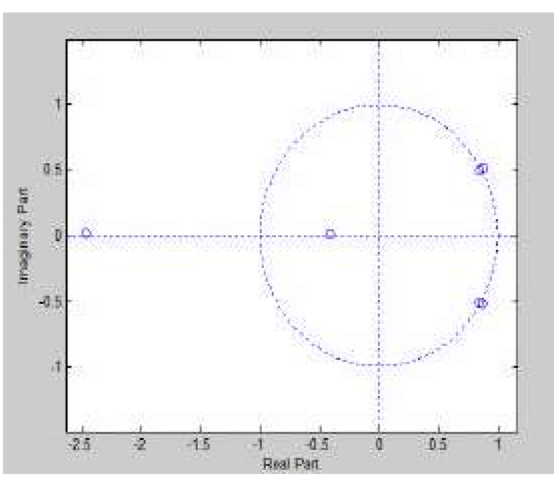

Fig. 10(b): Root Found with root-music for $\theta = \pm 10^0$ and array elements= 4

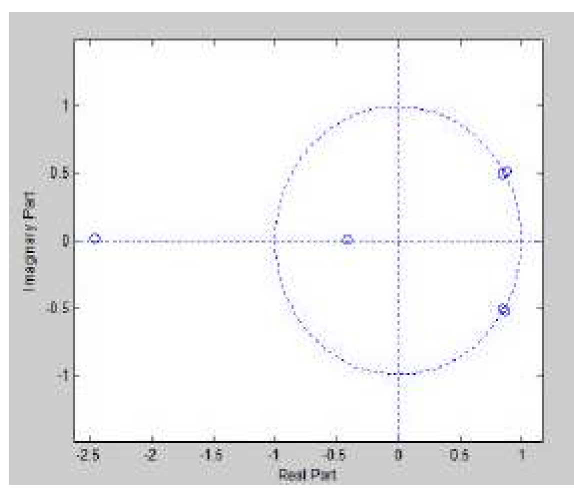

Fig. 10(e): Root Found with root-music for $\theta = \pm 10^0$ and noise variance $s^2_n=0.1$

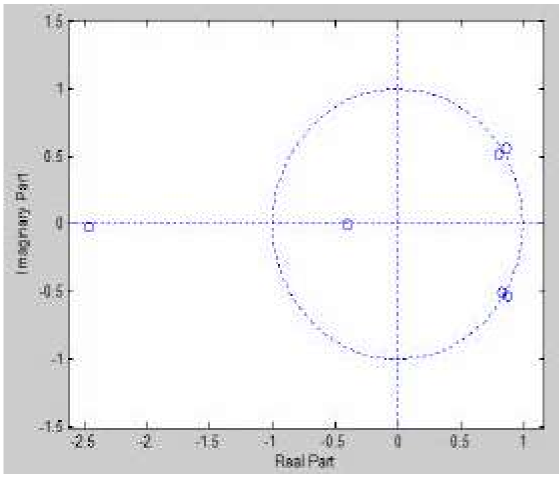

Fig. 10(f): Root Found with root-music for $\theta = \pm 10^0$ and noise variance $s^2{}_{n=}0.5$

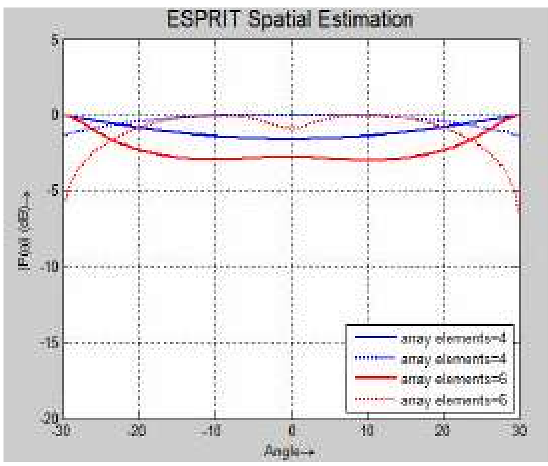

Fig. 11(a): ESPRIT Spatial Estimation for array elements M=4 and M=6

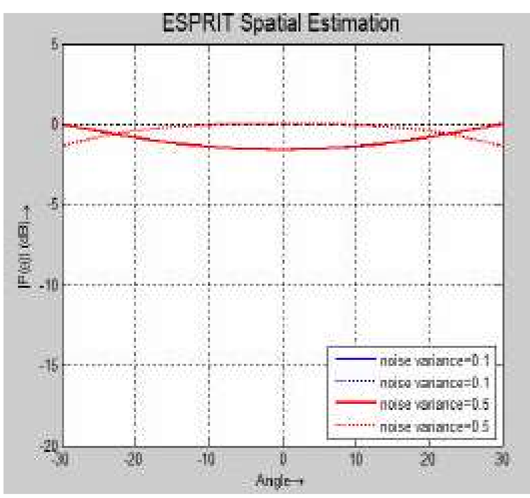

Fig. 11(b): ESPRIT Spatial Estimation for noise variance $s^2{}_{n=}0.1$ and $s^2{}_{n=}0.5$

CONCLUSION

his paper deliberates and relates the resolution of both Spectral Estimation based and sub-space based DOA algorithms. Simulation results show that Capon method has better resolution than Bartlett. Maximum Entropy estimate provides better results than Capon and Bartlett. In Linear Prediction method, resolution is improved as compared to MVDR (Capon), Bartlett and Maximum Entropy methods. Pisarenko Harmonic Decomposition method has a marginally enhanced resolution than Min-Norm estimate. MUSIC AOA estimate does not search for spectral peaks in the spatial spectrum as related with Root-Music AOA estimate. Music Algorithm does not resolve correlated signals, Resolution improves with an increase in array elements. In MUSIC, mean squared error increases with an increase in array gains and phased errors beyond certain values. While ESPRIT method is dependent on only phase errors, mean squared error will be lower for larger overlapping array elements; hence resolution will be higher. MUSIC algorithm gives best results of sources' arrival but it comes at costly search.

FUTURE WORK

rray Processing involve exploitation of signals impinging on array elements. The elements are capable of performing spatial filtering. There may exist errors and perturbations in antenna array elements i.e. Weight errors, steered vector errors, signal correlation errors and elements position errors under assumed conditions. A robust implementation of array elements should have ability to resolve these array parameters. Angle of Arrival estimation is dependent on different array structures used for DOA algorithms. Uniform linear array is the simplest structure of all. In future work we will emphasis on ULA because it is capable of assuming AOA estimate in one-dimensional applications. Despite of merits and demerits array configuration can be suggested in such a way that one can correctly estimate the AOA in comparison with simple ULA.

REFERENCES

1. Frank Gross, 2006. Smart Antennas for wireless communications with MATLAB. McGraw Hill, New York.
2. Constantine A. Balanis and Panayiotis I. Ioannides, 2007. Introduction to Smart Antenna Systems. Morgan and Claypool Publishers.
3. Balanis, C., 2002. Antenna Theory Analysis and Design. Wiley 2nd Ed., New York, 3rd Ed.

4. Michael Chryssomallis, 2000. Smart Antennas. IEEE Antennas and Propagation Magazine, 42 (3): 129-136.
5. Liberti, J.C. and T.S. Rappaport, 1999. Smart Antennas for Wireless Communications: IS-95 and Third Generation CDMA Applications. Prentice Hall, New York.
6. Stocia, P. and R. Moses, 1997. Introduction to Spectral Analysis. Prentice Hall, New York.
7. Godara, L., 2001. Smart Antennas. CRC Press, Boca Raton, FL.
8. Wang, H. and M. Glesner, 2006. Hardware implementation of Smart Antenna Systems. Adv. Radio Sci., 4: 185-188.
9. Godara, L.C., Application of Antenna Arrays to Mobile Communications-II Beamforming and Direction-of-Arrival considerations. Proceedings of IEEE, 85 (8): 1195-1245.
10. Lal Chand Godara, 2004. Smart Antennas, CRC Press
11. Raed, M. Shubair and A. Mahmoud, 2007. Al-Qutayri and M. Samhan, A Setup for the Evalution of MUSIC and LMS algorithms for a Smart antenna System. Journal of Communication, 2 (4): 71-77.
12. Salvatore Bellofiore, Jeffrey Foutz, Constantine A. Balanis and S. Andreas, 2002. Spanias, Smart-antenna System for Mobile Communication networks Part 2: Beamforming and Network throughput. IEEE Antennas and Propagation Magazine, 44 (4): 106-114.