



An improved direction of arrival (DOA) estimation algorithm and beam formation algorithm for smart antenna system in multipath environment

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Abstract – In recent years, adaptive or smart antennas have become a key component for various wireless applications such as radar, sonar and 4G cellular mobile communications. The DOA estimation and beamforming in array signal processing is one of the important and emerging research areas. The effectiveness of this direction of arrival estimation greatly determines the performance of smart antennas. This paper presents an overview of direction of arrival estimation using the MUSIC algorithm and beam formation using LMS algorithm. In presence of correlated input signals, the LMS have extremely slow convergence rates. The proposed improved LMS algorithm reduces mean square error and increases the convergence speed by large amount as compared to existing beamforming algorithms. As the conventional MUSIC algorithm is found to have less efficiency for coherent signals, better simulations using an improved MUSIC algorithm is provided in this paper.

Index Terms- DOA (Direction of Arrival), MUSIC (Multiple Signal Classification), Adaptive array beamforming, LMS (least square), mean square error.

I.INTRODUCTION:

In signal processing a set of constant parameters upon which the received signals depends are continuously monitored. DOA estimation carried out using a single fixed antenna has limited resolution, as the physical size of the operating antenna is inversely proportional to the antenna main lobe beam width. It is not practically feasible to increase the size of a single antenna to obtain sharper beam width. An array of antenna sensors provides

better performances in parameter estimation and signal reception. So we have to use an array of antennas to improve accuracy and resolution. Signal processing aims to process the signals that are received by the sensor array and then strengthen the useful signals by eliminating the noise signals and interference. Array signal processing (ASP) has vital applications in biomedicine, sonar, astronomy, seismic event prediction, wireless communication system, radar etc. Various algorithms like ESPRIT, MUSIC, WSF, MVDR, ML techniques [4] and others can be used for the estimation process.

It assumes that the signals are distributed in space in all the directions. So the spatial spectrum of the signal can be exploited to obtain the Direction of Arrival. MUSIC (Multiple Signal Classification) is widely used spectral estimation techniques which work on the principle of decomposition of Eigen values. These subspace based approaches depend on the covariance matrices of the signals. MUSIC algorithm is the most classic and accepted parameter estimation technique that can be used for both uniform and non-uniform linear arrays. The efficiency and resolution of the obtained spectrum using MUSIC algorithm can be improved by varying various parameters like the spacing between the array elements, number of array elements, number of snapshots and the signal incidence angle difference. An improved MUSIC algorithm is efficient while detection of coherent signals.

The purpose of beamforming is to form a multiple beams towards desired users while nulling the interferers at the same time, through the adjustment of the beamformer's weight vectors. A

beamformer is a set of sensors (antennas), arranged in a linear fashion (Uniform Linear Array), that extract spatial information from the waves emitted by signal sources in order to steer the beam electronically towards the look direction and nulls in the jammer directions.

The Least Mean Square (LMS) algorithm is an adaptive algorithm which uses a gradient-based method of steepest descent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation matrix inversions. Modified LMS algorithm is proposed by making the step size variable. The performance of LMS beamformer improves as more elements are used in the antenna array.

II. MUSIC ALGORITHM:

Schmidt with his colleagues proposed the Multiple Signal Classification (MUSIC) algorithm in 1979. The basic approach of this algorithm is the Eigen value decomposition of the received signal covariance matrix. As this algorithm takes uncorrelated noise into account, the generated covariance matrix is diagonal in nature. Here the signal and the noise subspaces are computed using the matrix algebra and are found to be orthogonal to each other. Therefore this algorithm exploits the orthogonality property to isolate the signal and noise subspaces.

Various estimation algorithms can be used to compute the angle of arrival, but this paper focuses on the most accepted and widely used MUSIC algorithm. The data covariance matrix forms the base of MUSIC algorithm. To find the direction of arrival we need to search through the entire steering vector matrix and then bring out those steering vectors that are exactly orthogonal.

The covariance matrix 'RJ' for the received data 'J' is the expectance of the matrix with its hermitian equivalent.

$$R_J = E[JJ^H]$$

Substituting the value of J we get,

$$\begin{aligned} R_J &= E[(AS + N)(AS + N)^H] \\ &= AE[SS^H]A^H + E[NN^H] \\ &= AR_JA^H + R_N \end{aligned}$$

Where R_N is the noise correlation matrix and can be expressed as:

$$R_N = \sigma^2 I$$

Where I represents an unit matrix for the antenna array elements $D \times D$. Practically, the signals are also associated with the noise, so now the computed correlation matrix along with noise can be represented as

$$R_J = AR_S A^H + R_N$$

Where R_S represents the covariance matrix for the signal $S_{\text{source}}(t)$ and A is the steering vector matrix.

When this correlation matrix is decomposed it results in 'D' number of eigen values out of which the larger F eigen values corresponds to the signal sources and the remaining smaller D-F eigen values are related to the noise subspace. If Q_S and Q_N denote the basis for signal and noise subspace respectively, the resultant decomposed correlation matrix can be represented as:

$$R_J = Q_S \Sigma Q_S^H + Q_N \Sigma Q_N^H$$

As the MUSIC algorithm exploits the orthogonality relationship between the signal and noise subspaces, the following relation holds true:

$$\beta^H(\theta) Q_N = 0$$

The direction of arrival angle can be represented in terms of incident signal sources and noise subspaces

$$\theta_{\text{MUSIC}} = \text{argmin. } \beta^H(\theta) Q_N Q_N^H \beta(\theta)$$

The above equation can be represented in terms of its reciprocal to obtain peaks in a spectral estimation plot:

$$P_{\text{MUSIC}} = \frac{1}{\beta^H Q_N Q_N^H \beta}$$

The above equation results in high peaks when the direction of arrival of the signal source is exactly equal to that of θ . The F higher peak are of greater power and corresponds to the estimated arrival angle. If the element spacing between the antenna array is maintained to be half the received signal wavelength. The SNR and number of snapshot is kept to be 10dB and 300 respectively. The signals considered are non-coherent and narrow banded. The number of antenna elements (D) is taken to be 10 and the noise here is considered to be additive white Gaussian noise.

The simulation for signal sources corresponding to arrival angles 50° and 70° is shown below:

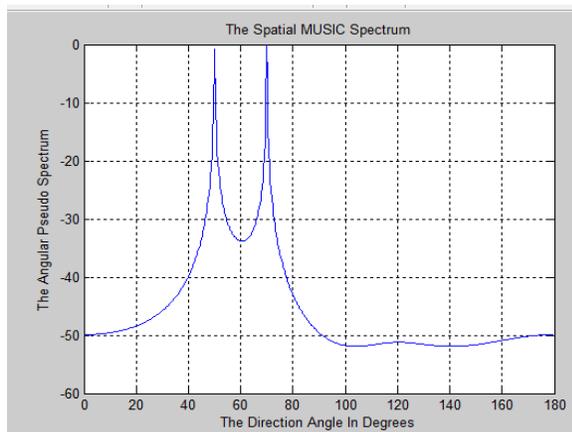


Fig: Spatial spectrum for MUSIC algorithm
The two independent spectrum peaks in the above graph correspond to the two signal sources and their arrival angles.

II. MUSIC AND IMPROVED MUSIC ALGORITHM FOR DETECTION OF COHERENT SIGNALS:

The MUSIC algorithm to estimate the direction has even proved to have better performance in a multiple signal environment. MUSIC algorithm has better resolution, higher precision and accuracy with multiple signals. But this algorithm achieves high resolution in DOA estimation only when the signals being incident on the sensor array are non-coherent. It loses efficiency when the signals are coherent. Keeping all the parameters same as those used for the conventional MUSIC in all the previous simulations and considering the coherent signals to be incident on the sensor arrays, we obtain the following result.

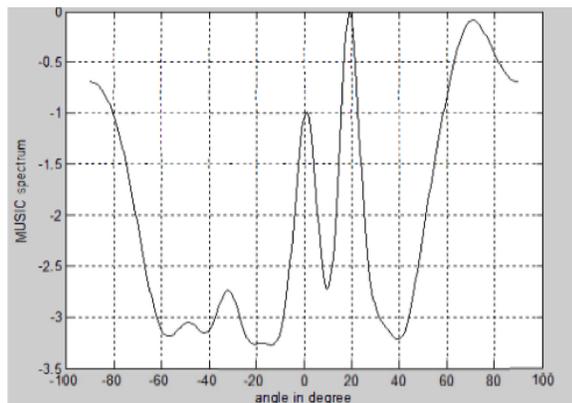


Fig : MUSIC algorithm for coherent signals

As the peaks obtain are not sharp and narrow, they fail to estimate the arrival angle for coherent signals. So we need to move towards an improved MUSIC

algorithm to meet the estimation requirements for coherent signals. To improve the results for MUSIC algorithm we simply introduce an identity transition matrix 'T' so that the new received signal matrix X is given as:

$$X = TJ^*$$

where J^* is the complex conjugate of the original received signal matrix.

$$R_X = E[XX^H] = TR_J^*T$$

Now the matrices R_X and R_J can be summed up to obtain a reconstructed matrix are summed up they will have the same noise subspaces.

$$R = R_J + R_X$$

$$R = AR_S A^H + T[AR_S A^H]^* T + 2\sigma^2 I$$

The noise subspace obtained after decomposition of R_J is filtered out and the new noise subspace obtained by the characteristic decomposition of the resultant matrix R is used for the spatial spectrum construction and to obtain peaks.

The same simulation of coherent source signals using the improved MUSIC algorithm is shown below.

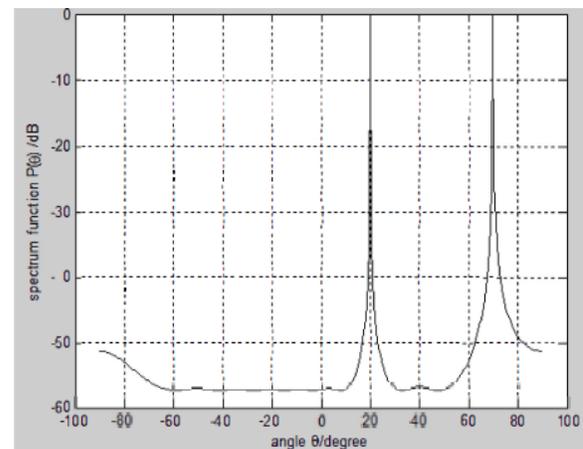


Fig: Improved MUSIC algorithm for Coherent signals

It can be seen that using the improved algorithm for direction of arrival estimation results in narrower peaks for coherent signals. Hence detection of coherent signals can be achieved satisfactorily by using the improved MUSIC algorithm.

IV. LEAST MEAN SQUARE (LMS):

The Least Mean Square (LMS) algorithm is an adaptive algorithm, which uses a gradient-based

method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions.

The progress of the adaptive algorithm is that it computes the output of the array based on the received signal and the current eight vector firstly and after that the error between the output and the expected signal can be achieved, then adjusting the weight vector automatically on the basis of the error which is computed with a certain law. We suppose the signal vector is $X(t) = (x_1(t), x_2(t), \dots, x_M(t))^T$ and the coefficient for each element is $W(n) = (w_1(n), w_2(n), \dots, w_M(n))^H$. Thus the output of the array is

$$y(n) = W(n)^H x(n).$$

If the expected signal is $d(n)$, the error between the output of array and expected is

$$e(n) = d(n) - W^H x(n).$$

LMS is an iterative adaptive algorithm that is based on furthest steep decline optimal method. The furthest steep decline optimal method can obtain the optimal weight by the means of scout along the minus grads. According to the rule of MMSE the iterative formula can be represented as following:

$$W(n+1) = W(n) + \mu e(n)X(n)$$

Where μ is step constant and it influences steady state error and convergence rate of LMS.

A. STEADY STATE OF ALGORITHM:

If the expectation is applied to LMS iterative formula, then the equation can reduce to:

$$\begin{aligned} E\{W(n+1)\} &= E\{W(n)\} + \mu E\{X(n)e^x(n)\} \\ &= E\{W(n)\} + \mu [E\{X(n)d^*(n)\} \\ &\quad - E\{X(n)X^H(n)W(n)\}] \end{aligned}$$

We suppose that the continuous input is not relative to each other, so the $W(n)$, $x(n)$ are independence. Thus equation can be represented so following:

$$\begin{aligned} E\{W(n+1)\} &= E\{W(n)\} + \mu [r_{Xd} - R_{XX}E\{W(n)\}] \\ &= (1 - \mu R_{XX})E\{W(n)\} \\ &\quad + \mu R_{XX}W_{opt} \end{aligned}$$

Where $W_{opt} = R_{XX}^{-1}r_{Xd}$ is the Winner solution. Now we define the weight warp vector $W_d(n)$ is the difference between the acquired weight $W(n)$ and the optimal weight W_{opt} . The expression of $W_d(n)$ is shown as follows:

$$W_d(n) = W(n) - W_{opt}$$

If we associate the equations, then the result can be written:

$$E\{W(n+1)\} = (1 - \mu R_{XX})E\{W_d(n)\}$$

We suppose that Q is unitary matrix of R_{XX} . Then multiple the from the left with Q^{-1} and define $W'_d = QW_d$. The result can be expressed as follows:

$$E\{W'_d(n+1)\} = Q^{-1}(I - \mu R_{XX})QE\{W'_d(n)\}$$

The previous equation can be written briefly like this:

$$E\{W'_d(n+1)\} = (I - \mu A)E\{W'_d(n)\}$$

$$E\{W'_d(n)\} = (I - \mu A)^n E\{W'_d(0)\}$$

Where A is the diagonal matrix which is composed of R_{XX} 's eigen value. $(I - \mu A)$ is a diagonal matrix, the previous equation can be represented in the following form:

$$E\{W'_d(n)\} = (I - \mu A)^n E\{W'_d(0)\}$$

If we want to obtain the optimal weight only making the $(I - \mu A)^n$ turn into 0 can satisfy the need when the N becomes infinite. So the conditional expression is acquired as follow:

$$|1 - \mu \gamma_i| < 1, i = 1, \dots, M$$

According to this equation, μ is fixed.

$$0 < \mu < 2/\gamma_{max}$$

Where γ_{max} is the maximal R_{XX} 's eigen value.

B. CONVERGENCE RATE OF LMS:

The rate of instantaneous weight converges at the optimal weight is determined by $(I - \mu A)$. Now define $\{W'_{di}(n)\}$ that is the element I of W'_d .

Thus the follow equation will come following existence.

$$W'_{di}(n) = (I - \mu\gamma_i)^n W'_{di}(0)$$

We can see that each element's convergence rate is decided by the corresponding $I - \mu\gamma_i$. If the signal environment is known, distribution of $R'_{XX}S$ eigenvalue is also ascertained. In this case if μ is much bigger and it satisfy the equation, then $I - \mu\gamma_i$ will be near to 0 and the algorithm will has faster convergence rate.

On the other hand, the convergence rate of algorithm is determined together by

$I - \mu\gamma_i (i = 1, \dots, M)$. When the distribution of eigen value is very large, that is, when the ratio of the maximal one and the minimal is large, the convergence rate will become slow.

Now we can draw the conclusion that for the traditional LMS step μ will affect the convergence rate and the steady state. If μ is too big, it will have faster convergence rate but the steady state error will increase greatly. By contraries if μ is too small although it will have lower error the convergence rate and the rate of tracing the time changing system signal will decrease obviously. This means that during the course of choosing μ we must consider two factors at the same time. In addition the distribution of $R'_{XX}S$ eigenvalue is also a factor which affects the convergence rate.

VI. IMPROVED LMS ALGORITHM:

A.PRINCIPLE AND REALIZATION OF VARIABLE STEP LMS:

The variable step LMS has been proposed based on the relationship between the performance and step μ . The basic principle of variable step-size LMs is that at the stage of beginning to converge or change of system parameter for the weight of adaptive algorithm is far away from the optimal weight, choose a bigger value to ensure it has faster convergence rate and tracking rate. When the weight of algorithm is near to the optimal one, in order to reduce the steady state error choose a smaller value .

During the adaptive process in smart antenna, the error between the output of antenna array and expected signal will be affected by the noise and interference. When there is serious noise and interference if μ is adjusted by only making use of the error signal LMS performance will be greatly affected. The result is that the instantaneous weight cannot be near to the optimal one, instead, it can only wave around the optimal weight. So in this paper we update the weight through the self correlation

estimate of the current error and the previous to eliminate influence of irrelevance noise. At the same time the unitary LMS is introduced to minish sensitivity of the algorithm depending on the received signal.

In this paper a new variable step μ is proposed as follows:

$$\mu(n) = \frac{\alpha(1 - e^{-\beta|e(n)e(n-1)|})}{x^H(n)x(n)}$$

$|e(n)e(n-1)|$ is introduced to adjust the weight at the stage of beginning to converge with big error, so the step $\mu(n)$ is big too. But for the noise is not relative and it has little impact on $\mu(n)$, the steady state error caused by noise for the adaptive algorithm will be effectively reduced and the algorithm will has good performance with faster convergence rate and less error. The unitary method introduced minishes sensitivity of the algorithm depending on the received signal to a certain extent.

B.ALGORITHM AND SIMULATION:

The experiment is based on uniform liner array and the number of elements is $M=16$. We assume that there are three signal from far space, their incidence angle is $-45, 0, 30$. The signal coming from 0 is the expected signal, the others are interference. The SNR is 30 dB and the noise is gauss white noise. The equal value of noise is 0 and the square error is 1. The step_ of traditional LMS is 0.000005, and the parameters of new algorithm are $\alpha = 0.225, \beta = 0.25$. The simulation results are shown in the Figure 2 and 3.

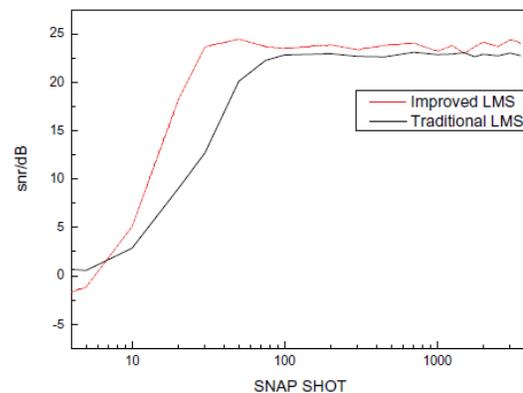


Fig1: SNR =INR=30dB curve of SNR

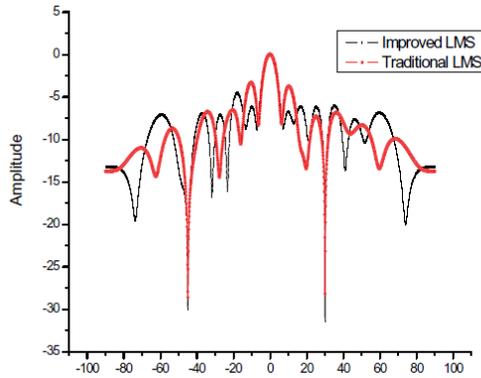


Fig3: SNR=INR=30dB Beam Pattern

VII. CONCLUSION:

The MUSIC uses the eigen values and eigen vectors of the signal and noises to estimate the direction of arrival of the incoming signals. It becomes easier to separate the signals from noise as the eigen vectors for signal and noise subspace are orthogonal to one another. It works efficiently when the signals that are being incident on the array of sensors are non-coherent. For coherent signals the conventional MUSIC algorithm fails to obtain narrow and sharp peaks. An improved version of the MUSIC algorithm as discussed in this paper can be implemented for coherent signals as well. This improved algorithm achieves sharp peaks and makes the estimation process much accurate.

In this paper the factors which affect the performance of the traditional LMS algorithm are analyzed. Then on the basis of the variable step a new variable formula is proposed to improve the LMS algorithm for acquiring faster convergence rate and lower steady state error. The simulation results with the Matlab show that the new algorithm has faster convergence rate and can form deeper nulls in the direction of interference.

VIII. REFERENCES:

- [1] L.N Yan, "Study of Factors Affecting Accuracy of DOA Modern Rader", June 2007. vol. 29. No. 6. pp 70-3.
- [2] Revati Joshi, Aswini Kumar Dhande, "Direction of Arrival Estimation using MUSIC algorithm", International Journal of Research in Engineering and Technology. EISSN: 2319-1163.
- [3] Fei Wen, Qun Wan, Rong Fan, Hewen Wei, "improved MUSIC Algorithm for Multiple Noncoherent Subarrays", IEEE Signal Processing Letters, vol. 21, no. 5, May, 2014.

[4] Debasis Kundu, "Modified MUSIC Algorithm for estimating DOA of signals", Department of Mathematics Indian Institute of Technology, Kanpur, India. November 1993.

[5] Marshall M.Grice, "Direction of arrival estimation using super resolution algorithms ", .M Sc. Thesis, California State Polytechnic University, Pomona, 2007.

[6] Li Li-Jun. Adaptive Algorithm for Beam Forming of Smart Antenna [J] communication technology.2009.04

[7] L. S. Reed, J. D. Mallett. Rapid Convergence Rate in Adaptive Arrays. IEEE Acoustics trans. Aerospace and Electronic Systems. 1974, 10(6):853-863
ao Ying, Xie Sheng-Li. The Analysis of a Variable Step LMS Adaptive Filter Algorithm [J] Electronics Transaction.2001, 29(8).

[8] Jin Yong-Hong, Geng Jun-Ping, Fan Yu. Smart Antenna in Wireless Communication [M] Beijing Post and Telecommunications University Press.2006

[9] Li Cun-Wu, Lin Chun-Sheng. Discussion on Variable Step LMS Algorithms [J] Ship and Electronic Engineering. 2008.05

[10] Gao Ying, Xie Sheng-Li. The Analysis of a Variable Step LMS Adaptive Filter Algorithm [J] Electronics Transaction.2001, 29(8).