



A Novel Approach to DOA Estimation in Radar Array Processing

A.Rafega beham

Asst. Professor, Dept. of ISE, New Horizon college of Engineering, Bangalore, India

ABSTRACT: In sensor array signal processing especially in Radar, there is a growing interest in the estimation of a targets direction of arrival (DOA) against strong background noise or interference. Many algorithms used to estimate target DOA broadly classified as classical beam forming techniques and subspace based techniques (high resolution algorithms). In this paper a new DOA estimator is proposed based on Adaptive Resonance Theory (ART) since neural network is an intelligent approach for solving problems efficiently and quickly. Classical beam forming techniques and subspace based methods such as MUSIC, ESPRIT are simulated and compared with ART algorithm using Matlab. The numbers of computations are very less for the ART algorithm compared to other algorithms.

KEYWORDS: Array signal processing, Direction of arrival (DOA), Neural networks, Radar, ART.

I. INTRODUCTION

Sensor arrays are used in a wide range of applications such as radar, passive sensors, sonar, communications, seismology, radio astronomy, medical diagnosis and chemical analysis. Sensor array signal processing emerged as an active area of research and was centered on the ability to fuse data collected at several sensors to carry out space-time processing. The methods have proven useful for solving several real world problems; such as source localization in radar, sonar and wireless communication. The subject of an array processing is concerned with the extraction of information from the signals collected using an array of sensors. These signals propagate spatially through a medium, and the resulting wave front is sampled by the sensor array. The information of interest in the signal may be either the content of the signal itself or the location of the source or the reflection that produces the signal (radar and sonar).

This paper deals with the problem of finding the Directions-Of-Arrival (DOAs) of electromagnetic waves impinging on a array of antenna elements. The attention is focused on radar applications, but the models and techniques treated in this paper are applicable to wide range of applications. In sensor array signal processing applications, especially in radar, there is a growing interest in the estimation of a target's direction of arrival (DOA) in strong background noise/clutter or interference. Following the undesirable consequences of poor resolution of the classical beam forming techniques (e.g. Bartlett's method, Min-Variance) in estimating the DOA, a number of efficient high-resolution algorithms have been developed to enhance the resolution of the estimated parameters. In this project the high resolution algorithms MUltiple SIgnal Classification (MUSIC), Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT)[5], are used since which give resolution far beyond the classical Fourier limit when the signal model is sufficiently accurate and require less computation compared to the optimal Maximum Likelihood method. These methods are compared with conventional beam former and capon's beam former methods. High-resolution methods typically provide asymptotically unbiased estimation and have proved effective in a great variety of applications[6]. In this paper neural network is focused to obtain direction of arrival estimation, since neural network in an intelligent approach for solving problems efficiently and quickly. The direction of arrival estimation obtained from the neural network will be better in spite of corruption in the data due to atmospheric noise. In this paper Adaptive resonance theory (ART) is attempted to estimate direction of arrival.

II. DOA ALGORITHMS

The first approach to carrying out space time processing of data sampled at an array of sensors was spatial filtering or beamforming. The beam former is a mere application of Fourier based spectral analysis to spatio-temporally sampled data. Later adaptive beam formers and classical time delay estimation techniques were applied to resolve

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

closely spaced signal sources. The spatial filtering approach, however suffers from fundamental limitations: its performance, in particular is directly dependant upon the physical size of the array (the aperture), regardless of the available data collection time and signal to noise ratio. From a statistical point of view the classical techniques can be seen as spatial extension of spectral wiener filtering (or matched filtering). The extension of time-delay estimation methods to more than one signal (these techniques originally used two sensors), and the limited resolution of beam forming together with an increasing number of novel applications renewed interest of researchers in statistical signal processing. Important inspirations for the subsequent effort include the maximum entropy spectral estimation method and early applications of the maximum likelihood principle. The introduction of subspace based estimation techniques marked the beginning of a new era in the sensor array signal processing literature[3]. The subspace based approach relies on certain geometrical properties of the assumed data model, resulting in a resolution capability, which is not limited by the antenna array aperture, provided the data collection time and SNR are sufficiently large and assuming the data model reflects the data model scenario[6].

III. DATA MODEL AND PROBLEM FORMULATION

A. Radar Array Signal processing

An object or target located within the path of the transmitted radar beam will intercept a portion of the EM energy. The intercepted energy will be scattered in various directions from the target depending on the target's physical characteristics. The radar antenna receives a portion of the backscattered wave or echo return. The echo returns, which are gathered by a set of sensors, are sampled, and the resulting data is processed to identify targets and perform parameter estimation. Targets can be detected by using spatial weighting of the data from each element of an antenna array.

By applying the computed weights to the data, the effects of interference can be reduced thus increasing the reception of the reflected signal. This signal processing method is referred to as Space time processing, which is an adaptive processing technique that simultaneously combines the signals received from multiple elements of an antenna array (the spatial domain) and from multiple pulses (the temporal domain) of a coherent processing interval (CPI).

Consider a K element radar array that transmits a coherent burst of M pulses at a constant pulse repetition frequency. Signal returns are composed of L range gates, M pulses, and K antenna array samples, the data may be visually represented by the three-dimensional data set shown in Fig.1. This KLM data set will be referred to as the CPI data cube. In general, a target present in a particular range bin during some CPI may be modeled as producing following base-band vector signal (after pulse compression and demodulation)

$$\begin{aligned} \text{Target signal } X(t) &= b_0 a(\theta_0) e^{j\omega_0 t} + N(t) \\ &= s(t) a(\theta_0) + N(t) \end{aligned} \quad (1)$$

Where $s(t) = b_0 e^{j\omega_0 t}$, b_0 is the complex amplitude of the signal, ω_0 is the Doppler shift due to the relative motion between the array platform and the target, and $a(\theta_0)$ is the response of the array to azimuth

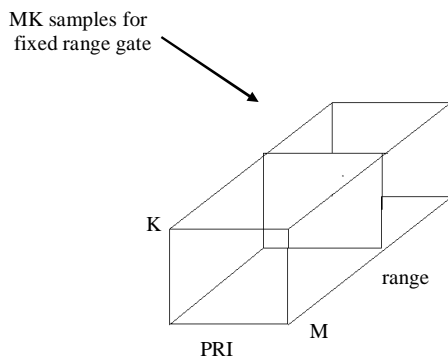


Fig.1



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

plane wave arriving from azimuthal direction θ_0 . $N(t)$ is considered as a stationary, temporally white Gaussian random process over the N samples of the CPI, with zero-mean and unknown spatial covariance.

Considering a uniform linear array with K identical sensors and uniform spacing d , the output is given by

$$X(t)=[x_1(t) \dots x_k(t)]^T + N(t) = A(\theta) S(t) + N(t) \quad (2)$$

The spatial covariance matrix is given by

$$R = E \{ X(t)X^H(t) \} \\ = AE\{s(t)s^H(t)\}A^H + E\{N(t)N^H(t)\} \quad (3)$$

B. DOA Estimation

The process of estimating the direction of arrival of signal of interest that impinges on the array of sensor model is termed as DOA estimation. DOA estimation involves a correlation analysis of the array signals. The fundamental principle behind direction of arrival (DOA) estimation using sensors arrays is to use the phase information present in signals picked up by sensors (antennas) that are spatially separated. When the antennas are spatially separated, the base band signals arrive at them with time differences. For an array geometry that is known, these time-delays are dependent on the DOA of the signal. The direction of a source is parameterized by the variable θ .

C. Beamforming Techniques

Conventional beamformer works by maximizing the output power for a given input signal and look direction θ . The array response is steered by forming a linear combination of the sensor outputs

$$Y(t) = \sum_{i=1}^I w_i x_i(t) = W^H X(t) \quad (4)$$

Given samples $y(1), y(2), \dots, y(N)$, the output power is measured by,

$$|P(W)| = \sum_{i=1}^N (1/N) |Y(t)|^2 \quad (5)$$

The weight vector of conventional beamformer is given by

$$WBF = a(\theta_0) / \sqrt{a^H(\theta_0) a(\theta_0)} \quad (6)$$

The weight vector of capons beamformer is given by

$$W_{CAP} = \hat{R}^{-1} a(\theta) / a^H(\theta) \hat{R}^{-1} a(\theta) \quad (7)$$

D. Subspace based Methods

The MUSIC algorithm is the eigenstructure-based methods in which search for directions such that the steering vectors associated with these directions are orthogonal to the noise subspace and are contained in the signal subspace. If M signals impinge upon the array, then R contains M large eigen values compared to the rest of $K-M$ eigen values. The M eigen vectors corresponding to those M eigen values span the signal subspace, and the space spanned by the eigenvectors corresponding to the remaining $K-M$ eigen values is called the noise subspace. These two subspaces are orthogonal to each other.

Since the steering vectors corresponding to the M signals span the same subspace as the eigenvectors corresponding to the largest M eigen values, they are also orthogonal to the noise subspace. Thus the direction of arrival is determined by searching through the array manifold corresponding to all angles, and finding the M elements that are most orthogonal to the estimated noise sub spaces. This is accomplished by searching for peaks in the MUSIC spectrum given by

$$P_M(\theta) = a^H(\theta) a(\theta) / a^H(\theta) \Pi^\perp a(\theta) \quad (8)$$

Where $\Pi^\perp = U_n U_n^H$ denotes an by $K-M$ dimensional matrix with its $K-M$ columns being the eigenvectors corresponding to the $K-M$ smallest eigenvalues of the array correlation matrix.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

The ESPRIT algorithm uses the structure of the ULA steering vectors in a slightly different way. ESPRIT relies on the properties of the eigen decomposition of the array covariance matrix. This algorithm is based on dividing the sensor array into subarray. The sub matrices A1, A2 are formed from A (θ) which has shift invariance and related by

$$A_2 = A_1 \Phi \quad (9)$$

where Φ is a diagonal matrix having the roots $e^{j\phi_m}$, $m=1,2,\dots,M$. on the diagonal.

E. Proposed Neural Network Approach

In this paper, as an alternate intelligent method artificial neural networks are attempted to estimate the DOA. Artificial neural networks provide good results even if there is a corruption in signal. In this paper Adaptive Resonance Theory (ART) is attempted. ART consists of a two layer network with feedback as shown in Fig.2. The ART network includes a bottom up competitive learning system (F1 to F2) combined with a top down (F2 to F1) outstar pattern learning system. The search process is controlled by two subsystem. The Orienting subsystem uses the vigilance parameter that establishes the criterion for matching the pattern. The attentional subsystem allows the units in the F1 layer to be engaged only when an input pattern is present and regulates the learning. For an input pattern 'a' to the F1 layer, determine the winner unit k in the F2 layer by computing

$$k = \arg[\max w_j^T a] \quad (10)$$

where W_j is the weight vector leading to the jth unit in the F2 layer from all the units in the F2 layer.

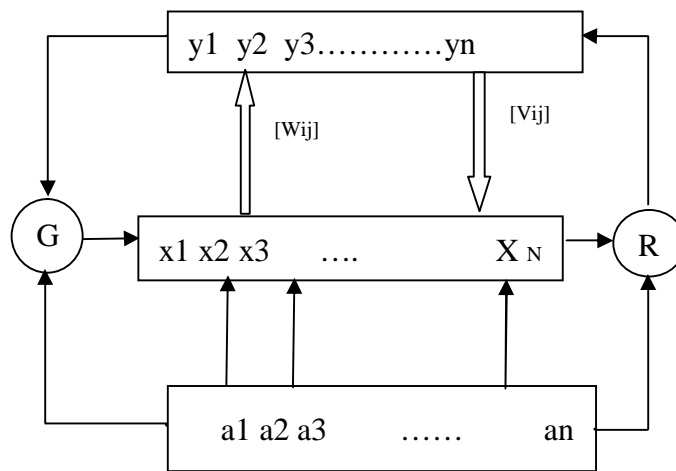


Fig.2

a similarity measure between the winning prototype v_k and the input a is computed and compared with a vigilance parameter ($0 < \rho < 1$). The weights are adjusted as follows.

$$V_{ik}(m+1) = v_{ik}(m) * a_i, \quad i = 1, 2, \dots, N \quad (11)$$

$$W_{ki}(m+1) = v_{ik}(m+1) / (0.5 + \sum_{i=1}^N v_{ik}(m+1)) \quad (12)$$

Where $i = 1, 2, \dots, N$

The input for the neural network is spatial covariance matrix. The output of neural network will be firing of a node in the output layer in the node with maximum value is associated with input values. The process has to be repeated for the spatial covariance matrix of the input signal obtained for target with different DOA. Training of the network with different spatial covariance matrix obtained from different target angles. Since ART comes under clustering or grouping concept a node has to be assigned for each spatial covariance matrix.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

III. SIMULATION & RESULTS

Simulation is performed with number of antenna elements $K=12$, wavelength $\lambda = 0.03$, interelement spacing $D=0.45 \lambda$. For pulse compression barker 13 code is used. Simulation results were obtained for beam forming techniques, high resolution subspace based techniques and neural networks. In MUSIC algorithm, an exhaustive search is performed looking for signals that are orthogonal to the noise subspaces. It requires a costly search function. The effect of increasing the number of array elements and Signal-to-Noise (SNR) ratio has also been investigated and it was found that the performance of the algorithms improves when more elements are used and when the SNR is increased. DOA estimation with unsupervised learning using adaptive resonance theory is done. Many numbers of iterations are done for training and selection of hidden nodes. After training is over, the weights are used for testing the network. The number of computations are less compared to the other DOA algorithms used in this project. The knowledge of array manifold is not required for neural network. Spatial covariance matrix is given as input to the network. The output of neural network will be firing of a node in the output layer in the node with maximum value is associated with input values. The process has to be repeated for the spatial covariance matrix of the input signal obtained for target with different DOA. Simulations are done with 12 antenna elements. By varying the weight and vigilance parameter many iterations are performed.

From the Fig.3 it is evident that when the angular separation between the incident signals is large, the conventional beam former resolves the targets well in the spectrum.

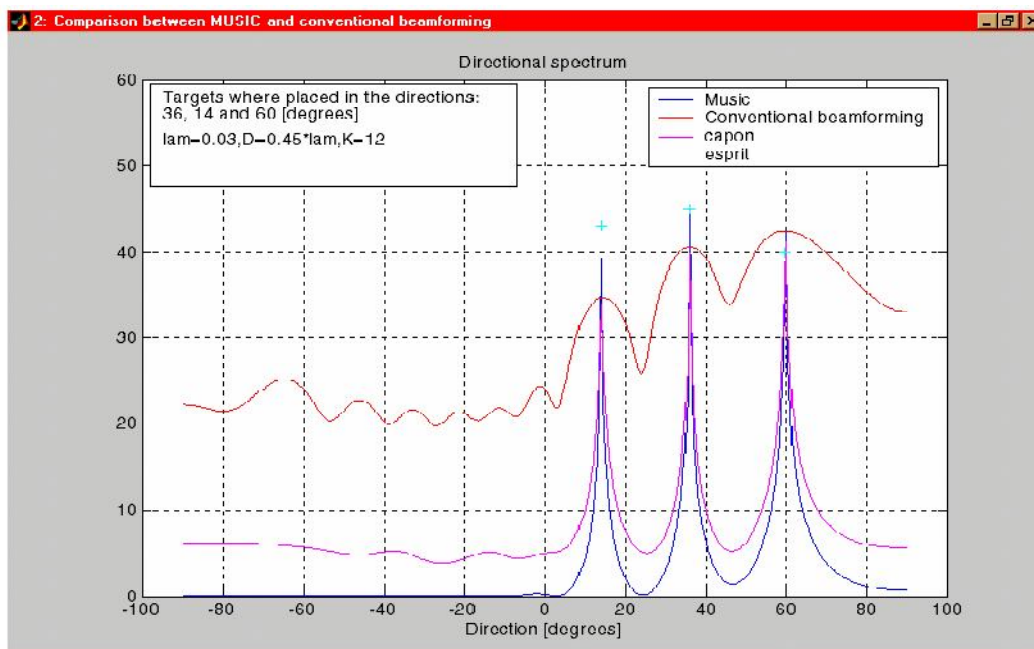


Fig.3

From the Fig.4 when the angular resolution between the incident signal is less conventional beamformer fails to resolve the target angle in its spectrum. Target angles are 25, 18, -3.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

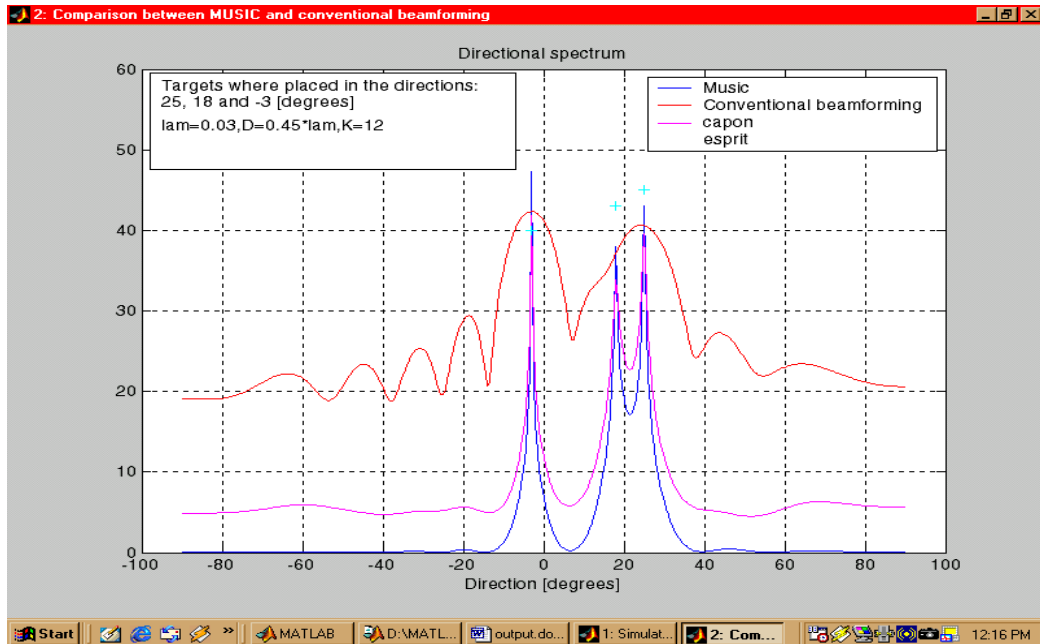


Fig.4

From the simulation results of Fig.5, when the incident signal is very less (target angles are 14,18,30)the beam forming techniques doesn't resolve well the signals in its spectrum as in the case of high resolutions algorithms.

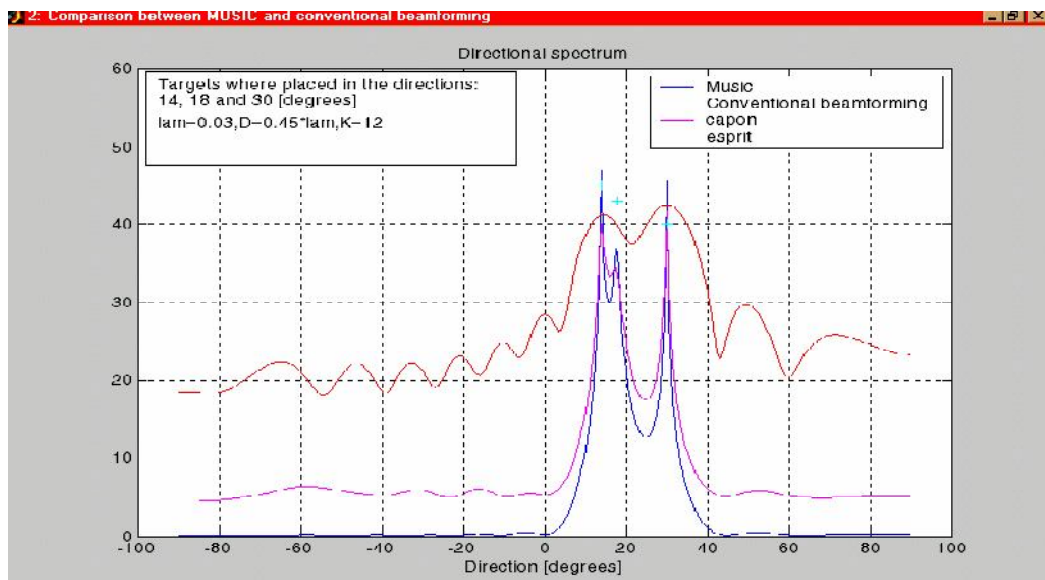


Fig.5

V.CONCLUSIONS

Performance evaluation of high-resolution DOA estimation algorithms including MUSIC, ESPRIT has been carried out. DOA estimation using the intelligent approach adaptive resonance theory is also performed and compared with high resolution DOA algorithms. All the algorithms were tested by varying the parameters such as i) number of



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

antenna elements, ii) antenna element spacing, iii) number of samples and iv) angular separation between the incident angles. The result showed that Performance of DOA algorithms improves by using more elements in the antenna array and more samples. As the neural network doesn't require the knowledge of array manifold the numbers of computations are very less compared to other algorithms.

REFERENCES

- [1]. "Multiple signal DOA estimation for a switched beam system using neural networks", K.A.Gotsis, J.N.Saholas, K.Siakavara, PERS, 2013
- [2]. "A new method for DOA estimation using RBF neural networks", WU.Jun wei, Zhang Min, XU xinkun, IPCSIT, 2012
- [3]. MUSIC and MVDR DOA estimation algorithms With higher resolution and accuracy", Akbari.f, Mohaddam.S.S, Vakili. IEEE conference Publications, 2010
- [4]. A.lee Swindlehurst and Peter Stoica "Maximum likelihood methods in Radar array signal processing" 422 Proceedings of the IEEE 1998.
- [5]. Richard Roy and Thomas Kailath, "estimation Of Signal parameters via rotational invariance Techniques" IEEE Transactions on acoustic, speech and signal processing, 1989
- [6]. A fast DOA estimation algorithm based on Subspace projection, IEEE conference Publications, 2014
- [7]. Monson H.Hayes, " Statistical digital signal Processing and modeling"
- [8]. Capon like DOA estimation algorithm for Directional antenna arrays, IEEE conference Publications, 2011
- [9]. Enhanced DOA estimation algorithm using MUSIC and MVDR, IEEE conference Publications, 2013
- [10]. High resolution two dimensional DOA estimation using artificial neural network, IEEE conference Publications, 2012