2016 European Modelling Symposium

# Direction of Arrival Estimation by Using Artificial Neural Networks

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***Abstract* — In the literature there are many algorithms for direction of arrival estimation like MUSIC, ESPRIT, First order forward prediction, Capon etc. These algorithms have heavy calculation operations. This situation could cause lags in response time of the algorithm, and may pose an important disadvantage in real time applications. To overcome this problem, artificial neural network (ANN) could be used. The training stage of an ANN needs significant time and sources but after training, the estimation by using ANN is very fast. In this study, an ANN approach has been proposed for direction of arrival estimation in uniform linear array antenna. In training, the whole pseudo spectrum is scanned by 10 degree steps. In the simulation process, it is accepted that a uniform linear array consists of 5 isotropic antenna elements and there are 1 to 4 arrival signals. Tests of the trained ANN have been done for various directions of arrival angles, and satisfactory results have been obtained.**

***Keywords - component; Direction of Arrival, Uniform Linear Array, Artificial Intelligence, Real Time Application.***

## I. INTRODUCTION

Antenna arrays have gained attention due to the abilities such as having changeable radiation pattern, high gain and directivity, multipath signal rejection, stationary beam and null steering. Due to these facts antenna arrays have a wide application area. The applications such as radar, sonar, seismic systems, electronic surveillance, medical diagnosis, treatment, radio astrology etc. use antenna arrays also called smart antenna [1].

One of the most important ability of antenna arrays is radiation pattern formability. The radiation pattern of an antenna array could be formed as needed by changing the excitation phase and amplitude. This skill is the origin of the Space Division Multiple Access (SDMA) techniques [2]. Additionally the ability of preventing co-channel fading and generating low-side lobes interferences improves the performance of cellular communication system [3].

Although antenna arrays have similar abilities during used as receiving antenna or transmitter antenna, they have an extra important ability while receiving. An antenna array could detect the directions of signals that incident on them. The problem of localization of sources radiating energy by observing their signal received at spatially separated sensors is called Direction of Arrival (DoA) estimation [4]. The DoA estimation is based on phase and amplitude differences between sensor elements. In literature several methods have been discussed. The DoA estimation algorithms can be divided into three groups as statistical methods, subspace spectral based and spectral based methods. First order forward prediction, Bartlett, Maximum entropy and Capon are the most reputable spectral based algorithms [5]. The most popular subspace spectral based methods are Multiple Signal Classifying (MUSIC), Min-Norm and Weighted Subspace Fitting (WSF). The statistical methods are Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), Root-MUSIC and Root-WSF [6, 7].

The algorithms mentioned above needs covariance calculation. Especially subspace based and statistical methods uses Eigenvalue and Eigenvector decomposition. All of these operations costs significant time during calculations. Due to this fact in real time application the response of the system may have lags. So the use of these algorithms in speedy real time applications may pose important drawbacks. To overcome this problem, artificial neural network (ANN) can be employed. Even though the training of an ANN needs too much source and time, a trained ANN calculates results very fast. Therefore, the ANN usage may be very beneficial especially in real time applications. In this study an ANN is designed, trained and tested for DoA estimation. The ANN results have been presented in pseudo spectrum.

## II. MATERIAL AND METHODS

In this study Uniform Linear Array (ULA) antennas have been used as smart antenna. A sensor set separated on a line with constant distance d is called ULA antenna. Usually N notation is used to symbolize the number of sensors in ULA antenna [8]. The structure of ULA antenna is presented in Figure 1.


DOI 10.1109/EMS.2016.51

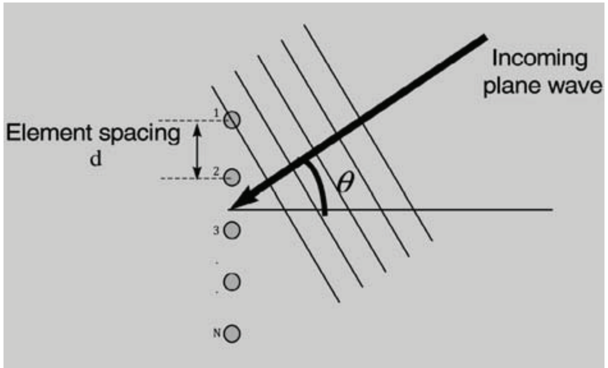


Figure 1. Structure of ULA antenna [8].

The number of plane wave incident to the ULA antenna (that is number of sources in the medium) is assumed as M. The receiving antenna outputs including the noise have been presented in Equation 1.

$$X_n(k) = A(\vartheta_m)\, S_m(k) + n_n(k) \qquad (1)$$

In Equation 1, k is the sample number (discrete time variable), $A(\vartheta_m)$ is the steering vector (array manifold), $S_m(k)$ is the signal matrix and $n_n(k)$ is the white Gaussian noise matrix. The $X_n(k)$ is output of sensor elements from the ULA antenna [9].

In the study, simulations have been done on the ULA antenna that consists of 5 isotropic elements. The distance between antenna elements have been accepted as half wavelength. The outputs of ULA antenna elements have been calculated by using MATLAB software according to Equation 1 [10].

A dataset have been created for training the Artificial Neural Network (ANN) by using MATLAB. Because of having 5 antenna elements in the ULA it is accepted that there would be maximum 4 signal source that incident onto antennas. Whole pseudo spectrum from -90 to 90 degree has been splitted into 19 parts. Angle of signal source has been changed from -90 to 90 degree by 10 degree steps for single source in the medium. At each point ULA antenna outputs have been collected to use as input of ANN. Also the angles of signal sources have been collected to use as target. While changing the number of signal sources in the medium from 1 to 4, angle of signal sources have been changed by 10 degree steps from -90 degree to 90 degree. During scanning whole pseudo spectrum, repetitions of previously calculated situations have been avoided. And at each point angles of signal sources and calculated outputs of ULA antenna have been recorded.

Number of samples when there is 1 signal source in the medium, is 19. This can be calculated by using combination. It is also number of 1 membered subset of a cluster with 19 elements. When there are 2 signal sources in the medium, number of all possible arrival angles is number of 2 membered subset of the cluster. So, all the possible situation can be calculated by using subset determination operation of a cluster. The mentioned cluster called Signal Source Position (SSP) cluster, is the possible positions where signal sources could be. This cluster is as follow.

$$SSP = \{-90, -80, -70, \ldots, 70, 80, 90\}$$

By using combination calculations, the possible position counts have been calculated as 19, 171, 969, and 3876 when there is 1, 2, 3 and 4 signal sources in the medium respectively. So the dataset contains the records of 5035 measurement. During all measurement the Signal Noise Ratio (SNR) of arrival signals have been assumed as -30dB.

In each record, 20 samples have been taken while sampling frequency/signal frequency ratio is 20. So each record becomes perfect cycle that has zero mean. This is very helpful during covariance calculation. The covariance of the ULA antenna's outputs has been calculated to make results independent from time. The dimension of covariance matrix is 5×5 and it consists of complex numbers. But the input of an ANN has to be real values in a 1D vector in MATLAB. So this covariance matrix divided real and imaginary parts first. Then all rows have been added end to end. The records have become a vector whose dimension is 1×50. To use as target during training, a vector has been created. This vector has 19 zero element but arrival angles have unit value.

The MATLAB software has been used to create, train and simulate an ANN. The number of inputs has to be 50 due to the number of elements in a record. The input values changes between -1 to 1. So the input activation function has been chosen tansig (hyperbolic tangent sigmoid transfer function). The output layer of the ANN has to have 19 neurons. These values changes between 0 and 1. So, the output layer activation function could be chosen logsig (logarithmic sigmoid). Number of neurons in hidden layer has been determined as 25 by trial and error method. The tansig function has been chosen as activation function in hidden layer. Whole ANN structure is presented in Figure 2.

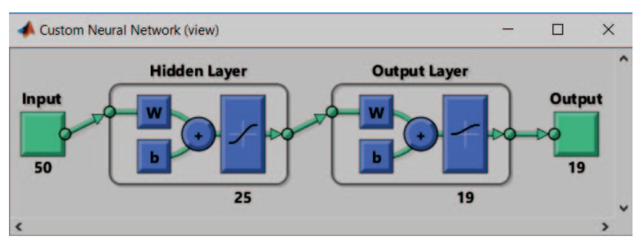


Figure 2. Whole ANN structure designed in MATLAB.

The ANN has been trained by using Levenberg-Marquardt backpropagation training algorithm (TRAINLM). The Gradient descent with momentum weight and bias learning function (LEARNGDM) has been chosen as adaption learning function. Mean Squared Error (MSE) has been preferred for performance function. Only one hidden layer has been proposed.

## III. Results and Discussion

In this study, an ANN has been employed for DoA (or Angle of Arrival) on an ULA antenna with 5 sensors. The dataset has been divided into 3 groups. These groups training, validation and testing are shared out as 60%, 10% and 30% of dataset respectively. The estimation error values have been calculated for various numbers of neurons in the hidden layer. The error values Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) change versus number of neurons in the hidden layer have been presented in Table 1.

TABLE I. MAE, MSE and RMSE change versus number of neurons in the hidden layer

| Number of Neurons in The Hidden Layer | MAE | MSE | RMSE |
|---|---|---|---|
| 1 | 0.4635 | 0.4473 | 0.6688 |
| 2 | 0.3328 | 0.2954 | 0.5435 |
| 3 | 0.3359 | 0.2551 | 0.5051 |
| 4 | 0.2748 | 0.1722 | 0.4150 |
| 5 | 0.3027 | 0.2145 | 0.4632 |
| 6 | 0.2748 | 0.1383 | 0.3718 |
| 7 | 0.2260 | 0.1236 | 0.3515 |
| 8 | 0.2490 | 0.1292 | 0.3595 |
| 9 | 0.2565 | 0.1501 | 0.3875 |
| 10 | 0.2240 | 0.1262 | 0.3552 |
| 15 | 0.1929 | 0.0996 | 0.3157 |
| 20 | 0.1833 | 0.0946 | 0.3076 |
| 25 | 0.1752 | 0.0937 | 0.3062 |
| 30 | 0.1600 | 0.0904 | 0.3007 |
| 31 | 0.2023 | 0.1256 | 0.3545 |
| 32 | 0.1648 | 0.0889 | 0.2981 |
| 33 | 0.1597 | 0.0887 | 0.2978 |
| 34 | 0.1672 | 0.0900 | 0.3000 |
| 35 | 0.1554 | 0.0869 | 0.2947 |
| 36 | 0.1633 | 0.0904 | 0.3007 |
| 37 | 0.1574 | 0.0876 | 0.2959 |
| 38 | 0.1541 | 0.0849 | 0.2914 |
| 39 | 0.1573 | 0.0868 | 0.2946 |
| 40 | 0.1557 | 0.0875 | 0.2958 |
| 45 | 0.2705 | 0.1891 | 0.4348 |
| 50 | 0.1541 | 0.0877 | 0.2961 |

In this study, the ANN result consists of 19 elements each indicates a specific angle between -90 to 90 degree with 10 degree steps. To calculate MAE, a subtraction between the designation values ($X_{REAL}$) and estimated values ($X_{ANN}$) is done. So a 19 elemented array of errors has been obtained. The absolute values of all the array is taken. As a result, the mean of whole array is calculated. The mathematical formulation of MAE is presented in Equation 2.

$$MAE = Mean( Abs( X_{REAL} - X_{ANN} ) ) \quad (2)$$

The MSE and RMSE are calculated by applying the same results to the Equation 3 an Equation 4 respectively. The RMSE value is square root of the MSE.

$$MSE = Mean( ( X_{REAL} - X_{ANN} ). ( X_{REAL} - X_{ANN} ) ) \quad (3)$$

$$RMSE = SQRT( MSE ) \quad (4)$$

The graph of MAE, MSE and RMSE change versus number of neurons in the hidden layer has been presented in Figure 3.

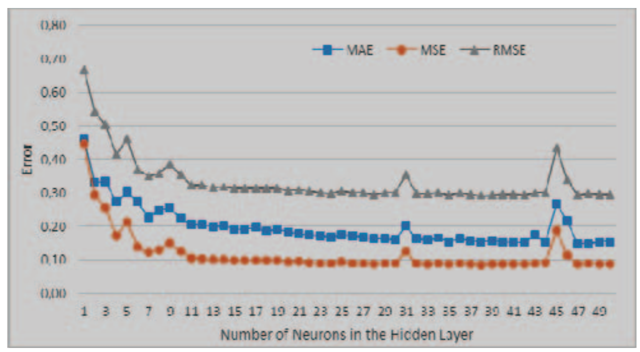


Figure 3. MAE, MSE and RMSE change versus number of neurons in the hidden layer.

The best performance has been obtained by ANN when there are 38 neuron in its hidden layer with the Tansig activation function. And the training algorithm is Levenberg-Marquardt Backpropagation (Trainlm). Some of the tests' results by using the ANN that has the best performance have been done. While there are two arrival signal in the angles of -10 and 30 degrees, the estimation result is presented in Figure 4.

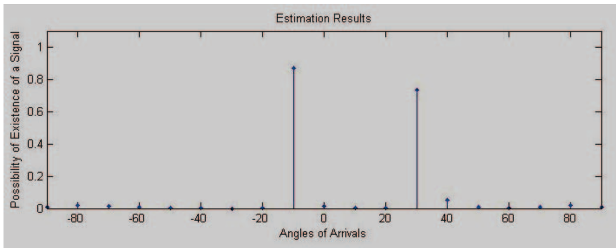


Figure 4. Estimation results when there are two arrival signals at -10 and 30 degree.

For simulation of unpredictable situation, the ANN is tested with arrival signals whose angles are not in the desired direction like -15 degree. The estimation results of this situation is presented in Figure 5.

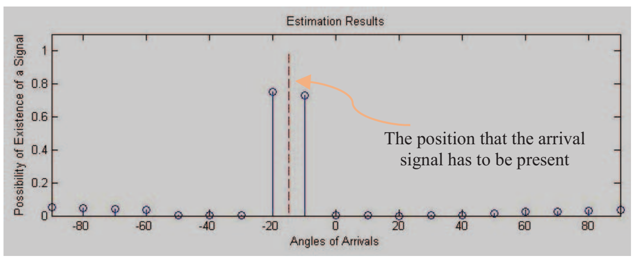


Figure 5. Estimation results when there is an arrival signals at -15 degree.

## IV. Conclusions

In this study, a direction of arrival estimation has been done by using artificial neural network for uniform linear array antenna. For artificial neural network input, covariance of uniform linear array antenna outputs has been used. The output has 10 degree resolution. The lowest estimation error with MSE has been obtained when there are 25 neurons in the hidden layer. The MSE value has been obtained as 0.0955.

At this point a question may occur in minds like "why is resolution 10 degree?". The dataset has been prepared for 5 degree steps. In this situation, the output has 37 points. So the dataset consists of 74.518 records. The required artificial neural network for this situation has to have 37 output neurons. But a problem has been occurred during training of artificial neural network. The MATLAB software has given "Out of Memory" error. This training attempt has been done on a PC that has 16GB RAM.

For future studies the training artificial neural network for the dataset that has 5 degree resolution, may done on a powerful computer. And a curve fitting algorithm may apply on the output of artificial neural network to determine position of arrival signals out of desired positions like 13 or -76 etc. degrees.

## Acknowledgment

This study has been supported by Scientific Research Project of Necmettin Erbakan University with the project number 162518001-734.

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