Multiple Sources Neural Network Direction Finding with Arbitrary Separations

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Abstract

This paper presents a modification to the radial basis function based direction finding algorithm where the DOA problem is approached as a mapping which can be modeled by training the network with input output pairs with multiple angular separations. The network is then able to track a fixed number of sources with arbitrary angular separations using a linear array. A novel training technique is suggested and the performance of the rbfnn algorithm is compared to ideal data.

1.Introduction

Interference rejection is very important and often represents an inexpensive way to increase the system capacity of cellular and mobile communication systems by allowing closer proximity of cofrequency cells or beams providing additional frequency reuse. Recently, neural networks have been proposed as successful candidates to carry on the computational tasks required in several array processing applications such as direction finding and adaptive nulling [1],[2]. In [3], a real-time neural network based direction finding algorithm was. For practical purposes, the rbfnn algorithm should be able to estimate an arbitrary number of sources with any angular separation. Further investigation of the networks presented in[3]showed poor generalization capability. The networks can estimate sources with only the single angular separation it was trained for. In this paper, we introduce a modification to the rbfnn algorithm as a first logical step toward a more general algorithm. This paper is organized as follows: Section 2 presents the DOA problem, section 3 discusses the modified rbfnn algorithm and in section 4 we present some simulation results. Section 5 offers some conclusive remarks.

2.Direction finding in linear arrays

Consider a linear array composed of M elements as shown in Figure 1. Let K (K<M) narrowband plane waves, centered at frequency ω_0 impinge on the array from directions $\{\theta_1 \quad \theta_2 \quad \cdots \quad \theta_K\}$. Using complex signal representation, the received signal at the i^{th} element can be written as,

$$x_i(t) = \sum_{m=1}^{K} s_m(t) e^{-j(i-1)k_m} + n_i(t) \qquad , i = 1,2,\cdots M \tag{1}$$

where $s_m(t)$ is the signal of the m^{th} wave, $n_i(t)$ is the noise signal received at the i^{th} sensor and

$$k_m = \frac{\omega_0 d}{c} \sin(\theta_m) \tag{2}$$

where d is the spacing between elements, c is the speed of light in free space. Using vector notation we can write the array output on the matrix form:

$$\mathbf{X}(t) = \mathbf{A}\,\mathbf{S}(t) + \mathbf{N}(t) \tag{3}$$

The received spatial correlation matrix, **R**, of the received noisy signals is given by,

$$\mathbf{R} = E\{\mathbf{x}\mathbf{x}^H \tag{4}$$

3. Radial Basis Function neural network

The architecture of the neural network [4],[5] used is shown in Figure 1 . The elements of the correlation matrix **R** are rearranged into a new input vector, **b**, which can be defined as

$$b = \left[R_{21},\cdots,R_{M2},R_{12},\cdots,R_{M2},R_{1M}\cdots,R_{M(M-1)}\right]^T \tag{5}$$

The input vector is then normalized by its norm in the training, testing and estimation phases, i.e.

$$\mathbf{z} = \frac{\mathbf{b}}{\|\mathbf{b}\|} \tag{6}$$

In order to reduce the dimension of the input layer, other preprocessing schemes have been suggested by researchers. The sum of the diagonal of the correlation matrix helps reduce the number of input nodes needed to 2M for an M element linear array. The training is performed offline by presenting input/output vector pairs ($\mathbf{b}$,θ) to the network.

Network generalization

The key to attain better generalization capability is in the selection of the training set. By including several angular separations in the training set such that the input vectors represent data of two sources with $\Delta\theta_1$, $\Delta\theta_2$, $\Delta\theta_3$ and so forth, it was found that the network can successfully estimate the directions of two sources with any separation. A high degree of accuracy can be obtained by selecting the $\Delta\theta$s fairly close, e.g. $2^0,4^0,6^0,\ldots\ \Delta\theta_{max}$.

4. Simulation results

Figure 2 shows an array of 8 elements trained and tested with the same angular separations of $3^0,5^0,10^0,25^0,30^0$. Figures 3 and 4 show the same array tested with angular separation that were not included in the training set. It can be seen that the network was able to generalize with good accuracy.

5. References

[1] D.Goryn and M.Kaveh."Neural networks for narrowband and wideband direction finding", *Proc. ICASSP*, pp.2164-67, April 1988.

[2] H.L.Southall, J.A.Simmers, and T.H.O'Donnell, " Direction finding in phased arrays with a neural network beamformer", *IEEE Transactions on Antennas and Propagation*, vol. 43, No.12, pp. 1369, December 1995.

[3] El Zooghby A. H., C.G. Christodoulou and M. Georgiopoulos," Performance of radial basis function networks for direction of arrival estimation with Antenna Arrays"; *IEEE Trans .on Antennas and Propagation*, vol. 45, No.11, pp. 1611-1617, November 1997.

[4] S.Haykin, Neural Networks A Comprehensive Foundation, Macmillan College Publishing, Ontario, 1994.

[5] T.J.Moody and C.J.Darken, "Fast learning in networks of locally tuned processing units", *Neural Computation*, vol.1, 281(1989).

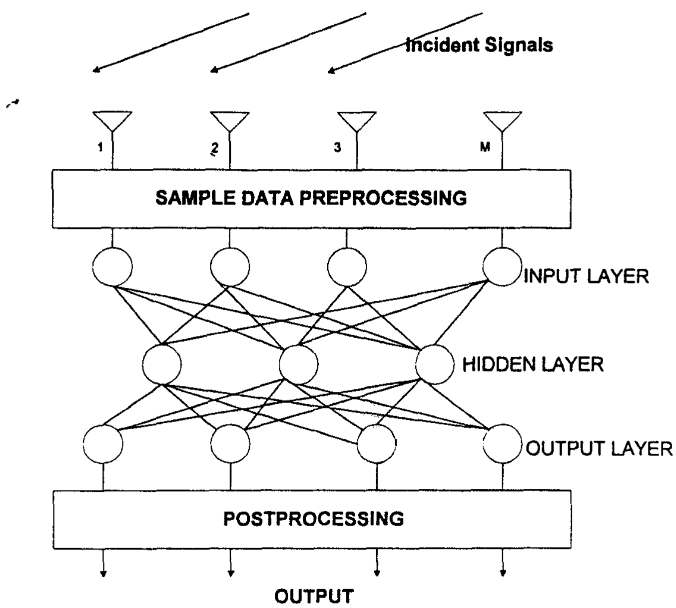

Figure 1 Neural network based array processing

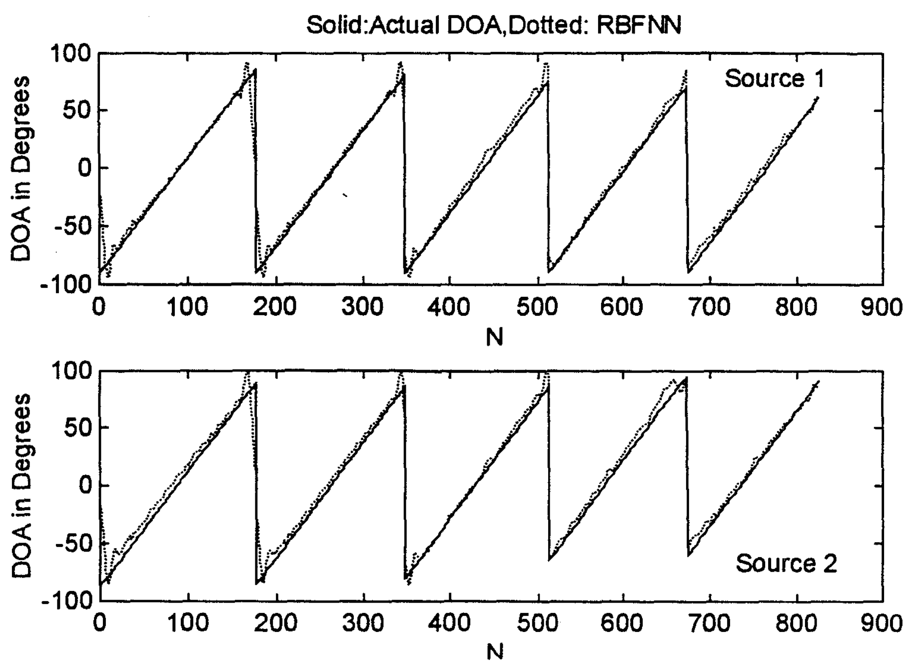

Figure 2 8 element array, Δθ=3,5,10,25,30 for training and testing

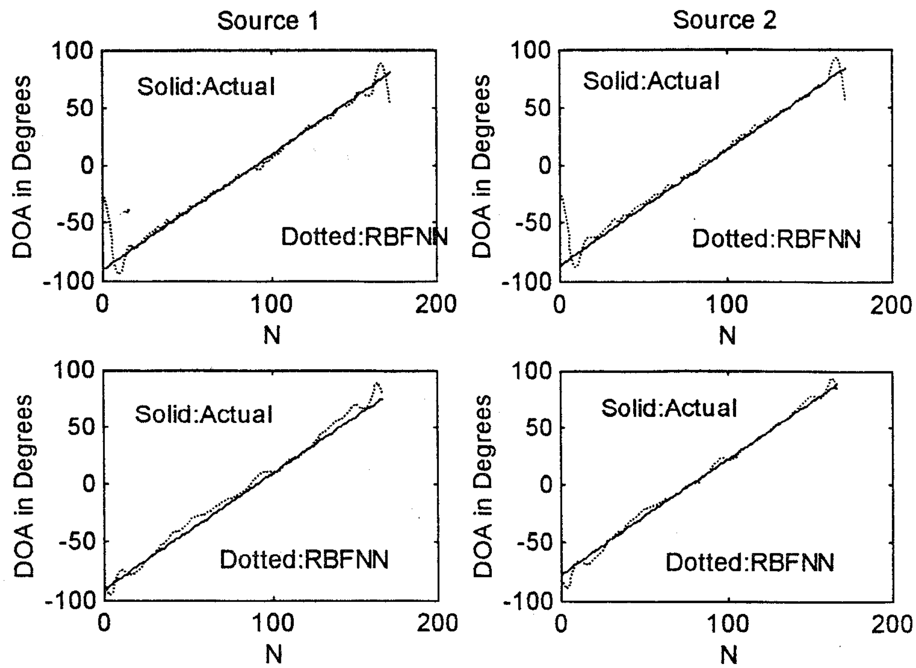

Figure 3 8 element array, $\Delta\theta$=3,5,10,25,30 for training and $\Delta\theta$ = 4,13 respectively for testing

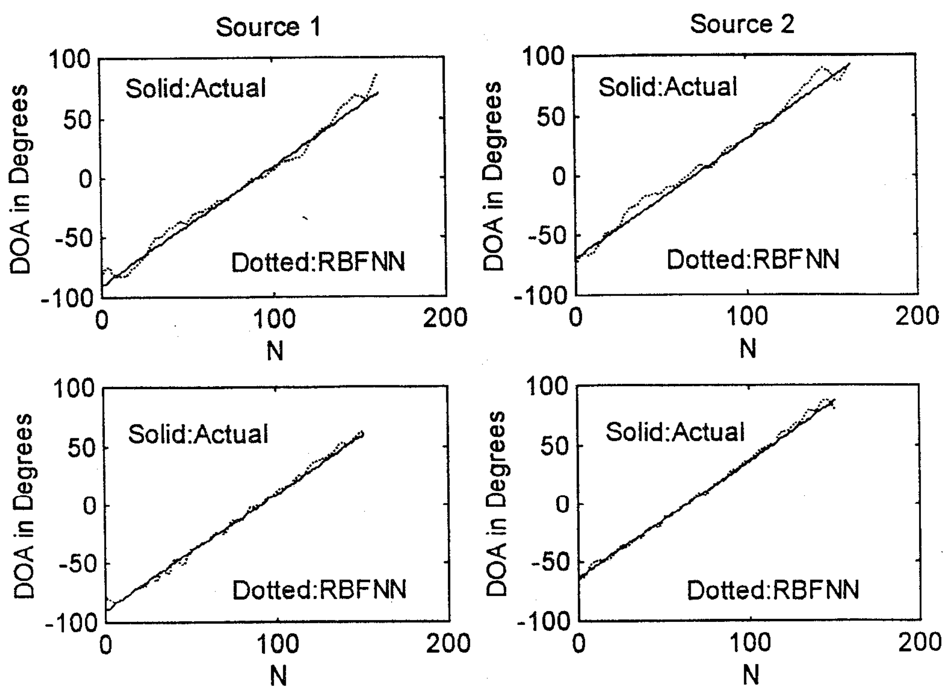

Figure 4 8 element array, $\Delta\theta$=3,5,10,25,30 for training and $\Delta\theta$ = 21,27 respectively for testing