Radial Basis Function Neural Network Algorithm For Adaptive Beamforming In Cellular Communication Systems

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Abstract

A smart antenna based on neural network implementation of the optimum Wiener solution for the problem of adaptive interference nulling using circular arrays is presented. Modern cellular, satellite mobile communications systems and in GPS systems suffer from different sources of interference which limit system. This paper develops a fast tracking system to constantly track the mobile users, and then adapt the radiation pattern of the antenna to direct multiple narrow beams to desired users and nulls to sources of interference. In the approach suggested here, the computation of the optimum weights is viewed as a mapping problem which can be modeled using a three-layer Radial Basis Function Neural Networks (RBFNN) trained with input /output pairs. The results obtained from this network are in excellent agreement with the Wiener solution. It was found that networks implementing these functions are successful in tracking mobile users as they move across the antenna's field of view.

1. Introduction

Multiple access techniques are often used to maximize the number of users a wireless communications system can accommodate. With frequency reuse, where the same frequency is used in two different cells separated far enough so that users in one cell do not interfere with the users in the other cell further improvements in the system capacity can be achieved. Moreover, adaptive arrays implemented in base stations allow for closer proximity of cofrequency cells or beams providing additional frequency reuse by rejecting or minimizing cochannel and adjacent channel interference. Motivated by the inherent advantages of neural networks, this paper presents the development of a radial basis function neural network-based algorithm to compute the weights of an adaptive array antenna . In this new approach, the adaptive array can detect and locate mobile users, track these mobiles as they move within or between cells, and allocate narrow beams in the directions of the desired users while simultaneously nulling unwanted sources of interference. This paper is organized as follows: In sections 2 a brief derivation of the optimum array weights in adaptive beamforming with circular arrays is presented. In Section 3 the RBFNN approach for the computation of the adaptive array weights is introduced. Finally, Section 4 presents the simulation results and Section 5 offers some conclusive remarks.

2. Adaptive beamforming with circular arrays

Using vector notation we can write the output of an M-element circular array, (see Figure 1), receiving K signals in a matrix form:

$$\mathbf{X}(t) = \mathbf{A}\,\mathbf{S}(t) + \mathbf{N}(t) \tag{1}$$

Where $\mathbf{A}$ is the steering matrix defined as:

$$\mathbf{A} = \left[a(\theta_1,\phi) \quad a(\theta_2,\phi) \quad \cdots \quad a(\theta_K,\phi)\right] \tag{2}$$

where $a(\theta_i,\phi)$ is given by

$$\mathbf{a}(\theta,\phi) = \left[e^{jkr\sin\theta\cos(\phi-\gamma_o)} \quad e^{jkr\sin\theta\cos(\phi-\gamma_1)} \quad \cdots \quad e^{jkr\sin\theta\cos(\phi-\gamma_{M-1})}\right]^T \tag{3}$$

where θ and ϕ are the elevation and azimuth angles,respectively.The spatial correlation matrix, $\mathbf{R}$, of the received noisy signals can be expressed as:

$$\mathbf{R} = E\{\mathbf{X}(t)\mathbf{X}(t)^H\} = A\,E[\mathbf{S}(t)\mathbf{S}^H(t)]A^H + E[\mathbf{N}(t)\mathbf{N}^H(t)]$$

$$= APA^H + \sigma^2 I = \sum_{i=1}^{M} \lambda_i \; e_i e_i^H \tag{4}$$

It can be shown that the optimal weight vector is given by[4]:

$$\hat{\mathbf{W}}_{opt} = \mathbf{R}^{-1}\mathbf{S}_d\left[\mathbf{S}_d^{\ H}\mathbf{R}^{-1}\mathbf{S}_d\right]^{-1}\mathbf{r} \tag{5}$$

In the above equation, **W** is the vector of the weights of the array element outputs, **r** is the V x 1 constraint vector, where V is the number of desired signals, and $\mathbf{S_d}$ is the steering vector associated with the look direction. Since the above equation is not practical for real time implementation, an adaptive algorithm must be used to adapt the weights of the array in order to track the desired signal and to place nulls in the direction of the interfering signals.

3. Neural Network –based interference cancellation:

This section describes a new implementation for the problem of beamforming using neural networks. The optimum weight vector is a nonlinear function of the correlation matrix and the constraint matrix. Therefore it can be approximated using a suitable architecture such as a radial basis function neural network. Note that a radial basis function neural network can approximate an arbitrary function from an input space of arbitrary dimensionality to an output space of arbitrary dimensionality. The RBFNN consists of three layers of nodes; the input layer, the output layer and the hidden layer. The input to the network is the correlation matrix **R** and the output layer consists of *2M* nodes to accommodate the output vector (i.e., $\mathbf{W}_{opt}$). The RBFNN is designed to perform an input-output mapping trained with examples ($\mathbf{R}^l$; $\mathbf{W}^l_{opt}$) ;l = 1,2,…,N_T, where N_T stands for the number of examples contained in the training set.

Generation of Training Data

1. Generate the spatial correlation matrix $\{\mathbf{R}^l; l = 1,2,\ldots,N_T\}$ using equation (4).
2. To reduce the number of input nodes, take the upper triangular part of $\mathbf{R}^l$ and rearrange the elements in a vector.
3. Normalize each one of the above vectors by its norm.
4. Using the calculated $\mathbf{R}^l$'s calculate the vectors $\{\mathbf{W}^l_{opt}; l = 1,2,\ldots, N_T\}$ from equation (5).
5. Produce the required training input/output pairs of the training set, that is $\{(\mathbf{R}^l; \mathbf{W}^l_{opt}); l = 1,2,\ldots,N_T\}$

Once the training data is generated, the RBFNN is trained to produce W^l_{opt} as output when it is presented with $\mathbf{R}^l$ as an input. After the RBFNN is trained with a representative set of training input/output pairs it is ready to function in the performance phase. In the performance phase, the RBFNN produces estimates of the optimum weights for the array outputs, through a simple, computationally inexpensive, two-step process, described below.

Performance Phase of the RBFNN

1. Generate **R** as described in steps 1-3 above.
2. Present the normalized array output vector at the input layer of the trained RBFNN. The output layer of the trained RBFNN will produce as an output the estimates of optimum weights for the array outputs (i.e., $\hat{\mathbf{W}}_{opt}$).

3. Simulation results

Figure 2 shows the adapted pattern of several circular arrays obtained from the RBFNN and how it compares with the optimum Wiener solution. The array has 13 elements, the power of the desired signal is10 dB while that of the interference is 30 dB. In Figure 3 the adapted pattern of an array of 16 elements tracking 4 signals with equal power of 10 dB is shown. It can be concluded from these figures that the RBFNN produced a solution for the beamforming weight vector that is very close to the optimum solution.

5. Conclusion

A new approach to the problem of adaptive beamforming was introduced. The weights were computed using an RBFNN that approximates the Wiener solution. The network was successful in tracking multiple users while simultaneously nulling interference caused by cochannel users.

6.Acknowledgement

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7. References

[1] 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.

[2] 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.

[3] Mozingo, Miller, Introduction to Adaptive arrays, John Wiley, 1980.

[4] El Zooghby A. H., C.G. Christodoulou and M. Georgiopoulos," adaptive interference cancellation in circular arrays with radial basis function neural networks", IEEE AP/URSI symposium, Atlanta, 1998.

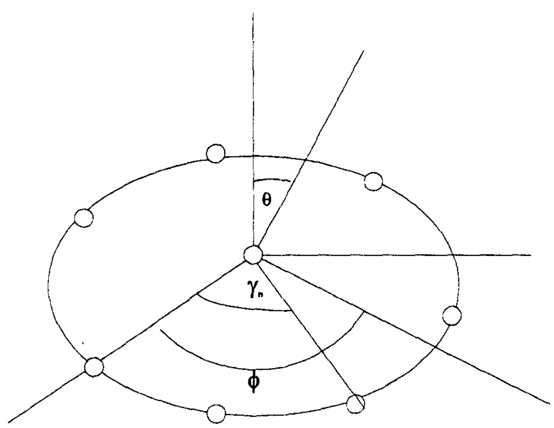

Figure 1 Circular Array geometry

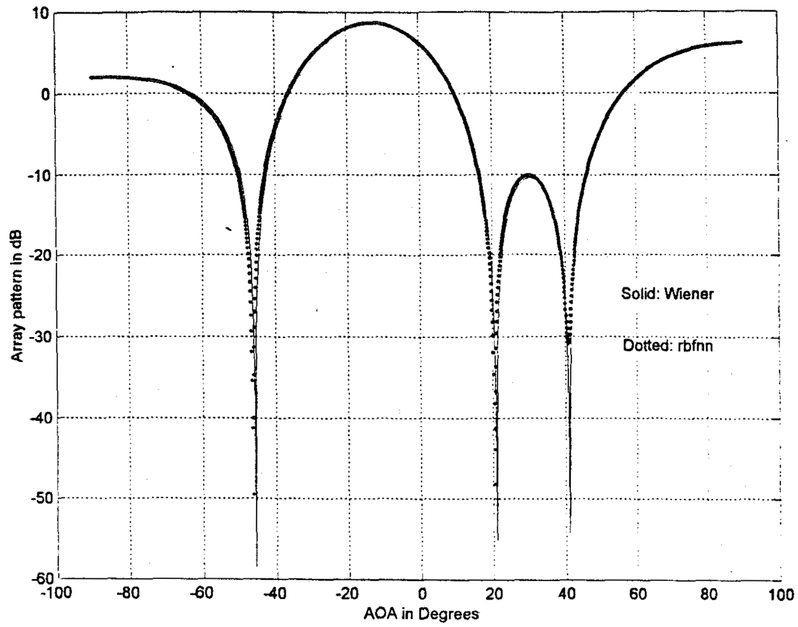

Figure 2 M=13, Signals are separated by 10^0 in the elevation in the $\phi=40^0$ plane. Radius is 0.7 λ, 1 desired signal(10 dB),2 interference(30 dB).

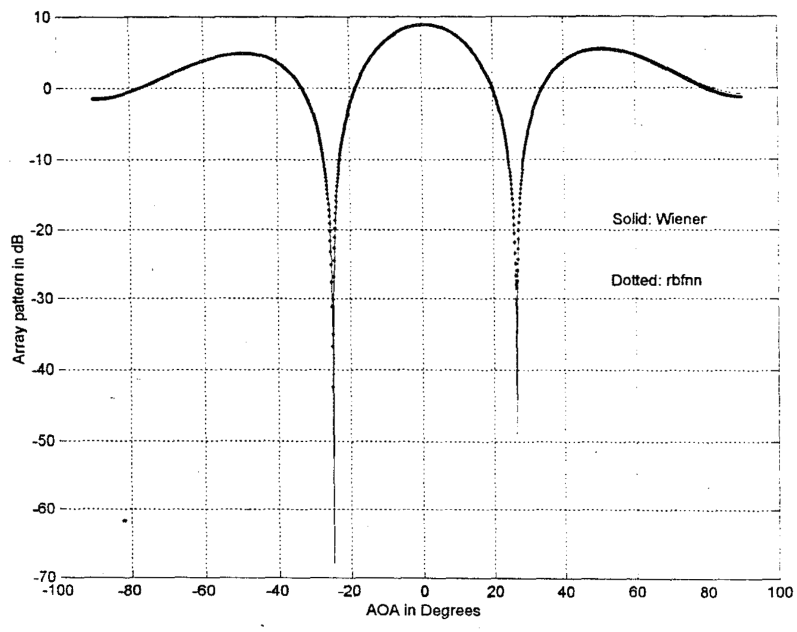

Figure 3 M=16, Signals are separated by 5^0 in the elevation in the $\phi=60^0$ plane. Radius is 0.7 λ, 2 desired signals(10 dB),2 interference(10 dB)