ADAPTIVE INTERFERENCE CANCELLATION IN CIRCULAR ARRAYS WITH RADIAL BASIS FUNCTION NEURAL NETWORKS

A.H.EL Zooghby, C. G. Christodoulou, and M. Georgiopoulos
Electrical and Computer Engineering Department
University of Central Florida
Orlando, Florida 32816

Abstract

A new neural network based approach to the problem of adaptive interference nulling using circular arrays is presented. In modern cellular, satellite mobile communications systems and in GPS systems, both desired and interfering signals change their directions continuously. This paper develops a fast tracking system to constantly track the 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.

I.Introduction

Interference rejection often represents an inexpensive way to increase the system capacity by allowing closer proximity of cofrequency cells or beams providing additional frequency reuse [1] in a cellular system. This paper presents the development of a neural network-based algorithm to compute the weights of an adaptive array antenna. In this new approach, the adaptive array can detect and estimate mobile users'locations([2],[3]), 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 adaptive antenna results in an increased system capacity for the existing cellular and mobile communications systems as well as improved interference rejection capabilities for satellite-based personal communication systems (PCS), geosynchronous satellites, low earth orbit satellites, and global positioning systems (GPS). The organization of the paper is as follows: In section II,a brief derivation of the optimum weights of a circular array for adaptive beamforming is presented. The RBFNN approach for the computation of the adaptive array weights is introduced in section III. Finally, Section IV presents the simulation results and Section V offers concluding remarks.

II. 1-D Adaptive beamforming

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 **A** is the steering matrix defined as:

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

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

$$\mathrm{a}(\theta,\phi) = \left[e^{jkr\sin\theta\cos(\phi-\gamma_0)} \quad e^{jkr\sin\theta\cos(\phi-\gamma_1)} \quad \cdots \quad e^{jkr\sin\theta\cos(\phi-\gamma_{M-1})}\right]^T \tag{3}$$

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

$$\begin{aligned} \mathbf{R} &= E\{\mathbf{X}(t)\mathbf{X}(t)^H\} = A\,E[\mathbf{S}(t)\mathbf{S}^H(t)]A^H + E[\mathbf{N}(t)\mathbf{N}^H(t)] \\ &= APA^H + \sigma^2 I = \sum_{i=1}^{M} \lambda_i \; e_i e_i^H \end{aligned} \tag{4}$$

P is the power matrix of the signals and λ_i are the eigenvalues of R. To derive the optimal weight vector, the array output is minimized so that the desired signals are received with specific gain, while the contributions due to noise and interference are minimized [4]. In other words:

$$\min \mathbf{W}^H \mathbf{R} \mathbf{W} \qquad \textit{subject to } \mathbf{W}^H \mathbf{S}_d = \mathbf{r} \tag{5}$$

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. It can be shown that the optimum weight vector is given by the following equation:

$$\hat{\mathbf{W}}_{opt} = \mathbf{R}^{-1}\mathbf{S}_d\left[\mathbf{S}_d^H \mathbf{R}^{-1}\mathbf{S}_d\right]^{-1}\mathbf{r} \tag{6}$$

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.

III. 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. In our application the input layer consists of $J=2M$ nodes for an M element circular array, to accommodate both the real and the imaginary part of the input vector (i.e., **X(t)**). The output layer consists of $2M$ nodes to accommodate the output vector (i.e., $\mathbf{W}_{opt}$). As it is the case, with most neural networks the RBFNN is designed to perform an input-output mapping trained with examples ($\mathbf{X}^l(t)$; $\mathbf{W}^l_{opt}$) ;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 array vectors {$\mathbf{X}^l(t)$) ;l = 1,2,...,N_T} using equation (1).

2. Normalize each one of the above array vectors by its norm. For simplicity of notation we still refer to these vectors by $\mathbf{X}(t)$'s.
3. Evaluate the correlation matrix $\mathbf{R}^l$ ($l = 1,2,\ldots, N_T$) for each of the array output vectors generated in Step 1; to do so use equation (2). Using the calculated $\mathbf{R}^l$'s calculate the vectors $\{\mathbf{W}^l_{opt};\ l = 1,2,\ldots, N_T\}$ from equation (6).
4. Produce the required training input/output pairs of the training set, that is $\{(\mathbf{X}^l(t);\ \mathbf{W}^l_{opt})\ ; l = 1,2,\ldots,N_T\}$

Once the training data is generated, the RBFNN is trained to produce W^l_{opt} as output when it is presented with $x^l(t)$ 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 the array output vector $\hat{\mathbf{X}}(t)$. Normalize this array output vector by its norm.
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., $\hat{\mathbf{W}}_{opt}$).

IV. 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. In Figure 2-a, the arrays have 11 and 9 elements, respectively, while the desired signal and the interference have the same power. Figure 2-b shows an array of 7 elements receiving one GPS signal at 18^0 of power 0 dB, while the power level of each of the two interfering signals is at 30 dB. 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.

V. 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.

VI. References

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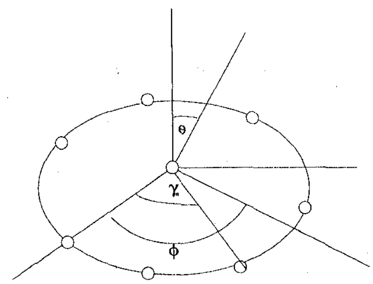

Figure 1 Circular Array geometry

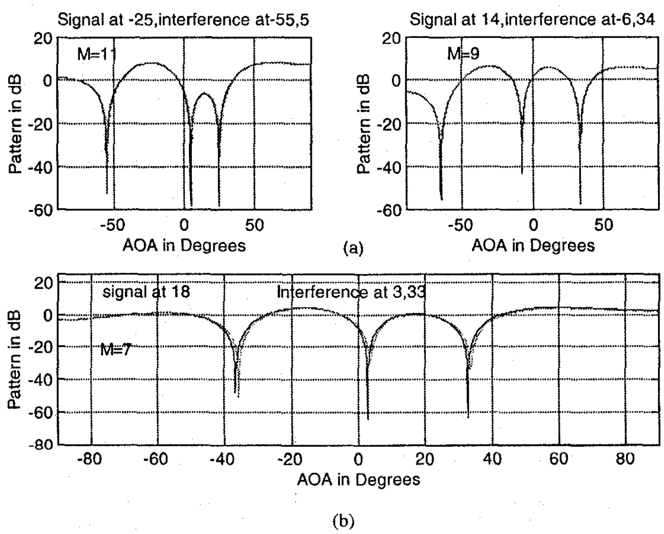

Figure 2 (a) Circular array of 0.8λ radius, equipower signals (10 dB), noise(0 dB), Solid: Desired Pattern, Dotted: RBFNN
(b) Circular array of 0.871λ radius, Solid: Desired Pattern, Dotted: RBFNN, desired signal power (0dB), interfering signal power(30 dB)