A Neural Network Approach to Design of Smart Antennas for Wireless Communication Systems

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Signal processing with neural networks has become popular in recent years. The inherent merits of neural networks make it attractive in many applications. In this paper, we propose the use of cross-correlation neural network models which makes use of the cyclostationary property inherent in many communication signals to perform blind beamforming.

The proposed approach is based on two sets of linear neurons with cross-coupled Hebbian learning rules orthogonalized to each other. Taking the array data and its time-frequency translated version as inputs, the neural network extracts and separates the desired signals simultaneously. This approach may have advantages in multi-user wireless communications where the co-channel interference condition is severe or the number of interferences is larger than the number of array elements.

1. Introduction

Signals in wireless communications suffer distortions such as multipath fading, co-channel interference and noise. Adaptive arrays can reduce these distortions. Conventional approach is to transmit a reference signal or to estimate the direction of arrival of the signal of interest followed by a constraint optimization rule. However the transmission of a reference signal decreases channel efficiency and the estimation of direction of arrival is difficult in a multipath reflection environment. Such factors limit its applications. Morever, if the number of interferences exceed the number of array elements the performance is degraded. Recently, blind beamforming algorithms exploiting the cyclostationary properties inherent in many communications signals have been developed [1] [3] [4]. These algorithms do not need prior information about the reference signals and the directions of arrival of the signals of interest. However, many of them suffer from slow convergence speed or high computational complexity. In this paper, we present a neural network solution to the blind beamforming of cyclostationary signals.

The word *cyclostationary* refers to the fact that the statistical properties of a signal vary periodically with time. The periodic-time varying components exhibit lines (impulse functions) in the spectrum at frequencies which are referred to as the *cyclic frequencies.* It has been shown that many communications signals subject to periodic transformations, such as modulation, sampling, coding, multiplexing, etc., are cyclostationary [2]. Signals with different periodic transformation schemes tend to generate spectral lines at different cyclic frequencies. By analyzing the cyclic spectrums, signals from different periodic time-varying sources can be differentiated.

A neural network is a computational model based on the biological nervous system. The neural network is composed by a set of neurons connected to each other. The output of a neuron is a function of the sum of the weighted outputs from other neurons as well as any external inputs. By repetive presentation of a stimulus to the input, the weights of the network are trained to converge to a set of stable values using a suitable learning algorithm.

In this paper, we consider the use of neural networks to perform adaptive beamforming of cyclostationary signals. A learning algorithm based on the Hebbian learning rule is developed. Simulation results demonstrate that the proposed network performs well in a variety of co-channel interference environments.

2. Cyclostationarity

For a cyclostationary signal $s(t)$, its autocorrelation function can be represented by a Fourier series expan-

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sion of the form

$$R_s(t,\tau) = \sum_\alpha R_{ss}^\alpha(\tau)e^{j2\pi\alpha t} \quad (1)$$

The Fourier coefficients in the above expansion represent the *cyclic autocorrelations*

$$R_{ss}^\alpha(\tau) = < s(t)s^*(t-\tau)e^{-j2\pi\alpha t} > \quad (2)$$

where $< \cdot >$ denotes the infinite durarion time-averaging operation. The *conjugate cyclic autocorrelation* is defined as

$$R_{ss^*}^\alpha(\tau) = < s(t)s(t-\tau)e^{-j2\pi\alpha t} > \quad (3)$$

Let

$$u(t) = s(t)e^{-j2\pi\alpha t} \quad (4)$$

Then the cyclic autocorrelation of $s(t)$ can be represented by the cross-correlation of $s(t)$ and $u(t)$, i.e.

$$R_{ss}^\alpha(\tau) = R_{su}(\tau) \quad (5)$$

where

$$R_{su}(\tau) = < s(t)u^*(t-\tau) > \quad (6)$$

The nonzero strength of $R_{su}(\tau)$ reveals that $s(t)$ is correlated with its frequency translated version $u(t)$.

Let the array data be given by

$$\mathbf{x}(t) = \mathbf{A}(\theta)\mathbf{s}(t) + \mathbf{n}(t) \quad (7)$$

where $\mathbf{A}(\theta)$ is the *array manifold*

$$\mathbf{A}(\theta) = [\mathbf{a}(\theta_0), \mathbf{a}(\theta_1), \ldots, \mathbf{a}(\theta_{N-1})] \quad (8)$$

$\mathbf{s}(t)$ is the signal vector

$$\mathbf{s}(t) = [s_0(t), s_1(t), \ldots, s_{N-1}(t)]^T \quad (9)$$

and $\mathbf{n}(t)$ reprents the array noise.

Let $\mathbf{u}(t)$ be the frequency translated version of the array data $\mathbf{x}(t)$, i.e.

$$\mathbf{u}(t) = \mathbf{x}(t)e^{j2\pi\alpha t} \quad (10)$$

Then the cyclic autocorrelation matrix of $\mathbf{x}(t)$ is equivalent to the cross-correlation matrix of $\mathbf{x}(t)$ and $\mathbf{u}(t)$:

$$\mathbf{R}_{\mathbf{xx}}^\alpha(\tau) = \mathbf{R}_{\mathbf{xu}}(\tau) \quad (11)$$

Let $y(t)$ be a linear combination of the array elements in $\mathbf{x}(t)$ and $r(t)$ be a linear combination of the array elements in $\mathbf{u}(t)$, i.e.

$$y(t) = \mathbf{w}^H\mathbf{x}(t) \quad (12)$$

$$r(t) = \mathbf{c}^H\mathbf{u}(t) \quad (13)$$

where $\mathbf{w}$ and $\mathbf{c}$ are complex weight vectors. We can maximize the cross-correlation between $y(t)$ and $r(t)$ subject to the constraint that $\mathbf{w}^H\mathbf{w} = 1$ and $\mathbf{c}^H\mathbf{c} = 1$, i.e.

$$\max_{\mathbf{w},\mathbf{c}} \frac{|\mathbf{w}^H\mathbf{R}_{\mathbf{xu}}\mathbf{c}|^2}{[\mathbf{w}^H\mathbf{w}][\mathbf{c}^H\mathbf{c}]} \quad (14)$$

The solutions obtained from the above maximization are the singular vectors of the cross-correlation matrix $\mathbf{R}_{\mathbf{xu}}$ in which $\mathbf{w}$ is related to the direction of arrival of the cyclostationary signal [5].

3. Neural Network Beamforming

Our beamforming approach is based on the cross-correlation neural network model proposed by Kung [6]. The neural network consists of two sets of linear neurons laterally connected to each other as shown in Figure (1).

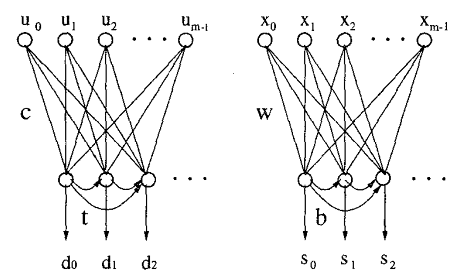

Figure 1. Cross-Coupled Orthogonalization Network Model

The inputs to the neural network are the array data $\mathbf{x}(t)$ and its time-frequency translated version $\mathbf{u}(t-\tau)$. The learning rules for the input weights are given as follows:

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \eta_i\mathbf{x}(t)d_i^*(t) \quad i = 0,1,\ldots,L-1 \quad (15)$$

$$\mathbf{c}_i(t+1) = \mathbf{c}_i(t) + \eta_i\mathbf{u}(t)s_i^*(t) \quad i = 0,1,\ldots,L-1 \quad (16)$$

and the learning rules for the lateral connection weights are

$$\mathbf{b}_i(t+1) = \mathbf{b}_i(t) + \mu_i\mathbf{s}_i(t)s_i^*(t) \quad i = 0,1,\ldots,L-1 \quad (17)$$

$$\mathbf{z}_i(t+1) = \mathbf{z}_i(t) + \mu_i\mathbf{d}_i(t)d_i^*(t) \quad i = 0,1,\ldots,L-1 \quad (18)$$

where η_i and μ_i are learning constants and $\mathbf{s}_i$, $\mathbf{d}_i$ are the output vectors. The element of $\mathbf{s}_i$ and $\mathbf{d}_i$ are given by

$$s_j(t) = \frac{\mathbf{p}_j^H(t)}{||\mathbf{p}_j(t)||}\mathbf{x}(t) \quad j = 0,1,\ldots,i \quad (19)$$

$$d_j(t) = \frac{\mathbf{q}_j^H(t)}{||\mathbf{q}_j(t)||}\mathbf{u}(t) \quad j = 0, 1, \ldots, i \tag{20}$$

where

$$\mathbf{p}_j = \mathbf{w}_j(t) - \sum_{k=0}^{k<j} b_k^*(t)\mathbf{w}_k^*(t) \tag{21}$$

$$\mathbf{q}_j = \mathbf{c}_j(t) - \sum_{k=0}^{k<j} z_k^*(t)\mathbf{c}_k^*(t) \tag{22}$$

4 Computer Simulations

In our simulations, we assume that all the impinging signals have the same carrier frequency f_c subject to BPSK modulation with 100% roll-off raised-cosine pulse shape at different symbol rates f_{T_i}. A 4-element uniform linear array with one half wavelength seperation distance between each element is employed. The output of each element is routed to a receiver where the received signals are down-converted to its baseband ($f_c = 0$). The baseband signals are then sampled at a fixed rate f_s. The receiver noise is assumed to be of unit variance and temporally and spatially uncorrelated at each element. The input power of each signal is given in dB relative to the element noise power. The symbol rate of each signal is normalized by the sampling rate, for example, $f_{T_i} = 0.1$ represents 10 samples in a symbol. The directions of arrival of the impinging signals are given in degree relative to its normal.

The initial weights for the neural network are set to be $\mathbf{w}_i = [1, 1, \ldots, 1]$, $\mathbf{c}_i = [1, 1, \ldots, 1]$ and $\mathbf{b}_i = \mathbf{0}$, $\mathbf{z}_i = \mathbf{0}$, for all i. The input weight learning constants ν_i are set to be arround $\frac{1}{100}$ of the input amplitude of the signals of interest s_i. The output weight learning constants μ_i are set to be around $\frac{1}{100}$ of the difference between the amplitudes of the signals of interest s_i and s_{i-1}.

Experiment 1

Two BPSK signals with different symbol rate are impinging on the array. Signal 1 has SINR=18.33dB with symbol rate 0.1 arriving at 30°. Signal 2 has SINR=20.59dB with symbol rate 0.25 arriving at −30°. The frequency shift α is set to be the same as the symbol rate of Signal 1. The input learning constant η_0 is set to be 0.025. The array pattern of the first node at t=600 is shown in Figure (2). It shows that the neural network converges to the direction of arrival of Signal 1 even though Signal 2 has higher power.

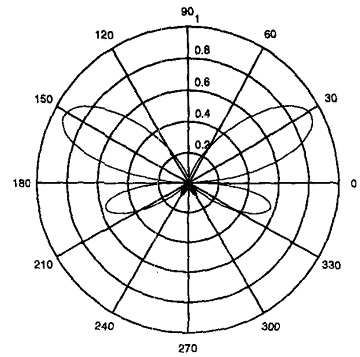

Figure 2. Array Pattern of the 1st Node

Experiment 2

Two BPSK signals with the same symbol rate 0.1 are impinging on a 4-element array. Signal 1 has SINR=18.33dB arriving at 30°. Signal 2 has SINR=13.86dB arriving at −30°. The frequency shift α is set to be the same as the symbol rate. The input learning constants η_0, η_1 are set to be 0.025, 0.02. The output learning constant μ_1 is set to be 0.005. The array pattern of the first and second node at t=600, see in Figure (3) and Figure (4), show that the neural network converges to the directions of arrival of the signals of interest accurately.

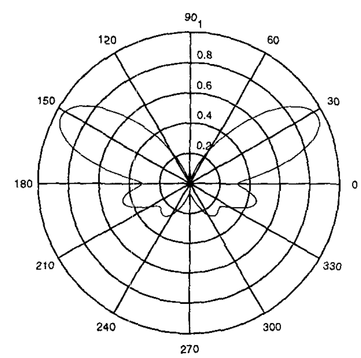

Figure 3. Array pattern of the 1st Node

5. Conclusion

We have shown that our neural network model converges to the directions of the signals of interest. The advantages of our approach is sumarized below: 1. The neural network performs beamforming without the

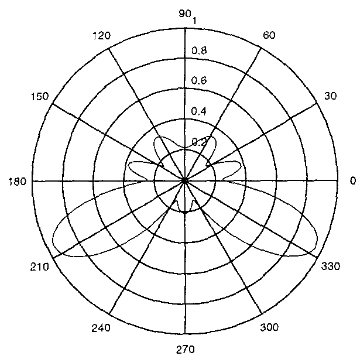

Figure 4. Array pattern of the 2nd Node

need of prior information about the directions of arrival or reference signals. 2. The neural network can operate in an environment where the total number of impinging signals is greater the the total number of array elements. 3. The neural network can extract and separate the desired signals simultaneously.

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