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A neural network approach of Ultra-wideband Nearfield Adaptive Beamforming

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Abstract. An adaptive beamforming method for ultrawide-band (UWB) array in the case of nearfield is proposed based on the radical basis function neural network (RBFNN) in this paper. The desired outputs corresponding with measured inputs for the nearfield impulse source are reflected into a set of training samples. Genetic algorithm and recursive least square algorithm are employed to determine the structure and the parameters of RBFNN. It can avoid the computation of an inverse matrix and alleviate the impact of the mutual coupling phenomenon. The experimental results also prove its efficiency and feasibility.

1 Introduction

Recently with the development of emerging ultra wideband (UWB) technology in noise radar, UWB positioning system and impulse-radio communication, the principle of space-time processing can be also applied in the design and research of the UWB system [1][2][3]. The common UWB beamforming method is to compensate time delay using a time delay-sum beamformer in UWB system. But time-delay in channels cannot be estimated accurately and compensated in easy. In the other hand, the UWB array should concerned a wide range of frequency band, and its response varies with frequency obviously. Moreover, many application occasions of the UWB pulse array cannot satisfy an ordinary farfield condition, such as in some scenarios of medical diagnosis appliances [3]. It is well know that dynamically adaptive beamformers can achieve better performance than fixed-weight beamformers when noise and interference are time-varying or location is unknown. Unlike usual monochromatic and broad electromagnetic (EM) waves, the radiated and received UWB signals are easy to be affected by the characteristics of propagation channels. One mainly problem is the mutual coupling between antennas, which should be considered for a class of EM waves with a UWB spectrum impinging on an antenna array while it is negligible in the most methods of beamforming such as linear constrained minimize variance (LCMV) method and the time domain method. The goal of this paper is to consider the adaptive realization of nearfield beamforming in UWB pulse array.

Neural methods have been applied for antenna array signal processing and reveal a lot of advantages [4][5]. In this paper, we attempt to examine the method of the radical basis function neural network (RBFNN) for the adaptive beamforming of nearfield UWB array. The construction of the network and its learning algorithm are depicted in detail. For the good characteristic of neural network (NN) such as its large capacity, parallelism, nonlinear mapping and self-learning, RBFNN can fulfill a rapid implementation of beamforming and is more robust to the environment disturbance.

Experimental results obtained with linear equi-spacing array processing UWB pulses train signal help to assess the usefulness of the proposed method.

2 Nearfield beamforming of UWB array

The commonly used UWB signal model is Gaussian impulse waveform, which is of high resolution and penetration for its very short duration. We give a representation of generalized Gaussian pulse (GGP) which has been tested in the transmission and receiving experiment in the following:

$$\Omega(t) = \frac{E_0}{1-\alpha}\left\{ e^{-4\pi\left(\frac{t-t_0}{\Delta T}\right)^2} - \alpha e^{-4\pi\alpha^2\left(\frac{t-t_0}{\Delta T}\right)^2} \right\} \tag{1}$$

Here E_0 is the peak amplitude at the time $t=t_0$ (usually E_0=1), $\triangle T$ is a nominal duration, and a is a scaling parameter.

Paper [2] gives a structure of UWB array beamformer with a linear array with omnidirectional sensors uniformly spaced. An adjustable digital delay line or transverse filter is employed to obtain the compensation of time delay. Thus a beam can be formed in the direction of desired signal.

Given the radial distance r_m, azimuth θ_m, and elevation angle ϕ_m in planar coordinate system. Consider a beamformer processing UWB pulse signal with M elements and K taps attached at each element. The elements of the array are located at $\{\mathbf{x}_m = (r_m, \theta_m)\}$, $m = 1,2,...,M$. The coordinate system is defined such that its origin is at the phase center of the array. If the signal target is located at $\mathbf{x}_s = (r_s, \theta_s)$ with $r_s < R_a^2/\lambda$, where R_a^2 is the largest array dimension and λ is the operating wavelength, the near-field propagation model is required and the near-field steering vector of the array beamformer is defined as [6]:

$$\mathbf{a}(\mathbf{x}_s, f) = \frac{r_s}{e^{j2\pi f r_s/c}}\left[\frac{e^{j2\pi f r_{1s}/c}}{r_{1s}}, ..., \frac{e^{j2\pi f (r_{ms}/c-k)}}{r_{ms}}, ..., \frac{e^{j2\pi f (r_{Ms}/c-K+1)}}{r_{Ms}}\right]^T \tag{2}$$

where f is the frequency, c is the propagation speed, $r_s = |\mathbf{x}_s|$ and $r_{ms} = |\mathbf{x}_m - \mathbf{x}_s|$ are the distances from the signal source to the phase center of the array and m-th element, respectively. For the incidence of an UWB EM wave formed by GGP trains, the representation of induced voltage included a coupling matrix $\mathbf{C}$ can be written as [7]:

$$\mathbf{u}(t) = \mathbf{C}\mathbf{a}(\mathbf{x}_s, f)\mathbf{s}(t) + e(t) \tag{3}$$

$$\mathbf{C} = (Z_A + Z_T)(Z + Z_T I)^{-1} \tag{4}$$

where $\mathbf{a}(\mathbf{x}_s, f)$ is the theoretical response matrix with size $MK \times L$ at incidence angle $\mathbf{x}_s$, $\mathbf{s}(t)$ is ultra wideband source compound with L monochromatic frequencies, Z_A is antenna impedance, Z_T is the impedance of measurement equipment at each element, Z is the mutual coupling matrix. The frequency response of beamformer and the output $y(k)$ can be expressed as matrix form in frequency domain:

$$\mathbf{b}(f, \mathbf{x}_s) = \mathbf{G}^H(f)\mathbf{a}(f, \mathbf{x}_s) \tag{5}$$

$$\mathbf{y}(f) = \mathbf{G}^H(f)\mathbf{C}^{-1}\mathbf{u}(f) \tag{6}$$

$$\mathbf{G}(f) = [g_1^*(f)\ g_2^*(f) ... g_M^*(f)]^H \tag{7}$$

Here $g_m(f)$ is the response of each element channel.

Using the LCMV method, the nearfield adaptive beamformer tries to minimize the output power subject to some constraints. If the point number L of $\mathbf{b}(f,\mathbf{x})$ is less than free degrees $N = MK$ of matrix $\mathbf{G}(\omega)$, equation (5) can be treated as the L linear constraints. Assume $\mathbf{R_{uu}}$ denotes the covariance matrix of input vector $\mathbf{C}^{-1}\mathbf{u}(k)$ measured and $\mathbf{A}$ is steering matrix, the optimal solution to the constrained minimization problem is obtained by:

$$\mathbf{G}_{opt} = \mathbf{R}_{\mathbf{uu}}^{-1}\mathbf{A}(\mathbf{A}^H \mathbf{R}_{\mathbf{uu}}^{-1}\mathbf{A})^{-1}\mathbf{b}(f,\mathbf{x}_s) \tag{8}$$

Theoretically, the matrix $\mathbf{C}$ related to nearfield position $\mathbf{x}_s$ could be determined if occupied frequency spectrum is known and a compensation matrix $\mathbf{C}^{-1}$ can be constructed. But in fact the $\mathbf{C}$ tends to vary with the changes of environment. Some presented compensation approaches of mutual matrix $\mathbf{C}$ are complicated and based on some approximate hypotheses. So they lack in some robustness to a certain extent. In following, we will examine a neural networks method for UWB signal beamforming over a near-field spatial region and its benefit in resisting the mutual coupling phenomenon.

3 Adaptive beamforming by Radical Basis Function Network

Paper [8] shows analogy of spatio-temporal processing between the biological neuron and digital spatio-temporal neural network system. RBFNN is derived form regular theory and has the optimal approximation ability for complicated functions [9][10]. It has a faster learning speed compared to global methods, such as the MLP with BP rule, and only part of the input space needs to be trained. The structure of the RBFNN for the beamforming of UWB array is shown in Fig.1. Assume the number of nodes in input layer, hidden layer and output layer are M, J and P respectively.

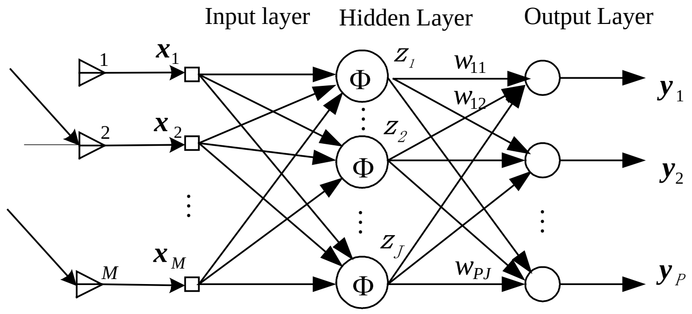

Fig.1: The structure of a RBFNN

Denote $\|X - C_j\|$ as the distance of input X=[x_1, x_2,…, x_M] to the j-th center C_j=[c_{j1}, c_{j2},…, c_{jL}]. The output of the j-th node for the n-th sample of the hidden layer is:

$$z_j = \Phi(\|X_n - C_j\|) = \exp[-\sum_{i=1}^{M}(x_i - c_{ji})^2 / \sigma_{ji}{}^2] \tag{9}$$

where σ_{ji} is the radius of the j-th Gaussian function in the hidden layer, and c_{ji} is the

i-th component of the j-th center. A linear layer then follows:

$$y_i = w_{i0} + \sum_{j=1}^{J} w_{ij} Z_j \quad (i=1,\ldots,P) \tag{10}$$

where y_i is the output of i-th neuron, w_{ij} is the connect weight of the j-th hidden neuron to the i-th output neuron and w_{i0} is the threshold of the i-th output neuron.

The beamformers for UWB pulse array can be regarded as a complex nonlinear system with delay. For UWB nearfield array described in above, the input data is given as GGP signal train and transformed into domain by FFT. Select the several signal source located in $\mathbf{x}_s$ uniformly distributed in the interested nearfield region. Firstly we should know the desired response of beamformer over the selected position. The $\mathbf{b}(f,\mathbf{x}_s) = \mathbf{b}_d(f,\mathbf{x}_s)$ is the dedicated response of UWB array without distortion in main bandwidth of UWB signal. Then from equation (5) we can obtain the $G(f)$. For the input samples, the desired output can be obtained from equation (6)(7), which makes up of the training sample set.

As we all know, the determination of the structure of the network, that is, the number of hidden neurons M is a headachy task in the training. A most often used approach is an experiential try. Take the error function in (12) as the cost function, here we use genetic algorithm (GA)[11] to determine M. Assume the incidence angle varies from -90° to + 90, and the training data are obtained by a sampling spaced d. Input them into the network, such a learning algorithm follows: 1. Firstly a random population is generated where each individual represent a network with different M; 2. For each network that is corresponding to an individual, a self-organized clustering learning method is used to select the centers of the basis function, and the variance is selected by a gradient descent algorithm. For the weight of output layer, a recurrent least square (RLS) is used. Let $W_k(n)=[W_{k0}(n),.., W_{kM}(n)]^T$ (k=1,..,N), $\boldsymbol{Z}(n)=[z_1(n),.., z_M(n)]^T$, then the K-th output is:

$$y_k(t) = \sum_{i=0}^{M} W_{ki}(t) z_i(t) = Z^T(t) \cdot W_k(t) \tag{11}$$

Define such a weighted error function J:

$$J(n) = \frac{1}{2}\sum_{i=1}^{n} \lambda^{n-i} \sum_{k=1}^{N} (d_k(t) - y_k(t))^2 = \lambda J(n-1) + \frac{1}{2}\sum_{k=1}^{N} [d_k(n) - Z^T(n)\hat{W}_k(n-1)]^2 \tag{12}$$

where λ is the weighted forget parameter which smoothes the effect of the foregoing samples little by little. Let $P(n) = \hat{R}^{-1}(n)$, the RLS algorithm is as follows:

$$\begin{aligned} K(n) &= \frac{P(n-1)\cdot Z(n)}{\lambda + Z^T(n)\cdot P(n-1)\cdot Z(n)} \\ P(n) &= \frac{1}{\lambda}[P(n-1) - K(n)Z^T(n)P(n-1)] \\ \hat{W}_i(n) &= \hat{W}_i(n-1) + K(n)[d_i(n) - Z^T(n)\hat{W}_i(n-1)] \end{aligned} \tag{13}$$

Train the network using (13), obtained J is use to define the fitness function of the population F=1/J. 3. Compute all the fitness functions, and a selection is executed. 4. Perform the crossover and mutation on the population. 5. Judge the stop condition, when the iteration number exceeds a given I or the obtained J is small enough, stop, else go to step 2. When the iteration process is completed, all the parameters are determined, so we can use the network in the beamforming.

4 Experiments and Preliminary Results

We demonstrate the feasibility of our constructed RBFNN in UWB array beamforming by applying it to a uniform linear array with element number M=11.

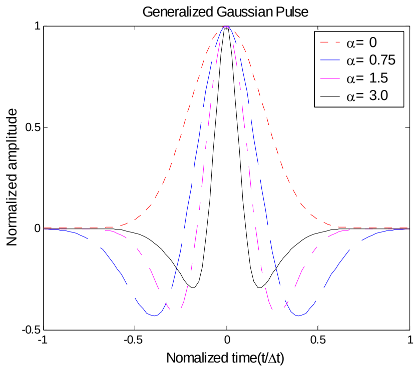

Fig.2: UWB monocyle waveform of GGP

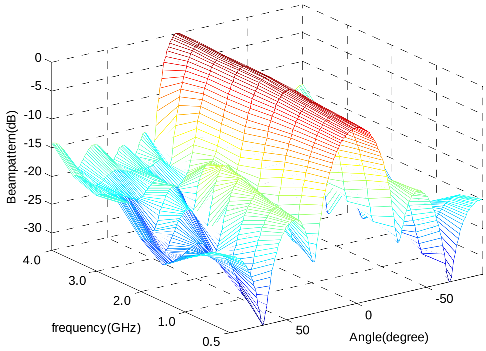

Fig.3: The Distortionless Nearfield UWB beampattern in certain bandwidth using RBFNN

The UWB signal being used in the experiments is a monocycle of GGP with nominal duration time $\Delta T = 2ns$, sample period $T_s = 100ps$. The time variation of the GGP with different values of α is plotted in Fig.2.

The system is trained to steer its beams toward desired UWB signals coming from the angle 30^0. The snap number is 200. In the RBFNN, the training samples of the network are obtained by a uniform sampling of θ from -90° to + 90° spaced s° . For the obtained network which has the optimal structure, Fig.4 gives variation of error with the iteration times in different *s*, from which we can see that more training samples we use, more fast of the convergence of the network. The performance of our method is also related with the parameters of the genetic algorithm, such as the probabilities of crossover p_c and mutation p_m, and the given number of iterations. Table 1 gives the average sidelobe suppression effect of beamformer with different p_c and p_m. Comparing with LCMV that neglect the mutual coupling compensation, the RBFNN method can improve the robustness resisting the mutual coupling phenomenon. From it, we can

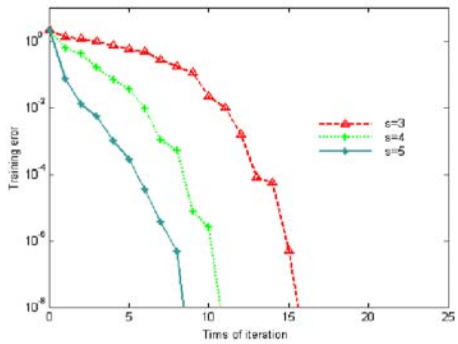

Fig.4: Convergence curves for different training samples

see that the performance of RBFNN beamformer is the highest when p_c=0.8 and p_m=0.2.

Iterations	p_c	p_m	Sidelobe suppression	
			LCMV	RBFNN
1000	0.9	0.1	-10.3db	-11.5db
1000	0.8	0.2	-12.05db	-14.7db
1000	0.7	0.3	-11.4db	-13.1db
1000	0.6	0.4	-10.9db	-11.8db

Table 1: The SINR of FIR and RBFNN beamformer with different p_c and p_m.

5 Conclusions

Preliminary simulation, experimental results for adaptive nearfield UWB array beamforming based on radical basis function neural network is examined in the paper. It can be inferable that neural network approach for nearfield beamforming of UWB array is helpful to reduce the influence of mutual coupling existing the UWB antennas array. The feasibility of this method is verified. But more improvement remains to do in further work.

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