Research on smart antenna beamforming by generalized regression neural network

Bin Pei[1,2], Hui Han[1], Ying Sheng[2], Bingyi Qiu[2]
1. The state key laboratory of complex electromagnetic environmental infects on electronics & information system, Luoyang, China
2. Luoyang Electronic Equipment Test Center, China
buffy719sheng @sina.com

***Abstract*—Based on array signal processing, the method that smart antennas beamforming by general neural network in wireless communication is proposed, which improves the accuracy of algorithms, such as MVDR algorithms, DOA algorithms etc. 10-elements uniform line array is simulated by computer, Simulation results have shown that we can obtain the extremely approximate weight vector by using the neutral network method. The method is much better than MVDR in computing speed. The proposed method is effective. Computer simulation experimental results are in line with the theoretical ones.**

***Index Terms*—beamforming; general regression neural network; smart antenna**

I. INTRODUCTION

Smart-antenna technology employs space-division multiplexing (SDM) and frequency-division multiplexing (FDM), time-division multiplexing (TDM) or code-division multiplexing (CDM), and thereby makes use of limited frequency band at its maximum. One of smart antennas main functions is adaptive beamforming, which forms a high-gain beam at the desirable signal direction and weakens interference signals in the other directions. In practical applications, weighting coefficients are required to adjust themselves under constantly changing signal environment to achieve adaptive interference injection in accordance with the environmental changes. However, the real-time calculation of adaptive weighting coefficients is computationally intensive, especially in the case of a larger number of antenna array elements. It is almost impossible to complete real-time calculations. Therefore, researchers target at reducing the amount of required computation by studying a variety of algorithms to meet the requirements of real-time processing.

As a computational structure, neural network has several capabilities, such as rapid response capability, excellent self-organizing and self-learning ability, good at obtaining the optimal answers that meet various constraints quickly by fully approximate any nonlinear system under complicated environment, high-degree robustness and fault tolerance. Therefore, it is proposed in [2] to approximate the nonlinear function from the array output data to optimize the weight vector by using the radial base function network. But the direct use of array output function as neural network output will result in the larger space complexity of sample output. In [3], the author has studied multi-beam antennas adaptive nulling using the radial base neural networks.

Minimum variance distortionless response (MVDR) beamformer can be seen as an array output covariance matrix and nonlinear function of the desired signal vector. Therefore, it is considered to take a covariance matrix as the output signal of a neural network with clearer mapping relationship so as to reduce the network complexity. Meanwhile, the author proposes in this paper that network parameters are easier to determine by generalized regression neural networks approximation. The simulation results show the effectiveness of this method.

II. GENERAL REGRESSION NEUTRAL NETWORK

Generalized regression neural network (GTNN) is a kind of radial basis function neural network. It consists of three layers, as shown in Fig. 1. The input layer nodes only pass input signals to the hidden layer. The hidden nodes layer consists of radial functions like Gaussian function, while the input layer nodes usually are simple linear functions. The functions (basis functions) of the hidden layer nodes are responsive to input signals locally. When the input signals approach the basis function central range, the hidden nodes will give rise to a larger output. Therefore, generalized regression neural network has the capability of local approximation. A GRNN topological structure is shown in Fig.1 [1]. It can be seen in the GRNN topological structure that the connection weight from the hidden layer to the input layer is IW1,1, and the threshold value of the hidden nodes is b1 for an input variables ρ. The hidden layer activation function can be defined as:

$$radbas(x) = \exp(-x^2/2) \qquad (1)$$

The connection weight from the hidden layer to the input layer is LW2,1. The network input is y. The hidden layer activation function can be defined as:

$$purelin(x) = x. \qquad (2)$$

The output from the hidden nodes can be defined as the dot product of the spatial distance $dist(\rho, IW_{1,1})$ between the input vector ρ and the connection weight IW1,1 and the threshold b1. The input of output layer can be defined as the

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output of the hidden nodes multiplying with weight LW2,1. It can adjust the smoothness of the network approximation function. (b1 is the hidden layer threshold value set as 0.18326/SPREAD. It can be adjusted by changing SPREAD value). A smaller threshold value can make network approximation function much smoother.

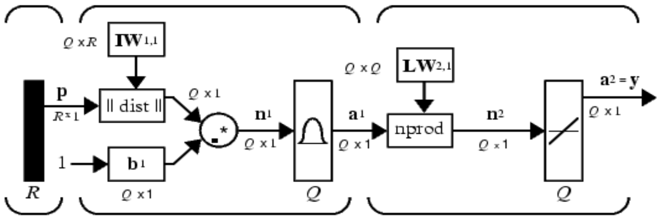

Fig. 1. Structure chart of GRNN

III. Smart Antenna Beamforming Based on General Neutral Network

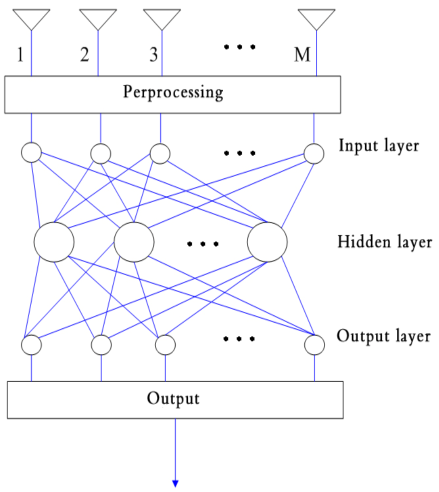

Fig. 2. DOA estimation system of GRNN

J1 hidden layer is a radial basis neuron. The input signals are nonlinearly mapped to a high-dimensional space [5]. Cover theorem shows that after the input-output nonlinear mappings are projected onto the high-dimensional space, its nonlinear degree will be reduced, which will contribute to the solution of the problem. The output is obtained by the optimal weight vectors.

Suppose there are K(K<M) narrowband signals, and signal received by equally-spaced line array is:

$$x_m = \sum_{k=1}^{K} s_k(t) e^{-j(m-1)2\pi \frac{d}{\lambda}\sin\theta_k} + n_m(t), m = 1, 2, \dots, M \quad (3)$$

In the equation, S_k and θ_k respectively refers to the Kth incident signal and its DOA, λ is the carrier wavelength, $n_m(t)$ is Gaussian white noise of zero-mean value in the mth array element, d refers to the internal between the antenna element. Equation (3) can also be expressed matrix form as:

$$X(t) = AS(t) + N(t), \quad (4)$$

A is the signal orientation of $M \times K$, and its matrix is:

$$A = [a(\theta_1), a(\theta_2), \cdots, a(\theta_K)], \quad (5)$$

$$a(\theta_k) = \left[1, e^{-j2\pi\frac{d}{\lambda}\sin\theta_k}, e^{-j4\pi\frac{d}{\lambda}\sin\theta_k}, \dots, e^{-j(M-1)2\pi\frac{d}{\lambda}\sin\theta_k}\right] \quad (6)$$

$$X(t) = [x_1(t), x_2(t), \dots, x_M(t)]^T \quad (7)$$

$$N(t) = [n_1(t), n_2(t), \dots, n_M(t)]^T \quad (8)$$

$$S(t) = [s_1(t), s_2(t), \dots, s_M(t)]^T. \quad (9)$$

The output of beamformer is:

$$y(t) = W^H X(t) \quad (10)$$

Its power is equal to:

$$P(W) = E\left[y(t)y(t)^H\right] = W^H R_{XX} W \quad (11)$$

$R_{XX} = E\left[XX^H\right]$ is the covariance matrix of the array output .

The MVDR algorithm is adjusted by the weight vector W, to ensure the beamform has constant gain for the desired signals. The total output power P(W) is minimum, which is equivalent to the minimum interference noise power, thus the interference signals can be effectively inhibited, that is:

$$\min_W \quad P(W) \quad \text{was restrained by} \quad W^H a_d = 1 \quad (12)$$

a_d is the steering vector of the desired signals. We can use Lagrange multiplier method to calculate the best solution of this constraint.

$$\hat{W} = \frac{R^{-1} a_d}{a_d^H R^{-1} a_d} \quad (13)$$

It can be seen from (13) that the optimal weight vector is the corresponding nonlinear function of an array output covariance matrix and the desired signals array. The latter is generally known. Therefore, beamforming can be seen as a nonlinear mapping from an array output covariance matrix to the optimal weight vector.

Pretreatment: Firstly, the output vector of the array needs to be converted to a suitable neural network input form. The covariance matrix of the array output is R. Since the relevant matrix contains all the information of incident signals, R is a Hermite array. Element R（i，j) and R（j, i) are the same, while the diagonal elements do not contain any information about signal directions, therefore, we can obtain a vector after taking the above elements into account:

$$r = [R_{12}, R_{13}, \dots, R_{1M}, \dots, R_{23}, R_{24}, \dots, R_{M-1M}]^T \quad (14)$$

The neural network can only handle real signals, and those elements extracted must be divided into two elements in accordance to a real and an imaginary parts. Therefore, each element in vector r changes into two, forming a new vector whose dimension is 2 times bigger than the original one. We take its normalized vector as the network output:

$$z = r' / \|r'\| \tag{15}$$

The output is obtained by the optimal weight vector. Considering the weight vector is a complex number, we separate the real and imaginary parts in order to facilitate the processing of the neural network, forming a 2M dimensional vector. We obtain $W = W' / \|W'\|$ after normalizing, hence to form an input-output pair.

The neutral network preserves the optimal weight after training and learning. When the data obtained by preprocessing section, it will adaptively tune the corresponding optimal weight, which will also generate beamform, to avoid DOA estimation and reduce the amount of budget.

IV. SIMULATION

Simulation experiment is specific to 10-elements uniform line array of $d = \lambda / 2$ (λ is vacuum wavelength, and the snapshot is 300 with 2 independent narrowband far-field signals. Training set and test set are created by using two unrelated received signals with angle intervals of 15 and 10. respectively. Assuming the signal arrival angles are distributed between -90 to 90. There are 200 training sets. The simulation result is shown in Fig. 3 and Fig. 4. The two directions of source in Fig. 3 are from -20 to -5, and those in Fig. 4 are from -20 to -10. The straight line is the optimal weight vector by using MVDR, and dotted line is the estimated result. It can be seen the high-gain main lobe can be formed in the directions of resource by GRNN in these two pictures. At the same time, it extremely is close to the direction of the optimal weight vector.

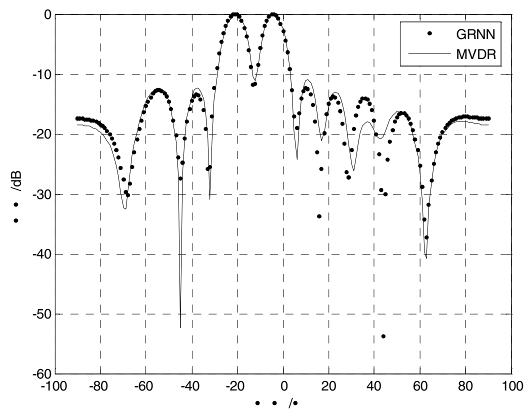

Fig. 3. beamforming based on GRNN, Interval training set Angle 15^{o}

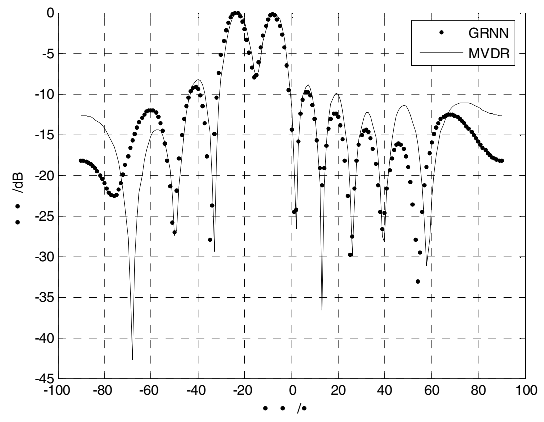

Fig.4 beamforming based on GRNN, Interval training set Angle 10^{o}

V. CONCLUSION

The generalized regression neural network has been used in this paper to realize the nonlinear mapping from antenna array output space to the optimal weight vector. Simulation results have shown that we can obtain the extremely approximate weight vector by using the neutral network method. The method is much better than MVDR in computing speed.

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