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A New Method for DOA Estimation Based on RBF Neural Network

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Abstract—A novel algorithm for optimizing the structure and parameters of DOA estimation model based on radial basis function neural network is presented in this paper. Firstly, by using the astringency of error criteria function, the number of hidden neurons can be decided reasonably, then according to the distribution characteristics of signal phase difference between the antenna arrays, the representative hidden neuron centers can be selected. By this way, the constructed RBF model can be more represented the direction finding capacity of the antenna array. Compared with the other RBF methods, the proposed model has the features of more generalization and accuracy DOA estimation. The experiment results show the effectiveness of the proposed approach.

Keywords: Direction of arrival ; Radial basis function neural network ; Error criteria function ; Initial center

1. Introduction

Direction of arrival (DOA) has been implemented in corresponding, radar and sonar more and more widely and successfully. However, under the complicated electromagnetic environment, some direction finding algorithms such as the traditional interferometer and Music have not achieved the demand of high accuracy, high resolution and real time. With the development of the intelligent information technique, Peoples have studied soft computing methods according to huge samples training to estimate the direction of arrival angle, which not only has a lower calculation requirement and higher accuracy but also has robustness against manufacturing errors and scattering from the antenna structure [1]. Radial basis function neural network is known to be able to estimation the direction (DOA) of arrival with a high accuracy and resolution [2~9],but the presented methods are all focus on researching the feasibility and validity on the direction of arrival estimation for the narrowband signal based on RBFNN [2~8], they have not studied the influence that the structure and the parameter of the neural network model exert on the estimation accuracy, the number of hidden neurons and the center of the hidden layer selection rely on the experience and attempting [3,5,8], thus ,these approaches have great randomicity and face difficulty in obtain the optimal model.

The paper provides an improved RBF algorithm to optimize the network structure and parameters of the DOA model, which has a excellent performance to solve the problem in the wideband DOA estimation based on RBFNN.

2. DOA Estimation model Based on RBF Neural Network

The antenna array performs a mapping G from the space of DOA to the space of sensor output, so the estimation of the DOA can approach by as an inverse mapping of G which can be modeled using radial basis

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function network trained with input-output pairs. In the paper, the RBF neural network of the DOA model is established with a uniform circular array composed of five elements, as is shown in Fig.1.

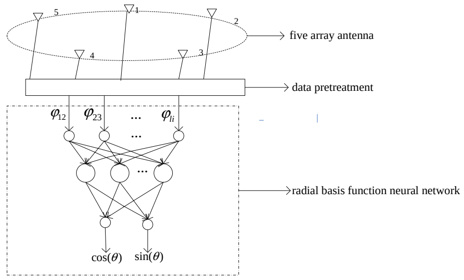


Fig.1. DOA Estimation model Based on RBF Neural Network

Consider a narrowband signal $s(t)$ impinging on M elements of the array, the received signal at

$$x_l(t) = g_l S(t-\tau_l) + n_l(t), \quad l = 1, 2, ..., M \tag{1}$$

where g_l is the gain of the l th element of the array; $n_l(t)$ is the noise signal received at the l th element; τ_l is the propagation delay from the l th element to a reference point on the array. Then signal phase difference between the antenna array elements can be simply obtained:

$$\varphi_{li} = \frac{4\pi Rf}{q} \sin\left(\frac{\pi(l+i-2)}{M} - \theta\right) \sin\left(\frac{\pi(i-l)}{M}\right) \quad l = 1, 2, \cdots M; i = 1, 2, \cdots M \tag{2}$$

R is the radius of circular array, f is the frequency of signal, q is the speed of light in free-space. Formula (2) shows that there lie in a mapping relationship among phase

difference, frequency and direction of arrival angle: $f, \theta \to \varphi$, RBFNN can perform the mapping from the phase difference φ to direction of arrival angle θ, input-output mapping relationship is given by:

$$\theta_k = \sum_{i=1}^{c} w_i^k h(\| \varphi - x(i) \|^2) \quad k = 1, 2, \cdots, m \tag{3}$$

Then w_i^k is the connection weight vector between the k th output neuron and the i th hidden neuron, generally, Gaussian function is used for the basis function, thus, formula (3) is expressed as the following:

$$\theta_k = \sum_{i=1}^{c} w_i^k e^{-\frac{\|\varphi - x(i)\|^2}{\sigma^2}} \quad k = 1, 2, \cdots, m \tag{4}$$

where c is the number of the hidden neuron, $x(i)$ （$i = 1, 2, \cdots, c$）is the center of basis function, σ^2 is the

length coefficient of Gaussian function. When estimating the DOA range from 0°~360°, it is necessary to consider the discontinuity that occurs close to 0° and 360°.If the network is trained with discontinuity data, a slight change in the input vector will result in a significant change in the network output. Therefore, the original 0°～360° phase difference is preprocessed to eliminate approximation error of discontinuous switch from 360° to 0°. For this purpose, the input of the model layer is $[\cos(\varphi_{ij}), \sin(\varphi_{ij})], (i, j = 1, 2 \cdots 5, i \neq j)$, which has 10 nodes, the output is $[\cos(\theta), \sin(\theta)]$, having 2 output nodes in output layer.

3. Establishing Improved DOA Estimation Model

3.1. Determining the number of hidden neuron

The basis function of the hidden neurons is radial symmetrical and the centers of the hidden layer are identified as the weight vectors from input layer to hidden layer, so the hidden layer has a clustering interaction for training samples and the center of the hidden layer is the mean of the cluster, the number of the hidden neurons represents the number of the cluster[10]. To obtain the appropriate number of the hidden neurons, Error Criteria Function is introduced, using convergence of Error Criteria Function to determine the correct division for training samples.

Suppose that all training samples divided into c class, considering each class as a sample set W_j, z_j is the center of the class j, x_i is the i th sample in the class W_j, J denotes the error criteria function and J is defined as the sum of Euclidean norm from x_i to z_j for the total samples. The formula is:

$$J = \sum_{j=1}^{c} \sum_{x_i \in W_j} \left\| x_i - z_j \right\|^2, \ j = 1, 2, \cdots, c \tag{5}$$

For a given c, we can choose c training samples randomly as the initial center $z_i, (i = 1, 2 \cdots c)$, according to minimum Euclidean norm rule, the total training samples are separated into c class set , a new center of the sample set $W_i^{'}$ is calculated:

$$z_j^{'} = \frac{1}{n_j} \sum_{x_i^{'} \in W_i^{'}} x_i^{'}, \ j = 1, 2, \cdots, c \tag{6}$$

where n_j is the number of training data within the sample set $W_i^{'}$, after some iterative computation, the center of the sample set is stable. Calculate the value of J , different c value exist a corresponding value of error criteria function J .

$$z_j^{'} = z_j \tag{7}$$

Analyzing the astringency of error criteria function J , we conclude that J humdrum decrease with c increasing, that's because the aggregation training sample always can be separated during c increasing. When c is up to a certain degree, the decreasing rate of J become smooth .According to the $J-c$ curve, the region of c where J vary smoothly is the reasonable number scope of training sample classification, that is also the optimal region of the number of the hidden neurons.

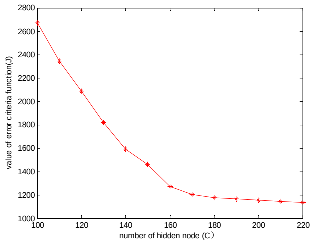


Fig.2. J-C curve

The experiment generates 1800 training samples under the 3.1 experiment condition, using the above approach to get a J-C curve,Fig.2 shows that when hidden neurons c increase from 100 to 160, error value decline rapidly, subsequently , decreasing rate of error value become more and more slow when c increasing, finally ,when c is up to 180～200, error value is almost stable. Therefore, considering the complexity and generalization of the network structure, selecting the number of the hidden neurons in 180～200 is appropriate.

3.2. Optimal selection for the center of hidden neuron

Commonly, for a given cluster number c , selecting c training samples as the initial center, all the training samples can be classified according to Nearest Euclidean norm, after some iterative computation, we obtain the stable center of the sample set z_j $(j = 1, 2, \cdots c)$. z_j can be seen as the center of the hidden neuron, however, selecting initial centre randomly is not considered the actual spatial distribution of the training samples, the algorithm perhaps falls into local optimal solution, as a result, the center of the hidden neurons haven't enough representation and the estimation accuracy may be greatly affected. Thus, it is important to improve the initial center selecting method, letting the distance between the final center of cluster and the initial centre as much closer as possible.

According to the feature of the UCA and attribute of the wave propagation, the distribution of signal phase difference contains some characteristics as following:

1)The value of the sample show periodic distribution with frequency f changing, various frequency f has similar φ on the same direction θ within narrowband;

2) Phase difference φ is very different beyond some region of the band even if the corresponding direction θ is the

same.

3) At the same frequency f , more adjacent directions have

almost the similar phase difference φ .

Fig.3 has shown one-dimensional sample shape chosen from ten-dimension, an approximate period wave represents an omnidirectional sample of the frequency, which manifests the above distribution characteristics of samples.

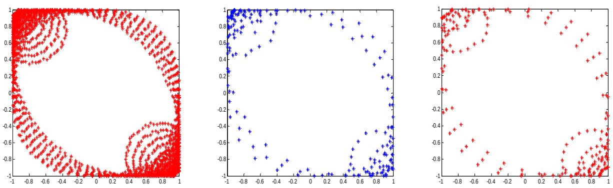
According to the distribution characteristics of samples varying with the frequency and the direction of arrival angle, the paper provides a heuristic method in initial centers selecting, the algorithm can be described as following:

1) Generate wideband and omnidirection training sample set, each frequency f corresponds the number of H samples, which denotes the omnidirectional training samples.

2) Select t groups sample in the total sample, $s=\{s_1,s_2,\cdots s_t\}$, s_t represents each frequency f corresponding H samples, therefore, the total groups contain $U=t\times H$ samples.

3) Divide U into C cluster set, according to the order of the frequency and direction of arrival angle, U will be separated into C set uniformly, compute the center of each set and the solution can be considered as the initial center.

Heuristic method takes characteristics of sample distribution into account, it divides similar sample into the same cluster as much as possible, by this means, the method enhance the stability and estimation precision of the model. Fig. 4(b) and 4(c) illustrate the center of the hidden neurons gained by two various methods, owing to the ten-dimensional data in this paper, ten-dimensional hyperplane is incapable of showing the effectiveness of heuristic method obviously, so when the final center of hidden neurons determined, we select two-dimensional data from the ten-dimensional sample randomly to carry out the contrast.



(a) Spatial distribution of two-dimensional sample (b) Spatial distribution of the hidden neuron center (1) (c) Spatial distribution of the hidden neuron center (2)

Fig. 4. Spatial distribution of two-dimensional sample and the center of the hidden neurons

In Fig 4(b), the initial centers are chosen randomly, while the initial centers are selected by using heuristic method in Fig 4(c). Obviously, Fig 4(c) shows that the center of the hidden neurons has better reflected the distribution rule of the actual two-dimensional sample in Fig 4(a).

4. Experimental results and analysis

4.1. Experimental circumstance

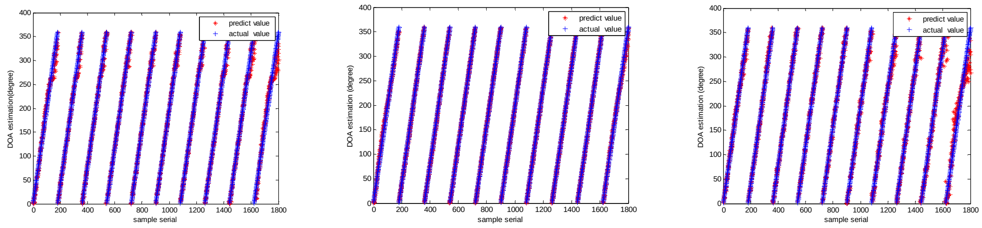
Antenna array uses UCA with five elements, radius is 0.75m, the frequency is 100MHz to 190MHz with step 10MHz， direction angle is 0°to 360°with space 1° and SNR ranges from 5 dB to 20dB， the total sample number is 3600. Choosing a sample at the interval 1° as the training sample, thus, the training sample number is 1800, other 1800 are testing samples.

4.2. Experimental results

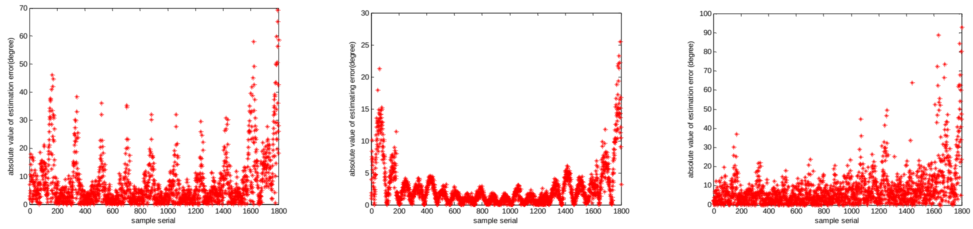
Experimental 1: Contrast the direction estimation results when the hidden neurons number is 100, 180 and 300 , Fig. 5(a)～5(f) shows the direction of arrival estimation accuracy and absolute error of the three cases.

As is shown in Fig. 5, the estimation accuracy is higher when the number of the hidden neurons is 180, the predict and actual value of the direction of arrival is more closer, mean error is 2.87°, the estimation precision decrease when the number of the hidden neurons is 100 and 300, mean error is 5.9867° and 6.7513°. The results obviously illustrate that the estimation precision is greatly sensitive to the number of the hidden neurons, by using J-C curve ,the reasonable scope of the number of the hidden neurons can be determined, reducing the blindness to select the number of the hidden neurons and also increasing the DOA estimation precision .

Experimental 2: After the reasonable number of the hidden neurons gained, contrast the direction estimation results when the initial centers are different. At the same number of hidden neurons, Fig. 5(b) and Fig. 5(e) shows the estimation accuracy and the absolute error whose initial center select randomly, the highest absolute error reaches to 28°, however, the initial center by the heuristic method acquired can optimize the center of the hidden layer, the model becomes more generalization, the direction accuracy improving is significant, as Fig. 6(a) and 6(b) are shown, the mean error decrease to 0.3474°.

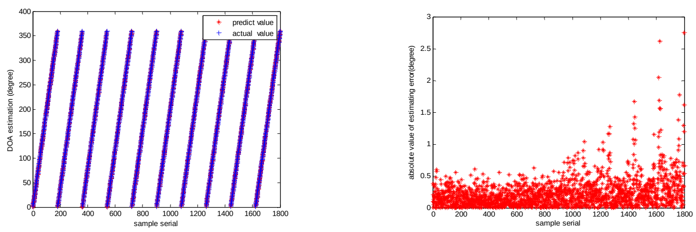


(a) The estimation result (100 hidden layers) (b) The estimation result (180 hidden layers) (c) The estimation result (300 hidden layers)



(d) The absolute estimation error (100 hidden layers) (e) The absolute estimation error (180 hidden layers) (f) The absolute estimation error (300 hidden layers)

Fig. 5. The direction of arrival estimation accuracy and absolute error



(a) The estimation result (b) The absolute estimation error

Fig. 6. The direction of arrival estimation accuracy and absolute error

5. Conclusion

A novel algorithm for optimizing the structure and parameters of DOA estimation model based on radial basis function neural network is presented in this article. Firstly, preprocessing the training samples in order to decrease approximation error of the neural network, using error criteria function to determine the reasonable number of the hidden neurons, then according to the distribution characteristics of signal phase difference, exerting heuristic method to select initial center and the representative hidden neuron centers can be acquired. Finally, the construction procedures of the improved DOA estimation model are given. The experiment results verify the effectiveness of the proposed approach.

6. References

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