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RBF Network Based on Artificial Immune Algorithm for Regional Head Conductivity Estimation

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Abstract—**This paper presents a novel Radial Basis Function (RBF) neural network model based on Artificial Immune principle, termed AI-based RBF, to estimate the regional head tissue conductivity. In this model, immune learning algorithm is used for determining the number and location of the centers of the hidden layer by regarding the input data of network as antigens, and the centers of the hidden layer as antibodies. The least square algorithm is adopted for achieving the weights of the output layer. With a 2-D concentric circular model of 3 layers, the higher precision and less computation time by this strategy are obtained than those by RBF model.**

I. Introduction

INFORMATION on intrinsic electrical properties of a head could potentially be used for monitoring brain function, internal bleeding. The localization of neural sources on the basis of measured electroencephalograms (EEGs) and the reconstruction of conductivities in Electrical Impedance Tomography (EIT) are receiving a wide interest and require the accurate knowledge of the electrical properties of head tissues. Because conductivities of different tissues of the head are of paramount importance for realistic head modeling used for the computation of the forward problem in the High-Resolution ElectroEncephaloGraph (HREEG) and EIT.

It is difficult to get the absolute conductivity value without the internal geometry known. In the strictest sense, this means knowing the geometry and impedance of each of head tissues, including inhomogeneities and anisotropies. However, in practice, one needs to know only the average regional conductivity of each part. Reference [1] developed a non-invasive measurement method for estimating regional head tissue conductivities in vivo, by injecting small electric currents into the scalp, and measuring the potentials at the remaining electrodes of the dense-array electroencephalography net. A multi-start version of the downhill simplex algorithm was adopted to minimize the error function. The iterative sensitivity matrix method also has been developed for the regional conductivity estimation [2]. It is necessary for both of them to solve the EIT forward problem. In this paper, a RBF neural network based on Artificial Immune (AI), termed AI-based RBF is proposed for the conductivity estimation of regional head tissues.

Recently, novel information processing mechanisms inspired by biological immune system are proposed and showed better capability than neural network and genetic algorithm. Immune system is a biology system with high evolution. It aims to distinguish and eliminate pathogen to keep the homeostasis of the organism. From the point of view of the computation, biological immune system is a highly parallel, distributed, adaptive and self-organizing system, which has characteristics of learning, recognition, learning and feature extraction. According to the theory of biological immune system, a new field of intelligent technique, Artificial Immune System (AIS), has been proposed and applied in various fields. In last years, it has been used as a rich source of inspiration to develop new computational tools for solving complex engineering problem, and display stronger robust for information processing.

The RBF neural network, which is an efficient learning algorithm for multi-layer network, is regarded as a feedforward network consisting of neurons of three layers with entirely different roles. It increases the learning speed by avoiding the complex computation in backward propagation network, and overcome the local minimum problem of the gradient descent algorithm in BP network. Therefore, it has a variety of applications, such as speech recognition, data qualification, function approximation, prediction of time series, graph manipulation. However, the number and the positions of its basis function centers influence the capability of the RBF network approximation. And the RBF centers are also needed covering the whole input space. It makes the computation increased significantly and leads to the generalization reduction of the network, if the number of the RBF centers is too much. Therefore, the key to construct the RBF network is the proper selection of RBF centers. At present, the primary algorithms to select the RBF centers are the clustering algorithm, orthogonal least square method. As we know that the other clustering algorithm, such as k-means, needs to specify the number of clustering previously, while the probability of an ill-conditioned matrix will be higher with larger input by orthogonal least square method [3].

In this paper, a strategy is presented for the selection and optimization of the RBF neural network based on an artificial immune algorithm coupled with De Castro's algorithm [4], as the immune system is able to recognize infinite antigens, create antibody memory and quick response to antigens

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having been recognized. This algorithm has been demonstrated using Fisher's Iris data for classification, recognition. With the suitable parameters, results showed that this method has good generalization, and performance on clustering and recognition [5].

This coupled strategy will be introduced in the second section. Its application and effectiveness for the conductivity estimation of regional head tissues will be in the third section, by a 2-D concentric circular model of 3 layers.

II. METHODOLOGY

A. RBF Network Model

A RBF network model is shown in Fig.1, including 3 layers, which are the input layer, the hidden layer and the output layer. For N-dimensional input vector $X=[X_1,X_2,\cdots,X_n]$ ($X_i=[x_{1i},x_{2i},\cdots,x_{pi}]^T\in R^p$, $i=1,2,\cdots,n$), the RBF network output $Y=[y_1,y_2,\cdots,y_k]$ can be computed as (1)

$$y_i=W_i^TG=\sum_{j=1}^{m}w_{ji}g_j\ ,\ i=1,2,\cdots,k \qquad (1)$$
$$W_i=[w_{1i},w_{2i},\cdots,w_{mi}]^T,\ i=1,2,\cdots,k$$

where W_i is the i^{th} network weight vector from the hidden layer to the output layer for the i^{th} output neuron, $G=[g_1,g_2,\cdots,g_m]$ is the vector of the radial basis function in hidden unit. The Gaussian function is employed as

$$g_j=\psi_j(\|x-c_j\|/\sigma)=e^{-\frac{\|x-c_j\|^2}{\sigma^2}}, \qquad (2)$$
$$\sigma=\frac{d_{\max}}{\sqrt{2m}},\quad j=1,2,\cdots,m$$

where c_j is the center of the j^{th} basis function, σ is the standard derivation, m is the number of centers, $d_{\max}$ is the maximum distance between the chosen centers to determine the width around the basis function center, $\|\cdot\|$ represents the Euclidean norm defined in input space. $\|x-c_j\|$ denotes the distance between x and c_j, ψ_j is the radial symmetrical function whose unique maximum is at the j^{th} center location c_j. With the increasing of $\|x-c_j\|$, ψ_j regresses rapidly to zero.

B. Algorithm Based on Artificial Immune Principle

Artificial Immune system (AIS) is a processing information system with high efficiency. Facing the large numbers of various antigens, immune system has to recognize and then eliminate them. The process of antigens recognition by antibodies includes: a) searching for antibodies having the maximum affinity with antigens, b) measuring the match degree between antibody and antigen which denotes the antibody's recognition extent to antigen.

1) Implementation of Affinity: The affinity $a_{ij}(0\le a_{ij}\le 1)$ between antigen Ag_j and antibody Ab_i is defined as (3)

$$a_{ij}=1-\frac{\|Ab_i-Ag_j\|}{\max\limits_{\substack{1\le i\le n\\1\le j\le m}}\|Ab_i-Ag_j\|}\quad \begin{cases}i=1,2,\cdots,n\\ j=1,2,\cdots,m\end{cases} \qquad (3)$$

where $\|Ab_i-Ag_j\|$ is the norm of Ab_i and Ag_j in S^L, S^L is an L–dimensional shape-space constructed by antigens and antibodies, $AB=\{Ab_i\mid i=1,2,\cdots,n\}$ is the aggregation of antibodies, $AG=\{Ag_j\mid j=1,2,\cdots,m\}$ is the aggregation of antigens, Ab_i and Ag_j are i^{th} and j^{th} vectors of the corresponding aggregation, respectively.

The affinity $s_{ij}(0\le s_{ij}\le 1)$ between two antibodies used for denoting the similarity of antibodies is defined as the same way in (4)

$$s_{ij}=1-\frac{\|Ab_i-Ab_j\|}{\max\limits_{\substack{1\le i\le n\\1\le j\le m}}\|Ab_i-Ab_j\|}\quad \begin{cases}i=1,2,\cdots,n\\ j=1,2,\cdots,n\end{cases} \qquad (4)$$

2) Antibody's clone and variation: In immune system, the antibody having higher affinity with the antigen is selected for proliferation and differentiation, termed clone. The cloned cell experiences a high variation at the same time so that the new generated cells are of higher affinity to match the selected antigens. Therefore, immune system has powerful and various recognition ability. The adopted variation strategy in this paper details as follows.

The Clone rate is in direct ratio to affinity and the number of the cloned antibodies Nc depends on the affinity defined in (5)

$$Nc=\sum_{i=1}^{n}round(N-norma\|Ab_i-Ag_j\|N) \qquad (5)$$

where N is the number of antibodies, $round(\square)$ is the function towards the nearest integer, $norma(\square)$ is the normalization function.

The antibody's variation Ab^* is shown in (6),

$$Ab_i^*=Ab_i-\alpha(Ab_i-Ag_j) \qquad (6)$$

where Ab_i is the mutated antibody, $\alpha=1-e^{-\|Ab_i-Ag_j\|}$ is the variation ratio set according to the antigen-antibody affinity. The higher the affinity, the smaller the α . Hence, the ability to recognize antigens is improved after antibody variation.

As $0\le 1-\alpha\le 1$, $\|Ab_i^*-Ag_j\|\le\|Ab_i-Ag_j\|$ can be proved [5], then $a_{ij}^*\ge a_{ij}$. This means the antibody-antigen affinity a_{ij}^* is larger than the previous affinity a_{ij} after mutation.

C. The Coupled Method of the Artificial Immune and RBF Neural Network

The key points to the RBF network include:

a) The adequate choice of the number M of the centers;

b) The positions of its basis function centers c_j;

c) The learning of the output weight w_{ij}.

As mentioned in the introduction, the number and the positions of its basis function centers influence the capability of the RBF network approximation. And the RBF centers are needed covering the whole input space, which leads to the computation increased significantly and the generalization capability of the network decreased, if the number of the RBF centers is too much.

In this part, the artificial immune principle is employed for the selection and optimization of RBF network centers. The group of antibodies with higher affinity is increased by selection. The most various possible antibodies against the antigens are produced to make the RBF centers cover the input space as much as possible. The whole process is as follows.

Step1: To determine centers of RBF network model by the center selection algorithm based on the immune algorithm, from (3) to (6).

In this algorithm, inputs of the network are regarded as antigens, while centers of the hidden unit as antibodies. By applying the immune principle described as above, the set can be reproduced including a variety of memory antibodies, which are just centers of hidden unit of RBF network. Because assemble of memory antibodies is a mapping of compression clustering, it is possible to cover the whole input space by a few number of hidden unit centers of RBF network. Thus, the convergence speed will be improved distinctly if the similar data is input to this RBF network for recognition, because of the existence of memory centers.

Step2: To obtain the output of the hidden unit with the determined centers by (2).

Step3: To calculate weights of the output layer by the least square method.

Step4: To substitute the weights into (1) to get the output vector *Y* of the network.

III. Simulation

Usually, the regional conductivities for the different tissues are estimated according to measured boundary potentials of the target object, induced by the injected current. For the case of the regional estimation, the boundary voltages are the input *X* of the RBF network, while the conductivities for the different tissues are the output *Y*. In order to construct the training set, the EIT forward problem should be solved, which is to calculate the potential distribution induced by the injected current at the surface of the target object with the regional conductivities given.

The adopted head models are a 2-D concentric circular model of 3 layers and analytic solution is used for solving the EIT forward problem [2].

A. EIT Forward Problem

Low-frequency (f<10kHz) current injected into the surface gives rise to quasistatic electric fields, which may be computed using techniques from electrostatics. To a good approximation, the electric and magnetic fields are decoupled and the local tissue impedance is real. With these simplifications, electric current in the conductive media is governed by (7) for the electric potential φ,

$$\nabla \cdot (s\ \nabla\varphi) = 0 \qquad \text{in } \Omega \tag{7}$$

where s is the conductivity of the media.

The EIT forward problem is to estimate the potential distribution induced by the current injected at the surface of the target region, with the conductivity s known. The boundary conditions are followed as (8),

$$\begin{cases} -s\dfrac{\partial\varphi}{\partial n} = \pm I\delta & \text{at points where current } I \text{ is injected} \\ & \text{through the boudary } \Gamma \\ s\dfrac{\partial\varphi}{\partial n} = 0 & \text{at other points of } \Gamma \end{cases} \tag{8}$$

For the regular geometry, like the 2-D concentric circular model of 3 layers and the 3-D concentric spherical model of 4 layers, there exists analytic solution for solving the EIT forward problem.

When current *I* are injected at the two electrodes *A*, *B* on the surface, the analytic solution for concentric circle of 3 layers is shown in (9)

$$\varphi^{\mathrm{P}}(r,\theta) = \frac{I}{\pi s}\sum_{n=1}^{\infty}\frac{1}{n}\left(\frac{r}{a}\right)^n\left[\cos\ n(\theta_A-\theta) - \cos\ n(\theta_B-\theta)\right] \tag{9}$$

where φ^{P} is the potential at the observation point $\mathrm{P}(r,\theta)$, s is the conductivity at P, a is the external radius of the circle. The detail derivation is shown in reference [2].

B. Simulation Results

The 3 layers imitate the scalp, skull and brain with the radius of 92mm, 87mm and 80mm from external to internal, respectively. In order to verify the effectiveness of the AI-based RBF model, the comparison between the AI-based RBF and the traditional RBF model is carried out. The simulation consists of 98 trails and noise free. The computer is with 1.6 GHz CPU, 256Mbyte of RAM.

1) Computation time: For the AI-based RBF model, inputs *X* of the RBF network are the boundary potentials regarded as antigens. Centers of RBF network are regarded as antibodies. The outputs *Y* of the network are conductivities of the three layers. The 98 inputs, i.e., boundary potentials, are used for the center determination of RBF network model. It takes about 5s for this step. Then, the leave-one-out technique is adopted for a final test in order to use the largest number of examples for training. In this case, all examples apart from one are used for training, while the generalization is tested on the single left-out example. The experiment is repeated by considering each pattern in turn as the left-out example. It takes 3s for this step. So the total computation time for the whole process is about 8s.

For the traditional RBF model, the same leave-one-out technique is adopted too. The total computation time for these 98 trails is about 52s.

2) Computation precision: For the AI-based RBF model, the maximum relative error is 0.061% located in the brain region. For the RBF model, the maximum relative error is 0.180% located in the scalp region. The relative errors estimated for each layer are list in Table I. And the error curves for each layer are shown in Fig.2. From the Table I, we can see that, the maximum relative errors for both scalp and brain layers by AI-based RBF are lower than the traditional RBF model. Averaged relative errors have the same results. For the skull layer, both of these RBF model can obtain the estimation with very high precision.

IV. Discussion and Conclusion

This paper presents a hybrid algorithm by combining the RBF neural network with a learning algorithm of artificial immunity based on the principle that immune system has the capability of recognizing a variety of antigens, reproducing antibody memory. By applying this strategy for the estimation of regional head conductivity with a 2-D concentric circle of 3 layers, the higher precision and lesser computation time are achieved than the traditional RBF network model. Results show that this algorithm has higher learning speed, higher recognition rate and better generalization. It should be adopted for further investigation of regional conductivity estimation with a 3-D head model.

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TABLE I
RELATIVE ERRORS AND COMPUATION TIME

Layer	Maximum Relative error (%)		Averaged Relative error (%)	
	AI-based RBF	RBF	AI-based RBF	RBF
Scalp	0.048	0.180	0.002	0.008
Skull	0.014	0.000	0.000	0.000
Brain	0.061	0.076	0.004	0.008

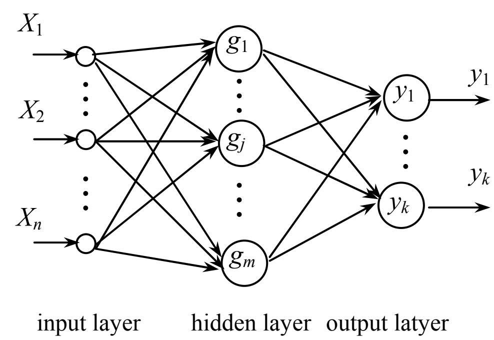

Fig. 1. Radial Basis Function (RBF) neural network

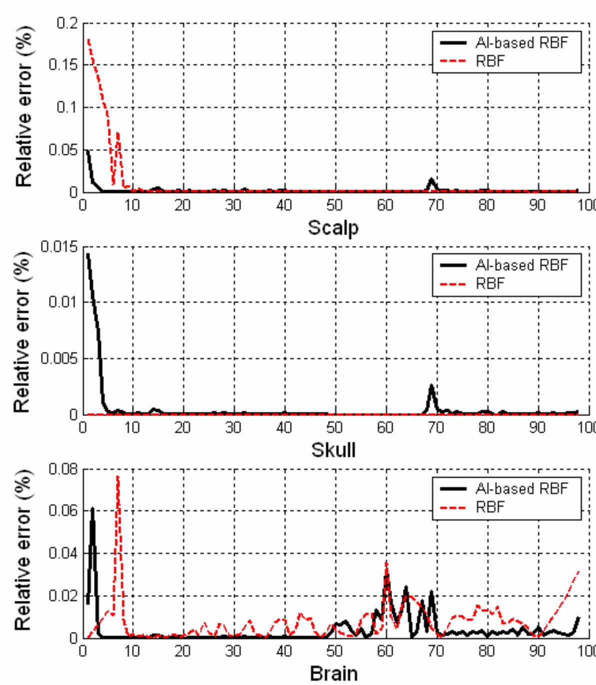

Fig.2. Comparison of elative errors for each layer between AI-based RBF and RBF model