Hybrid RBF training algorithm based on artificial immunology

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Abstract: Based on artificial immune clustering and Immune Evolutionary Algorithm (IEA), a novel hybrid RBF design method is proposed. The artificial immune clustering is used to adaptively specify the amount and initial position of centers of basis functions in RBF network according to input data set. Then immune evolutionary algorithm is used to train the RBF network, which reduces the searching space of canonical evolutionary algorithm and improves the convergence speed. Computer simulations demonstrate that the RBF network designed in this method has a concise structure with good generalization ability.

Key words: Artificial immune clustering; Immune evolutionary algorithm; RBF network
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基于人工免疫机制的RBF网络混合训练算法

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摘要：基于人工免疫聚类机制和免疫进化算法，提出了一种新型的设计RBF网络的混合算法。该方法利用人工免疫聚类机制，根据输入数据集合自适应地确定RBF网络核函数的数量及其中心的初始位置。采用免疫进化算法训练RBF网络，进一步缩小了标准进化算法搜索空间的范围，提高了算法的收敛速度。计算机仿真表明，这种RBF网络结构精简并具有较强的泛化能力。

关键词：人工免疫聚类； 免疫进化算法； 径向基函数网络

0 Introduction

Radial Basis Function (RBF) network[1] has been widely used in pattern recognition, function regression, signal processing and system control, etc. In RBF network the centers and width of the basis functions in the hidden layer have great influence on the performance of the network, but common RBF training algorithms cannot find the global optima of the network, and will often have too many hidden units to reach certain approximate ability,

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which will lead to too large scale for the network and the decline of generalization ability.

In order to solve the problem, a hybrid method combined with artificial immune clustering[2] and Immune Evolutionary Algorithm (IEA)[3] is used to design the RBF network. Combining fuzzy C-means clustering method with immune algorithm, the immune clustering method can adaptively specify the amount and initial positions of the RBF centers according to input data set. IEA is then used to train the RBF network. The algorithm extracts the preliminary knowledge about the width of the basis function as the vaccine to form the immune operator, which reduces the searching space of canonical evolution algorithm. The applications of the RBF network designed with the hybrid method in the radar-scanning style recognition problem demonstrate the good performance of the network.

1 RBF network

RBF network is a three-layer feedforward neural network including a single hidden layer. For a p-dimensional input vector $\boldsymbol{x}_i=(x_1,x_2,\cdots,x_p)$, where $\boldsymbol{x}_i\in\boldsymbol{X}\subset\mathscr{R}^p$, the output of the RBF network can be computed as follows

$$y_i = \boldsymbol{w}_i^{\mathrm{T}}\boldsymbol{g} = \sum_{j=1}^{m} w_{ij}\exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{z}_j\|^2}{\sigma_j^2}\right)$$
$$i = 1,\cdots,o,\ j = 1,\cdots,m \tag{1}$$

where $\boldsymbol{w}_i=[w_{i1},\cdots w_{im}]^{\mathrm{T}}$ is the ith weight vector from hidden layer to the output layer, $\boldsymbol{g}=[g_1,g_2,\cdots,g_m]^{\mathrm{T}}$ is the vector of Gaussian basis functions, with centers $\boldsymbol{z}_j\in\mathscr{R}^p$ and width σ_j, o is the number of network output units.

The positions of center $\boldsymbol{z}_j$ and width σ_j have great impact on the performance of RBF network. But common RBF training algorithms have the possibility of only reaching the poor local minimum of the network, which will degrade the performance of the system. Therefore, a hybrid method is proposed in the paper to design the RBF network.

2 Description of the hybrid algorithm

The major steps of the hybrid algorithm can be described as the following

(1) Generate an initial population A_1 using real number encoding, where each individual in A_1 is corresponding to a certain network structure. The amount and initial positions of center $\boldsymbol{z}_j$, $j=1,\cdots,m$ in RBF network are determined by artificial immune clustering, while the width σ_j, $j=1,\cdots,m$ and weight vector $\boldsymbol{w}_i$, $i=1,\cdots,o$ are initialized randomly.

(2) Extract vaccine according to preliminary knowledge.

(3) Compute the fitness function of each individual. If the current individual is acceptable or the maximum number of generations has been reached, stop the evolutionary process, otherwise continue.

(4) Perform mutation on the current population A_k and obtain the results B_k.

(5) Perform vaccination on B_k and obtain C_k. "Vaccination" is to select certain individuals from the current population according to certain percentage and change certain gene bits of the selected individuals according to the vaccine extracted in step (2), so as to improve their fitness.

(6) Perform immune selection on C_k and obtain the next population A_{k+1}, then go to step (3). Immune selection is to perform the fitness test on the individuals after vaccination, and select best individuals into the next population.

The fitness of each individual is determined by $f=1/E$, where E is the error function of the network

$$E = \sum_{t=1}^{N}\sum_{i=1}^{o}\left(Y_i(t) - \bar{Y}_i(t)\right)^2 \qquad (2)$$

where $Y_i(t)$ and $\bar{Y}_i(t)$ are the actual and desired outputs of node i for input pattern t, o and N are the number of output nodes and input patterns, respectively. Artificial immune clustering in step (1) and vaccine extraction in step (2) are introduced in section 3 and section 4, respectively.

3 Specify RBF centers with artificial immune clustering

Artificial Immune Clustering(AIC) is used in the paper to specify RBF centers[2]. Assume that the training data set has N input vectors, $\boldsymbol{X}=\{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots \boldsymbol{x}_N\}$, $\boldsymbol{x}_i \in \mathcal{R}^p$. The problem is to find a new set $\boldsymbol{Z}=\{z_1, z_2, \cdots, z_m\}$ composed of m patterns to form the centers of RBF network. It is hoped that the elements in $\boldsymbol{Z}$ can cover all the input vectors in space $\mathcal{R}^p$, while the distances among the elements in $\boldsymbol{Z}$ is as far as possible. In the algorithm, each input vector $\boldsymbol{x}_i$, $i=1,\cdots,N$ in $\boldsymbol{X}$ corresponds to an antigen (Ag), while each candidate center z_j, $j=1,\cdots,m$ in $\boldsymbol{Z}$ corresponds to an antibody (Ab). Matching degree (affinity) among the vectors is measured by their Euclidean distance in space $\mathcal{R}^p$; the smaller the distance, the greater the affinity is among the vectors.

Immune algorithm[2] is an improved evolutionary algorithm based on immunity. Inspired by somatic theory and immune network theory, immune algorithm realizes the self-control mechanism and diversity similar to natural immune system. Compared to other heuristic optimization algorithms, immune algorithm improves the searching ability through immune memory mechanism and combats the immature convergence through affinity calculation. In immune clustering algorithm, the antigen and the antibody correspond to the objective and the feasible solution, respectively.

The objective function of fuzzy C-means (FCM) is

$$J(\boldsymbol{X};\boldsymbol{U},\boldsymbol{Z}) = \sum_{k=1}^{N}\sum_{i=1}^{m} u_{ik}^F D_{ik}^2 \qquad (3)$$

$$D_{ik}^2 = (\boldsymbol{x}_k - \boldsymbol{z}_i)^{\mathrm{T}}(\boldsymbol{x}_k - \boldsymbol{z}_i) \qquad (4)$$

where D_{ik} is the distance of kth input data to ith RBF center. $\boldsymbol{Z}=\{z_1, z_2, \cdots z_m\}$ denotes the centers of RBF network. F is fuzzy exponent. $\boldsymbol{X}=\{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N\} \subset \mathcal{R}^p$ denotes the input pattern. $\boldsymbol{U}$ is defined as

$$\boldsymbol{U} = \{U \in \mathcal{R}^{M\times N} \mid u_{ik} \in [0,1], \forall i,k; \; 0 < \sum_{k=1}^{N} u_{ik} < N, \forall i\}$$

In the immune clustering algorithm, clustering centers $\boldsymbol{Z}$ is encoded. Fitness function is constructed as

$$f_c = \frac{1}{J(\boldsymbol{X};\boldsymbol{U},\boldsymbol{Z}) + 1} \qquad (5)$$

The fuzzy C-means clustering based on immune algorithm (IFCM) can be described as

(1) Specify number of RBF initial centers $\boldsymbol{Z}$ and fuzzy exponent F, where $1 \leqslant m \leqslant N-1$ and $F \in (1, +\infty)$. Set stop criterion S_c, crossover probability P_c and mutation probability P_m. Produce initial antibody population $P(k)$, $k=0$.

(2) Calculate affinities: calculate the affinity ax_v between antigen and antibody v, the affinity $ax_{v,w}$ between antibody v and w.

1) Decode each individual and compute prototype parameter $\{z_i, 1 \leqslant i \leqslant m\}$.

2) Compute D_{ik}^2 according to equation (4)

3) $\boldsymbol{U}=[u_{ik}]_{m\times N}$ can be computed as

$$I_k = \phi \Rightarrow u_{ik} = 1\Big/\sum_{j=1}^{m}\left[\frac{d_{ik}^2}{d_{jk}^2}\right]^{\frac{1}{F-1}}$$

$$I_k \neq \phi \Rightarrow u_{ik} = 0, \forall i \in \bar{I}_k, \sum_{i\in I_k} u_{ik} = 1$$

where $I_k=\{i \mid 1 \leqslant i \leqslant m, d_{ik}=0\}$, $\bar{I}_k=\{1,2,\cdots,m\} - I_k$.

4) Calculate $J(\boldsymbol{X};\boldsymbol{U},\boldsymbol{Z})$ and f_c.

(3) Update memory repertoire: the antibodies that show high affinity with the antigen are added in the memory repertoire.

(4) Promotion and suppression of antibody-production: the expectation value e_i of antibody i is calculated, and the antibodies that have low expectation values are extinguished.

$$e_i = \frac{ax_i}{c_i}$$

where c_i is the density of antibody i.

(5) Update antibodies: according to the expectation value, new generation of antibodies $P(k+1)$ are produced through mutation and crossover on $P(k)$.

(6) Termination criterion: if the termination criterion S_c is satisfied, the clustering procedures end.

4 Immune evolutionary algorithm and vaccine extraction

The evolutionary algorithm is a kind of generation-and-test algorithm. On condition of preserving the advantages of evolutionary algorithm, the immune evolutionary algorithm utilizes some characteristics and knowledge in the pending problems for restraining the degenerative phenomena during evolution, so as to improve the algorithmic efficiency. The core of the immune algorithm is the construction of the immune operator, which is realized through two steps, i. e. , vaccination and immune selection.

The width σ has great impact on the RBF network performance. In the algorithm, the approximate range of σ is used as the vaccine to reduce the searching space and improve the fitness of population. The vaccine is extracted as follows

(1) Use artificial immune clustering described in section 3 to specify the positions and amount of RBF Centers. Assuming all the basis functions have the same σ, let σ have different values in the possible range according to the same length. For instance, let σ start from 0. 1, and length is 1, and σ equal to 0. 1, 1. 1, 1. 2…, respectively.

(2) Compute different interpolation matrix $\boldsymbol{G}$ corresponding to the training data sets for different σ. Using regression procedure to compute linear output weight matrix $\boldsymbol{w}$ according to the equation

$$\boldsymbol{G}\boldsymbol{w} = \boldsymbol{d} \tag{6}$$

Where $\boldsymbol{d}$ is the desired outputs of the training data.

(3) Compute the fitness of the RBF networks using different σ. In a certain range centered on the best σ, repeat step (1) and (2).

Generally speaking, iteration of two times for the above algorithm is enough. This is because we can only estimate the possible range of σ. If the range is too small, we can possibly get the wrong vaccine.

5 Simulations

The RBF network designed with the hybrid method suggested in the paper is applied in the radar-scanning style recognition problem. Fast recognition of scanning style of radar antennas is very important in modern electronic warfare. In essence, the recognition of scanning style is based on the character parameters of radar signals after pre-processing. Typical signal parameters influenced by scanning styles include[4]: zenith of radar impulses $P_{a_{max}}$, scanning period of radar antennas T_a, time intervals between the zenith of different impulses $T_{a'}$ and the width of radar impulses T_s.

In simulation the RBF networks have 4 input nodes, corresponding to 4 input signal parameters. The network is trained with 80 samples and then tested with 500 samples. The Wrong Recognition

Rate/*SNR* curves of radar scanning style recognition by RBF networks trained with the hybrid algorithm, Evolutionary Programming (EP)[5], *k*-means[6] and OLS[7] algorithms are shown in Fig. 1. It can be seen that the RBF network trained with hybrid algorithm has the best recognition rate, demonstrating the strong generalization ability of the network.

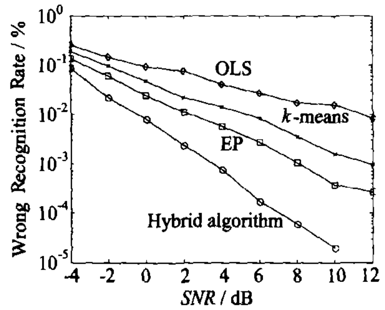

Fig. 1 Wrong Recognition Rate/*SNR* of radar scanning style recognition

6 Conclusion

A hybrid evolutionary RBF network based on artificial immune clustering and IEA is proposed in the paper. The artificial immune clustering is used to adaptively specify the amount and initial centers of basis functions in RBF network. Then immune evolutionary algorithm is used to train the RBF network. The applications of the RBF network in radar-scanning style recognition problem demonstrate the efficiency of the algorithm.

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