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Person Recognition Optimization Method Relying on Radial Basis Function Network

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Abstract: Artificial NN is an intelligent model for information processing by simulating the organization and mechanism of the nervous system of the brain. Thanks to its strong self-learning ability, artificial NN can liberate people's labor force to a large extent, so it has been widely studied and alied. The theoretical study of artificial NN can effectively explain the alication principle and potential problems of NN, so that it can be effectively improved and developed. Therefore, the main purpose of this paper is to study the optimization method of person recognition (PR) based on RBF network. In this paper, the damping coefficients of RBF networks with uniform center distribution are studied. This stochastic learning method is an important sulement to how to determine the center and limiting factor of the RBF of the NN, and can also improve the training efficiency of the network. The main research results of this paper are developed by analyzing the convergence of stochastic RBFNN and constructing corresponding models and algorithms. Compared with other algorithms, the results show that the ARBFNN algorithm can make the RBFNN obtain a smaller training error, improve the generalization ability of the network, and have the ability to deal with large data sets and fast convergence. Recognition is more convenient and quicker.

1. Introduction

With the development of artificial intelligence technology, the recognition technology of people and faces has been gradually integrated into people's work and life. These technologies could allow machines to have human-like discrimination capabilities. But the face image is only a part of the character image. Most of the character images not only contain the face of the character, but also include the image background, body outline and other factors. From the perspective of face recognition technology, most of these factors will be judged as noise that interferes with recognition [1, 2].

In related research, Cagla proposed an adaptive traffic signal control system to manage intersections [3]. A hybrid RBFNN is developed to predict adaptive green light times, trained and tested using historical arrival and simulation results. Sarker proposed to analyze the effect of changing TNO filters of a convolutional NN (CNN) model on the accuracy of a single biometric-based classifier using face, fingerprint, and iris for PR [4], as well as using bagging- and iris simultaneously a programming-based aroach to lifting.

Based on the stochastic RBFNN regularization model, an adaptive regularization model is proposed by changing the regularization factor into a function of the OL weights. An aropriate form of the adaptive factor function needs to be chosen to ensure a convex adaptive regularization model. Correspondingly, an iterative algorithm ARBFNN for the adaptive regularization model is presented. The random RBFNN can reduce the training error, improve the generalization RT, and ensure the ability to deal with big data problems.

2. Design Research

2.1. Radial Basis Function Neural Network (RBFNN)

RBF NN is a kind of forward network with good performance, there are three layers: input layer, HL with nonlinear activation function and linear output layer (OL) [5, 6]. According to TNO (HL) units, it can be divided into two models, namely normalized network and generalized network [7, 8].

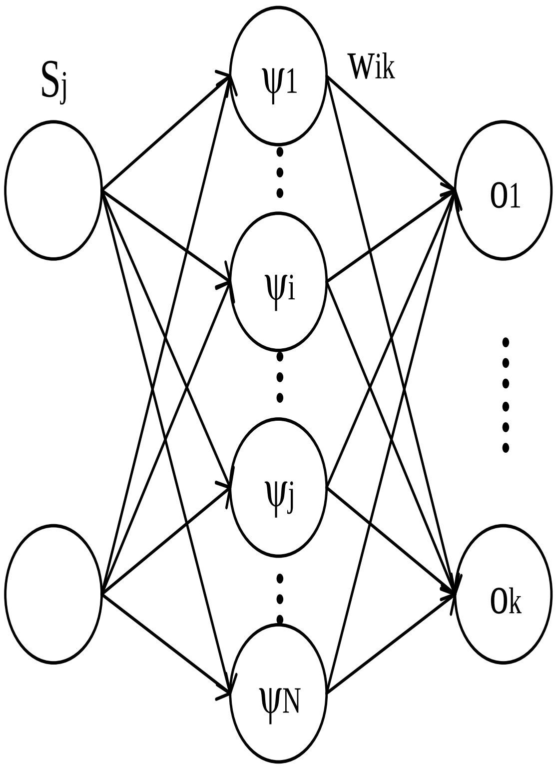

Figure 1. Regularized network structure

(1) Normalized network

The HL unit of the network corresponds to an activation function, and the training sample is its center point. Therefore, TNO HL nodes is equal to the number of (TNO) training samples [9, 10]. Figure 1 is the structure diagram of the network.

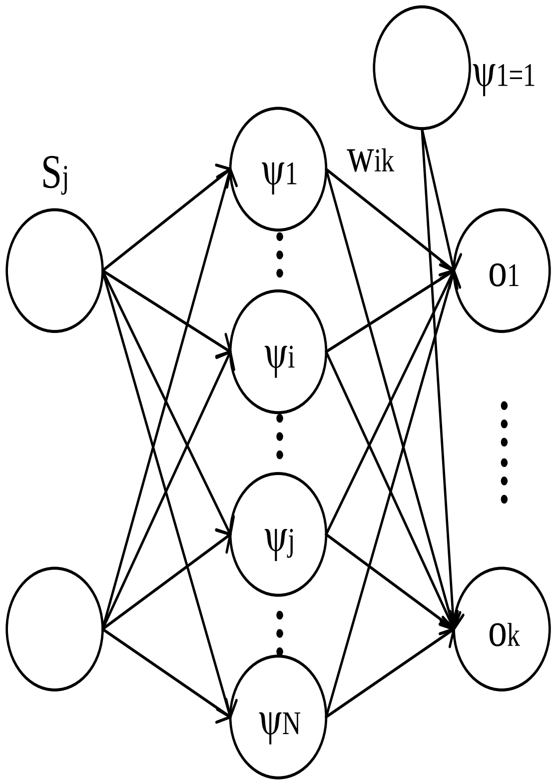

Figure 2. Generalized network structure

(2) Generalized network

In conventional networks, the training samples are the center points of the network [11, 12]. Therefore, when TNO training samples is large, TNO hidden nodes is also large, and the implementation of the network is very complex, and the network is solved from the HL to the OL. Galerkin method can reduce TNO HL parts to solve this problem [13, 14].

Let P be TNO training samples, iV is TNO hidden units, generally N<<P. Ci is the center sample of the ith hidden unit, and ψ(Sj, Cj) is the activation function of the HL [15, 16]. Figure 2 is the structure diagram of the network.

Except that TNO HL units is different, the representation of the input, output and activation function of the generalized network is the same as that of the regularized network introduced above, and we will not repeat it here.

For the convenience of realization, a generalized network is usually used.

2.2. Performance Analysis of RBF NN

Both RBF NNs and multi-layer perceptrons are general aroaches, and as with any RBF NN, it can be seen that multi-layer perceptrons can completely replace NNs with perceptron layers RBF [17, 18]. But they also have the following differences:

(1) From the perspective of the network structure, the multilayer perceptron may have one or more HLs, while the neural RBF network has only one HL.

(2) The hidden and OL maing of the multilayer perceptron can be linear or non-linear, while the HL of the neural RBF is local.

(3) The neurons in the HL of the multilayer perceptron calculate the inner product of the input unit and its connection density, and the neurons in the HL of the RBF neural network calculate the distance between the two.

In the process of constructing RBF NN, the commonly used RBFs are:
Gaussian function:

$$\varphi(r) = \exp(-\frac{r^2}{2\sigma^2}) \tag{1}$$

Invert the S-function:

$$\varphi(r) = \frac{1}{1+\exp(\frac{r^2}{\sigma^2})} \tag{2}$$

Inverse multiple quadratic function:

$$\varphi(r) = \frac{1}{(r^2-\sigma^2)^{\frac{1}{2}}} \tag{3}$$

The strong alicability of the Gaussian function makes it widely used in the fields of social science, natural science, mathematics and engineering. In statistics, the Gaussian function is used to describe the normal distribution; the rise of computer vision in recent years has made it a The most widely used kernel function in image processing; Gaussian function also has a good performance in the field of signal processing (Gaussian filter). The RBFs are all radially symmetric functions of the center, and the RBFs are non-negative nonlinear functions with symmetrical decay. Scientific research shows that different parts of the human brain have different sensitivities to external stimuli. The stimuli that neurons respond to are all within a certain range, otherwise they will not respond or respond very weakly. This range is called the receptive field. The inspiration of the NN is a kind of biomimetic that human neurons make regular responses to external stimuli.

2.3. RBFNN Algorithm

The stochastic radial basis NN function can aroximate any continuous function and is also an efficient function aroximation. To verify the above theoretical results, we use the RBFNN algorithm to train the parameters of a random radial function NN. For given N training samples $\{(x_j, t_j): x_j \in R^m, j = 1,2,\cdots,N\}$, the mathematical model of a three-layer radial network function with HL nodes can be expressed as:

$$\sum_{i}^{n} \beta_i g(\frac{\|x_j - y_j\|_2^2}{\sigma_i}) = t_j,\ j = 1,2,\Lambda\ ,N \tag{4}$$

It can be rewritten into a simpler matrix form by observing equation (4):

$$H\beta = T \tag{5}$$

Where, $\beta = [\beta_1, \beta_2, \cdots, \beta_n]^T, T = [t_1, t_2, \cdots, t_N]^T$, and

$$H = \begin{bmatrix} g(\frac{\|x_1 - y_1\|_2^2}{\sigma_1}) & \Lambda & g(\frac{\|x_1 - y_n\|_2^2}{\sigma_n}) \\ M & \Lambda & M \\ g(\frac{\|x_N - y_1\|_2^2}{\sigma_1}) & \Lambda & g(\frac{\|x_N - y_n\|_2^2}{\sigma_n}) \end{bmatrix} \tag{6}$$

However, when TNO HL nodes n is inconsistent with TNO training samples N, the matrix H is irreversible, so the OL weight β cannot be obtained by solving the inverse operation of the linear equation system. It can be converted to solve the following optimization problem by the least squares method to obtain:

$$\min_{\beta \in R^n} \{\|H\beta = T\|_2^2\} \tag{7}$$

$\beta = H^{\dagger}T$ can be obtained by the least squares method, where $H^{\dagger} = (H^T H)^{-1} H^T$. Thus, the EBFNN algorithm can be generalized:

Known: Given a training sample $\{(x_j, t_j): x_j \in R^m, t_j \in R^m, j = 1,2,\cdots,N\}$, a Gaussian activation function g, and TNO HL nodes n.

(1) According to the data structure of the training samples, select the center point yi and the smoothing factor σi that satisfy the uniform distribution (i=1, 2,..., n)

(2) Calculate the output matrix H.

(3) Calculate the weight $\beta = H^{\dagger}T$.

3. Experimental Study

3.1. Experimental Design

This experiment mainly uses the RBF width learning method proposed in this section to conduct experiments on image recognition methods in Vehicle, WDBC, ORL, and ExYaB datasets, and compare them with traditional algorithms.

The steps of the radial basis width learning network algorithm are as follows:

(1) Input the data set, use the Vehicle data set, the WDBC cancer cell data set, and the ExYaB data set to conduct experiments respectively, and compare the traditional experimental methods to observe the experimental results.

To select a data set, first organize the data set to determine the parts of the data set for training and testing.

(2) Select fuzzy C-means clustering algorithm to optimize the center of membership function and RBF of RBF network.

After the dataset is determined, TNO clusters of fuzzy C-means is determined by TNO categories of the dataset. For example, the Vehicle data set has a total of 6 categories. In this paper, TNO clusters of fuzzy C-means is set to 6. If the network inputs the data of the same data set again, TNO clusters remains unchanged; data, then TNO clusters needs to be recalculated.

(3) Use the momentum gradient descent method to determine the coefficients of the polynomial.

The objective function is determined according to the output value of the RBF network and the sample label value. Determine the coefficients of the polynomial calculated by the momentum gradient descent method. Before gradient descent, this paper needs to determine the learning rate and momentum coefficients. After the objective function is determined, the gradient vector is calculated and the momentum coefficient is set.

(4) Enhance the geometric details of the image by adding a graph regularization term to the loss function graph. Through the derivative operation of the loss function, the pseudo-inverse is obtained, and the final output value of the network is finally obtained.

Add the graph regularization term to the loss function to determine the penalty mechanism. If they are assigned to different classes, they will be punished, and if they are assigned to the same class, they will be rewarded to enhance the geometric details of the image. Then, the weights are updated by the calculation method of the width learning pseudo-inverse. Set thresholds to determine whether the weights meet engineering requirements. After the requirements are met, the weights are output and used for testing.

3.2. Related Operations

(1) Input to the network

1) Image croing

In this paper, the existing image data set downloaded from the Internet is firstly stored, and then the images are croed into images of the same size. The purpose of croing the image to the same size is that the dimension of the input vector must be fixed, otherwise the dimension of the weight vector cannot be determined.

2) Standardization

The input vector X of the network is directly obtained from the image matrix through the standardized formula. The main purpose of this is to convert uniform data of different sizes to the same size and scale it with the calculated Z-score value to ensure comparability between the data.

(2) Selection of parameters

This paper selects the optimal parameters of the proposed method as the final parameters of the algorithm model. During model training, TNO OL nodes of feature nodes (RBF nodes) is determined by TNO categories (labels) of the dataset itself. TNO OL nodes = TNO labels.

TNO HLs: determined by the dimension of the data, the dimension of the image data = TNO HLs.

Momentum Gradient Descent: Using default parameters, the momentum coefficient is 0.9, and the learning rate is 0.001.

TNO characteristic nodes and TNO enhanced nodes are adjusted by grid search algorithm.

4. Experiment Analysis

4.1. Comparison of RBF-BLS+ and RBF-BLS

Through experiments, this paper further analyzes the effect of the RBF-BLS+ method on the training recognition rate (RT) and test RT. Compared with the RBF-BLS method, inputting more data information into the enhancement node can enhance the information amount of the enhancement node, thereby improving the performance of the network.

As can be seen from Figure 3, through comparison, it is found that the RBF-BLS+ method proposed in this chapter has a higher training RT than the RBF-BLS method. The RT has been significantly improved on the Heart, Vehicle, Wine, WDBC, Balance, and Iris datasets. It shows that the RBF-BLS and RBF-BLS+ methods proposed in this paper have high RTs. It has strong transferability and robustness in the dataset.

Table 1. Experimental comparison of RBF-BLS and RBF-BLS+

Data set	RBF-BLS		RBF-BLS+	
	Training RT (%)	Test RT (%)	Training RT (%)	Test RT (%)
Heart	91.24	85.33	92.53	86.08
Vehicle	94.67	91.30	95.57	92.72
Wine	99.36	99.15	99.88	99.22
WDBC	99.36	97.92	99.12	98.13
Balance	97.33	93.88	98.33	95.56
Iris	99.87	99.23	99.90	99.88

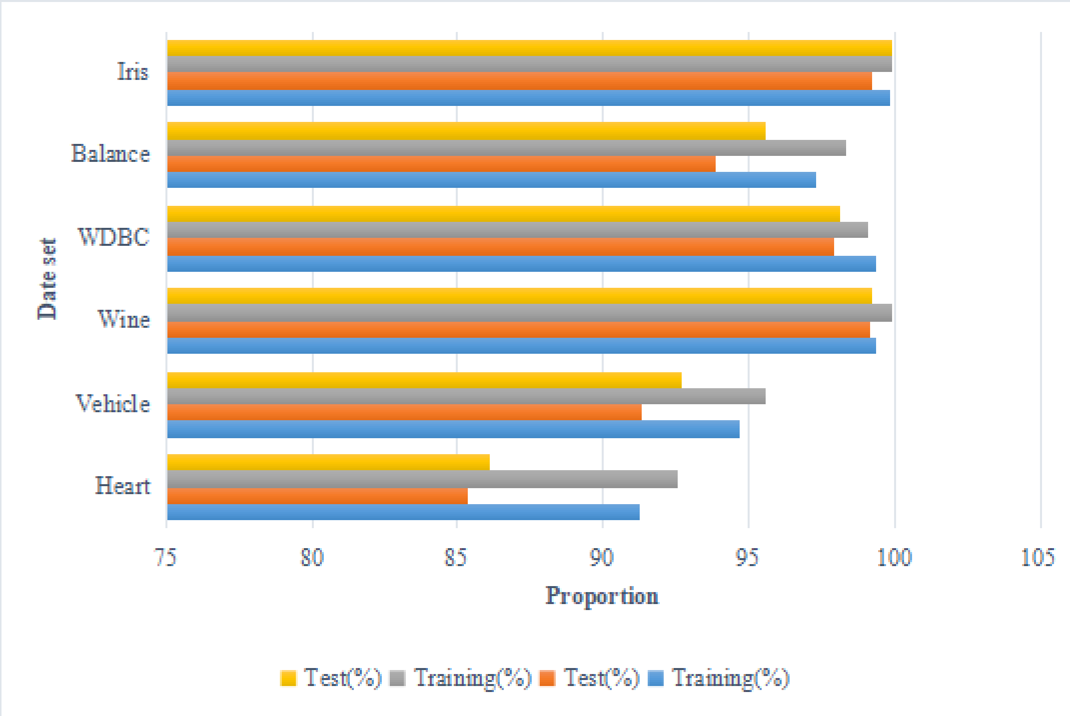

Figure 3. Experimental comparative analysis of RBF-BLS and RBF-BLS+

4.2. Improve Network Analysis

Next, we tentatively adjust the value of g until the fitting effect reaches the desired level. Some experimental results are shown in Table 2.

Table 2. Statistics on the effect of improved network q value on experimental results

q-value	HL neurons	Mean square error	Output mean	Relative mean difference (%)	Training time (s)
50	20	0.006	0.054	18.73	1090.6
100	27	0.003	0.028	20.71	1256.4
150	39	0.002	0.025	16.11	1233.4
160	42	0.002	0.012	8.26	1251.1
170	43	0.002	0.025	20.31	1257.9
180	43	0.002	0.031	13.26	1384.1
190	46	0.002	0.028	20.46	1567.7
200	48	0.002	0.027	21.84	1546.4

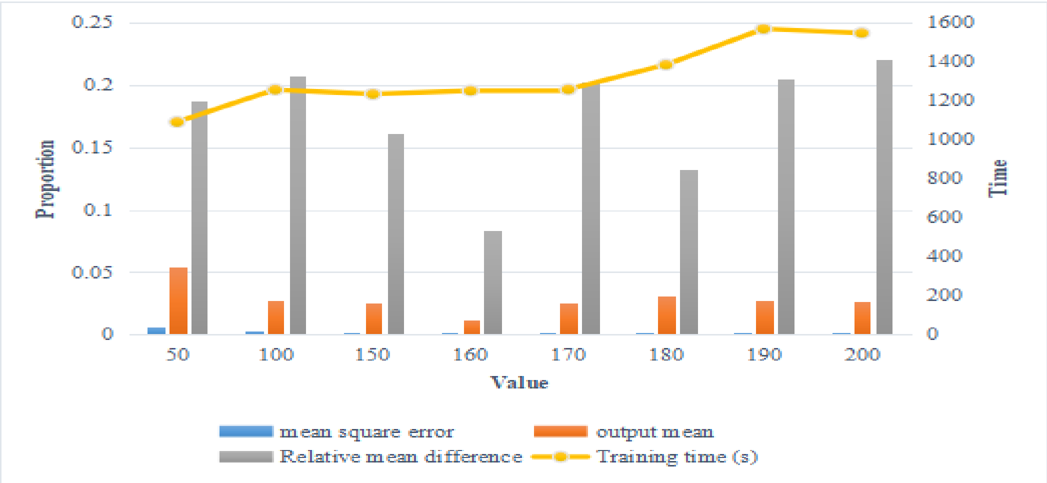

Figure 4. The influence of the improved network q value on the experimental results

It can be seen from Figure 4 that when q=160, the fitting effect of the RBF NN is good.

It can be seen from the figure that when the noise is small, the networks trained by these two methods have a strong fitting effect. The output value of the network is very close to the theoretical output (expected output) and the change trend is basically the same as the actual situation. When the noise is large, the NN trained by the suort vector machine to determine the basis function method has a better fitting effect, and the mean square error of the network (0.0020) is also smaller than that of the system method (0.0028).

The relevant parameters when the networks of the two methods achieve a better fitting effect are shown in Table 3.

Table 3. Experimental results table

	HL neurons	Mean square error	Output mean	Relative mean difference	Training time (min)
Improvement method	42	0.002	0.019	0.83	18.18
Systematic aroach	20	0.003	0.021	0.87	20.94

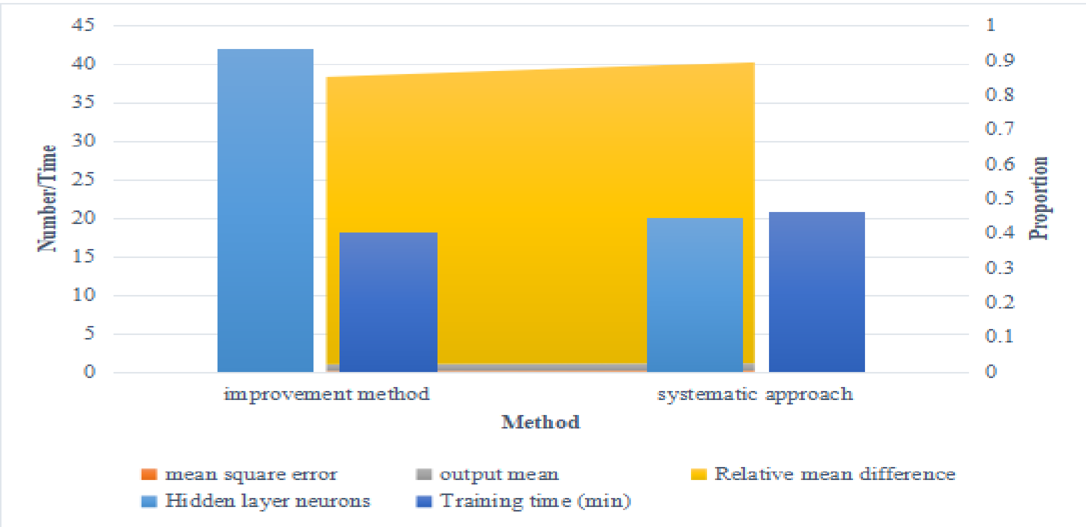

Figure 5. Analysis of experimental results

By analyzing and comparing the experimental results, it is found that the improved network is better than the system clustering method in terms of relative error and output error, the performance of the improved network is obviously better, and it can better aroximate the expected value in the case of noise interference.

It can be seen from Figure 5 that the network of the improved method is much higher than the system clustering method in terms of convergence speed, fitting accuracy and network stability. The disadvantage is that the time complexity of the improved method to train the RBF NN is relatively high. With the rapid development of computer hardware level, the impact of this aspect becomes smaller and smaller.

5. Conclusion

RBF NN is a local aroximation NN with a simple structure and has a good theoretical basis. This paper introduces the structure and basic principle of RBF NN in detail, and analyzes the principles and respective advantages and disadvantages of several commonly used RBF NN learning methods. The self-organizing learning method first determines the parameters related to the RBF center through the clustering method, and then determines the network weights through the supervised learning method. The calculation is simple and the learning speed is fast. The traditional algorithm using k-means clustering method to determine the basis function center needs to give TNO categories and the initial cluster center in advance, and the basis function center obtained when the initial cluster center is different is different; the systematic clustering method also has all the greedy algorithms There are disadvantages, even if each step is the optimal choice, the final result is not necessarily optimal, and is greatly affected by singular values.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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