Study on RMB Number Recognition Based on Genetic Algorithm Artificial Neural Network

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***Abstract*—BP artificial neural network based on genetic algorithm training method was proposed in this paper to solving Renminbi (RMB) number recognition and artificial neural network BP algorithm problems in order to satisfy the technical requirements of financial sector sorter. The BP artificial neural network based on genetic algorithm training method combined the global search ability of genetic algorithm and local search ability of BP algorithm. Genetic operators such as selection, crossover and mutation were studied and chosen according to the object. Experiments show that RMB number recognition based on genetic algorithm and BP artificial neural network improves recognition accuracy and speed, and provide a new means of RMB number recognition.**

Keywords-RMB number recognition; genetic algorithm; artificial neural network;BP algorithm;

I. INRODUCTION

Renminbi （RMB）is the legal currency of China. Its number is unique. RMB number becomes identification number of Renminbi. RMB number contains printed English letters and numbers. Research of RMB number recognition method is important for financial crime cases reduction, financial markets stability and social security. RMB circulation management is a serious problem to China's financial industry which has rapid development today. RMB number recognition has become a much-needed support technology in financial field. It will create the appropriate economic benefits and social benefits that building complete solutions of RMB number recognition according to the characteristics of the financial sector.

Artificial neural network (ANN) is able to learn nonlinear function, and realize parallel operation, so ANN has excellent fault tolerant ability. ANN is widely used in pattern recognition, classification, and function approximation fields. ANN learns with gradient descent method, which brings shortcomings of slow convergence and local minimum point into ANN. Genetic algorithm (GA) is an optimization algorithm simulating natural selection mechanism. GA can reach global minimum point in complicated, multi-peak, nonlinear, and non-differentiable space. Genetic algorithm needn't grad information of error function, too. Because genetic algorithm is good at global research, while BP network is good at local research, it is an effective way that combining GA with ANN to train samples. RMB number recognition based on genetic algorithm and artificial neural network is an effective method for RMB number recognition.

II. IMAGE PREPROCESSING

Image preprocessing is an important task before image recognition for image recognition accuracy improvement. Image preprocessing includes image binary, image enhancement, edge detection, positioning segmentation, slope correction, and character normalization. CCD camera collects RMB images. There are 2 editions of RMB 100 yuan in current circulation, one is 2005 edition, and the other is 1999 edition. Numbers of both editions include horizontal and vertical numbers. This paper only processes, extracts and recognizes horizontal numbers because vertical numbers are the same as horizontal numbers and it is easier to deal with horizontal ones. Horizontal numbers of RMB have following features:

(1) Two capital English letters at the beginning, followed by eight numbers.

(2) There is background noise in horizontal number areas and man-made noise inside number fonts.

(3) Range of numbers is from 0 to 9, and range of English letters is from A to Z.

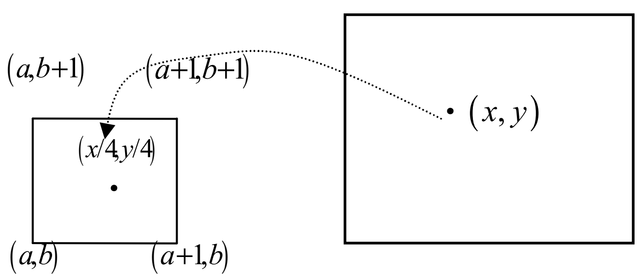
CCD camera creates RGB true color image. Transforming RGB true color image to grayscale image could reduce the memory consume. It is simple and fast that median filter method transforms RGB true color image into grayscale image. Iterative method [1,2] binaries grayscale image to binary image. Sobel operator extracts the borders of binary image, because it is good at number area location and slope correction.

RMB images usually have different slope degrees during camera process. Slope of RMB image should be corrected in order to ensure the accuracy of number segmentation and extraction. Image rotation method [3] calibrates image slope in this paper. After slope correction, RMB image is a parallelogram, whose two horizontal sides are parallel with the x-axis, because there is lateral movement in RMB image collection process. Left and right sides slope angle of image can correct this distortion [3].

RMB numbers location is import for numbers segmentation, therefore the system must improve the positioning accuracy in order to ensure the performance of identification number. As horizontal numbers are in the left-bottom of RMB, the left-bottom area of RMB image is the location searching area. Number location includes line and column position. Image scan is from top to bottom to find out the first and the last bounds of numbers area. If there is non-zero bit of a certain line, and then there is non-zero bits in its k following lines, the line will considered to be the first line of numbers area [3]. The same method is used to find the last line of numbers area. Scanning RMB image from left to right will find out the left and right bounders of numbers area, and then these numbers will be separated from each other by vertical projection segment method [4]. The number character segmentation threshold *thresh* of vertical projection segment method approximately equals to the width of a number character. Let the width of the image number be n, then thresh is obtained by equation (1):

$$thresh = n/20 \tag{1}$$

It will result in slow convergence speed of the network, or even the network doesn't converge at all, that using different sizes image samples train ANN, therefore normalization is the key step of RMB number recognition. Bilinear interpolation method [1] normalizes the number character image size in this paper. Bilinear interpolation method diagram is shown in Fig. 1.



(A) original image (B) enlarged image

Figure1. Bilinear interpolation method

Number character image need to be moved to a defined position in order to eliminate characters position deviation in the image, and this movement process is called location normalization. Location normalization method based on character outside matrix [5] is used to resize number image into 9×9.

Final RMB number character images after image preprocessing are shown in Fig. 2.

Figure2. RMB number character images

III. RMB Number Recognition Based on Genetic Algorithm and BP Artificial Neural Network

A. BP Artificial Neural Network

Back propagation (BP) artificial neural network is one of the most widely used types of artificial neural network. BP ANN uses Least Mean Square (LMS) algorithm to minimize the square error of expected output and real output of neural network, and finds the best weights and basis of it, too. BP ANN structure contains input layer, hidden layers and output layer. Nodes of each layer are connected. Nodes in the same layer are not connected with each other. The input signals firstly propagate to the hidden layers, and then through the activation function, finally forward propagate to the output layer. There are two different types of RMB number recognition objects, those are, English letters and numbers. This paper designs 2 ANN to separately recognize English letters and numbers. The normalized image size is 9×9, and the whole picture is used to train ANN, so the input nodes number of ANN is 81. ANN with one hidden layer is adopted. The nodes number of hidden layer is gained according to equation (2)[6]:

$$n = \sqrt{n_i + n_o} + a \tag{2}$$

Where, n is the nodes number of hidden layer, n_i is the nodes number of input layer, n_o is the nodes number of output layer, and a is a constant between 1 and 10. For English letters ANN, a=5. For number ANN, a=4. The nodes number of hidden layer obtained according to equation (2) is between 10 and 20. Considering the convergence speed and recognition accuracy, the number of nodes in the hidden layer is determined to be 15. We choose *logsig* equation to be activation function of output layer, and *tansig* equation to be activation function of hidden neurons.

logsig equation:

$$f(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

tansig equation:

$$f(x) = \frac{1-\exp(-x)}{1+\exp(-x)} \tag{4}$$

In the recognition process, the first two characters is put into the English letters ANN, the other eight numbers are sent into the number ANN. Table 1 is expected outputs table of number ANN, Table 2 is expected outputs table of English letters ANN. The learning rate of BP algorithm defaults to 0.01[7].

B. Genetic Algorithm

The paper uses real number coding since the connection weights and the threshold of network nodes are real numbers. Genetic algorithm chromosomes are the ANN weights and thresholds in the encoding process. ANN weights and threshold ranges are between -1 and 1. In this paper, neural network has three layers, and hence its coding order is the connection weights of the input layer to the hidden layer, and the connection weights of the hidden layer to the output layer. A set of ANN weights and thresholds are randomly generated, then arranged according to above order. Genetic algorithm population size is generally between 20 and 200. Population in this paper is between 10 and 30 because BP algorithm has optimal ability itself. After several times of debugging, the final population is determined to be 20.

TABLE 1 EXPECTED OUTPUTS TABLE OF NUMBER ANN

Number	Binary code	Expect output
0	0000	0.01,0.01,0.01,0.01
1	0001	0.01,0.01,0.01,0.99
2	0010	0.01,0.01,0.99,0.01
3	0011	0.01,0.01,0.99,0.99
4	0100	0.01,0.99,0.01,0.01
5	0101	0.01,0.99,0.01,0.99
6	0110	0.01,0.99,0.99,0.01
7	0111	0.01,0.99,0.99,0.99
8	1000	0.99,0.01,0.01,0.01
9	1001	0.99,0.01,0.01,0.99

TABLE 2 EXPECTED OUTPUTS TABLE OF ENGLISH LETTERS ANN

English letters	Binary code	Expect output
A	001010	0.01,0.01,0.99,0.01,0.99,0.01
B	001011	0.01,0.01,0.99,0.01,0.99,0.99
C	001100	0.01,0.01,0.99,0.99,0.01,0.01
D	001101	0.01,0.01,0.99,0.99,0.01,0.99
E	001110	0.01,0.01,0.99,0.99,0.99,0.01
F	001111	0.01,0.01,0.99,0.99,0.99,0.99
G	010000	0.01,0.99,0.01,0.01,0.01,0.01
H	010001	0.01,0.99,0.01,0.01,0.01,0.99
I	010010	0.01,0.99,0.01,0.01,0.99,0.01
J	010011	0.01,0.99,0.01,0.01,0.99,0.99
K	010100	0.01,0.99,0.01,0.99,0.01,0.01
L	010101	0.01,0.99,0.01,0.99,0.01,0.99
M	010110	0.01,0.99,0.01,0.99,0.99,0.01
N	010111	0.01,0.99,0.01,0.99,0.99,0.99
O	011000	0.01,0.99,0.99,0.01,0.01,0.01
P	011001	0.01,0.99,0.99,0.01,0.01,0.99
Q	011010	0.01,0.99,0.99,0.01,0.99,0.01
R	011011	0.01,0.99,0.99,0.01,0.99,0.99
S	011100	0.01,0.99,0.99,0.99,0.01,0.01
T	011101	0.01,0.99,0.99,0.99,0.01,0.99
U	011110	0.01,0.99,0.99,0.99,0.99,0.01
V	011111	0.01,0.99,0.99,0.99,0.99,0.99
W	100000	0.99,0.01,0.01,0.01,0.01,0.01
X	100001	0.99,0.01,0.01,0.01,0.01,0.99
Y	100010	0.99,0.01,0.01,0.01,0.99,0.01
Z	100011	0.99,0.01,0.01,0.01,0.99,0.99

Each chromosome is decoded and assigned to corresponding weight and threshold of BP ANN. BP ANN with these weights and thresholds values is trained by the sample set. Mean square error is gained according to equation (3) and equation (4). For neural networks, mean square error is the smaller the better, so we use correlation of mean square error as fitness function. MSE equation:

$$E = \frac{1}{N}\sum_{p}\sum_{l}(t_l - o_l)^2 \tag{3}$$

Where, p is the samples number, l is the output nodes number, t_l is expected output, and o_l is the real output. $N=l\times p$.

Fitness function defined as equation (4):

$$f = \frac{1}{E+1} \tag{4}$$

There is constant 1 in the denominator of equation (4) in order to prevent fitness function aberration when E is very small.

IV. GENETIC ALGORITHM OPERATORS CHOOSE

A. *Select operator*

Roulette combined with best individual preservation strategy and Monte Carlo proportion method determine the selection probability of individual based on its fitness value together [8]. Selection probability P_i is:

$$P_i = \frac{f_i}{\sum_{i=1}^{m} f_i} \tag{5}$$

Where, $1\leq i\leq m$. m is the individual number in a population, f_i is the fitness value of selected individual. Best individual preservation strategy is adopted to prevent the best individual of a generation destroyed by crossover and mutation operations in the roulette wheel selection process. It is proved theoretically that the best individual preservation strategy can converge to the global optimal solution with probability 1.

B. *Crossover operator*

Crossover probability is chosen according to the individual fitness. Individual that has bigger fitness value uses smaller crossover probability, while individual that has smaller fitness value adopts bigger value [8].

$$P_c = \begin{cases} P_{c1}, & f' \geq f_{avg} \\ P_{c2}, & f' < f_{avg} \end{cases} \tag{6}$$

Where, f' is the fitness of two mutated individuals. f_{avg} is the average fitness value of current generation. P_{c1} and P_{c2} could be modified according to final searching values of genetic algorithm. P_{c1} is 0.9, and P_{c2} is 0.5 in this paper.

C. *Mutation operator*

Random p is circularly generated for each chromosome. If p is less than setting value Pm, the corresponding chromosome will mutated. Mutation probability is modified based on individual fitness as equation (7).

$$P_m = \begin{cases} P_{m1}, & f \geq f_{avg} \\ P_{m2}, & f < f_{avg} \end{cases} \tag{7}$$

Where, f is the fitness of two mutated individuals. f_{avg} is the average fitness value of current generation. P_{m1} and P_{m2} could be modified according to final searching values of genetic algorithm. P_{m1}=0.01, and P_{m2}=0.001 in this paper.Fig. 3 is the flow chart of GA-BP ANN.

The terminal rule of GA is given training time. If reach the training time , program stop searching and give the final neural network structure.

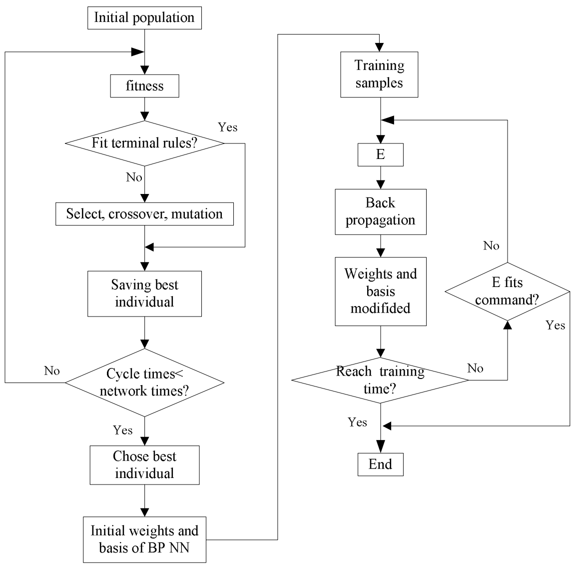


Figure3 Flow chart of GA-BP ANN

V. GA-BP ANN TRAINING RESULTS

Each RMB number character has 20 samples. There are 520 samples for English letters GA-BP ANN and 200 samples for number GA-BP ANN. 50 images which are not in the samples set test the trained networks. Fig. 4 is parts of the training samples.

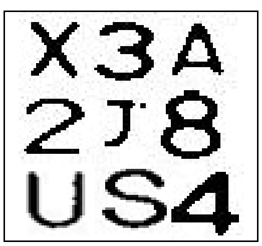


Figure4 Parts of training samples

GA-BP ANN is established and then trained by samples. Training results of GA-BP ANN are compared with the results of BP ANN. Maximum permissible error is 0.001. The maximum training steps number is 5000. The steepest descent method trains both networks for 100 times. Statistical results are shown in table 3.

TABLE 3 AVERAGE TRAINING STEP AND UN-CONVERGENCE TIME OF GA-BP AND BP ANN

training method	Average training step	un-convergence time
BP ANN	3393.5	16
GA-BP ANN	2627.5	9

Fig. 5 is the convergence curve of GA-BP ANN. Fig. 6 is the convergence curve of BP ANN.

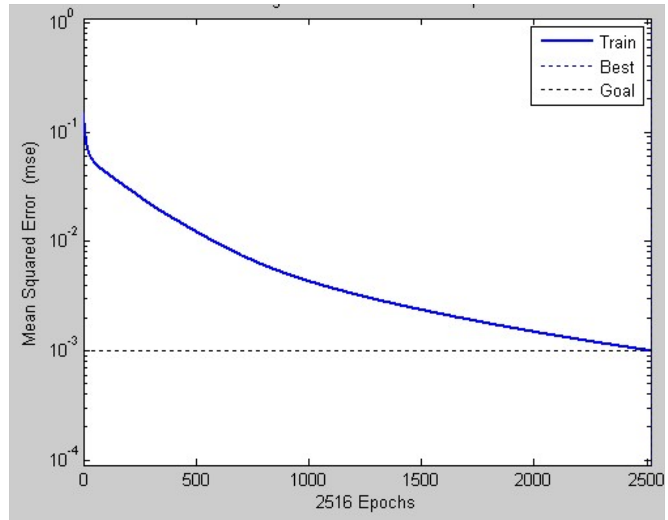


Figure5 Convergence curve of GA-BP ANN

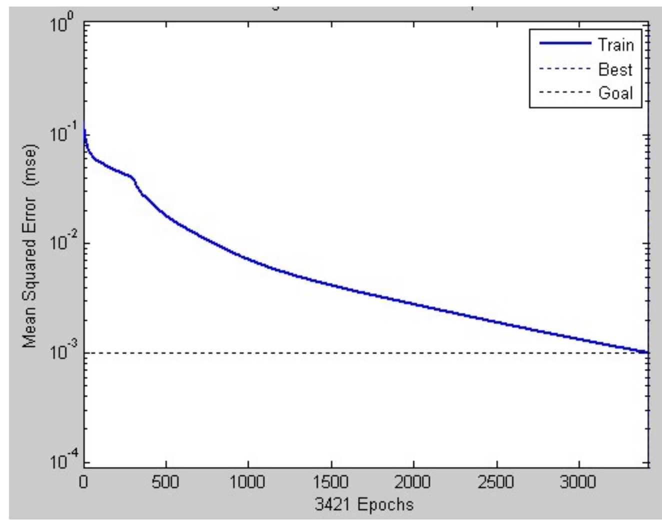


Figure6 Convergence curve of BP ANN

Fig. 5 and Fig. 6 demonstrate that using the same training methods, GA-BP ANN has less training times and more convergence times than BP ANN. Convergence times of GA-BP ANN improves over 22.6% of BP ANN. GA-BP ANN can improve convergence speed and stability.

VI. EXPERIMENTS AND CONCLUSIONS

Firstly, Genetic Algorithm optimizes weights and thresholds of BP ANN. Secondly, decoded network weights and threshold values are used as the initial weights and thresholds of BP ANN. Thirdly, GA-BP ANN will be trained by English letter samples and number samples. Finally, 50 images test trained GA-BP ANN. Results of GA-BP ANN are shown in table 4. Results of BP ANN are shown in table 5.

Experiments indicate that GA-BP artificial neural network improves the convergence rate of 22.6% compared to BP artificial neural network. GA-BP ANN has better performance on convergence speed and stability than BP ANN. RMB number recognition accuracy of GA-BP ANN is 95% , which increases by 15.8% than BP ANN. GA-BP ANN also reduces neural network training times, and effectively improves RMB number recognition accuracy and speed. GA-BP ANN has better performance than BP ANN for RMB number recognition.

TABLE 4 RMB NUMBER RECOGNITION RESULTS OF GA-BP ANN

	training samples	test samples	training time(s)	recognition rate
English letter	520	50	18	97%
number	200	50	15	98%
total				95%

TABLE 5 RMB NUMBER RECOGNITION RESULTS OF BP ANN

	training samples	test samples	training time(s)	recognition rate
English letter	520	50	21	89%
number	200	50	19	92%
total				82%

ACKNOWLEDGE

This work is supported by China Nationality Science Found (08DL06), Natural Science Foundation of Liaoning Province (20082174) and Science and Technology Foundation Project in Introducing Specialist of Dalian Nationalities University (20086201).

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