A New Recognition Method of Vehicle License Plate Based on Genetic Neural Network

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***Abstract*—A new recognition method of vehicle license plates based on neural network is presented in this paper. For the Back Propagation (BP) neural network often trap into the local minimum in the training process, a Genetic Neural Network (GNN), GABP was constructed by combining the Genetic Algorithm（GA）with BP neural network. The training of the GABP neural network was finished in two steps. The GA was firstly used to make a thorough searching in the global space for the weights and thresholds of the neural network, which can ensure they fall into the neighborhood of global optimal solution. Then, in order to improve the convergence precision, the gradient method was used to finely train the network and find the global optimum or second-best solution with good performance. On the other side, feature extraction is also important for improving the recognition rate of the network. So both the structure features and the statistic features are used in this paper, which include mesh feature, direction line element feature and Zernike moments feature. Experimental results show that the proposed method can save the time of training network and achieve a highly recognition rate.**

Keywords-GABP; global optimal solution; feature extraction; character recognition

I. INTRODUCTION

With the development of transportation technology and the universality of the vehicles, automatic vehicle license plate management system has become a popular subject[3]. License plate is the ID of a vehicle. Therefore, as a part of vehicle license plate recognition system, character recognition becomes more and more important. Former researchers have already put forward many solutions[3] [5] [7] [12], and these methods can be grossly divided into two categories: based on template matching and based on artificial neural networks. Template matching method can quickly recognize the character by computing the correlation between the module and the image. But when the license plate has deformation or rotation, the recognition rate will greatly reduce.

Artificial neural network (ANN) is an interdisciplinary method of biology and computer science, which has been widely used in signal processing, pattern recognition, nonlinear optimization and so on[1] [3] [10] [12]. It can arbitrarily approach to a highly nonlinear function without pre-determined mathematical model. The network can achieve non-linear approximation only through its own learning from a certain amount of samples. However, the neural network algorithm is gradient-based, the optimization process is very slow, and it often falls into local minimum[4] [12]. To solve the problem, we construct a new neural network called Genetic BP neural network, which is the BP network optimized by Genetic algorithm (GA). GA is a global optimization algorithm based on natural selection and genetic theory, combining the principle of survival of the fittest and random information exchange mechanism in the process of biological evolution[1] [3] [4] [12]. The algorithm starts searching from the population, which can easily find the global optimal solution or sub-optimal solution instead of local optimal solution. The results show that Genetic BP neural network can effectively improve the network performances and recognition rate.

On another hand, feature extraction can affect the recognition rate of vehicle license plates. The feature can roughly divide into structure feature and statistic feature[2]. As the two methods have merits and demerits respectively, the extracted features in the paper are comprehensively considered structure and statistic features.

II. FEATURE EXTRACTION

Feature extraction which comes after character segmentation and before character recognition, is one of the key processes in license plate recognition system. Since good features can make the recognition process easier and reduce the error rate, how to select the most effective features to improve the accuracy is very important.

There are several types of features[2], which have been introduced by former researchers and categorized into two groups: structural feature and statistic feature. Structural features reflect the character's structure information, such as skeleton property, contour feature, stroke feature and topological characteristic. Statistic feature is the most relevant information extracted from the raw data, which minimize the inner-class distance and maximize the between-class distance. The statistic features commonly used are as follow: complexity index, four-edge code, stroke density, meshing feature and transform domain feature.

Thus there currently have two feature extraction techniques: method based on character's structure feature and method based on character's statistic feature. The former method has a strong adaptability of character font changes, so it can easily differentiate the similar characters. However its computational complexity is large and its ability of anti-interference is so bad. As for another method, it has advantage of anti-interference and simple algorithm of classification and matching. But it can hardly differentiate the similar characters.

Considering the merits and demerits of two techniques, in this paper we combine the structure feature with statistic

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feature to compensate mutually. Following are the features that we extract for recognition.

A. Elastic Mesh Feature

Mesh feature[8] is one of the common-used characteristics for character recognition. It can be divided into uniform mesh feature and elastic mesh feature. Uniform mesh is a fixed-size sub-grid by evenly dividing the character image according to the size of the grid. It reflects the distribution of characters' overall shape, but its ability of location anti-interference is poor. Elastic mesh is a sub-grid whose location is dynamically determined according to the density of character image. When compared to the uniform mesh, elastic mesh has better adaptability while the strokes have some deformation, and it also reflects the character's global feature.

For a character imager sized $N \times M$, the steps of extracting elastic mesh feature are as follows:

1）The number (n, m) of mesh is determined.

2）The pixels of each line and each column are calculated along the horizontal direction and vertical direction, which to be used as horizontal and vertical projection feature (Horn(j),Vert(j)), with the dimension of eigenvector is M and N.

3）The location of gridlines in the horizontal and vertical directions are determined according to the formula (1) and (2):

$$\sum_{i=I_k}^{I_{k+1}} Horn(i) = \sum_{i=I_{k-1}}^{I_k} Horn(i), I_k = I_2, I_3, \cdots, I_n, i = 1,2,\cdots,n \tag{1}$$

$$\sum_{i=I_k}^{I_{k+1}} Vert(j) = \sum_{i=I_{k-1}}^{I_k} Vert(j), I_k = I_2, I_3, \cdots, I_m, j = 1,2,\cdots,m \tag{2}$$

4) The pixels of the image are divided into meshes and the number of pixels in each mesh is accounted, which compose the elastic mesh's eigenvector.

B. Direction Line Element Feature

Generally speaking, a Chinese character is composed of four strokes: 一, 丨, ㇓, ㇏. The number of each stroke and their inter-relationship of location can uniquely decide the Chinese character. Fortunately, direction line element feature[8] can reflect the number of four strokes in different spatial location, that express the Chinese character's characteristics of stroke and location. In this paper, we extract the character's direction line element feature to recognize the first character of the license plate.

The steps of extracting the direction line element feature are as follows:

1). The objective pixel is gotten from the character image and the character's contour f(i,j) is extracted.

2). The contour is divided into $m \times m(m > 3)$ meshes.

3). The number of the mesh E_s is selected as $s = 1,2,\cdots,m \times m$.

4). For the mesh E_s, the quantity of four strokes is separately accounted according to the definition of their direction property as formulas (3).

$$\begin{aligned} H &= \{(i,j) \mid i-k=0 \wedge l-j=1\} \\ V &= \{(i,j) \mid j-l=0 \wedge i-k=1\} \\ P &= \{(i,j) \mid i-k=1 \wedge j-l=1\} \\ N &= \{(i,j) \mid i=k=1 \wedge l-j=1\} \end{aligned} \tag{3}$$

where point (i,j) and point (k,l) are the adjacent contour points.

5). An eigenvector with $m \times m \times 4$ dimensions is gotten by accounting above for every mesh continually.

C. Zernike Moment Feature

Since Hu[5] introduced the algebraic moment invariance, moments have been widely used for the recognition of different types of shapes and images. And low-order moments just describe the general shape of the image, yet high-order moments can describe the details of the image. It's known that Hu moment[5] has been used in many cases, but it is composed of some low-order moments. Whenas Zernike moment[5], [6] can get the high-order coefficient, so in this paper we choose Zernike moment as an eigenvector of the character.

Zernike moment is defined as follows[7]:

$$Z_{nm} = \frac{n+1}{\pi} \iint_{x^2+y^2 \le 1} V_{nm}^*(x,y) f(x,y) dxdy \tag{4}$$

Where $V_{nm}(x,y)$ represents orthogonal Zernike polynomials, which are orthogonal inside the unit circle $r = 1, n = 0,1,2,\cdots,\infty$, and $n - m(n \ge m \ge 0)$ must be even.

$$V_{nm}(x,y) = V_{nm}(r,\theta) = R_{nm}(r)e^{jm\phi} \tag{5}$$

When compared to other moments, Zernike moment has some merits: (1) It has inverse transform; (2) It has rotation invariance; (3) It has the least redundant information[2].

III. GABP NEURAL NETWORK

Artificial Neural Network (ANN) is an interdisciplinary study of biology and computer science, which has been widely used in signal processing, pattern recognition, computer vision, intelligent control, nonlinear optimization, and so on. Back Propagation (BP) algorithm is one of the most effective methods of ANN. The structure of the BP neural network (BPNN) is shown in Figure 1. Any continuous function in a closed interval can be approximated by using a BPNN. For any complicated system, if its samples are more enough, a BPNN model can be constructed after repeated learning and training, which reflects the relationships between the input and output. So, BPNN has very strong capabilities of nonlinear modeling and analysis for huge and complex system.

However, since the initial interconnecting weights and thresholds of BPNN are often stochastically, the learning times and final interconnecting weights of the network change with training times. That is to say, the network is not unique and it possibly traps into local optimal. Moreover, the blindness of the determination of initial interconnecting weights always results in too much training time and slow speed of convergence. These shortages of BPNN seriously impact its precision and effects of application. It is quite necessary to optimize and improve BPNN.

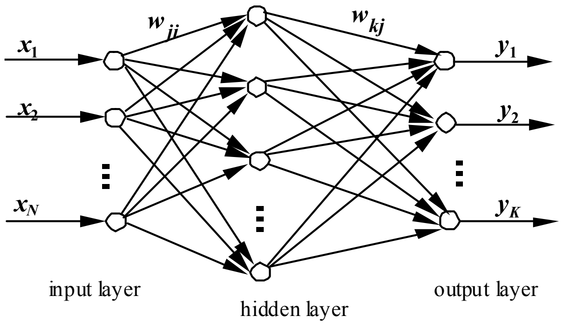

Figure 1. Sketch of structure of BP Neural Network

Genetic algorithm (GA) is a kind of global optimization search algorithm, which based on natural selection and genetic theory. In the genetic algorithm, the individual is called a chromosome. By simulating the organisms' evolutionary processes such as natural selection and evolution, the colony is repeatedly selected, crossed and mutated. Based on the fitness function and the stochastic exchange mechanism of chromosome, better and better colony is gradually evolved. At the same time, the best adaptive individuals in the optimized colony are searched by global and parallel ways.

Comparing with the traditional optimization algorithm, GA starts searching not from a single individual but a population. And in the process of searching optimal solution, it only needs fitness function converted from objective function without any other auxiliary information. That can ensure the search process converging in the global optimal solution or suboptimal solution, not a local optimal solution. Therefore, using the global optimization strategy of GA to optimize the neural network can avoid the neural network trap into local extremum.

Generally there are three ways to optimize the neural network with GA: optimizing the weights of neural network, optimizing the structure of the neural network and optimizing the learning rules of neural network. For weights are the primitive elements of neural network, and the initial weights determine where the network start training, thereby we use GA to optimize the weights to improve the performance of neural network.

In this paper we introduce GA to the weights' training process of BP network, and construct a new neural network—genetic algorithm BP (GABP) neural network. The GABP neural network and BP network are the same with structure, but different with the training process. In the training process of GABP, firstly GA is used to optimize the weights and threshold of the network, which should assure it get into the neighborhood of global optimal solution. Then the gradient method is used to finely train the weights until the network converges to the global optimal solution or suboptimal solution. The algorithm flowchart shows in Figure 2.

GA is based on the fitness function in the search process, so the choice of fitness function directly affects the convergence speed and the probability of searching the optimal solution. And in the paper the weights of GABP are the individuals of the population, thus the reciprocal of the error function can be the fitness function.

$$fitness(sol) = 1/[\sum_{i=1}^{K}(o_i - y_i)^2] \tag{6}$$

Where sol presents any individual of a population, o_i presents the output of *i-th* output-neuron., y_i presents the expected output of *i-th* output-neuron., K presents the number of output-neuron. The smaller the difference-value between the actual output and expected output is, the larger the fitness value is.

IV. CHARACTER RECOGNITION WITH OPTIMIZED GABP

A. Hierarchical Network[1]

A standard Chinese vehicle license plate has seven characters, the first character is a Chinese character which represents province, the second one is a capital letter, the rest are capital letters or Arabic numerals[10]. Fig. 3 shows two examples of Chinese license plate. With its rules as introduced, we construct a hierarchical network composed of Chinese character network, letter network and letter/digital hybrid network. After location and segmentation, the character image is sent to the specified network to recognize. This strategy can not only simplify the network structure, but also save time to train and improve the recognition rate.

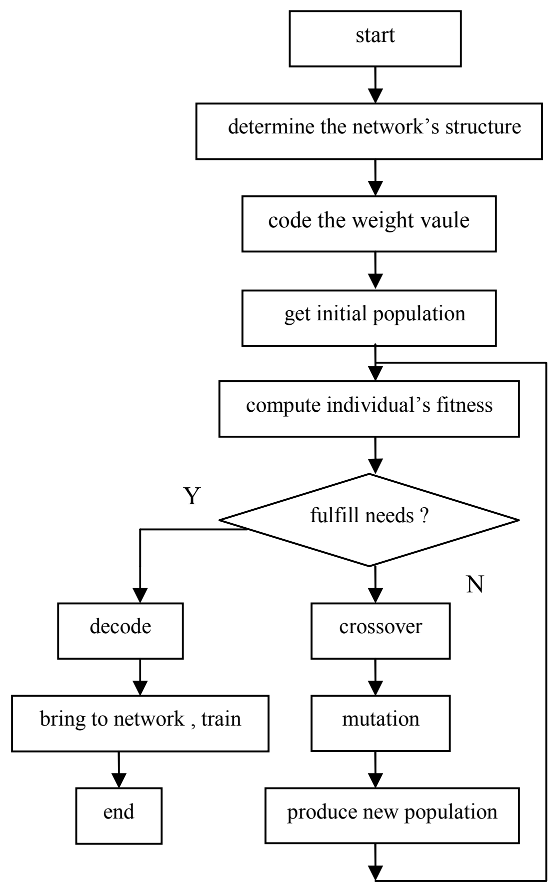

Figure 2. Flow chart of Genetic BP Neural Network

Figure 3. Vehicle license plates in China

B. *Feature Extraction*

According to the preceding analysis, the feature we extracted contains both structure feature and statistic feature. For the Chinese character images, we extract mesh feature and direction line element feature. The image is divided into 2×4 meshes, and each mesh has 4 direction vectors, so its eigenvector is 33 dimensions while the total pixels of the image is added. For the letter images and Arabic numerals images, elastic mesh feature and Zernike moment feature are selected. Like Chinese character images, the images are divided into 2×4 meshes, but each mesh is decided by the pixel value. Through adding 9 order Zernike moments (Z_{00}, Z_{11}, Z_{20}, Z_{31}, Z_{40}, Z_{51}, Z_{60}, Z_{71}, Z_{80}, Z_{91}) and the total pixels of the image, its eigenvector is 19 dimensions.

TABLE I. FEATURE EXTRACTING IN THE PAPER

style of network	features to be extracted	feature dimension
Chinese character network	mesh feature + direction line element feature + all pixels	33
letter network	elastic mesh feature + Zernike moment feature + all pixels	19
Arabic numerals/letter network	elastic mesh feature + Zernike moment feature +all pixels	19

C. *Character Recognition Result With GABP*

After extracting features from the character images, it's time to construct the network. In this paper, the number of input nodes is the dimensions of image's eigenvector, and the number of output nodes is the Binary encoding with the number of license plate character (Chinese character:34, letter character:24, Arabic numerals chatacter:10). The network here just needs one hidden layer, but the number of hidden node is very important. If the quantity is few, the network has poor accuracy, while the quantity is too much the complication may reduce the training speed or trap the network into local convergence. So the number of hidden nodes should be determined by trial-and-error method according to the empirical formula[9]。Then select the S-type nonlinear function as transfer function, and select refine training / learning function adding momentum item and self adjusting learning rate.

For the neural network is ascertained, so the chromosome of individual is $P = N \times M + M + M \times K + K$ (while the number of input nodes is *N*, the number of hidden nodes is *M* and output nodes is *K*). And set the number of initial population 80, the maximum generation 100 and the target error 0.00001.

In order to compare, we have construed a BP network and a GABP network with the same training samples in the paper, the convergence curves are shown in Fig. 4 and Fig. 5. It is obvious that the time consumption of training BP network is more than that of GABP network. And the GABP can achieve lower error rate. That is to say, the BP network optimized by GA can greatly reduce the training time and improve convergence accuracy.

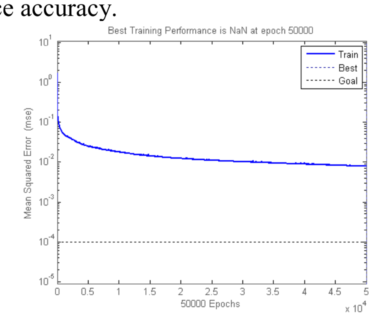

Figure 4. The convergence curve of BP

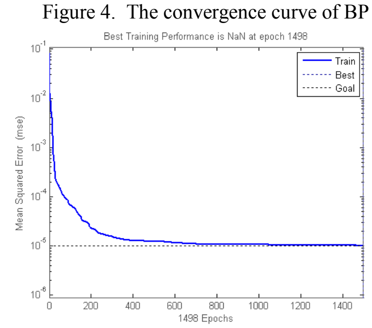

Figure 5. The convergence curve of GABP

TABLE II. RECOGNITION RESULTS

Number of correctly recognized characters on a license plate	Number of license plate recognized by BP	Recognition rate of BP	Number of license plate recognized by GABP	Recognition rate of GABP
seven	98	81.67%	104	86.7%
more than five	102	85%	110	91.7%
more than four	108	90%	115	95.8%
more than three	111	92.5%	118	98.3%
Total license plate	120			

V. CONCLUSIONS

BPNN has ability of learning, self-adaption, self-organization and fault tolerance. But its convergence is very slow and can easily plunge into local extremum, in addition, the selection of the initial weights and thresholds are random. GA is globally convergent and independent of the initial values. We construct a new network called GABP by integrating the advantages of global searching of GA and the instructive searching of BPNN. In the GABP network, the initial interconnecting weights and thresholds of BPNN are optimized with GA so that the learning and training velocity is increased and the best network convergence performance is obtained. Experimental results show that both the precision and robustness are obviously improved. Using the GABP network to recognize characters with eigenvector which considering both structure feature and statistic feature, it can greatly improve the recognition rate.

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