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Application of Improved BP Algorithm in Vehicle License Plate Recognition

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***Abstract*—First, the background, significance and general implementation of vehicle license plate recognition (VLPR) are introduced. Based on analyzing the theory of neural network pattern recognition system, toward the limitation of standard BP , this thesis offers its improved method and a real recognition example. Finally, conclusion on its characteristic is given. The improved BP algorithm had some advantages in reaching high error precision, fast convergence speed, short recognition time and high recognition rate.**

Keywords-neural network; vehicle license plate recognition; BP Algorithm; pattern recognition

I. INTRODUCTION

With the development requirement of the traffic modernization, the Intelligent Traffic System (ITS) is the future development in traffic system. ITS is a kind of integrated transportation management system, which makes advanced information technology, data communication transmission technology, electronic sensor technology, electronic control technology and computer transaction technology combine to apply for the whole ground transportation management system[1][2][3]. As computers widely use in traffic manament system, Technology of Automatic License Plate Recognition(TALPR) can resolve a lot of problems existed in traffic system and get more attention.

There are many factors that can influence the image. Even if , to a great extent , kinds of disturbance noise factors may cause image distortion. Usually there has complex nonlinear relation between the distortion and the vehicle license plate recognition. Neural network has high self-learning performance, adaptability and fault tolerance. So it is a better choice in processing non-linear problem.

BP Neural Networks Model is one of the important model of artifical neural networks. Through some learning rules, BP algorithm can adjust the connection weights among neurons. BP study algorithm has the characteristics of clear thinking, precise structure, stable working state and strong maneuverability.

II. THE BASIC THEORY OF FORWARD NEUTRAL NETWORK

A. *Neurons Information Processing*

For input signal: $X_1, X_2, \dots, X_N$, the input signal weighted sums decides the variable quantity of membrane potential. The expression is shown as (1):

$$u = \sum_{i=1}^{N} w_i X_i \tag{1}$$

Then the output signal Y is shown as (2):

$$Y = f(u - \theta) \tag{2}$$

where θ is threshold. Usually in the continuous-time model, membrane potential obeys equation in below:

$$\tau \frac{du}{dt} = -u(t) + \sum_{i=1}^{N} w_i X_i - \theta \tag{3}$$

where τ is the time interval. And then output Y is $Y=f(u(t))$.

B. *Forward Neutral Network Structure*

For the neutral network which is no feedback, suppose that there is a feed-forward neutral network which has three layers including input layer, hidden layer and output layer(See Fig. 1).

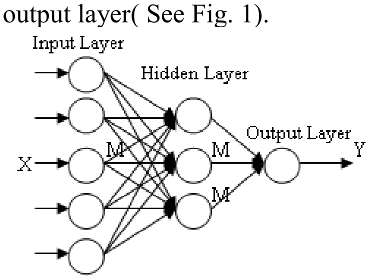

Figure 1. Forward neutral network structure

The mapping for input $X=(X_1, X_2, \dots\dots, X_N)$ to output $Y=(Y_1, Y_2, \dots\dots, Y_M)$ is:

$$Y_j = F_i\left(\sum_j w_{ij} h_j - \theta_j\right) \quad (i=1,2,\dots,M; j=1,2,\dots,N)$$

$$h_j = f_{i-1}\left(\sum_k w_{ij} X_k - \theta_k\right) \quad (k=1,2,\dots,N) \tag{4}$$

Where M and N are the dimensions of input and output in the neutral network, $H = (h_1, h_2, ..., h_N)$ is the output of hidden neurons. Network parameters that are connection weight and threshold decide that mapping. So the neutral network mapping can express as follows:

$$Y=f(Y,C) \quad C=(C_1, C_2, ..., C_N)$$

When there is feedback connections in neutral network, the equation is:

$$\tau \frac{du[\varepsilon(t)]}{dt} = -u(\varepsilon) + \sum_{\varepsilon} w(\varepsilon, \varepsilon') f[u(\varepsilon)] + Z(\varepsilon) \quad (5)$$

Where τ is time interval, Z is the external input summation of direct excitation. $u(\varepsilon)$, that is the neurons position coordinate in neutral network, is the membrane potential of position ε. $w(\varepsilon, \varepsilon')$ is the connection weight fromε' position neurons toε position neurons.

III. BP ALGORITHM AND IMPROVEMENT

A. Standard BP Algorithm Computing Steps

BP algorithm includes two sapects: forward transmission of information and back propagation of error. During the forward transmission from input layer by hidden layer to output layer, the input information is computed in every layer. But the state of every layer neurons can only effect the state of next layer. If there is no expected output result in output layer, it would compute the error variation, then turning to back propagation. That is to say, it would transmit the error signal from output layer to input layer to modify the weight of every layer neuron by internet until reaching the expected result.

(1) Initialization. Determine the action function of neurons(usually use type S function, $f(x) = \frac{1}{1+e^{-x}}$), then give the permissible error$\varepsilon(\varepsilon>0)$, the learning rate μ and the inertial factor $\alpha(\alpha \geq 0)$, at last choose the initial weight $w = w^{START}$.

(2) Compute network output Y, then obtain the misclassification output node index set B. If $B=\Phi$ (expressed empty) then goto (3) else goto (4)

(3) Compute error function $E(w)$ (Jacobian Matrix $\|\nabla J(K)\|^2$), if $E(w) < \varepsilon (\|\nabla J(K)\|^2 < \varepsilon)$ then goto (5) else goto (4).

(4) Modify the weight $w(k+1) = \mu w(K).\nabla J(K) + \alpha \Delta w(K-1)$, goto (2).

(5) Save the best weight $w' = w$, end.

B. Improved BP Algorithm and Checking

BP network is widely applied in function approximation, pattern recognition and system identification. But BP algorithm is slow in convergence speed. So an improved BP algorithm is put forward to accelerate the network convergence and to reduce the training time. It has been illustrated by simulative calcuation that the improved BP has advantages of fast convergence and high precision function approximation comparing to the standard BP. The improved BP can be summarized in the following three aspects:

(a) Modify the action function In standard BP algorith, usually the action function of neurons is type S $f(x) = \frac{1}{1+e^{-x}}$. Because of the constant action function, it effects the convergence speed. So the modified action function follows:

$$f(x, s, \sigma) = \frac{1}{1+e^{-s(x+\sigma)}} \quad (6)$$

In contrast, (6) was added a parameter σ in neuron model. When σ>0, action function would move to left along the horizontal direction. And when the error of BP network propagated back, the slope S and the offsetσ is modified with error signal. So the improved BP not only could improve the adaptive ability of neurons, but also could fastly speed up the convergence speed of algorithm.

(b) Learning rate Learning rate decides the weight variation procucting in cyclical training. Large learning rate may cause an unstable system and the small one may cause relatively long training time. Therefore, good idea is that the system can automaticly regulate the learning rate.

(c) Choice of initial weights To the nonlinear system, the choice of initial weights is very important. It directly effects the convergence of study and training time. If the initial value is too large, the weighted input sum n may be in saturation region of type S activation function, and then the regulation almost stops. Therfore, the initial weight should be a random number in (-1,1).

In order to verify the better convergence rate of improved BP algorithm, there was constructed a BP network. In BP network, input nodes x1,x2, then the obtained output nodes were Logic And y1, Logic Or y2 and Xor y3. TABLE I lists the results of standard BP and improved BP and time-consuming(where learning rate μ=0.20, inertial factor α=0.10).

TABLE I. COMPARE THE CONVERGENCE SPEED OF TWO ALGORITHM

Algorithm	One Iteration Time/ms	Average Iteration Number			Total Iteration Time/s		
Standard BP	0.26	4.662	20.441	224.128	1.21	5.31	58.27
Improved BP	0.68	1.367	2.803	10.778	0.93	1.91	7.33

IV. VEHICLE LICENSE PLATE RECOGNITION BP NETWORK MODEL

A. Vehicle License Plate Recognition Pretreatment

License plate region should be extracted from the vehicle image in highway traffic after processed by eliminating noise, graying and binary. The license plate can be located by scanning or color. There had Chinese characters , Letters and Arabic numerals on the vehicle license plate which had been segmented. These characters must be normalized to a standard and single character should be recognized and pretreated to prepare the characters recognition before recoginizing them one by one[4]. By pretreatment, each letter and number in license plate can be independent. The whole realization process of license plate recognition includes six aspects(See Fig. 2).

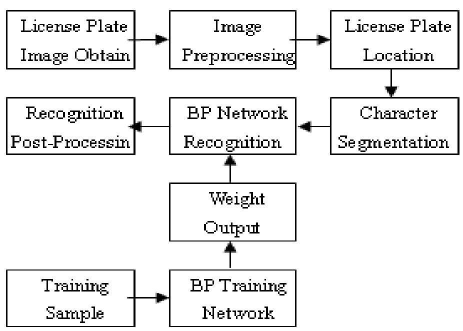

Figure 2. The realization process of license plate recognition

B. License Plate Character Recognition by BP Algorithm

1)Character encoding and grouping: By license plate location and recognition and pretreatment, gray images which were formed by every letter and number in license plate were extracted.To the grayscale image of single character,it can use the grids of 5*5 for segmentation. The black grids represented 1 and the white grids represented -1. The array x[25] represented BP network input value of the character (See Fig. 3) [5]. Where the encode was the character E.

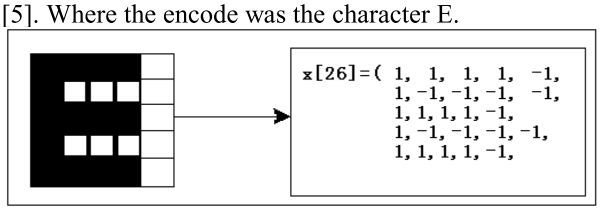

Figure 3. Character encoding example

If a group of 36 characters should be discriminated with BP network to this system. Then the input layer need 25 nodes,the output layer need 36 nodes and the hidden layer at least need 50 nodes.This kind of BP network need larger computational complexity and had slow convergence speed. Even it often appeared unpredictable results. So author thought an idea which changed a big problem into some small problems, that is to say, the 36 characters were divided into 4 groups sequentially and each group had 9 characters. Namely, ABCDEFGHI was included in the first group, JKLMNOPQR was in the second group, STUVWXYZ0 was in the third group and 123456789 was in the last group. To reduce network scale and be a better recognition effect, the characters of each group can be recognized by 4 BP networks which were numbered 1-4.

2)The design of BP neural network classifier: The 4 BP networks had a same structure according to symmetry principle. There was 25 nodes in input layer of each network and 6 nodes in output layer .And after test the 15 nodes were choosed. Based on the former idea about 36 characters being divided into 4 groups, BP networks should be designed to correctly divide the characters and sending these characters to the corresponding network to be recognized for realizing automatic recognition. The recognition process can be shown as Fig. 4.

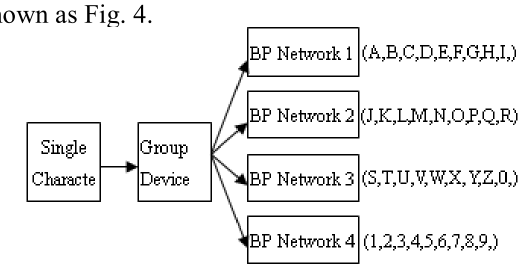

Figure 4. Recognitong process of single character

C. Analysis of test result

1) Analysis of convergence rate: The recognition of a same character was studied in the improved BP algorithm. For convenience, we only considered a group data of TABLE Ⅱ for being trained. The training results can be shown as TABLE Ⅲ.Where learning rateμ= 2.0, inertial factorα= 0.

TABLE II. TRAINING SAMPLE SETS

Letter	Input Samples					Output samples
	1 2 3 4 5	6 7 8 9 10	11 12 13 14 15	16 17 18 19 20	21 22 23 24 25	1 2 3 4 5 6
A	00100	01010	1 0 0 0 1	1 1 1 1 1	1 0 0 0 1	100000
B	11100	10010	1 1 1 1 0	1 0 0 0 1	1 1 1 1 0	010000
C	01110	10001	1 0 0 0 0	1 0 0 0 1	0 1 1 1 0	001000
D	11110	10001	1 0 0 0 1	1 0 0 0 1	1 1 1 1 0	000100
E	11111	10000	1 1 1 0 0	1 0 0 0 0	1 1 1 1 1	000010
F	11111	10000	1 1 1 0 0	1 0 0 0 0	1 0 0 0 0	000001

TABLE III. COMPARE THE CONVERGENCE SPEED OF TWO BP IN LETTER RECOGNITION

Algorithm	**One Iteration Time/ms**	**Average Iteration Number**			**Total Iteration Time/s**		
Standard BP	0.35	1103	4803	52960	6.13	28.18	308.93
Improved BP	0.92	323	661	2547	4.95	10.14	39.05

From the TABLE Ⅲ we can see,the iteration times and total learning time of improved BP are shortest compare to the standard BP algorithm. In different precision, the difference of two algrithm is different. When the precision requirement is low, the difference is little in time needed for two algorithm. With the improvement of precision requirement, the difference of two algorithm is becoming larger and larger. So advantages of improved BP are given full play.

2) Analysis of hidden layer nodes and learning rate: To the current BP network,when error is determined, the training precision should be decreased with the larger the learning rate and the lower the learning times. When error limit is 0.0001,the relation between hidden layer nodes and learning rate is showsn as TABLE Ⅳ. When learning rate is certain,the memory of BP network is being stronger with the more the hidden layer nodes and the lower the learning times. But the excess of hidden layer nodes could be caused the network to lose the distinguished ability because of oscillation.

TABLE IV. THE RELATION BETWEEN HIDDEN LAYER NODES AND LEARNING RATE

Learning Rate	Hidden Layer Nodes 5	10	15	20	25
0.2	1010	680	612	480	420
0.6	316	233	189	Oscillation	150
1	213	115	90	Oscillation	Oscillation

From the TABLE Ⅳ, we can obtain the best parameters to solve the BP network: the number of hidden layer nodes is 15, learning rate is 0.6 and error limit is 0.0001.

3) Test result comparison: During the test, the standard BP and improved Bp were tested with non-noisy and noisy license plate character. The testing samples were 2800 characters of 400 license plates. The recognition object was the 200 license plates. The test result is shown as TABLE Ⅴ[6].

TABLE V. TEST RESULT COMPARISON

Algorithm	Correct Recognition Rate Non noisy	10% noisy	20% noisy	Training time/min	Recognition time /min
Standard BP	96%	80%	68%	5.36	61
Improved BP	98%	92%	85%	1.84	22

From the testing result, we can see that the recogintion rate of improved BP is higher than standard BP. Training time and recognition time of improved BP are better than standard BP. There has been some difference in testing result and theoretical result for the effect of external factors(weather, ray,etc..).

V. CONCLUSIONS

With the development of modern traffic, technology of automatic license plate recognition will be widely researched and applied. By modifying the BP algorithm action function, automaticly regulating the learning rate and choosing the Initial Weights, we improved the recognition ability of neural network for pattern recognition system. It was proved that the improved BP was faster than the standard BP. It had some advantages in reaching high error precision, fast convergence speed, short recognition time and high recognition rate.

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