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Damaged RMB Recognition Algorithm Based on Statistical Feature

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Abstract*—In view of imbalanced training samples of training samples in traditional neural network algorithm, a new algorithm for recognizing damaged degree of banknotes is proposed based on the statistical features. We describe uniformity of features by standard deviation and intermittent strength of the banknote images, all neurons in competitive layer of LVQ network are used to classified the input space, and the improved Kohonen rule is used to realize LVQ network learning. The results of simulation prove that the proposed algorithm improves the recognition accuracy.

***Keywords*—Statistical feature; Damaged degree; RMB; Recognition; LVQ**

I. INTRODUCTION

Recognizing, sorting, and recycling the damaged RBM banknotes are a necessary work for banks or financial institutions [1,2]. An accurate and effective recognition algorithm that could greatly improve the efficiency of recognition is of great significance for banks or financial institutions, thus becoming a focus of research [3-5].

Due to imbalanced training samples in the process of recognition, traditional neural network algorithms deviate from reasonable results when the training results converge to local optimum.

According to statistical features of RBM images, a new algorithm is put forward to recognize the damaged degree in the paper. Sorter is used to calculate average gray-values of new and old feature blocks of pre-circulating banknotes. The average gray-values are taken as standard brightness of the currency and stored in computer memory, and calculated after feature blocks of rate of damaged degree of the currency are positioned. The measured values are calculated and quantified, damaged degree of RMB is judged based on uniformity features of currency images, and uniformity features are described with standard deviation and intermittent strength. LVQ network model is analyzed, and input space of all neurons in competitive layer of LVQ network are classified with learning prototype vector. Network is trained with a set of correct network behaviors, and the improved Kohonen rule is used to realize LVQ network learning. The results of simulation prove that the proposed algorithm achieves high accuracy of recognition [6-7].

II. RECOGNITION PRINCIPLE

Position of recognition, which changes with image sizes of notes of different denominations, should be fixed by denomination and aspect recognition, to realize recognition.

A. Determination of standard brightness

A sorter is used to calculate average gray-value of new and old feature blocks of pre-circulating banknotes; the average value is taken as standard brightness of the notes and stored in computer memory, specifically,

(a) The locations of blocks with different damaged degrees are determined by the recognition results. Taking 100-yuan RMB as the example, the damaged location is shown in Fig. 1.

Fig. 1 Fixing of the new and old feature blocks

(b) Calculating average gray-value of features blocks of 20 RMB images $G_i(x,y)$, $i=1,2,\cdots,20$. $G(x,y)$ denotes gradation of images of new RBM images, W width of feature blocks, L width of feature blocks, and $W \times L$

dimension of feature blocks. Assume that (x_0, y_0) is coordinates of top left corner of the feature block, average gray-value of features blocks can be got by

$$G_i(x,y) = \frac{1}{W \times L} \sum_{x=x_0}^{x_0+W} \sum_{y=y_0}^{y_0+L} G(x,y) \tag{1}$$

(c) Calculating the standard brightness

Average of the average gray-values of features blocks of new and old notes is taken as the standard V_S for recognition of the notes.

$$V_S = \sum \frac{G(x,y)}{n} \tag{2}$$

(4) Calculating standard brightness of RMB images of different face values with the steps stated above and storing the results in memory.

B. Determination of brightness of feature blocks

Average grey-values are obtained after the feature blocks are fixed.

Assume that average gray-value of notes after noise processing [8], tilt correction and other pre-processing is $G^{'}(x,y)$, average gray-value can be by

$$V_A = \frac{1}{W \times L} \sum_{x=x_0}^{x_0+W} \sum_{y=y_0}^{y_0+L} G^{'}(x,y) \tag{3}$$

C. Measurements for damage recognition

V_A-to-V_S ratio is taken as the measurement for old and new recognition:

$$V_{new} = \frac{V_A}{V_S} \tag{4}$$

For a RMB image recognized as 100 yuan, its measurement can be described as:

$$V_{new} = \frac{V_A}{V_{S100}} \tag{5}$$

The greater the value V_{new} , the newer RMB.

According to code requirement released by People's Bank of China in 2000 on cleanliness [9], RBM images in circulation must be at least 70% new, and those below 70% are old and should be prevented from circulation. Measurements will be quantized by V_{new}:

$0.9 \le V_{new} \le 1$ indicates 90% new;

$0.8 \le V_{new} \le 0.9$ indicates 80% new;

$0.7 \le V_{new} \le 0.8$ indicates 70% new;

Notes with $V_{new} \ge 0.7$ are circulatable, while those with $V_{new} < 0.7$ are old notes.

III. RECOGNITION ALGORITHM BASED ON STATISTICAL FEATURES

A. Acquisition of uniformity features of RMB images

As RMB images are composed of a large amount of fine lines and complex textures, clearness of the edge and smoothness of the texture area effectively reflect the rate of newness. Uniformity feature of notes in circulation under the condition of normal wear becomes more obvious, so that it can be used to determine the rate of newness.

Uniformity features mainly depends on the local information acquired from the images, and mainly include standard deviation and intermittent strength. Standard deviation reflects local area contrast, and discontinuity reflects mutation of grayscale, it can be got with boundary operator of the corresponding area.

For an image of $M \times N$ in size, if gray value of coordinate (x,y) is $I_{x,y}$, in the process of calculating the standard deviation, in the process of calculation, window $w_{x,y}^1$ of $d \times d$ centered by (x,y) is selected; in the process of calculating the intermittent strength, window $w_{x,y}^2$ of $t \times t$ centered by (x,y) is selected (where, d and t are odd integers greater than 1), and windows $w_{x,y}^1$ and $w_{x,y}^2$ are local areas to calculate point coordinate (x,y) of uniformity feature.

Standard deviation $v_{x,y}$ at (x,y) can be got by

$$v_{x,y} = \sqrt{\frac{1}{d^2} \sum_{i=x-(d-1)/2}^{x+(d-1)/2} \sum_{i=y-(d-1)/2}^{y+(d-1)/2} \left(I_{i,j} - \mu_{x,y}\right)^2} \tag{6}$$

Where, $0 \le x$, $i \le M-1$, $0 \le y$, and $j \le N-1$, if $\mu_{x,y}$ is introduced in $w_{x,y}^1$,

$$\mu_{x,y} = \frac{1}{d^2} \sum_{i=x-(d-1)/2}^{x+(d-1)/2} \sum_{i=y-(d-1)/2}^{y+(d-1)/2} I_{i,j} \tag{7}$$

Discontinuity at pixel (x, y) can be represented with marginal value. Sobel operator, Laplace operator and Canny operator are the common edge detection operators. As no precise positioning of image edge is required in this paper, to facilitate calculation, Sobel operator is used to calculate horizontal gradient G_x and vertical gradient G_y at coordinate (x, y). Discontinuity of image at (x, y) can be described as

$$e_{x,y} = \sqrt{G_x^2 + G_y^2} \tag{8}$$

To obtain consistent results and realize normalized operation of standard deviation and intermittent value, uniformity feature $h_{x,y}$ of coordinate points in the image can be described as:

$$h_{x,y} = 1 - \frac{v_{x,y}}{v_{\max}} \frac{e_{x,y}}{e_{\max}} \tag{9}$$

Where, $v_{\max} = \max\{v_{x,y}\}$, $e_{\max} = \max\{e_{x,y}\}$, $0 \le x \le M-1, 0 \le y \le N-1$. All uniformity eigenvalues of all points in the image fall in interval [0, 1], and the more consistent with local area adjacent to a pixel, the smaller the uniformity eigenvalues. For images with fold or stain, the uniformity intensity of the area stated above will mutate, and uniformity intensity of the notes will reduce gradually.

B. Recognition Methods based on LVQ network model

LVQ network model described in Fig 2 functions mainly based on three layers of structure, i.e. information input layer, calculating layer and output layer. Data of several layers work together in calculation; however, the layer-to-layer process is not completely based on information communication. If there is no special instruction between different layers, weight is set to be l, and the output neurons are divided into different classes.

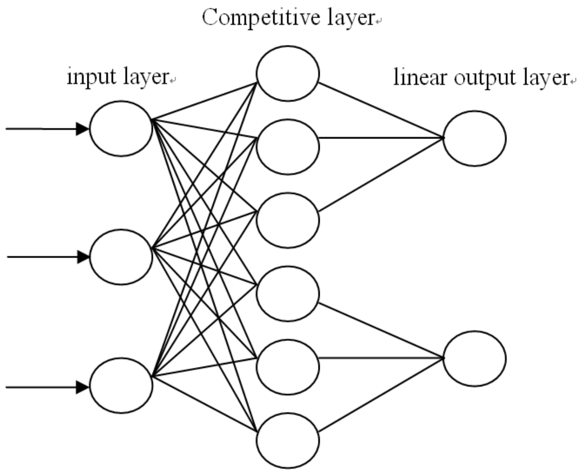

Figure 2 LVQ network model

Assume that input vector of the network input layer is described with $X = (x_1, x_2, \cdots, x_M)$, M denotes the total number of input neurons; the connection weight matrix between input layer and competitive layer can be described as $W^1 = (w_1^1, w_2^1, \cdots, w_p^1)$, $w_i^1 = (w_{i1}^1, w_{i2}^1, \cdots, w_{iM}^1)$. In w_{ij}^1, $i = 1, 2, \cdots, P$ and $j = 1, 2, \cdots, M$ are used to describe the connection weights between i th neurons of competitive layer and j th neurons of input layer, P denotes the total amount of competitive neurons, and output vector of the competitive layer can be described as $V = (v_1, v_2, \cdots, v_p)$, and connection weight matrix of neurons between competitive layer and output layer can be described as $W^2 = (w_1^2, w_2^2, \cdots, w_N^2)$, where, $w_k^1 = (w_{k1}^1, w_{k2}^1, \cdots, w_{kP}^1)$. In w_{kr}^2, $k = 1, 2, \cdots, N$, $r = 1, 2, \cdots, P$ are used to describe the connection weights between k th neurons of output layer and r th neurons of competitive layer, N denotes the total amount of neurons of the output layer. Input space of all neurons of competitive layer are classified with the learning prototype vector, the category acquired in competitive layer through learning is classified as subclass, while that in output layer is classified as target class.

Considering the rules of competitive learning and supervised learning of LVQ network, a set of correct network behaviors are used in network training:

$$\{x_1,t_1\},\{x_2,t_2\},\cdots,\{x_Q,t_Q\} \tag{10}$$

Where, if and only if each target output vector $t_j\left(j=1,2,\cdots,Q\right)$ has one component of 1. To guarantee smooth progress of learning, neurons of competitive layers are generally divided to an output neuron, to complete definition of the matrix W^2. Columns of W^2 represent subclasses and lines represent classes. Among columns of W^2, there is only one 1 line, used to describe that the class falls into the class of the line, namely:

$$W_{kr}^2=\begin{cases}1 & if\ r\in K\\ 0 & else\end{cases} \tag{11}$$

W^2 is unchangeable, neural network learning changes W^1 with the optimized Kohonen rule. Specifically, LVQ learning algorithm is realized by:

(a) Assuming that variables and parameters $x(n)=\left[x_1(n),x_2(n),\cdots,x_N(n)\right]^T$ are input vectors, $W_{ij}(n)=\left[w_{i1}(n),w_{i2}(n),\cdots,w_{iN}(n)\right]^T$ is weight vector, $i=1,2,\cdots,M$. Function for selecting the learning rate $\eta(n)$, n denotes number of iterations and N total number of iterations;

(b) Initializing the weight vector $W_i(0)$ and learning rate $\eta(n)=\eta(0)$;

(c) Selecting input vector X from the training set;

(d) Calculating the Euclidean distance, to obtain the minimum standards:

$$\|X-W_c\|=\min\|X-W_i\| \tag{12}$$

Retrieving the neuron c succeed in competition, to complete neuron competition;

(e) Determining the accuracy of classification, and increasing the obtained weight vector by the following rules:

Lw_c denotes the category associated with the winning neuron weight vector, and Lx_i denotes the category associated with input vector.

If $Lx_i=Lw_c$,

$$W_c(n+1)=W_c(n)+\eta(n)\left[X-W_c(n)\right] \tag{13}$$

On the contrary, if $Lx_i\neq Lw_c$,

$$W_c(n+1)=W_c(n)-\eta(n)\left[X-W_c(n)\right] \tag{14}$$

Weights of other neurons stay the same;

(f) Adjusting learning rate $\eta(n)$:

$$\eta(n)=\eta(n)\left[1-\frac{n}{N}\right] \tag{15}$$

(g) Determining whether the number of iterations is greater than N , if $n\leq N$, return to step (c), otherwise, stop iteration.

IV. SIMULATION ANALYSIS

To verify effectiveness of the proposed algorithm, experimental analysis is required. Six kinds of Chinese notes are taken as the research object and analyzed respectively with the proposed algorithm and traditional algorithms. Experimental training sample size, test sample size and the accuracies achieved by the two algorithms are shown in Table I.

Training sample in Table 1 refers to the number of reference RMB images involved in the training. The accuracy of recognition rate is the damaged degree of the area where the statistical features are extracted.

TABLE I
ACCURACIES ACHIEVED BY THE PROPOSED ALGORITHM AND THE TRADITIONAL ALGORITHM

RMB	training samples	test samples	Accuracy (%)	
			the proposed algorithm	the traditional algorithm
1 Yuan	100	800	99.3	93.1
5 Yuan	100	800	99.8	90.6
10 Yuan	100	800	99.1	91.4
20 Yuan	100	800	98.5	88.7
50 Yuan	100	800	98.8	91.3
100 Yuan	100	800	99.2	90.6

Based on analysis of Table 1, it can be seen that compared with the traditional neural network algorithm, the proposed algorithm achieves obvious higher accuracy and has achieved higher accuracy in recognizing the old and new banknotes, demonstrating that this algorithm improved the accuracy of recognition.

To further verify effectiveness of this algorithm, based on above experiments, the time of recognition taken by the algorithm and the traditional algorithm are compared, and the results are shown in Fig 3.

Based on analysis of Fig 3, it can be seen that the algorithm proposed in this paper takes significant shorter time than the traditional neural network algorithm in recognizing same size of same currency, showing that this algorithm not only reaches high accuracy of recognition, but also achieves high efficiency of recognition, which verifies the effectiveness of the algorithm.

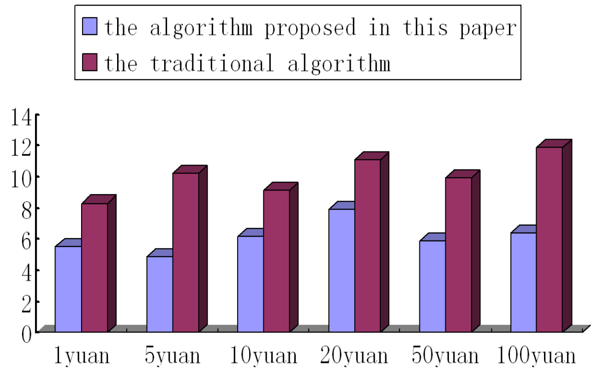

Fig 3 Comparison of time taken by this algorithm and the traditional algorithm

V. CONCLUSIONS

In this research, a new algorithm, which judges rate of newness of banknotes according to statistical characteristics of images, is put forward; sorter is used to calculate average gray-values of new and old feature blocks of pre-circulating banknotes; the average gray-values are taken as standard brightness of the currency and stored in computer memory, and calculated after feature blocks of rate of newness of the currency are positioned; measured values are calculated and quantified, rate of newness of currency is judged based on uniformity features of currency images, and uniformity features are described with standard deviation and intermittent strength; LVQ network model is analyzed, input space of all neurons in competitive layer of LVQ network are classified with learning prototype vector; network is trained with a set of correct network behaviors, and the improved Kohonen rule is used to realize LVQ network learning. The results of simulation prove that the proposed algorithm achieves high accuracy of recognition.

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