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Intelligent Classification of Bills by Neural Networks

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Abstract

For the pattern classification problems the neuro-pattern recognition which is the pattern recognition based on the neural network approach has been paid an attention since it can classify various patterns like human beings. In this paper, we adopt the learning vector quantization (LVQ) method to classify the various money. The reasons to use the LVQ are that it can process the unsupervised classification and treat many input data with small computational burdens. We will construct the LVQ network to classify the Italian Liras. Compared with a conventional pattern matching technique, which has been adopted as a classification method, the proposed method has shown excellent classification results.

1. Introduction

Bill money classification by transaction machines has been important to make progress the office automation [1]. Since sizes of bills are different according to kinds of bills, the measurement data of bills include various variations. Human being can classify the bills correctly even if they are suffered from those variations such as rotation and shift. But usual pattern recognition using a conventional transaction machine cannot give us the correct classification result under such cases since the basic method is a pattern matching principle. Furthermore, the conventional pattern matching method requires many template patterns for many kinds of bills, which takes much time and needs much experience [1].

Recently, neural networks which are based on the biological mechanism of human brain have been focussed since they have intelligent pattern recognition ability [2]. In this paper, we will apply the neural network approach to classify the bill money under various conditions by using transaction machines. The learning vector quatization (LVQ) has been used to classify the bills since it can treat high dimensional input and has simple learning structure [3]. The LVQ network adopted here has 64x15 units in the input layer and many units at the output layer. The bills are Italian Liras of 8 kinds, 1,000, 2,000, 5,000, 10,000, 50,000 (new), 50,000 (old), 100,000 (new), 100,000 (old) Liras with four directions A,B,C, and D where A and B mean the normal direction and the upside down direction and C and D mean the reverse version of A and B. The simulation results show that the proposed method can produce the excellent classification results.

2. Competitive Neural Networks

We will explain the competitive neural networks that are used to classify the bill money. The structure of a LVQ competitive network is shown in Fig. 1. The input for the LVQ is bill money data where an original image consists of 128x64 pixels and the input data to the network is compressed as 64x15 pixels to decrease the computational load. The output of the network consists of the Italian Liras of 8 kinds, 1,000, 2,000, 5,000, 10,000, 50,000 (new), 50,000 (old), 100,000 (new), 100,000 (old) Liras with four directions A,B,C, and D where A and B mean the normal direction and the upside down direction and C and D mean the reverse version of A and B.

In the input layer the original bill money data are applied and all the units at the input layer are connected to all the neurons at the output layer with connection weight W_{ij}. W_{ij} denotes the connection weight from the unit j in the input layer to unit i in the output layer. The output layer will output only one neuron which is called winner neuron. The winner neuron is selected as the neuron with the minimum distance between an input vector and its connection weight vector. The connection weights W_{ij} are set by the random number at the beginning. Here, we set the mean vector of the cluster plus small random number. Then the following learning algorithm of the connection weight vector is used.

LVQ algorithm

Step 1. Find the unit c at the output layer which has the minimum distance from the input data **x** (t)

$$\|\mathbf{x}(t) - \mathbf{W}_c\| = \min_i \|\mathbf{x}(t) - \mathbf{W}_i\|$$

where $\|\ \|$ denotes the Euclidean norm and t denotes the iteration time.

Step 2. If the input **x** (t) belongs to Category c, then

$$\mathbf{w}_c(t+1) = \mathbf{w}_c(t) + \alpha(t)(\mathbf{x}(t) - \mathbf{w}_c(t))$$

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t)\,,\ \ i \neq c$$

and if the input **x** (t) belongs to the other Category j (j$\neq$c), then

$$\mathbf{w}_c(t+1) = \mathbf{w}_c(t) - \alpha(t)(\mathbf{x}(t) - \mathbf{w}_c(t))$$

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t)\,,\ \ i \neq c$$

where $\alpha(t)$ is a positive function and denotes learning rate.

In the usual LVQ $\alpha(t)$ is given by

$$\alpha(t) = \alpha_0(1 - \frac{t}{T})$$

where (0<α_0<1) is a positive and T is a total number of learning iterations.

The above algorithm for selection of new weight vector $W_c(t+1)$ can be explained graphically as shown in Fig. 2 .

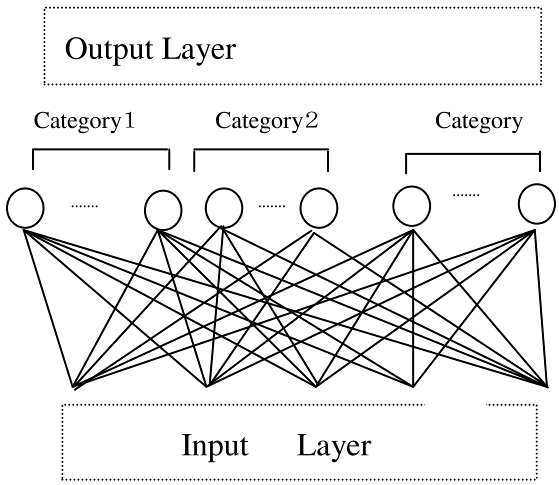

Fig. 1. Structure of the LVQ networks.

In the above LVQ algorithm, the learning rate $\alpha(t)$ plays an important role for convergence. To adjust the parameter, Kohonen has proposed an optimization method without proof as follows:

$$\alpha_c(t) = \frac{\alpha_c(t-1)}{1 + s(t-1)\alpha_c(t-1)}$$

where s(t) =1 if **x**(t) belongs to the same Category c and s(t)=-1 if **x**(t) does not belong to the same Category c. Here, $\alpha_c(t)$ denotes the learning rate for the pattern of Category C. In what follows, we will prove the above relation. From the learning rule of the LVQ, we have

$$\begin{aligned}\mathbf{w}_c(t+1) &= \mathbf{w}_c(t) + s(t)\alpha_c(t)(\mathbf{x}(t) - \mathbf{w}_c(t))\\ &= (1 - s(t))\alpha_c(t)\mathbf{w}_c(t) + s(t)\alpha_c(t)\mathbf{x}(t)\end{aligned}$$

and

$$\begin{aligned}\mathbf{w}_c(t) &= \mathbf{w}_c(t-1) + s(t-1)\alpha_c(t-1)\\ &\quad (\mathbf{x}(t-1) - \mathbf{w}_c(t-1))\\ &= (1 - s(t-1))\alpha_c(t-1)\mathbf{w}_c(t-1)\\ &\quad + s(t-1)\alpha_c(t-1)\mathbf{x}(t-1)\end{aligned}$$

Substituting the latter equation the former one, we have

$$\mathbf{w}_c(t+1) = (1 - s(t)\alpha_c(t))(1 - s(t-1)\alpha_c(t-1))\mathbf{w}_c(t-1)$$
$$+ s(t)\alpha_c(t)\mathbf{x}(t) + s(t-1)\alpha_c(t-1)(1 - s(t)\alpha_c(t))\mathbf{x}(t-1).$$

We assume that the optimal rate adjusts the effect of x(t) and x(t-1) equally within the absolute value, that is,

$$\alpha_c(t) = (1 - s(t)\alpha_c(t))\alpha_c(t-1)\,.$$

Then we have

$$\alpha_c(t) = \frac{\alpha_c(t-1)}{1 + s(t-1)\alpha_c(t-1)}\,.$$

From the above equation, we can see that the value of $\alpha_c(t)$ become larger than 1 when s(t-1)= - 1, which may make the learning algorithm unstable. Thus, we must fix the $\alpha_c(t)$ to a boundary value α_0 when it becomes larger than 1.

$$\alpha_c(t+1) = \alpha_0 \quad \text{if} \quad \alpha_c(t+1) > 1\,.$$

Using the above OLVQ1 algorithm, we will classify the Italian bills in the following section.

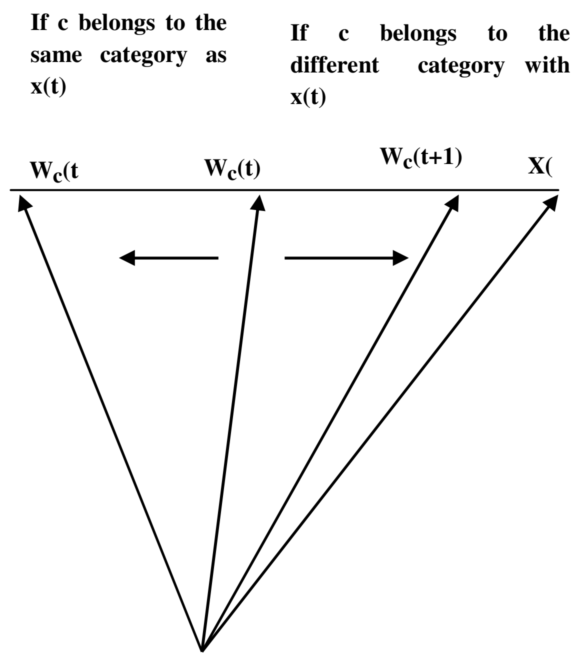

Fig.2. Principle of the LVQ algorithm where the right hand side shows the same category case of **x**(t) and Category c and the left hand side denotes the different category case.

3. Preprocessing Algorithm

The images obtained by transaction machine, there are variations such as rotation or shift. Therefore, we must adjust the images such that the variations may be reduced as much as possible by using the preprocessing. The flow char of the preprocessing procedure is illustrated in Figure 3. In this figure, the original image with 128x64 pixels are observed at the transaction machine in which rotation and shit are included. After correction of these effects, we select a suitable aria which show the bill image and compressed as the image with 64x15 pixels to the neural networks. Although the neural network of the LVQ type could process any order of the dimension of the input data, the small size is better to achieve the fast convergence result. Thus, we have selected the above size of the image.

4. Italian Lira Classification

The bills used here are Italian liras, which have 8 kinds such as 1,000 Liras, 2,000 Liras, 5,000 Liras, 10,000 Liras, new 50,000 Liras, old 50,000 Liras, new 100,000 Liras, and old 100,000 liras. Those Lira bills are used at the input of the transaction machine where four directions such as A, B, C, and D appear since normal direction, reverse direction, and their upside down directions occur at the input as shown in Fig.4. Thus, thirty-two bill images are one set of the classification pattern of the experiment.

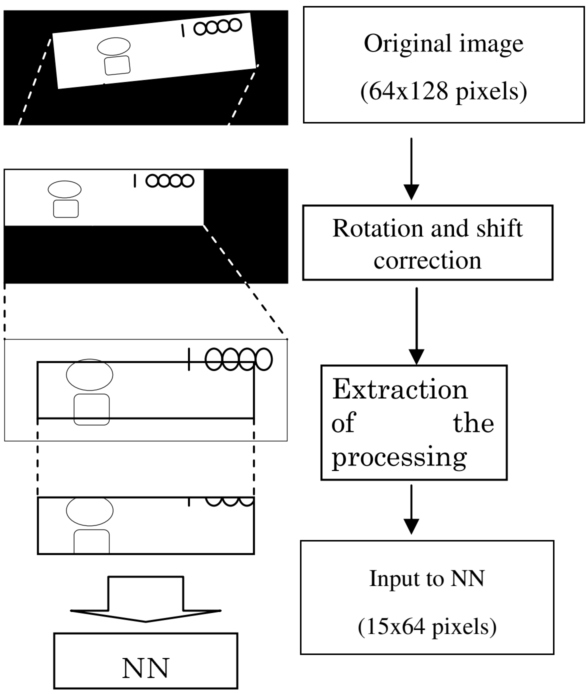

Fig. 3. Preprocessing algorithm.

Total number of data sets is 30 and 10 data sets are

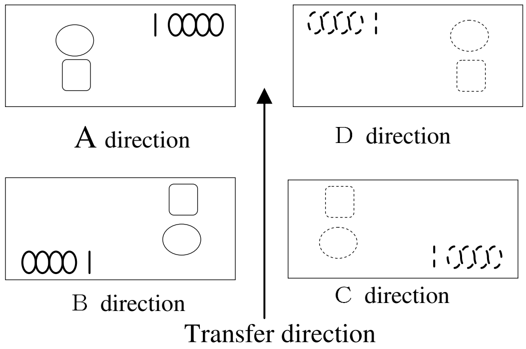

Fig. 4. Four directions of bill money.

used for training of the network and the remaining 20 data sets are used to test the network. In order to reduce the misclassification, we have set the threshold value d_θ such that if $d_c > d_\theta$, unit c is not fired. This means that if the minimum distance is not less than d_θ, the input data is not classified. The parameters of the neural network used here are as follows:

Number of units in the input layer=960

Number of units in the output layer in the initial state=32 where every 50 iterations the number has been adjusted.

Total learning time T=150, $\alpha_i(0) = 0.5$, $i = 1, \cdots M$

Initial values of the weight vectors=mean vectors for training patterns $d_\theta = \min_c (m_c + 4.5\sigma_c)$

After training the neural network, 20 data sets are tested how well the LVQ network could work. Tables 1 and 2 show those values at t=160. We can see the improvement by learning. Table 5 shows the number of the neuron units at t=160 which are determined by increasing them.

Table 1. Recognition rate (%) at t=160.

		Directions			
		A	B	C	D
Italian Liras	1,000	100	100	100	100
	2,000	100	100	100	100
	5,000	100	100	100	100
	10,000	100	100	100	100
	50,000(new)	100	100	100	100
	50,000(old)	100	100	95	95
	100,000(new)	100	100	90	100
	100,000(old)	100	100	95	90

From the original image data we can see that the difference between 50,000 Lira old and new is slight and the difference between old and new100, 000 Liras as shown in Figs. 5 and 6. Therefore, it is rather difficult to recognize them so perfectly. But in this case the misclassification like old and new bills within the same values is not serious. Thus, we have regarded this misclassification as the correct one. Furthermore, we have introduced the threshold value to prevent from making the misclassification. Thus, even if the minimum distance criterion results in the correct classification, we have decided these bells are unknown. Without threshold constraints, we could obtain 100% classification rate.

Table 2. Not fired rate (%) at t=160.

		Directions			
		A	B	C	D
Italian Liras	1,000	5	0	5	0
	2,000	0	10	25	25
	5,000	15	20	5	0
	10,000	10	0	0	5
	50,000(new)	5	0	0	0
	50,000(old)	0	5	0	0
	100,000(new)	0	0	0	0
	100,000(old)	0	5	0	0

5. Conclusions

We have proposed a new classification method of Italian Liras by using the OLVQ1 algorithm. The experimental results show the effectiveness of the proposed algorithm compared with the conventional pattern matching method.

References

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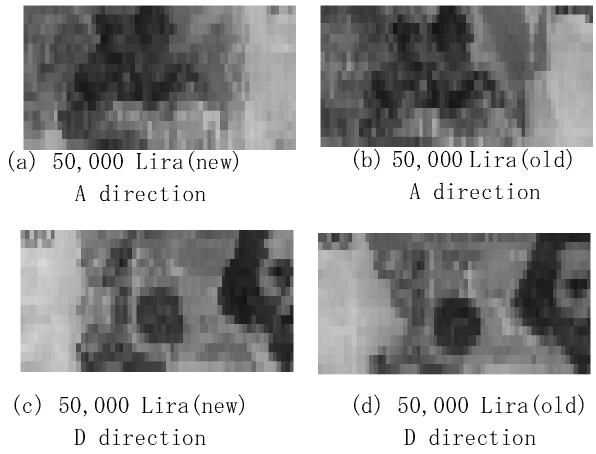

Fig. 5. New and old 50,000 Liras.

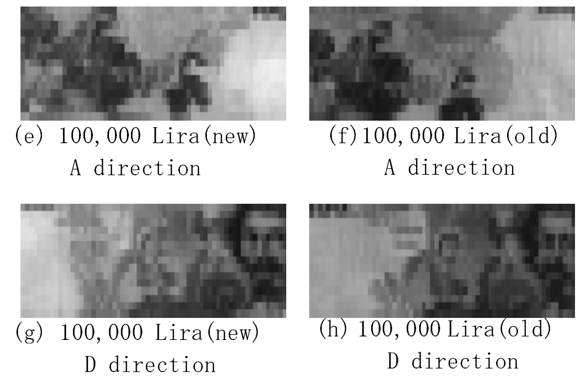

Fig.6. New and old 100,000 Liras.

Table 3. Number of units after learning.

		Directions			
		A	B	C	D
Italian Liras	1,000	2	2	2	2
	2,000	2	1	1	1
	5,000	1	1	1	1
	10,000	1	2	2	1
	50,000(new)	2	1	1	1
	50,000(old)	2	1	3	1
	100,000(new)	1	1	1	1
	100,000(old)	1	1	1	1