3層パーセプトロンとRBFネットによるユーロ紙幣識別システム

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概要. 本論文では，金種判別部分に3層パーセプトロンを，真偽判定部分に複数のRBFネットを用いたユーロ紙幣識別システムを提案する．この2段構成のシステムは，RBFネット単体でシステムを構築する場合と比較していくつかの長所がある．また，赤外画像と可視画像を入力データとして用いる．提案システムの評価実験として，真券受付性能と偽データの排除性能を評価した．

キーワード： 3層パーセプトロン，RBFネット，ユーロ紙幣，赤外，分類，真偽判定

An Euro banknote recognition system using a three-layered perceptron and RBF networks

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Abstract. We propose a Euro banknote recognition system using two types of neural networks; a three-layered perceptron for classification and Radial Basis Function (RBF) networks for validation. The proposed system has some advantages over the system using only one RBF network. We also propose to use infra red (IR) and visible images as input data to the system. We have tested our system in terms of acceptance rates for valid bills and rejection rates for invalid data.

Keywords: three-layered perceptron, RBF network, Euro banknote, IR, classification, validation

1. Introduction

Banknote recognition systems using neural networks to classify known banknotes have been reported in some papers [1] [2], and they do not mention about rejection performance of unknown banknotes. In some patents, a Probabilistic Neural Network (PNN) and a Learning Vector Quantization (LVQ) network were used for validation [3] [4], while they have problems in terms of the size of the networks and the difficulty of setting thresholds. Broomhead and Lowe introduced Radial Basis Function (RBF) network in 1988 [5]. However, any banknote recognition system that implements an RBF network has never been reported.

In this paper, we propose a banknote recognition system composed of two parts; the classification part using a three-layered perceptron and the validation part using several RBF networks. The proposed system has two advantages over the system using only one RBF network. The feature extranction area can be defined simply, and the calculation cost does not increase when the number of classes increases.

We apply above idea to Euro banknote recognition system and also propose to use infra red (IR) and visible images as input data to the system.

2. Overview of the system

The overview of the proposed system is shown in Fig.1. The input data to the system are obtained by an image sensor that has a green LED and an IR LED. Once the image sensor gets image data, the pre-processing component transforms images into the right position. The recognition component is divided into two parts; the classification part using a trained three-layered perceptron and the validation part using several RBF networks.

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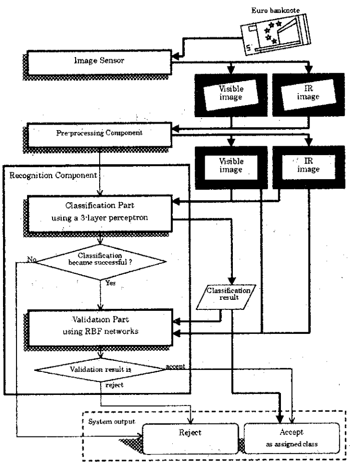

Fig.1. Overview of the system

3. Classification part

The overview of the classification part is shown in Fig.2. Multiresolutional input values extracted from the image data are used as the input vector **x** to the three-layered perceptron since image data has significant features in various resolutions. Matsunaga et al. proposed a learning method to remove redundant hidden neurons [6] and we improve that method in order to remove redundant input neurons.

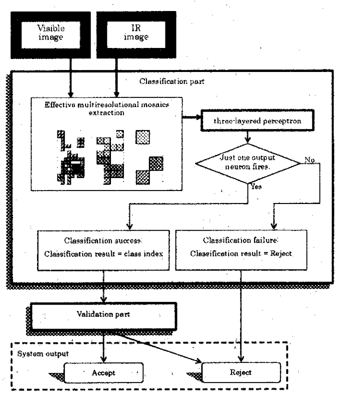

Fig.2 Overview of the classification part

At first, the three-layered perceptron is trained by backpropagation method [7]. Once the network converges to a stable state, the cost g_i is calculated for each input neuron i,

$$g_i = \sum_p \sum_j z_{ip} w_{ij} \quad (1)$$

where j is the index of the hidden neuron, p is the index of the input datum and z_{ip} is the output value of the input neuron i for the data p. The input neuron i whose g_i has the smallest value among all input neurons is removed. Until the number of the input neurons becomes a certain number, the backpropagation learning and the reducing redundant input neurons is repeated.

4. Validation part

The overview of the validation part is shown in Fig.3. The validation part is composed of some validation blocks and each validation block corresponds to each given class. A validation block has several RBF networks and each RBF network corresponds to each small area of image data. Only if the all outputs of the networks in the selected block are "True", the output of the validation part is "Accept". Otherwise, the output of the validation part is "Reject".

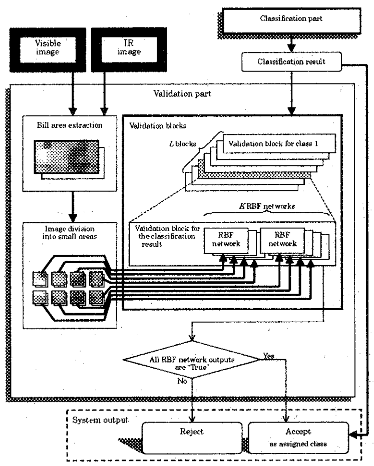

Fig.3. Overview of the validation part

An RBF network is a three-layered network. Each hidden neuron calculates a kernel function which is usually defined as Gaussian function,

$$h_j(\mathbf{x}) = \exp\left(-(\mathbf{x}-\mathbf{c}_j)^T \mathbf{R}_j^{-1} (\mathbf{x}-\mathbf{c}_j)\right) \quad (2)$$

where $\mathbf{c}_j$ is the center of the hidden neuron j. $\mathbf{R}_j$ is a M×M diagonal matrix defined by kernel width vector $\boldsymbol{\sigma}_j$ as below,

$$\mathbf{R}_j = diag\left(\frac{1}{2\sigma_{j1}^2}, \cdots, \frac{1}{2\sigma_{jM}^2}\right) \quad (3)$$

where M is the dimension of the input vector $\mathbf{x}$. The output value of the output neuron is calculated by the following equation,

$$y(\mathbf{x}) = \sum_{j}^{N} h_j(\mathbf{x}) w_j \tag{4}$$

where N is the number of the hidden neurons in the hidden layer and w_j is the weight between the hidden neuron j and the output neuron.

Schwenker et al. reported that the three-phase learning is the best learning method for an RBF network [8]. In the first phase, the centers of the hidden neurons are adjusted by SOM,

$$\Delta \mathbf{c}_{j^*} = \alpha(t)(\mathbf{x} - \mathbf{c}_{j^*}) \tag{5}$$

where $\mathbf{c}_{j^*}$ is the nearest hidden neuron vector to the input $\mathbf{x}$ and $\alpha(t)$ is the learning rate. In the second phase, the components of kernel width vector $\boldsymbol{\sigma}_j$ are set as the average of the distance to the p nearest hidden neuron vectors of $\mathbf{c}_j$. After that, the output weights are adjusted by following delta learning rule,

$$\Delta w_j = \eta h_j(\mathbf{x})(y - F) \tag{6}$$

where η is a learning rate. In the third phase, backpropagation learning is applied to improve the performance of the network.

$$\Delta w_j = \eta h_j(\mathbf{x})(y - F) \tag{7}$$

$$\Delta c_{jk} = \eta h_j(\mathbf{x}) \frac{x_k - c_k}{\sigma_{jk}^2} w_j (y - F) \tag{8}$$

$$\Delta \sigma_{jk} = \eta h_j(\mathbf{x}) \frac{(x_k - c_k)^2}{\sigma_{jk}^3} w_j (y - F) \tag{9}$$

5. Training condition

The system is designed to recognize all kinds of Euro banknotes (EUR 5, 10, 20, 50, 100, 200, 500). We use 200 pieces of bills for each kind of Euro banknote for training.

For the classification part, the size of dots in the highest resolutional data is 4[mm] × 4[mm] and the other sizes are defined as 8[mm] × 8[mm], 16[mm] × 16[mm], 32[mm] × 32[mm]. The number of the hidden neurons in the three-layered perceptron is 64. The initial number of the input neurons is 416, and it is finally reduced to 64.

Each available area for the validation part is divided into eight small areas. Each size of all dots in image data is 4[mm] × 4[mm]. The number of the hidden neurons in each RBF network is 20. The number of the input neurons in each RBF network is 60 (for EUR 5, 10), 72 (for EUR 20, 50) and 98 (for EUR 100, 200, 500), respectively.

6. Experimental results

We use other 200 pieces of bills for each kind of Euro banknote to verify the acceptance performance of the system for valid bills. Table 1 shows the acceptance performance of the system.

Table 1. Acceptance rates for valid bills

	Acceptance Rates [%]						
	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
Classification Part	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Validation Part	100.0	100.0	99.5	100.0	100.0	100.0	100.0
System Performance	100.0	100.0	99.5	100.0	100.0	100.0	100.0

In order to verify the rejection performance of the system for invalid data, we use two sets of the invalid data as the input data to the validation part; 200 simulated color-copied data and 200 size-normailzed data. Table 2 and 3 show the rejection performance of the validation part.

Table 2. Acceptance rates for simulated color-copied data in the validation part

	Acceptance Rates [%]						
	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
Validation Part	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 3. Acceptance rates for size normalized data in the validation part

	vs Size normalized Data Acceptance Rates [%]						
Validation Part for	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
EUR 5	-	0.0	0.0	0.0	0.0	0.0	0.0
EUR 10	0.0	-	0.0	0.0	0.0	0.0	0.0
EUR 20	0.0	0.0	-	0.0	0.0	0.0	0.0
EUR 50	0.0	0.0	0.0	-	0.0	0.0	0.0
EUR 100	0.0	0.0	0.0	0.0	-	0.0	0.0
EUR 200	0.0	0.0	0.0	0.0	0.0	-	0.0
EUR 500	0.0	0.0	0.0	0.0	0.0	0.0	-

In order to test if our system has a good performance, the system is tested on various conditions. Table 4 shows the rejection performance for simulated color-copied data and Table 5 shows the rejection performance for size normalized data in the classification part. The acceptance performance for valid bills and the rejection performance for size-normalized data by using only visible images as input data are shown in Table 6 and 7 respectively.

Table 4. Acceptance rates for simulated color-copied data in the classification part

	Acceptance Rates [%]						
	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
Classification Part	0.0	31.0	67.5	100.0	44.5	0.0	0.0

Table 5. Acceptance rates for size normalized data in the classification part

	vs Size normalized Data Acceptance Rates [%]						
Base Size Bill	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
EUR 5	-	98.0	59.0	6.0	3.0	6.5	21.0
EUR 10	97.5	-	100.0	79.0	19.5	19.0	33.0
EUR 20	54.0	99.0	-	99.0	74.5	48.5	15.0
EUR 50	48.5	73.0	99.5	-	100.0	79.5	35.5
EUR 100	0.0	34.0	96.5	100.0	-	100.0	100.0
EUR 200	69.0	61.0	93.5	99.5	100.0	-	100.0
EUR 500	89.0	99.0	99.5	100.0	100.0	100.0	-

Table 6. Acceptance rates for valid bills in the validation part using only visible image data

	Acceptance Rates [%]						
	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
Classification Part	94.0	99.0	99.0	98.0	99.0	94.5	100.0

Table 7. Acceptance rates for size-normalized data in the validation part using only visible image data

	vs Size normalized Data Acceptance Rates [%]						
Validation Part for	EUR 5	EUR 10	EUR 20	EUR 50	EUR 100	EUR 200	EUR 500
EUR 5	-	11.5	16.0	2.5	0.5	17.0	1.5
EUR 10	11.5	-	14.5	0.0	0.0	0.0	0.0
EUR 20	22.0	22.5	-	0.0	0.0	13.5	0.0
EUR 50	5.0	0.0	0.0	-	0.0	0.5	1.0
EUR 100	4.0	0.0	0.0	22.5	-	34.5	0.0
EUR 200	26.5	0.0	1.5	1.0	0.0	-	0.0
EUR 500	0.0	0.0	0.0	0.0	0.0	0.0	-

7. Discussion

The results of acceptance rates of the system for valid bills are shown in Table 1. This results assure that the system has a good performance for accepting valid bills. On the other hand, Table 2 and 3 show that the validation part performs perfectly for rejecting invalid bills in our test. Note that any negative data had not been given to the RBF network at learning procedure.

Table 4 and 5 show the classification part in itself has poor performance for rejecting invalid data. The poor performance is based on the fact that the backpropagation method for a three-layered perceptron does not promise performance for unknown data. Thus the validation part is quite important in our system.

The results in Table 6 and 7 show that the IR image in the validation part for Euro banknote is necessary.

Here we discuss the advantages of dividing the system into two parts. It is able to configurate the system employing only one RBF network, however, it has two problems. First, definition of the available area in image data is complicated. The size of the available area is fixed for all inserted bills, while each banknote class has its own size. Second, the calculation cost increases when the number of the given classes becomes larger. The number of connection between the hidden layer and the output layer is mn^2 where m is the number of kernels for each class and n is the number of given classes. Our proposed system solves these problems. For the first problem, each size of the available area can be defined simply for each class. For the second problem, each RBF network has m hidden neurons respectively and the calculation cost does not increase when the number of the classes increases. The size of the three-layered perceptron in the classification part has less effect than that of the validation part.

8. Conclusion

The system has a good performance for both accepting valid bills and rejecting invalid bills. By comparative experiments, we confirm that the three-layered perceptron cannot reject all invalid data in itself, thus the necessity of the validation part using RBF networks is justified. In addition, the advantages in dividing the system into two parts are shown in our discussion. We also verify that IR images are quite significant for Euro banknote validation.

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