Distinctive Point Extraction and Recognition Algorithm for Various Kinds of Euro Banknotes

Jae-Kang Lee, Seong-Goo Jeon, and Il-Hwan Kim*

Abstract: Counters for the various kinds of banknotes require high-speed distinctive point extraction and recognition. In this paper we propose a new point extraction and recognition algorithm for Euro banknotes. For distinctive point extraction we use a coordinate data extraction method from specific parts of a banknote representing the same color. To recognize banknotes, we trained 5 neural networks. One is used for inserting direction and the others are used for face value. The algorithm is designed to minimize recognition time by using a minimal amount of recognition data. The simulated results show a high recognition rate and a low training period. The proposed method can be applied to high speed banknote counting machines.

Keywords: Counters for banknotes, distinctive point extraction, neural network.

1. INTRODUCTION

Common banknote counting machines only count one single type of banknote. When depositing more then one kind of banknote we first must sort the banknotes based on their face value before counting the total sum. Doing so takes time and is also very complex. To solve these problems, counters for the various kinds of banknotes have been developed. Counting machines for the various types of banknotes require high-speed recognition and counting because the two processes are performed simultaneously.

Most recognition algorithms utilize the sizes or colors of banknotes. Gori and Priami [1] and Kim [6] used banknote size and their featured character for recognition. However, it is assumed that the inserted banknote must be authentic. If any paper that has the same size as a banknote is inserted, an error will occur. Furthermore, Kim [6] used a CCD camera to recognize the kind of banknote by applying it to any selected area of the image for banknote classification. Takeda and Nishikage [2] used two sensors to increase the number of recognition patterns. The purpose of the first sensor is discrimination for a known image and the second sensor is for exclusion of an unknown image. But, these methods require too much time to recognize a banknote because the obtained image using a CCD camera is very large and also includes too much information such as noise. Therefore it is unsuitable for high-speed recognition processing. Lee [4] performed training and recognition through neural network and CIS sensor. He did not use the entire image but rather any one selected horizontal line as input data for recognition. It is necessary to reduce the amount of data for high speed recognition.

In this paper, to reduce the amount of data required in the recognition process, we proposed a method using a lesser amount of input data than the other methods. For data reduction, particular blocks such as characters of banknotes should be selected. This is considered to be an effective way to reduce the amount of data. We used 4-bit gray scale images of banknotes. There are many black colored parts in gray scale banknote images, particularly the face value number. Black color features are also robust to noise. When noise is added to the black color, the noise is unnoticeable with the exception of some bright color noise. By using this feature, the black colored parts can be a distinctive data of banknotes for recognition and classification. For the banknote recognition process, a back-propagation neural network that has input vectors consisting of distinctive points was designed. The input vectors were created from distances between distinctive points and the origin of the unique block. Seven kinds of Euro banknotes were used as sample banknotes.

2. EXTRACTING DISTINCTIVE POINTS

It is important to find characteristic data that is suitable for high-speed processing and high recognition rate. The information representing banknote character is the color and face value number.

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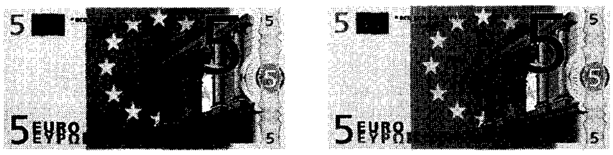


(a) 256-color image. (b) 4-bits gray image.

Fig. 1. Pre-processing.

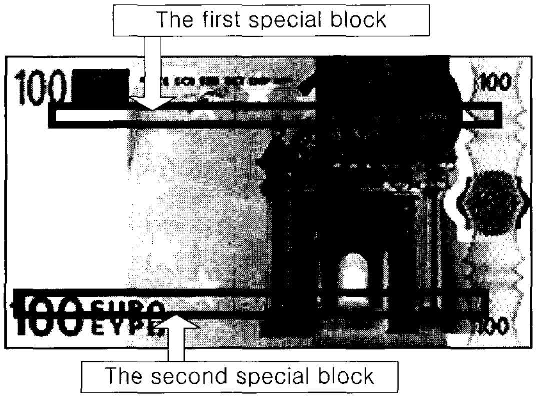


Fig. 2. Two special blocks on a banknote.

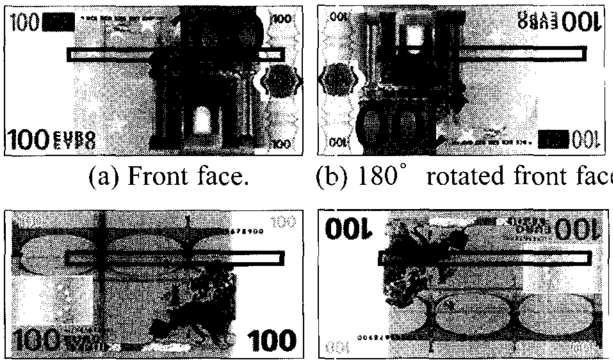
2.1. Pre-processing

Originally we used scanned 256-color banknote images because the color provides information representing banknote character. However, it was difficult to find distinctive banknote data from those images because even neighboring pixels are not the same color. In Fig. 1(a), we can see black color on all the areas of the face value number. Nevertheless, the data are not identical all of the time. To overcome this problem we converted scanned 256-color images to 4-bit gray scale image mapping during pre-processing. This resulted in larger continuous identical colored areas than with scanned 256-color images. We were also able to achieve a faster, easier and more exact algorithm to locate the dark areas in the special block by pre-processing.

2.2. Special block

To reduce recognition time we must select a part of the special block (not the entire image) of a banknote and apply the appropriate algorithms in order to obtain the characteristic data of the banknotes.

The two special blocks depicted in Fig. 2 were first considered. In Fig. 2, the distinctive points of the banknote are the starting point coordinates of the continuous black areas. Because these black areas are clearly distinguishable, it is easy to obtain the distinctive points. If we acquire enough distinctive points at the first special block, we do not need additional processing. If the back face of the banknote has been inserted, we cannot find any distinctive points in the first special block, because there are no continuous black areas. In that case, distinctive areas must be



(a) Front face. (b) 180° rotated front face.

(c) Back face. (d) 180° rotated back face.

Fig. 3. The special block and inserting directions.

acquired at the second special block. The second block contains a continuous black colored area. The second special block also includes the face value number. However, it causes low-speed processing because it needs two processing steps for the first and second special blocks. Furthermore, we can't obtain sufficient distinctive points on the face value number at the second special block because it is smaller than on the first special block as shown in Fig. 2. Consequently, the processing time for each face of banknotes is different and also the extracted distinctive points are too few for recognition of the banknote. To avoid slow processing time and to get enough dark images, the distinctive point extraction method for only one special block is needed. So we chose a special block that is located on the common area of banknotes regardless of the inserting direction. There are four possible inserting directions. The special block includes dark parts for all inserting directions. Fig. 3 shows inserting directions and special blocks.

The width of special blocks is 230 pixels and the height is 10 pixels. The widest width of a euro banknote is 300-pixels.The special block is located on the same position for each type of banknote because the inserting direction of a banknote isn't known. We chose this location by trying many other locations to determine the proper location of the special block. This particular location contains enough dark areas regardless of inserting direction. In Fig. 3, the special blocks include not only very dark areas but also areas slightly less dark. In Fig. 3(a), we can easily get distinctive points because the black area is on the face value number. However in (b), (c) and (d), it is not simple. In (c), there are particularly fewer dark areas on the special block. Therefore, we may select all the points as distinctive points except the right side of the special block because the right side is white. So, in the case of (c), we have to select areas that are as dark as possible because some bright areas are sensitive to noise such as user scrawl.

There are seven kinds of euro banknotes; 5, 10, 20, 50, 100, 200, and 500 euro. Each banknote has a face

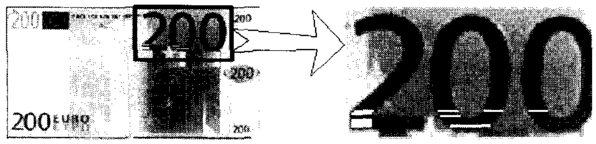
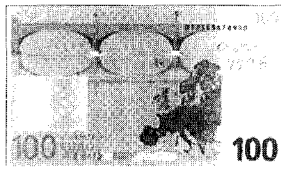


Fig. 4. Same-intensity area.

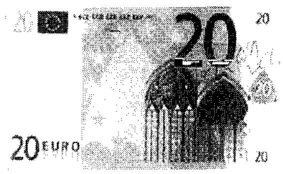
value number. The positions of the face value number and starting points of continuous Same-Intensity areas are different for each banknote. It is those differences that classify the various types of banknotes.

2.3. Same-intensity area

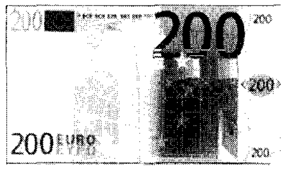
We define the Same-Intensity area as distinctive data area. The Same-Intensity area has 8 continuous same intensity pixels, which is the darkest region on the special block in the banknotes. The continuous Same-Intensity area is found by using a search algorithm. The search algorithm locates the next 7 pixels, which are the same intensity as the base pixel on the special block. The Same-Intensity area is 1-pixel long and 8-pixels wide. Of importance is that continuous Same-Intensity areas have to be as dark as possible, because black color features are robust to noise. When noise is added to black color, the noise goes unnoticed, except in the case of certain bright color noises. For a banknote, the Same-Intensity area can be found from 30 to 40. This includes areas that are continuous with some bright colors. Subsequently, we must remove those bright colored areas. To remove



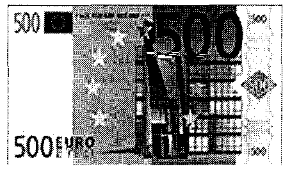
(a) Number noise.



(b) Letter noise.



(c) Fold noise.

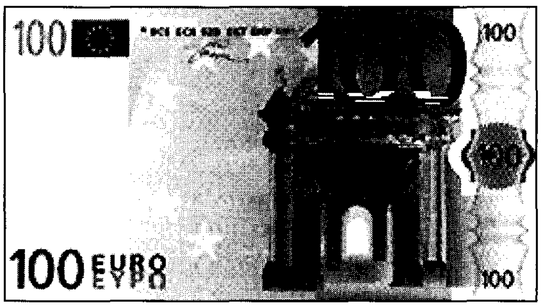


(d) Fade noise.

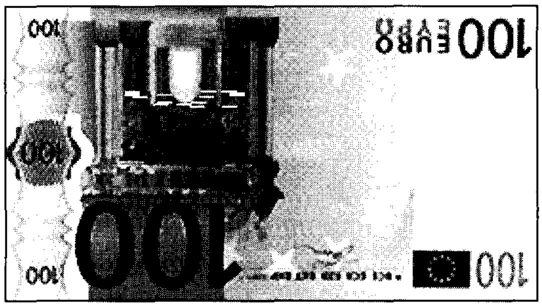
Fig. 5. Extracting distinctive areas of a banknote including noise.

the bright colored areas, we selected 11 distinctive areas from the selected distinctive areas by arranging continuous Same-Intensity areas according to black intensity. Then we extracted the starting point of the arranged 11 distinctive areas. Fig. 5 shows extracted distinctive areas of banknotes which include noise.

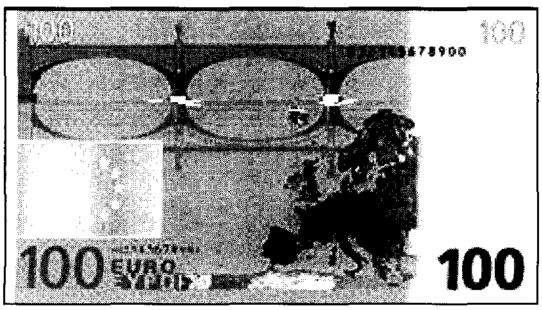
We can obtain proper distinctive data from the starting points. The coordinates of the starting point of that area becomes the distinctive point. In this way we can reduce the number of distinctive data. In Fig. 4, the lines mean Same-Intensity areas. The distinctive point is the starting point of the Same Intensity



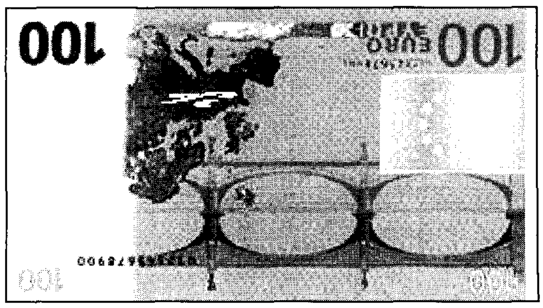
(a) Continuous same intensity areas of front face.



(b) Continuous same intensity areas of 180° rotated front face.



(c) Continuous same intensity areas of back face.



(d) Continuous same intensity areas of 180° rotated back face.

Fig. 6. The continuous same-intensity areas.

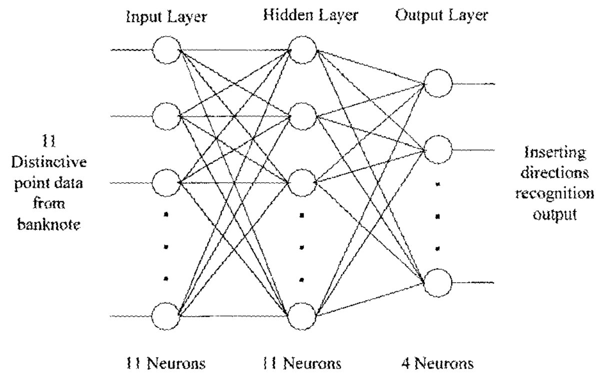


Fig. 7. Neural network to detect inserting direction.

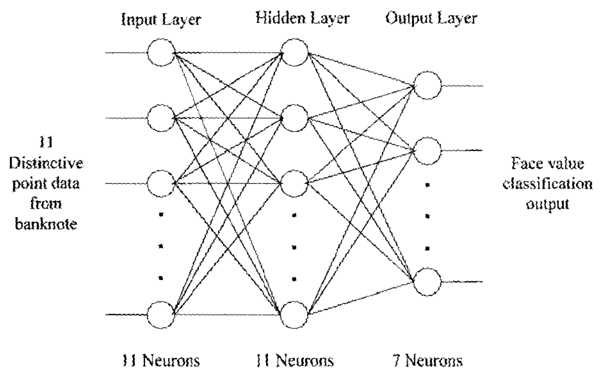


Fig. 8. Neural network to recognize face value.

areas. The origin of the distinctive point is the upper left corner point of the banknote image. The reason why we choose the starting point of the continuous Same-Intensity area as the distinctive point is that the continuous Same-Intensity area is located in a different position on each kind of banknote. We applied the proposed extracting algorithm to banknotes that include noise that is a user scrawl, a folded banknote and a faded banknote. In Fig. 5, we can see that the proposed extracting algorithm is robust to the noise. The starting point of the continuous Same-Intensity area is not changed by the noise. Fig. 6 shows the distinctive areas of all the possible images of one face value banknote.

3. RECOGNITION AND CLASSIFICATION

3.1. Neural network

Figs. 7 and 8 represent two kinds of back propagation neural networks that we use. Fig. 7 is used for detection of inserting direction and Fig. 8 is used for recognition of face value. Both networks use 11 distinctive point data as the input. The supervised learning needs a desired target (output) pattern for each input pattern. After obtaining an actual output pattern through applying an input pattern to the neural network, the error is computed by comparing the desired output pattern with the actual output pattern. To minimize the error, the weight matrix is modified through feedback of the error to the neural network. We performed recursive calculation until the error no longer exceeds a threshold value. Weight W denotes the degree of connection between the neurons and p = 1, 2, 3 … n which denotes the input pattern. We consider t_p (the desired target pattern), O_p (real output pattern) and e_p (error). Thus, the error is given by

$$e_p = (t_p - O_p(W)). \tag{1}$$

The cost function of pattern p is defined by

$$E_p = \|e_p\|^2 = \|t_p - O_p(W_p)\|^2. \tag{2}$$

The cost function of the entire pattern is defined by

$$E(W) = \sum_{p=1}^{n} E_p(W). \tag{3}$$

As a result, the back-propagation algorithm minimizes the error by modifying the weight, which is calculated repeatedly by using the steepest descent method. Weight W is given by

$$W_{ij}(n+1) = W_{ij}(n) + \Delta W_{ij}(n+1), \tag{4}$$

$$\Delta W_{ij}(n+1) = \eta \delta_i O_j + \alpha \Delta W_{ij}(n), \tag{5}$$

$$b_i(n+1) = b_i(n) + \Delta b_i(n+1), \tag{6}$$

$$\Delta b_i(n+1) = \eta b_i + \alpha \Delta b_i(n), \tag{7}$$

where, W_{ij} is the weight between neuron U_i and neuron U_j, O_j is the output of U_j, b_i is the bias value of U_i, δ_i is the backward error, η is the learning rate constant and α is the momentum term. We used 'purelin' for hidden layer transfer function and 'logsig' for the output layer. The maximum training period is 10,000 times for each neural network. The momentum constant is 0.98.

4. SIMULATION

We used a two step procedure to recognize banknotes. The first step is to find the inserting direction of banknotes; front, rotated front, back and rotated back. The second step is to recognize the face values of banknotes; 5, 10, 20, 50, 100, 200 and 500 euro. The distinctive data pattern according to the inserting direction shows a relatively clearer tendency than that of the face value. The recognition process compares the target value with the output vectors of the trained neural networks.

We trained 5 neural networks. One is used for inserting direction and the others are used for the face value. In step 1, a neural network was trained to rec-

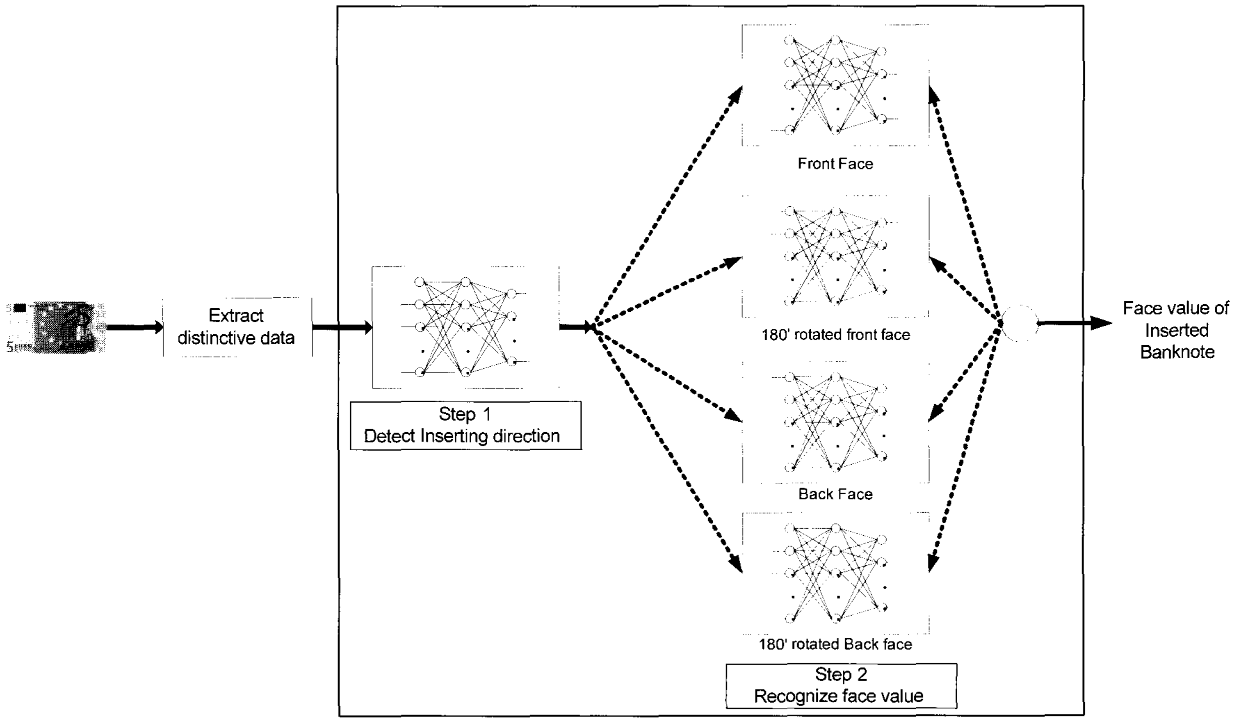


Fig. 9. Recognition steps.

ognize only the inserting direction of banknotes. In step 2, the other 4 neural networks were trained to recognize the face values of the different banknotes. The recognition of all seven banknotes is accomplished by comparing target output vectors with output vectors of the trained neural networks. Fig. 9 shows the recognition steps.

The width is much longer than the height of the banknotes. This means that the distance is easily influenced by the width. Therefore, we need to change the width range of special blocks to make the width and the height of equal distance. Before using distinctive points as input vectors of the neural networks, we changed the width range from 0 to 10 (same range with the height). The target outputs are shown in Table 1 and Table 2.

Table 1. Target output value for inserting direction recognition.

Direction	Output	Direction	Output
Front	0.1	Rotated front	0.3
Back	0.5	Rotated back	0.7

Table 2. Target output value for face value recognition.

Kind	Output	Kind	Output
5 euro	-0.5	100 euro	0.3
10 euro	-0.3	200 euro	0.5
20 euro	-0.1	500 euro	0.7
50 euro	0.1		

Table 3. Recognition rate with untrained sample euro banknotes.

Kinds	Sample	Recognition	Recognition Rate
5 euro	20	20	100%
10 euro	20	20	100%
20 euro	20	20	100%
50 euro	20	20	100%
100 euro	20	19	95%
200 euro	20	19	95%
500 euro	20	20	100%

The input value is normalized to range from 0 to 1.0 to avoid a weighted effect of the network weight. Target value range is also from 0 to 1.0. The input vectors of the neural networks are starting points of Same-Intensity areas. With this target vector and input vectors consisting of distinctive points, we trained the back-propagation neural networks. For a high recognition rate of the inserting direction, we trained the neural networks by increasing the neuron number of each layer from 9 to 30, and the learning rate from 0.01 to 0.1. In the case of 11 neurons and 0.02 learning rate without momentum constant, we can obtain the highest recognition rate and the lowest training period. For face value recognition, we can get 11 neurons and 0.1 learning rate with 0.98 momentums constant. The reason for the learning rate and momentum constant differences between inserting direction and face value recognition is that the distinctive data pattern according to inserting direction shows relatively clearer tendency than that of face value.

Table 3 shows the simulated results. We used 20 samples of each euro banknote for training neural networks and another 20 samples for recognition. These simulation results are taken from untrained sample banknotes. From Table 3, we can get relatively good results except for 100-euro and 200-euro. As the sizes of two banknotes and images are very similar, the rotated back faces of 100-euro and 200-euro have similar distinctive point positions. In particular, if two euro banknotes have the same brightness, it is difficult to classify those two euro banknotes.

5. CONCLUSION

In this paper, we considered the distinctive point extraction and recognition algorithm for various types of banknotes. By converting the scanned 256-color image data to 4-bit gray data as pre-processing, we can get a better algorithm to find the dark areas on the special block because the dark color is robust to noise. By applying the continuous Same-Intensity area recognition algorithm to the face value of the banknote, we can extract distinctive data to classify the kind of banknotes, as the area is located in different positions on each kind of banknote. For banknote recognition, we trained 5 neural networks. One is used for inserting direction and the others are used for the face value. The distinctive data pattern according to the inserting direction shows relatively clearer tendency than that of the face value. With this method, we can get a high recognition rate except for 100 and 200 euro banknotes.

The proposed recognition algorithm does not include position correction. In banknote counting machines, the origin position of the distinctive points may be changed when banknotes are not perfectly inserted into the counting machine. This occurs frequently and thus additional research will be needed.

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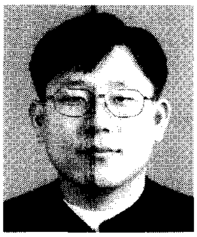

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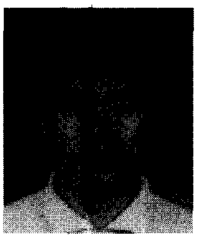

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