Using Hidden Markov Models for Feature Extraction in Paper Currency Recognition

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Abstract - This paper proposes a new feature extraction technique for paper currency recognition. In this technique, the texture characteristic is used in the recognition. The Markov chain concept has been employed to model the texture of paper currencies as a random process. The method proposed in this paper can be used for recognizing paper currencies from different countries. In this method only intact examples of paper currencies from each denomination are used for training the system. We tested this method on more than 100 denominations from different countries, and the system was able to recognize 95% of data, correctly.

I. INTRODUCTION

With the development of modern banking services, automatic methods for paper currency recognition are important in many applications such as in Automated Teller Machines and automatic vending machines. The need for an automatic banknote recognition system encouraged many researchers to develop a robust and reliable technique [1], [2], [3]. Speed and accuracy of processing are two important factors in such systems. Of course, the accuracy may be more important than the speed.

Paper currency recognition systems should be able to recognize banknotes from each side and each direction. Since banknotes may be defaced during circulation, the designed system should have a meaningful accuracy in detecting torn or worn banknotes.

Currently, there is a number of techniques for paper currency recognition [1][2][3]. Symmetrical masks have been used in [2] for recognizing paper currency in any direction. Using this method, the summation of non-masked pixel values in each banknote is computed and fed to a neural network for recognizing paper currency. This method uses two sensors for the recognition of the front and back of the paper currency, but the image of the front is the only criterion for decision. In other research for paper currency recognition [1], initially the edges of patterns on a paper currency are detected. In the next step, paper currency is divided into N equal parts along a vertical vector. Then, for these parts on each edge the number of pixels is counted and fed to a three-layer, back propagation neural network. For this method, to overcome the problem of recognizing dirty worn banknotes, the following linear function is used as a pre-processor:

$$f(x) = F_a x + F_b \qquad (1)$$

where x is the input image in gray scale, f(x) is the output image; and F_a, F_b and N have the values 3, -128 and 50 respectively [1]. In this method, the algorithm depends on the number of paper currency denominations. In other words, complexity of the system increases by increasing the number of classes. Therefore, this method can be used only for recognition of a few banknote denominations, for example, banknotes of one country.

In [4], we employed characteristics of paper currencies used by people for distinguishing different banknote denominations. In fact, at first glance, people may not pay attention to the details and exact characteristics of banknotes for their recognition, rather they consider the general characteristics of banknotes such as the size, the background color (the main color), and templates (texture) appearing on the banknotes

In many countries, the size and color spectrum of some banknotes are very close to each other. Further more, these characteristics of banknotes from different countries may be too similar to each other. Hence, these characteristics may not be enough to easily distinguish between the different banknotes. Consequently, we consider template of the banknotes in addition to the forgoing characteristics.

55	32	15	12	10	7	4	5	0	0
50	**806**	301	73	48	24	11	22	3	0
10	292	**1252**	527	168	118	40	28	18	0
9	65	579	**2192**	622	624	94	68	13	0
2	47	170	783	**6838**	1869	278	135	65	0
7	41	65	180	239	**5148**	562	261	82	0
6	53	37	61	288	566	**1267**	1000	213	0
1	7	25	41	112	265	1004	**12668**	522	0
0	2	9	18	62	143	225	451	**304**	0
0	0	0	0	0	0	0	0	0	0

Table 1. Transition matrix (N_x) for a 5 Euro banknote whose image was quantized to a 10-level gray scale.

II. FEATURE EXTRACTION

In this paper, texture characteristics of banknotes are used for recognition. We use the Markov chain concept [6] to model texture of the banknotes as a random process. The features employed in this paper are independent of the way that a paper currency is placed in front of the sensor. It needs to be noted that the proposed technique may not be able to distinguish genuine notes from counterfeits. Indeed, techniques such as [8] which use infrared or ultraviolet spectra may be used for discriminating between genuine and counterfeit notes.

A random process $\{x_k, k = 0,1,2,...\}$ is called a Markov chain if the possibility value in state x_{n+1} depends on just the possible value in state x_n, that is:

$$P(x_{n+1} = \beta \mid x_n = \alpha, \quad x_{n-1} = \alpha_{n-1},...,x_0 = \alpha_0)$$
$$= P(x_{n+1} = \beta \mid x_n = \alpha) \qquad (2)$$

This possibility can be shown by P_{ij}. The state space of a Markov chain can be shown in a matrix, that is:

$$P = \begin{bmatrix} P_{11} & P_{12}\cdots & P_{1n} \\ P_{21} & P_{22}\cdots & P_{2n} \\ \vdots & \vdots & \vdots \\ P_{n1} & P_{n2}\cdots & P_{nn} \end{bmatrix} \qquad (3)$$

where n, is the number of states in the chain. In a discrete time Markov chain, the possibility value of different states in the matrix is computed as follow:

$$P_{ij} = \frac{n_{ij}}{\sum_{k=1}^{n} n_{ik}} \qquad (4)$$

where n_{ij}, is the number of transitions from state i to state j. Considering (4), matrix P can be multiplied by the factor $\sum_{k=1}^{n} n_{ik}$ to obtain

$$N = \begin{bmatrix} N_{11} & N_{12} & \dots & N_{1n} \\ N_{21} & N_{22} & \dots & N_{2n} \\ \vdots & \vdots & & \vdots \\ N_{n1} & N_{n2} & \dots & N_{nn} \end{bmatrix} \qquad (5)$$

We use this matrix in this paper to differentiate between textures in different denominations. Although an image is recognized by the value of its pixels at different places, the way that adjacent pixels vary can also be used to distinguish different images [7]. Therefore, we consider the value of each pixel as one state, hence, we compute the matrix in (6) for each banknote.

We can scan the banknotes from top to bottom and from left to right to obtain the transition matrix across the row (N_x) and across the column (N_y). Table 1 shows the transition matrix N_x obtained for a 5 Euro banknote whose image was quantized to a 10-level gray scale. To reduce the feature space we only use the values on the main diagonal in this paper.

Countries	Kinds of paper currency	Main Diagonal
U.S.A	20 (B)	22 863 3913 8480 10431 12408 46574 44053 74 0
U.S.A	20 (F)	0 95 4616 8808 10112 11860 36505 65997 2550 0
U.S.A	50 (B)	0 399 3020 6708 9483 7676 15642 63371 23012 0
U.S.A	50 (F)	0 0 0 47 508 4653 12968 24605 7591 0
EURO	5 (B)	55 806 1252 2192 6838 5148 1267 12668 304 0
EURO	5 (F)	5 121 1242 2867 3746 7288 5846 10954 167 0
EURO	50 (B)	0 770 663 2142 5451 8240 9487 27912 31068 0
EURO	50 (F)	3 23 448 1523 7027 9603 16062 26328 23621 1
U.A.E	10 (B)	22 58 330 684 1567 4123 8848 14439 983 0
U.A.E	10 (F)	0 0 108 954 2499 3541 11242 14063 6278 0
U.A.E	20 (B)	41 300 450 782 1361 3733 5081 27814 2521 1
U.A.E	20 (F)	0 5 304 525 1227 2291 6940 34987 3783 0
IRAN	1000 (B)	7 21 74 1866 4239 3716 3564 34123 3068 0
IRAN	1000 (F)	0 0 0 47 508 4653 19968 24605 7591 0
IRAN	10000 (B)	0 51 2403 3326 2727 4228 11950 10488 19868 0
IRAN	10000 (F)	0 12 61 498 2429 5035 14631 12657 21796 0

Table 2- Name of the countries, their banknote denominations and the main diagonal of the transition matrix used in the assessment process. In this table B and F represent the back and front of the paper currency.

Our investigation shows that the main diagonal values are enough to distinguish different denominations.

Table 2 shows the main diagonal of different paper currencies. These values associated with the transition matrix extracted from the back of 20$, 50$, 5€, and 50€ represented in Table 2 have been drawn in Figure 1. As can be seen from Table 2 and Figure 1, the values on the main diagonal of the transition matrix of different paper currencies are different. Hence, it can be used as a feature for recognition.

III. PAPER CURRENCY RECOGNITION

The technique proposed in this paper is independent of the number of paper currency classes. The algorithm of the proposed paper

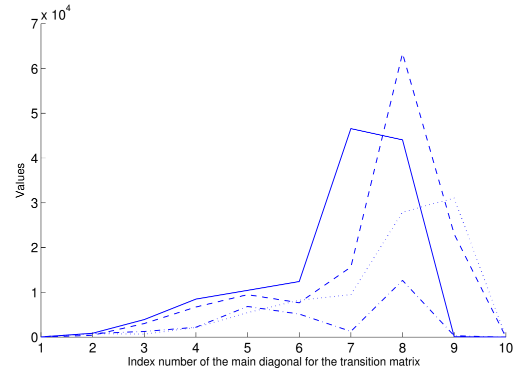


Figure 1. The main diagonal values of the transition matrix extracted from the back image of 20$ (solid line), 50$ (dashed line), 5€ (dash dotted line), and 50€ (dotted line) represented in Table 2.

currency recognition system is described as follows:

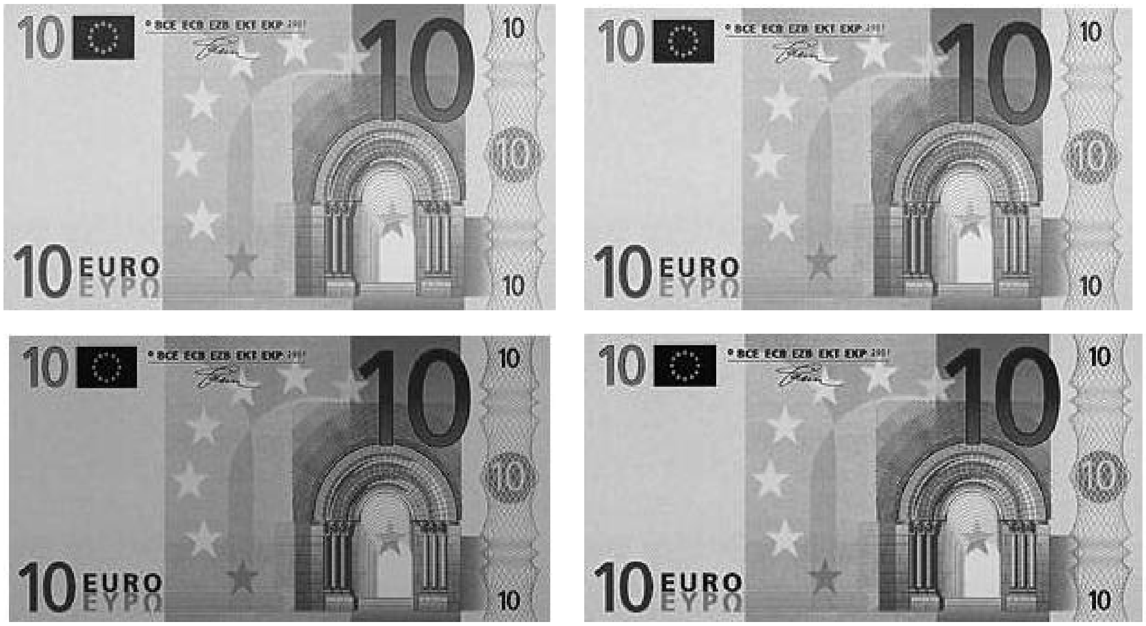
a) Image of the banknote is transformed to an image in gray scale [5].

b) The transition matrices (N_x and N_y) are computed for the banknote, then, the main diagonal values of the matrices (namely D_x and D_y) are extracted as a feature for distinguishing between different denominations.

c) The paper currency under analysis is assigned to a denomination class if the Euclidean distances between the main diagonal elements of its transition matrices (D_x and D_y) and the main diagonal elements of the corresponding matrices of the reference banknote (D_{Rx} and D_{Ry}) are smaller than a predefined value.

IV. RECOGNITION OF DIRTY BANKNOTES

The above algorithm has good accuracy in recognizing banknotes which are not dirty. In other words, it has the desired accuracy in recognizing banknotes, even torn banknotes.



(a) (b)

Figure 1- Using the linear transform function to reduce the effect of dirt: a) before filtering , b) after filtering.

To improve the accuracy of the proposed method in recognizing dirty banknotes, it is necessary to pass the paper currency through a filter in order to reduce the effect of dirt by improving the lightness of the image. In fact, a dirty paper currency is one for which the darkness of its image has increased. The important point is that the severity of the increased darkness is almost the same on the whole surface of the paper currency. Consequently, to reduce the effect of dirt on the image a linear transform function could be very helpful [1]. Hence pixels of the images are multiplied by a factor as follows:

$$f(x) = F_a x \qquad (6)$$

where x is the gray scale of the input image and F_a >1. Applying the linear transform function on a clean banknote gives it an excessive lightness. In the proposed method all banknotes (dirty or clean) are passed through the preprocessing stage, hence, the filter should not cause a noticeable change on clean banknotes. For this reason we suggest the following function:

$$f(x) = \begin{cases} F_a x & \text{if} \quad x < 125 \\ x & \text{if} \quad x \geq 125 \end{cases} \qquad (7)$$

In Figure 1, images of a dirty paper currency and a clean paper currency have been shown before and after implementing the filter in (6). As the figure shows, the image of the dirty banknote has been improved and the lightness of the clean banknote after filtering is acceptable.

In the proposed method, both sides of the banknotes have been used in the recognition. In fact, both sides are processed separately. The system should assign the same denomination to both sides; otherwise the banknote is assigned to an unknown class.

V. PERFORMANCE EVALUATION

To assess the performance of the proposed method the technique was applied on 101 different denominations from 23 countries (see Table 3). The technique described in Section 3 was applied

Countries	Kinds of paper currency
Azerbaijan	500,1000,10000,50000
Jordan	1,5,10,20
Afghanistan	5,10,20,50,100,500
U.A.E	5,10,20
Iran	1000,2000,5000,10000, 20000
U.S.A	1,2,10,20
Pakistan	5,50,100,500,1000
Turkmenistan	500,1000,5000,10000
Turkey	10,20,50,100
China	10,20,50,100
Russia	10,50,100,500
Japan	1000,2000,5000,10000
Syria	100,200,500,1000
Iraq	250,5000,10000,250000
Saudi Arabia	5,10,20,50
Kazakhstan	200,500,1000,5000
Qatar	1,5,10,50
Kuwait	1/4 ,1,10,20
Euro	5,10,20,50,100,200,500
India	5,20,100,500,1000
Kyrgyzstan	20,50,100,500,1000
Uzbekistan	100,200,500
Armenia	500,1000,2000,5000,20000, 50000

Table 3- Name of the countries and their banknote denominations that were used in the assessment process.

to both sides of the banknotes, and it could successfully recognize all of the banknotes. In this experiment the algorithm was set for $F_a = 1.2$ and gray scale level for the transition matrix was 10.

VI. CONCLUSION

This paper proposed a new technique for recognizing paper currencies of different countries. The technique uses texture characteristics of paper currencies. For this method the system can be trained for a new denomination banknote by just introducing one intact example of the banknote to it. In addition the system may recognize the banknote on each side or in any direction. The performance results of applying the proposed methods on banknote denominations of 23 different countries indicate that the technique has 95% accuracy.

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