RES MILITARIS
REVUE EUROPEENNE D ETUDES EUROPEAN JOURNAL OF MILITARY STUDIES
Social Science Journal

An intelligent paper currency recognition system

[1]P. Chaitanya, [2]Dr. G. JawaherlalNehru, [3]Dr. R. Santhoshkumar, [4]S. BavanKumar
[1,4]Assistant Professor, [2,3]Associate Professor
[1,2,3,4] Department of CSE, St. Martins Engineering College, Secunderabad, Telangana

Abstract

Paper currency recognition (PCR) is an important area of pattern recognition. A system for the recognition of paper currency is one kind of intelligent system which is a very important need of the current automation systems in the modern world of today. It has various potential applications including electronic banking, currency monitoring systems, money exchange machines, etc. This paper proposes an automatic paper currency recognition system for paper currency. A method of recognizing paper currencies has been introduced. This is based on interesting features and correlation between images. It uses Radial Basis Function Network for classification. The method uses the case of Saudi Arabian paper currency as a model. The method is quite reasonable in terms of accuracy. The system deals with 110 images, 10 of which are tilted with an angle less than 15o. The rest of the currency images consist of mixed including noisy and normal images 50 each. It uses fourth series (1984–2007) of currency issued by Saudi Arabian Monetary Agency (SAMA) as a model currency under consideration. The system produces accuracy of recognition as 95.37%, 91.65%, and 87.5%, for the Normal Non-Tilted Images, Noisy Non-Tilted Images, and Tilted Images respectively. The overall Average Recognition Rate for the data of 110 images is computed as 91.51%. The proposed algorithm is fully automatic and requires no human intervention. The proposed technique produces quite satisfactory results in terms of recognition and efficiency.

1. Introduction

Object recognition[1-7] is an important and highly demanded area of pattern recognition. An object can be anything in real life. It can be text in a document, a license plate of a vehicle, an iris in a person's eyes, a sign in a sign language, a face of a person, and so on. Similarly, paper currency recognition[8-15,17-20] is as important as any other object recognition.

Some authors, in the recent years, have contributed to the subject of paper currency recognition systems. For brevity, the reader is referred to[9-15]. These existing paper currency recognition methods, in the literature, mainly involve image processing and/or neural network techniques[11-15].

This paper deals with a simple, efficient and very accurate approach in the system design. In designing such a system, it considers different dimensions, areas, Euler numbers, correlations as features. A different method using radial basis Function networks, is utilized for developing an intelligent system which can recognize paper currency. This research is specifically designed for recognizing paper currency from the Kingdom of Saudi Arabia (KSA). It uses fourth series (1984–2007) of currency issued by Saudi Arabian Monetary Agency (SAMA)[18] as a model currency under consideration. The proposed paper recognition technique has been designed in such a way that it can be used for recognizing paper currency form different values in KSA. To overcome the problem of recognizing dirty banknotes, the pre-processing stage is also considered.

The proposed scheme is different from various existing methods[1-21] because of its approaches in the recognition phases. Specifically, for example, symmetrical masks have been used in[11] for considering specific signs (images) in a paper currency. Using this method, the summation of non-masked pixel values in each banknote is computed and fed to a Neural Network (NN). The technique in[20] deals with Pakistani paper currency with very different feature set which is specific to regional currency marks and color of the currency. Similarly, the technique introduced in[21] is different from the proposed technique as it introduces much more number of features than the ones introduced in the proposed method.

The organization of the paper is as follows. Section 2 introduces the overall mechanism for PCR, In Section 3, the pre-processing steps are briefly introduced. Section 4 describes the problem formulation for the Saudi PCR System (SPCRS). The proposed PCR approach, together with feature extraction method as well as classification has been completely discussed in Section 5. Section 6 describes details of demonstration for the case of KSA Paper Currency. Finally, Section 7 concludes the paper.

2. Structure of Typical PCR System

The system presented is designed to recognize paper currency. Input to the system is an image acquired by a scanner or a digital camera, containing the paper currency and its output is the features of the paper currency. The system consists of the modules: Image acquisition, pre-processing including noise removal, feature extraction, classification and recognition. The structure of the system is shown in **Fig. 1**.

3. Pre-processing

In the proposed system a high resolution scanner is used to acquire the image. The acquired image of a paper currency is first converted to gray scaled image. Conversion to gray scale facilitates further pre-processing. The task of pre-processing is achieved by converting colored currency images into grayscale, then black-white images. After that, the edge of the image is filtered using Prewitt method. Then, the image edge is detected using Canny's edge detection method. Different stages of an image are shown in **Fig. 2**.

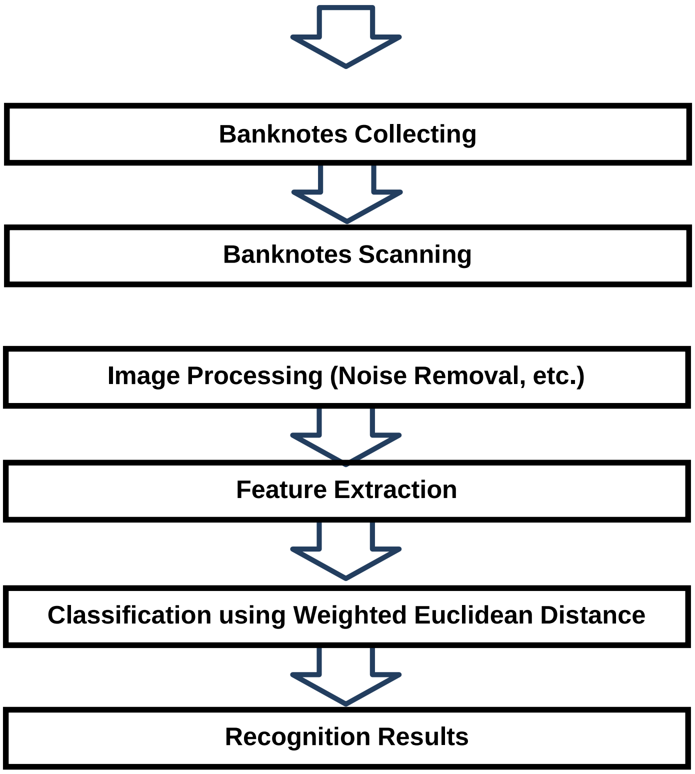

Fig. 1. The Typical Structure of a Paper Currency Recognition System.

(a) (b)

(c)

Fig. 2. Results Showing Different Stages in a Paper Currency Recognition System (a) Original Image, (b) Gray Scaled Image, (c) Black & white image.

This paper is meant for Saudi Paper Currency Recognition System (SPCRS). The SPCRS is designed to just recognize Saudi paper currencies. This means that this system will not be concerned with currencies other than Saudi currencies. In addition, the system will focus on paper currencies, not coins. Moreover, the system is not concerned with verification of the validity of the paper currencies (i.e. verifying that the paper currency is genuine and not faked). This is usually done using other methods which might involve sensing the magnetic string embedded inside the currency, or some other methods. There are 8 Saudi paper currencies, which are given in Table 1 together with other assumptions and settings for the system developed.

Table 1. Settings and assumptions for the proposed system.

#	Items	Specifications
1	Resolution	200ppi, 24-bit picture scan mode
2	Image Type	Jpeg
3	Number of Banknotes scanned	110 including clean, noisy and tilted banknotes
4	Values of currency Notes (in Riyals)	1, 5, 10, 20, 50, 100, 200 and 500

The goal of the paper is to achieve the best accuracy in recognizing patterns with the lowest cost possible. Given the fact that paper currencies are usually recognized by machines that have small power (such as auto-seller machines and ATM’s), the cost is a limiting factor. Therefore, it is really urgent for all paper currency recognizers to minimize the power consumption, and, at the same time, achieve high level of accuracy.

4. Problem Formulation of the Saudi PCR System

Before presenting the proposed approach for SPCRS in Section 5, this section is dedicated for the problem formulation of SPCRS. The system presented is designed to recognize Saudi paper currency from the front. Input to the system is an image acquired by a scanning device, and its output is set of features. The system deals with 110 images, 10 of which are tilted with an angle less than 15o. The images, under consideration, are taken as jpeg images with 200ppi and 24-bit picture scan mode. The values of the currency Notes (in Riyals) are those of 1, 5, 10, 20, 50, 100, 200 and 500.

The rest of the currency images consist of mixed images including noisy and normal images 50 each. The system consists of four tasks: image acquisition, pre-processing including noise removal, feature extraction, classification and recognition. The structure of the system is shown in **Fig. 1**. The first task acquires the image of a paper currency using a scanning device. The second task then removes the noise by using filters which are explained in Section 3. The third task extracts the features of image dimensions, image areas, Euler number, and image correlation reported in detail in Section 5. The last recognizes the targeted paper currency, it uses Radial Basis Function Network for classification. The used Radial Basis Function Network Classifier contains 25 neurons in the hidden layer. The system calculates all the correlations and then it builds and trains the network, and finally classifies the image.

5. Proposed Approach for SPCRS

Since, the objective of the paper is to come up with an optimal technique which can lead to an intelligent system for SPCRS. Therefore, the interest would be to, first of all develop a mechanism to produce suitable features for each paper currency. A classification, afterwards, would be required for recognition part.

5.1. Feature Extraction

The features extracted constitute the input vector to the system. The input vector can be written as follows:

$$F(h, w, a_1, a_2, a_3, e, r),$$

which consists of the features, as its arguments, shown in Table 2.

Table 2. Experimental Results of the Radial Basis Function Network Classifier.

#	Feature Notation	Feature Specification
1	h	the height of the image (in pixels)
2	w	the width of the image (in pixels)
3	a_1	the image area (sum of 1-pixels) without a mask.
4	a_2	the image area with the first mask (Prewitt Method).
5	a_3	the image area with the second mask (Canny Method)
6	e	the Euler number of the image
7	r	the image correlation with the template images

Euler number of an image is a scalar value which represents the number of objects in the image minus the total number of holes in those objects[5].

$$e := Euler = \sum (O - H_o)$$

where O stands for any object in the image, and H_o stands for any hole in that object. In fact, Euler is an attractive feature of the currency image, since it makes use of the whole image, whose distinctive features are spread in many different positions.

The correlation coefficient of two different image matrices gives very important information about the similarity matching between them. It can be evaluated by the following formula:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right)\left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

where A is the first $m \times n$ matrix, B is the second $m \times n$ matrix, $\bar{A}$ is the mean of A, $\bar{B}$ is the mean of B, and r is the correlation coefficient between A and B[5]. The value of r lies between 0 and 1. The greater the value of r, the more the two matrices are similar.

If A and B are two binary pictures (arrays of bits or pixels) then the correlation coefficient r gives the degree of resemblance between the two pictures. Again, this is an attractive feature since it deals with the whole currency image, which contains several distinctive feature distributed in many different places in the image.

It is worth mentioning that since the correlation values cannot be evaluated before hand, they are only evaluated after the input image is provided. This cause some delay as the input image is not directly compared to pre-stored values. However, correlation values are important and provide a very robust classification power.

One of the mostly used types of Radial Based Neural Networks is the one based on Gaussian radial basis functions. This type uses the following general formula[2,6]:

$$\phi_j(x) = e^{\left[-\frac{1}{2}(x - c_j)^T \sum_j^{-1} (x - c_j)\right]}$$

where: x is the input vector with elements x_i, and c_j is the vector determining the center of the radial basis function ϕ_j with elements c_{ji}.

The used Radial Basis Function Network Classifier contains 25 neurons in the hidden layer. Since the correlations are not available before hand, when the image is input, the system calculates all the correlations, then it builds and trains the network, and finally classify the image.

5.2. Classification

Radial Basis Function Networks originate from the problem of interpolating a set of data in a hyperspace to find the best hyper-plane that interpolates that set of data. In Radial Basis Neural Networks, there are three layers: input layer, hidden layer and output layer. The input layer consists of the data (or the pattern) that is to be interpolated (or classified). The hidden layer provides a nonlinear transformation from the input layer space to the hidden layer space. It usually consists of a high number of neurons. The output layer provides a linear transformation from the hidden layer space to the output layer space[6].

6. Experimental Results

The above mentioned scheme has been implemented and tested for a database of 110 images. Reasonably quite elegant results have been observed. An interface of the implementation is shown in **Fig. 3**.

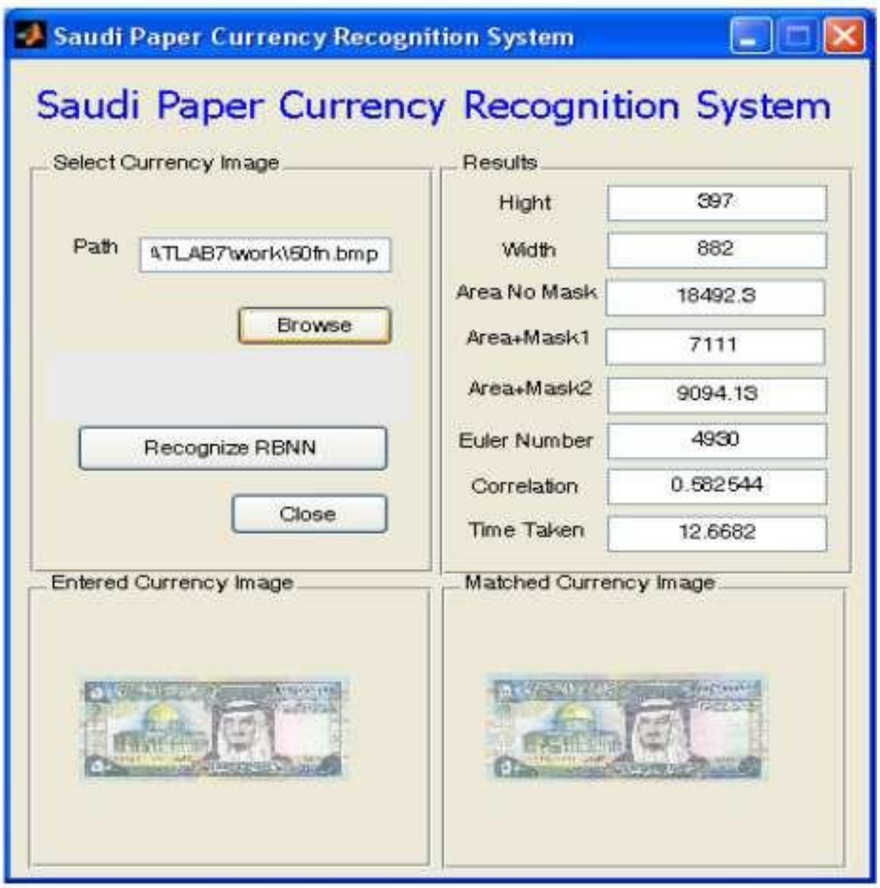

Fig. 3. Interface for Implementation.

The Radial Basis Function Network Classifier was tested with a database of 110 images, 10 of which are tilted with an angle less than 15°. The rest of the currency images consist of mixed including noisy and normal images 50 each. The recognition results are as shown in Table 3. Average recognition rate was seen as 91.51% which is quite reasonable and acceptable in various cases. As far as computation time is concerned, the Radial Basis Function Network Classifier took almost 3 seconds per image, in average, for classification.

Table 3. Experimental Results of the Radial Basis Function Network Classifier.

Normal Non-Tilted Images	Noisy Non-Tilted Images	Tilted Images	Average Recognition Rate
95.37%	91.65%	87.5%	91.51%

As shown in the experimental results, the Radial Basis Function Network Classifier has provided with quite satisfactory results. But, still one can search for a better method of recognition which can provide superior results than the Radial Basis Function Network Classifier. The reason for improvement can be seen due to the reason that, in the case of Radial Basis Function Network, the Network is built when the image is input. Afterwards, the Network is trained with a few number of input vectors, due to time constraints, and finally the image is classified. This way of building the network does not allow the weights of the connections between neurons to converge to the best values. This might be the primary reason for the performance is not reaching to 100% recognition.

7. Conclusion and Future Work

Paper Currency Recognition is an important application of Pattern Recognition. Many studies were made to recognize paper currencies using Neural Networks. In this paper, another method of recognizing currencies has been introduced, which is based on correlation between images. The method uses Radial Basis Function Network. The method is quite reasonable in terms of accuracy. However, there is a room to improve the processing time.

The proposed algorithm is fully automatic and requires no human intervention. The author is also thinking to apply the proposed feature methodology for another model of classification. It might improve the accuracy and efficiency process. This work is in progress as a subsequent work together with the issue of considering multiple currencies with one system.

Acknowledgements

This work was supported by Kuwait University, Research Grant No. [QI 01/13].

References

1. Hassanpour H, Farahabadi, PM. Using Hidden Markov Models for paper currency recognition, *Expert Systems with Applications* 2009; **36(6)**: 10105-10111.
2. Gonzalez RC, Woods RE. *Digital image processing*, Prentice Hall; 2009.
3. Hassanpour H, Mesbah M. Neonatal EEG seizure detection using spike signatures in the time-frequency domain, *IJE Transactions A: Basics* 2007; **20(2)**:137-146.
4. Hassanpour H, Yaseri A, Ardeshir G. Feature Extraction for Paper currency Recognition. *In International symposium on signal processing and its applications (ISSPA)*, Sharjah, UAE; 2007.
5. Iosifescu M. *Finite Markov process and their applications*. New York, NY: Wiley; 1980.
6. Jae LS. *Two-dimensional signal and image processing*. Englewood Cliffs, NJ: Prentice Hall; 1990.
7. Kim M, Kim D, Lee S. Face recognition using the embedded HMM with second-order block-specific observations. *Pattern Recognition* 2003; **36(11)**:2723–2733.
8. Takeda F, Nishikage T. Multiple kinds of paper currency recognition using neural network and application for Euro currency. *In IEEE International Joint Conference on Neural Networks*, Como, p. 143–147; 2000.
9. Toussaint GT. Proximity graphs for nearest neighbor decision rules: Recent progress. *Proceedings of the 34th Symposium on the INTERFACE*, p. 17-20; 2002.

10. Vila A, Ferrer N, Mantecon J, Breton D, Garcia, JF. Development of a fast and non-destructive procedure original and fake euro notes. *Analytica Chimica Acta* 2006; **559**:257–263.
11. Zhang EH, Jiang B, Duan JH, Bian ZZ. Research on paper currency recognition by neural networks. *In Proceeding of the second international conference on machine learning and cybernetics*, p. 2193–2197; 2003.
12. Liu Q, Tang L. Study of Printing Identification Based on Multi-spectrum Imaging Analysis, Proceedings of the *International Conference on Computer Science and Software Engineering*, p. 229 – 232; 2008.
13. Ahmadi A, Omatu S, Yoshioka M. Implementing a Reliable Neuro-Classifier for Paper Currency Using PCA Algorithm, *Proceedings of the 41st SICE Annual Conference*, p. 2466-2488; 2002.
14. Takeda F, Omatu S. High Speed Paper Currency Recognition by Neural Networks, *IEEE Transactions on Neural Networks* 1995; **6(1)**:73-77.
15. Takeda F, Omatu S, Onami S, Kadono T, Terada K. A Paper Currency Recognition Method by a Small Size Neural Network with Optimized Masks by GA, *Proceedings of the IEEE World Congress on Computational Intelligence*, Orlando, USA, **7**, p.4243-4246; 1994.
16. Bow, Sing-Tze. *Pattern Recognition and Image Preprocessing*. New York: Marcel Dekker, Inc., 2002.
17. Hasanuzzaman FM, Yang X, Tian YL. Robust and effective component-based banknote recognition by SURF features, *Proceedings of the 20th Annual Wireless and Optical Communications Conference*, p. 1-6; 2011.
18. He J, Hu Z, Xu P, Jin O, Peng M. The design and implementation of an embedded paper currency characteristic data acquisition system, *Proceedings of the International Conference on Information and Automation*, p. 1021-024; 2008.
19. Junfang G, Yanyun Z, Anni C. A reliable method for paper currency recognition based on LBP, *Proceedings of the 2nd IEEE International Conference on Network Infrastructure and Digital Content*, p. 359-363; 2010.
20. Sargano AB, Sarfraz M, Haq N. An Intelligent System for Paper Currency Recognition with Robust Features, *Journal of Intelligent and Fuzzy Systems* 2014; **27(4)**: 1905 –1913.
21. Althafiri E, Sarfraz M, Alfarras M. Bahraini Paper Currency Recognition, *Journal of Advanced Computer Science and Technology Research* 2012;**2(2)**:104 –115.
22. From Wikipedia, the free encyclopedia, Saudi Riyal, http://en.wikipedia.org/wiki/Saudi_riyal.