ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, Vol 8(10), 913-918, May 2015
DOI: 10.17485/ijst/2015/v8i10/53961

Old and Worn Banknote Detection using Sparse Representation and Neural Networks

Seyed Aliakbar Mousavi[1*], Majid Meghdadi[2], Zahra Hanifeloo[2], Putra Sumari[1] and Muhammad Rafie Mohd Arshad[1]

[1]School of Computer Science, Universiti Sains Malaysia (USM), Malaysia; pouyaye@gmail.com
[2]Computer Department, Faculty of Engineering, University of Zanjan, Iran

Abstract

This paper provides a fast method to recognize a variety of Persian banknotes at different scales. In this technique, the PCA, LDA and sparse representation methods are utilized at feature extraction stage and follows with MLP neural networks, LVQ and SOM in classification. Finally, the application of sparse matrix representation method and combination of both SOM and LVQ neural networks would lead to the best efficiency with precision of 91.15% in recognition of Persian banknotes particularly the worn ones.

Keywords: Banknote Recognition, LVQ, Neural Network, PCA, Sparse Representation

1. Introduction

In today's technological and growing world, the human life is becoming more mechanized and the daily activities are performed according to a combination of mechanical and digital technologies and undoubtedly by learning the path of human and societies' development. The effects of these technologies are obvious with respect to the investments and savings in business issues. Nowadays, most of the banking operations are conducted in mechanized ways and there is no choice but using the new and advanced technologies for increasing the accuracy and speed of affairs due to the high volume of this operation. The automatic vending machines have made a huge leap in this direction compared to the conventional systems with the aim at saving the rates of money received and paid to customers. In typical banking processes, these machines do the money transfer, receipt and payment as well as other services such as receiving the payment bill, providing the bank accounts and transfer funds between different accounts in a large number of transactions. Despite the development and widespread in this regard, the money transfer in these machines is still done manually and through the labor in this process. The banknote recognition is one of the most important applications in banking and commercial activities. Yet there is no public system for doing the proper recognition in many countries[1]. However, the visual recognition of banknotes is along with challenges such as torn part of banknote (Figure 1A) and worn and dirty banknote (Figure 1, B and C) in addition to the changes in brightness of image (Figure 1D) and its rotation (Figure 1E).

A B

*Author for correspondence

C D E

Figure 1. The complexities of banknote recognition (from the left, A B, C, D, E).

Due to the mentioned problems, the proposed method for recognizing the banknotes should be resistant to these challenges. This paper investigates several methods for recognizing the Persian banknotes with different shooting angles and ultimately a method which is resistant to banknote rotation and its tear and wear is selected as the final method. This article includes the following sections: Section 2 provides a brief review of methods which were applied for banknote recognition in the past. Section 3 introduces the procedure to recognize the banknote in this paper and defines different methods of pattern recognition in this paper; Section 4 presents the results and finally Section 5 provides the conclusion.

2. Related Works

Various methods have been studied for banknote recognition so far[2]. Five different neural networks are applied for automatic recognition of banknotes[3]. In this method, one of the networks is applied for determining the direction of banknote and the others for determining the type of banknote. The Quaternion Wavelet Transform (QWT) is utilized for extracting the features of banknotes[4].
The generalized Gaussian Density (GGD) is applied to capture the statistical characteristics of QWT coefficients. The neural network is used as classifier in the framework of banknote classification. Experimental results demonstrate its effectiveness and the proposed method obtains a higher recognition rate in the banknote classification. The use of probabilistic neural networks is proposed to recognize the banknote with the aim at solving the problems of banking system[5] and it has been able to achieve the desired result in recognizing and classifying various types of banknotes and especially invalid and counterfeit banknotes. The hybrid neural network consisting of perceptron neural network and radius-based neural network are also applied[6]. The use of Fuzzy Hamming distance has a good selection power[7].
The Gaussian mixture model based on minimizing the risk error is applied to reduce the recognition error of banknotes and it is shown that the recognition error can be reduced for Chinese banknotes by changing the number of Gaussian models[8]. The features of banknote texture are extracted by Hidden Markov Model (HMM) and then the banknotes are recognized by a similarity measure[9].
The Mexican banknotes are recognized based on the color and texture features[10]. The Local Binary Patterns are applied for extracting the texture features.

3. Introducing the Proposed Algorithm

The scanned and photographed images are taken from a variety of Persian banknotes including 320 images of 8 types of Persian banknotes and 40 front and back images of each banknote. Some of the banknotes are normal and others damaged. The samples of banknote images are shown in Figure 2. All images are converted into the dimensions of 90*64 and gray level in preprocessing. K validation with k-5 is applied to create a testing and training set. Moreover, the applied methods are examined on an experimental set of rotated banknote images in order to observe the effect of rotation on the banknotes. Figure 3 shows an example of such these images as the experimental set 2 which is presented in Results section.

Several methods are compared to recognize the banknotes in this paper. The first method applies the PCA technique after data preprocessing to reduce the dimensions, and then the Euclidean minimum distance criterion is utilized to recognize the banknotes. In the second method, a LVQ network is applied for classification after using a combination of PCA and LDA in order to reduce the dimensions. The third method utilizes a MLP network. The number of feature vectors sent to this neural network is equal to C-1 in which C is the number of classes. The fourth method initially applies a SOM neural network to produce a lower dimensional state space, and then applies the PCA in each of created cluster to reduce the data size. After reducing the dimension, a LVQ neural network is applied for final

Figure 2. Images of banknotes.

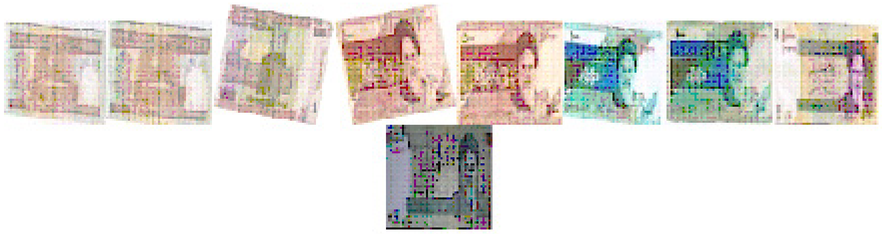

Figure 3. Image of experimental set 2.

classification. Finally, the fourth method initially utilizes the sparse representation to improve the images and then classifies the banknotes by combining two MPL and LVQ neural networks.

3.1 Principal Component Analysis

The Principal Component Analysis (PCA) is one of the most important ways to reduce the redundancy in order to facilitate the data processing and classification. This conversion is widely used in data analysis for dimension reduction. This feature reduces the data size as well as keeping the basic information of image.

In this way, the new coordinate axes are defined for data, and the data are based on these new coordinate axes. The first axis should be in the direction in which the data variance is maximal (i.e. in a direction in which the data dispersion is higher). The second axis should be perpendicular to the first axis in a way that the data variance is maximal. Similarly, the next axes should be perpendicular to all previous axes in a way that the data has the maximum dispersion in that direction[11].

3.2 Linear Feature Transformation Methods

LDA is one of the famous methods to establish the distinction between the features and linear reduction of supervised feature dimensions. In classical LDA, the inter-class and intra-class covariance matrixes are calculated as follows in Equations (1) and (2).

$$S_w = \frac{1}{n}\sum_{j=1}^{c}\sum_{x\in c_j}(X-\overline{X_j})(X-\overline{X_j})^T \quad \text{...............(1)}$$

$$S_b = \frac{1}{n}\sum_{j=1}^{c}(\overline{X_j}-\overline{X})(\overline{X_j}-\overline{X})^T \quad \text{.....................(2)}$$

Where, N is the total number of samples; Ni is the number of samples in class I. μi is the mean of class I. I is the number of classes, and Xni is the sample ni of class I. Trace (SW) measures the inter-class solidarity and the trace (Sb) calculates the intra-class distinction. Trace Function refers to the values on the main diagonal of arrival square matrix. The purpose of LDA is to get the transformation matrix of W in a way that the Fisher equation is maximized[12] [Equations (1), (2) and (3)].

$$J(W_{LDA}) = \frac{W_{LDA}^T S_b W_{LDA}}{W_{LDA}^T S_w W_{LDA}} \quad \text{.............................(3)}$$

3.3 Sparse Representation

The sparse representation is a method which shows the whole data of signal linear combination as a small number of basic signals, called atoms, in the form of an optimal dictionary. Therefore, each signal is displayed as a combination of different atoms.

The sparse representation has various applications such as noise reduction, compression, pattern classification and feature extraction. The method to find the lower number of main factors called sparse encryption. In this method, the data vectors are expressed as linear combination of lower components of an over-complete matrix. Sparse encryption is a successful method in feature selection and can estimate the signal with lower dimension. Unlike PCA, this is not necessary for base units to be orthogonal components and there is also the possibility of adoption[13].

4. Results and Discussion

Initially, PCA and the recognition based on the minimum distance reduced the dimension. It is observed that 96.75% of banknotes are recognized by maximum 6 feature vectors in Experimental Set 1. The image of banknote that could not be recognized is shown in Figure 4.

Figure 4. Image of wrongly recognized banknote.

Table 1 shows the Euclidean results of dimension reduction using PCA and Euclidean distance method for recognition. This method would be able to recognize 100% of banknotes by increasing the number of feature vectors by 150. However, the increased number of selected vectors has no significant impact on the result in experimental set 2.

Table 2 shows the results of combining PCA and LDA methods using LVQ neural network for classes and Table 3 shows the results of applying a combination of PCA and LDQ, and LVQ neural network with 50 neurons. Along with, Table 4 presents the results of Applying the PCA and LVQ neural network with 80 neurons, and Table 5 shows the results of applying the PCA and LDA, and LVQ neural network with 80 neurons.

It is observed that the combination of LDA and PCA methods leads to better results, but when the numbers of vectors are increased, it would have a negative impact on the network performance. Furthermore, If MLP neural network and a combination of PCA and LDA

Table 1. Euclidean results of dimension reduction using PCA and Euclidean distance method for recognition

Number of Selected Vectors	Experimental Set 1	Experimental Set 2
1	25%	18.75
2	56.25	25
3	75	37.5
4	84.375	37.5
5	84.375	37.5
6	90.62	34.37
7	96.875	37.5
8	96.875	40.62
9	96.875	37.50
10	96.875	36.51
20	96.875	40.62
100	100	48.78
150	100	50
200	100	50
500	100	50

Table 2. Applying the PCA and LVQ neural network with 50 neurons

Number of Feature Vectors	Experimental Set 1	Experimental Set 2
5	64.37	38.75
7	62.49	40.14
10	73.09	59.99
20	73.12	57.50
30	85.43	59.65
50	93.32	55.73
100	91.09	53.75
200	95.70	50.62
300	93.79	53.71

according to the number of selected vectors equal to c-1 (C is the number of classes) is used, then the network is properly recognized with a precision of 97.50%. Figure 5 shows the images of banknotes which are wrongly recognized. Table 6 and 7 present the results of application of SOM and LVQ networks and reduced dimensions with PCA.

Table 3. Applying a combination of PCA and LDQ, and LVQ neural network with 50 neurons

Number of Feature Vectors	Experimental Set 1	Experimental Set 2
5	67.45	35.62
7	69.99	38.12
10	70.62	41.87
20	77.44	58.12
30	92.18	45.31
50	93 08	46.87
100	96.34	52.34
200	91.66	42.31
300	93.73	30.41

Table 4. Applying the PCA and LVQ neural network with 80 neurons

Number of Feature Vectors	Experimental Set 1	Experimental Set 2
5	63.12	40.62
7	63.125	47.5
10	71.62	50.851
20	81.25	47.25
30	97.5	50.41
100	94.37	52.77
200	91.25	52.87
300	64.37	53.12

Table 5. Applying the PCA and LDA, and LVQ neural network with 80 neurons

Number of Feature Vectors	Experimental Set 1	Experimental Set 2
5	71.5	35
7	72.53	48.12
10	87.25	41.87
20	87.62	46
30	93.12	52.45
50	92.87	56.75
100	90.62	55.62
200	90.37	10:15
300	61.5	25

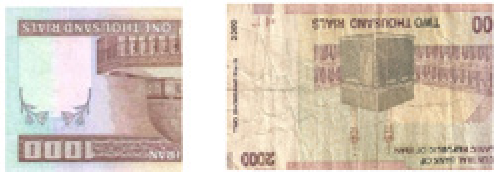

Figure 5. Images of wrongly-recognized banknotes.

Table 6. Application of SOM and LVQ networks and reduced dimensions with PCA and 50 neurons

Number of Feature Vectors	Experimental Set 1
1	80.12
5	82.01
10	89.6
15	89.07
20	90.42
30	90.7
40	94.7

Table 7. Application of SOM and LVQ and reduced dimensions with PCA and 80 neurons

Number of Feature Vectors	Experimental Set 1
1	96.3
5	96.61
10	98.4
15	98.71
20	99.2
30	99.2
40	99.31

Using the sparse representation, the precision of proper recognition of banknote images especially the worn banknotes reaches 91.15 percent. Also, the worn banknotes with improper alignments can be recognized as presented in Figure 6.

Figure 6. Image of recognized worn banknotes with improper alignment.

5. Conclusion

With the aim at identifying the Persian banknotes, this paper investigates four different classification methods in which the dimensions of banknote images are reduced through PCA before preprocessing on them, and then the classification is done on them by different methods. According to the results, it was found that the fourth method of using the combination of SOM and LVQ neural networks and sparse representation has had the best performance. Furthermore, the use of PCA and LDA and the selection of C-1 vector features have led to appropriate results. Finally, the use of PCA and the minimum Euclidean distance has the lowest implementation time according.

6. Acknowledgement

This research is funded and supported by global fellowship from Institute of Postgraduate Studies (IPS) in Universiti Sains Malaysia (USM). I would like to thank school of computer science to provide the facilities for this research.

7. References

1. Jahangir N, Chowdhury AR. Bangladeshi banknote recognition by neural network with axissymmetrical masks. 10th International Conference on Computer and Information Technology, ICCIT, Dhaka, Bangladesh; 2007 Dec. p. 1–5.
2. Lee J, Jeon S, Hwan K. Distinctive point extraction and recognition algorithm for various kinds of euro banknotes. Int J Contr Autom Syst. 2004; 2(2):201–6.
3. Gai S, Yang G, Wan M. Employing quaternion wavelet transform for banknote classification. Neurocomputing. 2013; 118:171–8.
4. Nastoulis C, Leros A, XBardis N. Banknote recognition based on probabilistic neural network models. WSEAS Transactions on Systems. 2006; 5(10):2363–7.
5. Debnath KK, Ahmed S, Shahjahan Md, Murase K. A paper currency recognition system using negatively correlated neural network ensemble. J Multimed. 2010; 5(6):560–7.
6. Aoba M, Kikuchi T, Takefuji Y. Euro banknote recognition system using a three-layered perceptron and RBF networks. IPSJ Transactions on Mathematical Modeling and its Application. 2003; 44(7):99–108.
7. Ionescu M, Ralescu A. Fuzzy hamming distance based banknote validator. Proceedings of the 14th IEEE International Conference on Fuzzy Systems; 2005 May. p. 300–5.
8. Kong F, Ma J, Liu J. Paper currency recognition using gaussian mixture models based on structural risk minimization. International Conference on Machine Learning and Cybernetics; 2006. p. 13–6.
9. Hassanpoura H, Farahabadib P. Using hidden markov models for paper currency recognition. Expert Syst Appl. 2009; 36(6): 10105–11.
10. Garcia-Lamonta F, Cervantesb J, Lopezc A. Recognition of Mexican banknotes via their color and texture features. Expert Syst Appl. 2012 Aug; 39(10): 9651–60.
11. Zhao W, Chellappa R, Krishnaswamy A. Discriminant analysis of principal components for face recognition. Proceedings of the 3rd IEEE International Conference on Automatic Face and Gesture Recognition; 1998. p. 336–41.
12. Kamran E, Rama C. Discriminant analysis for recognition of human face images. First International Conference on AVBPA'97 Crans-Montana, Switzerland; 1997. p. 125–42.
13. Wright J, Ma Y, Mairal J, Sapiro G, et al. Sparse representation for computer vision and pattern recognition. Proceedings of the IEEE. 2010; 98(6):1031–44.