Principal Component Analysis on Indian Currency Recognition

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Abstract— **Technological advancement had replaced humans with machines in almost every field. Banking automation have reduced human workload by introducing machines. Tedious task like currency handling that require more care are simplified by banking automation. When machines are handling currency they should recognize it. In this paper a method for currency recognition using principal component analysis is implemented. Principal components of currency features are extracted and weight vector is computed for the same. The weight vector similarities are then computed using Mahalanobis distance measure. For prediction the image having least distance measure with a class is determined. We observed that both the central numeral feature and RBI seal could classify the unknown currency with 96% accuracy. Thus our proposed currency recognition system can be integrated with the currency sorter of ATM machines.**

Keywords—automatic banking; principal component analysis; automatic teller machine;weight vector;

I. INTRODUCTION

Currency is the medium for exchanging goods and services. Currencies are issued by the governing bodies to circulate within an area. Currency recognition is a simple process of identifying the denominational value of a currency.

Currency recognition is a simple job for normal human beings, but for a visually challenged person the currency recognition is a challenging task. In ATM counters and vending machines currencies are handled by machines. The currency detection is a challenging task for the both visually challenged and machines. Moreover humans can identify currency by the pattern recognizing ability inherently available within themselves. But currency detection is a complicated task concerning machines. An optimal currency recognizer shall make use of all available features pertaining to a currency.

Currency has intrinsic as well as extrinsic properties. Extrinsic features comprises of physical properties of the currency (size, width etc.). But these physical features are not reliable. Sometimes currencies may get damaged during circulation. Hence system fails to identify damaged currencies. Color and texture forms the intrinsic currency features. Reserve Bank of India follows a specific color and texture pattern for currencies of each denomination.

Previous research in the field of currency recognition is predominantly based on neural networks [2, 3 and 4]. Major drawback of using neural networks was the processing overhead. Further research was based on image processing methods where the properties and patterns of currencies are used for recognition [5, 6, 7 and 8].

In this paper intrinsic features are used for detecting Indian currency. Principal Component Analysis (PCA) is applied on each feature individually. Normalized weight vector is generated for all images in training set and distance measure of these weight vectors are determined using Mahalanobis distance. Based on the distance measure the class to which the currency belongs is determined.

The paper is organized as follows, Section II describes the previous research articles in the field of currency recognition. Section III and Section IV explains the proposed method and its experimental results respectively. Conclusion to our work is depicted in Section V.

II. RELATED WORKS

Paper currency recognition system is designed to gather visible or hidden currency features for classification. Previously several methods were employed for recognizing paper currencies. Hassan pour et al. [6] introduced a simple method to extract visible features from the currency. But such a method fails when dealing with similar sized currencies of different countries or currencies whose visible features are damaged.

Current research in the domain of currency recognition is based on the image processing and neural networks [2, 3, and 4]. Vila et al. designed a currency recognition system using a symmetric mask for signs contained in the paper currency [5]. In this method sum of all non-masked pixel values are computed and given as input to the neural network. Zangh et al. proposed detection based on pattern edges of the currency [4]. In this method the paper currency is vertically divided into several parts and the system will find the number of pixels representing each edge. The pixel value obtained is later fed to the back propagation neural network. Hassan pour et al. introduced a method for recognizing paper currency using

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Hidden Markov Model (HMM) [7]. In this method the currency textures are modeled as a random process using HMM.

Seung-Hoon Chae et al. [8] introduced a novel approach for recognizing Korean bank note using the RGB color and UV information of the currency. In this method the RGB color information is used to classify the bank note. Size information is used along with the color information in order to improve the confidence of classification. The currency recognition method using the color information classifies 99.1% of the bank notes. Training overhead of back propagation neural network is because of its slow convergence speed and indeterminate initial weights. Training of neural network require more time because of the rigorous need of samples. Since training time for a back propagation neural network is exceedingly high they are not considered for a real time system.

CAO Bu-Qing et al. [9] proposed a method which make use gene algorithm to improve the training time of the back propagation neural network. In this method the gene algorithm is used to determine appropriate weights and network structure so that the network can be trained in less time. Junfang Guo et al. [10] introduced another method based on Local Binary Pattern (LBP). Authors used block LBP method which is an improved version of normal LBP method. In this method the input image is segmented into several blocks and LBP value for each block is computed. Later histogram for each block of image is generated using the LBP value. The resultant histogram is termed as block histogram. The block histogram is further normalized based on the number of pixels in each block. Finally the LBP block histograms of all blocks are integrated to a multi-dimensional vector. The system will generate such a vector for each input image and compares it with the vector generated from the template image. Kuldeep Verma et al. [11] proposed another method for paper currency recognition of Indian currency using texture features. In this method five features are extracted from the input currency image. These features are extracted based on region of interest. From these extracted features texture features are obtained. Best texture feature from the group is used for classification.

Authors in [12] proposed a method for face recognition using eigen face. Eigen vectors for the normalized face images are computed using Principal Component Analysis.

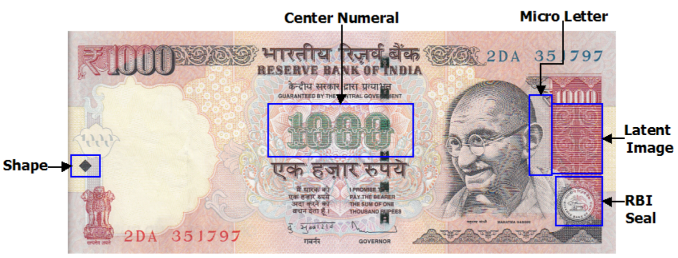

Figure 1 : Region of Interest marked on a sample Indian currency

III. PROPOSED METHOD

A. *Dataset Preparation*

Preparation of dataset is done by scanning paper currency using a flatbed scanner. Front side of paper currencies are scanned at 150 dots per inches (dpi) resolution. In our study only Indian currencies (□) of denominations 50, 100, 500 and 1000 printed from the year 2011 is considered.

B. *Feature Extraction*

During feature extraction phase a total of five features are extracted from the scanned currency by marking Region of Interest (ROI). The extracted features are 1) Shape, 2) Center Numerical Value, 3) RBI Seal, 4) Latent Image and 5) Micro Letters. During preprocessing stage scanned currency image in RGB color model is converted to grey scale format. The feature set is normalized since the ROI for each feature follows a standard dimension. Dimension of ROI for a feature will be same for currencies of all 4 denominations. Dimensions of ROI for a currency image is depicted in Table I.

Table I : Dimensions of Region of Interest

Region of Interest	**Size of Window**
Shape	80 pixel x 70 pixel
Center	240 pixel x 180 pixel
RBI seal	150 pixel 150 pixel
Ashoka	80 pixel x 160 pixel

1) Shape :

Indian currencies with denomination 50 or above will contain a shape feature (refer Figure 2). The shape feature for 50 rupee note will be different from that of 100, 500 and 1000. Thus this shape feature could contribute towards classification. The shape feature for different currency denominations are recorded in Table II.

Figure 2 : Shape feature of Indian Currency

Table II : Shape Feature

Denomination	**Shape**
50	Square
100	Triangle
500	Circle
1000	Diamond

2) Center :

Front side of Indian currency contains a central numerical value (refer Figure 3). Currencies of different denominations will have distinct central numerical values. Hence this feature is unique for a specific currency denomination and could contribute towards classification.

Figure 3 : Center Numeral Value feature of Indian Currency

3) RBI Seal :

The RBI seal feature is found at the right bottom corner at the front face of a currency (refer Figure 4). Reserve Bank of India (RBI) is solely authorized to print and circulate Indian currency. The RBI seal also shows a slight difference for different denominations.

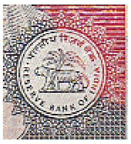

Figure 4 : RBI Seal feature of Indian Currency

4) Micro Letter :

Micro letter is another security feature provided by RBI for recognizing currency (refer Figure 5).This feature is located at the right side of Gandhi portrait. In this feature the currency value is printed in tiny fonts along with text "RBI Bharath" written in both English and Hindi. This feature will be different for currencies of different denominations.

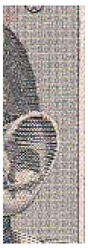

Figure 5 : Micro Letter feature of Indian currency

5) Latent Image :

The latent image can be located at the right center position of the currency (refer Figure 6). Within this feature currency value is printed using a special ink that is visible by naked eye at certain angles. The pattern of this feature will be different in currencies of different denomination.

Figure 6 : Latent Image feature of Indian Currency

C. Principal Component Analysis :

Principal component analysis method is employed in our study for currency recognition. Authors in [12] employed principal component analysis to develop Eigen image from face images. Later input weight vector is obtained by projecting the vector representation of N dimensional input images (where N is the resolution) to K dimensional space (where $K < N$). This weight vector obtained is a composition of the Eigen vectors. From the training phase sample weight vector is obtained. Prediction is done by computing the distance between input weight vector and sample weight vector. In our paper Mahalanobis distance metric is used to compute distance.

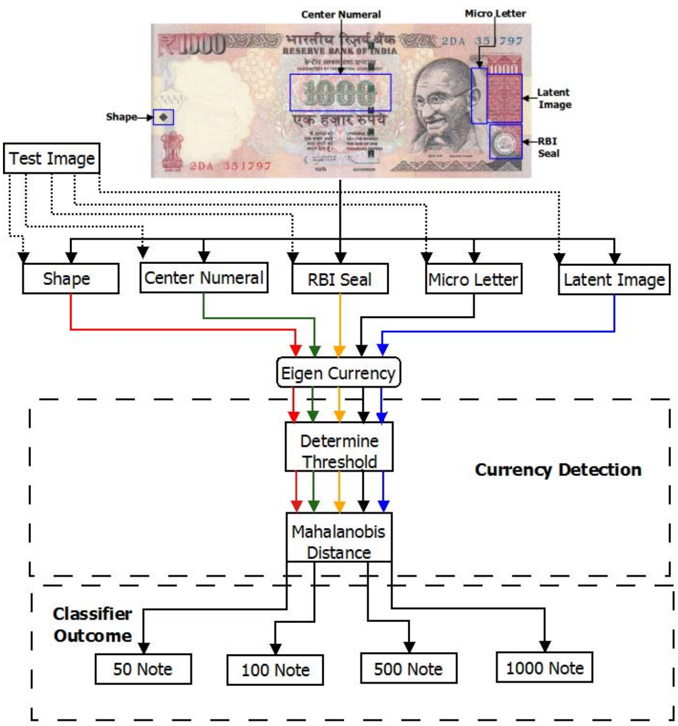

Figure 7 : System Architecture of PCA based Currency Detection System

Data set contains 200 scanned images (50 scanned images for each denomination) of Indian currencies. Currencies of denomination 50,100,500 and 1000 are only used in our study. Five features were extracted from each currency using ROI. Then Principal component analysis is applied on the extracted features. If the sample image is of resolution N x N then each sample is represented as a vector Γ of dimension N^2 x

1(resolution will be different for distinct features refer Table I). A 5 x 5 matrix that represent a portion of actual image (refer Table III) is used to demonstrate the functioning of PCA.

Table III : A sample 5 x 5 matrix

192	125	99	121	156
199	162	85	110	168
200	153	105	135	145
185	168	110	175	126
205	186	124	199	166

1. Calculate Ψ average image of the training set using (1).

$$\psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \quad (1)$$

Where Γ_i is the i^{th} image and Ψ is the average of M images in our training set. Average for the above given matrix (refer Table III) as [138.6 144.8 147.8 152.8 176].

2. Then each vector Γ_i is normalized using (2) and arranged as a columns matrix $A = [\Phi_1, \Phi_2, \ldots\Phi_M]$. (Refer Table IV).

$$\phi_i = \Gamma_i - \psi; \forall i = 1,2,3,\ldots M \quad (2)$$

Table IV : Normalized Matrix

53.4	-13.6	-39.6	-17.6	17.4
54.2	17.2	-59.8	-34.8	23.2
52.4	5.4	-42.6	-12.6	-2.6
32.2	15.2	-42.8	22.2	-26.8
29	10	-52	23	-10

In matrix A each column represents the normalized vector for a sample image.

3. A symmetric matrix L is computed from the normalized matrix A using equation (3) refer Table V.

$$L = A^T A \quad (3)$$

Table V : Covariance Matrix

5217.2	6044.6	4588.2	2350.6	2893.0
6044.6	8558.8	5858.6	3171.8	3821.0
4588.2	5858.6	4755.2	3382.6	3525.0
2350.6	3171.8	3382.6	4310.8	4090.0
2893.0	3821.0	3525.0	4090.0	4274.0

From the resultant symmetric matrix L eigen values and eigen vectors are computed. Principal components are the corresponding eigen vectors of the largest eigen values.

$$u_i = Av_i \quad (4)$$

Table VI : Eigen Vectors

0.446	0.339	-0.723	-0.316
0.585	0.426	0.664	-0.176
0.459	0.030	-0.186	0.637
0.337	-0.651	0.016	-0.562
0.368	-0.52	0.041	0.384

The K = 4 Eigen vectors that corresponds to the top Eigen values that obtained using (4) are selected refer Table VI. In PCA there is no option for selecting the K value so here also we are fixing the K value as 4 since we are having currencies of 4 denomination (50,100,500 and 1000) and at a time we are considering only one feature. After selecting the K value the sample images are normalized and organized to [u] matrix and stored. The principal components or Eigen images at K=4 is shown in the figure (3) the top 4 Eigen values are also saved.

The vector containing training samples (each vector in matrix A) is projected to the Eigen space using (5) as shown in Table VII. Here $[u]^T$ is the transpose of Eigen vector. As a result of this projection sample weight vector is computed [Ω]. This computed sample weight vector will be in a reduced dimension space (4 x 1).

$$\Omega = u^T A \quad (5)$$

Table VII : Sample Weight Vector (Ω)

1.409	-6.432	-6.661	-11.779
85.659	1.042	-73.346	-35.346
19.792	-2.948	-8.630	-6.207
-45.653	-28.066	68.873	-4.763
54.633	-1.445	-35.440	35.121

When input image is given to a system, images in higher dimension (N x N) are transformed to lower dimension space as in the training phase (refer equation 6).

$$\omega_i = u_i^T(\Gamma_{in} - \Psi); \forall i = 1,2,3,\ldots K \quad (6)$$

Where Γ_{in} is a vector of input images. u_i is the eigen image, ω_i is weight vector of i^{th} image, Ψ is the average image and the value of i is ranging from 1 to K where K is the new size of eigen space . Finally the above Equation is applied on all input images to obtain an input weight vector $\Omega_{in} = [\omega_1, \omega_2, \ldots\omega_K]$.

Recognition Phase:

To determine the class of input currency mahalanobis distance [13] d is applied between input images weight vector Ω_{in} and sample weight vector Ω. The Mahalanobis distance is computed as below.

$$d_m(\Omega_{in},\Omega_i)=\sqrt{\sum_{j=1}^{K}\frac{\left(\Omega_{in_j}-\Omega_{i_j}\right)^2}{\lambda_j}}\ ;\forall i=1,2,3,......M \quad (7)$$

Where K is the size of reduced dimension here it is 4 and λ_j is the eigen value of j^{th} image. Sample weight vector closer to the input weight vector is computed using nearest neighbor method. Moreover the sample weight vector with least distance d with input weight vector is obtained. Denomination of the test currency is assigned the class of the nearest weight vector.

IV. EXPERIMENT AND RESULTS

A. Experiments

Database of Indian currencies are created by scanning 25 currencies of each denomination (50,100,500 and 1000).The currencies that were printed from the year 2010 is considered in dataset. These currencies are scanned in 150 dpi (dots per inch) resolution. Dataset is divided into two equal halves one for training and the other used in testing phase.

Images are normalized using histogram equalization. In the training phase five features are extracted from images of currency by placing a rectangular box which identifies the Region of Interest (ROI). Once the features are extracted then each of these features are given to the PCA module which generates average image (Ψ) of the n inputted images (Γ). Then normalized vector (Φ_i) is computed as given in equation 3. Finally, the eigen values and its corresponding eigen vectors are determined from the covariance matrix of the training set (computed using the equation 4). Finally, images are projected in new space known as eigen space, where top principal component indicates high variance.

In the prediction phase normalized images are considered. Extracted feature of each sample is inputted to PCA module where these the normalized vector (Φ_{in}) of the test feature is computed and this is projected to the eigen space, to determine its weight vector (ω_{in}). Finally, the Mahalanobis distance[13] between the weight vectors of each training sample with weight vector of test image is computed using the equation (7). Then the test image is assigned same class with which the similarity of the training image is found to be high.

B. Results

The system has been developed using Open CV 2.3. This system is tested with 100 currencies of different denominations. The result obtained after prediction is shown in Table VIII.

Table VIII : Results (Feature wise)

Denomination	# Test Sample	Features				
		Shape D.T (%)	Center D.T (%)	RBI Seal D.T (%)	Latent Image D.T (%)	Micro Letter D.T (%)
50	25	92	96	92	72	88
100	25	92	92	96	76	92
500	25	88	96	92	76	92
1000	25	96	92	96	68	96

The performance of the system in recognizing each feature is computed separately in terms of True Detection Rate (TDR) as shown in equation 8.

$$TDR=\left(\frac{TD}{TD+FD}\right)*100 \quad (8)$$

TDR is the proportion of the number of correctly identified denomination to the total number of instances. Incorrectly identification is designated as False Detection (FD).

From our experiment it is clear that both the RBI seal and Center Numerical can identify currencies. RBI seal is one of the best feature which provide more information for classifying an Indian currency. RBI seal is different for currencies of different denominations. Another best feature is Central Numeral Value which also gives high detection rate. This Central Numeral Value is the numerical representation of value of currency. Currencies of different denominations are having different central numerical value. Hence this feature is unique for distinct class of currency.

Even though shape feature is unique for each class of currency, it is not reliable. Because the system cannot appropriately identify shape from the currency. Currency may get polluted or damaged when they are in circulation. In this polluted currency detecting the shape feature is challenging task. Latent image is another feature which cannot be used for identifying currency. In this feature the denomination value is printed in certain special ink. Micro letter is a feature that less detected correctly by our proposed system. In this feature the value of the currency is printed in tiny size which is readable only under the lens. When currency get contaminated these tiny sized fonts become blurred or become difficult to read.

V.CONCLUSION

The aim of our experiment was to develop a method to detect Indian currency using principal component analysis. Five features are selected for detecting the currency. Eigen vector and eigen value of these feature are generated using principal component analysis. Weight vector is generated from the eigen vectors generated for each currency image in both train set and test set. Finally Mahalanobis distance is computed between test weight vector and train weight vector. This experiment gives 96% accuracy. From our experiment it can be concluded that out of five feature RBI seal and Center Numerical Value contributes to detection of currency.

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