Novelty Journals

International Journal of Novel Research in Electronics and Communication
Vol. 3, Issue 1, pp: (1-8), Month: March 2016 - August 2016, Available at: www.noveltyjournals.com

Detection and Implementation of Indian Currencies Based on Computer Vision Approach

[1]T.P.Kavinila [2]B.Melita, [3]P.Kiruba, [4]S.Mercy Sheeba, [5]Mr.M.Naveenraj

[1,2,3,4] B.E(ECE), [5] M.E (Ph.D), Assistant Professor, Kathir College of Engineering,Coimbatore-42, India

***Abstract*: Currency recognition is a simple process of identifying the denominational value of a currency. But currency detection is a complicated task concerning machines. Currency has intrinsic as well as extrinsic properties. In this method preprocessing steps like edge detection, character extraction will be involved. After extracting the feature, pattern recognition technique is used to find the value of money. And based on the algorithm developed the currencies were correctly classified with a success rate of approximately 97%.The processing time taken is 2.52 seconds. Fourier Descriptors are used for feature extraction of unique I.D. Mark. Water marking of currency note is used to find whether the note is real or fake.**

***Keywords:* Currency Recognition; Artificial Neural Network (ANN); Feature Extraction; Identification Mark Detector (IMD); Fourier Descriptor.**

I. INTRODUCTION

MONEY transaction is mainly done in the form of paper money. The attractive features of the paper currency include intrinsic and extrinsic features. But as a means of value transaction it lacks intrinsic values and mechanism of reversal in case of repudiation, except the credential support by the state. Recent phenomena of self financial service being supported by the banks and other financial institutions have started different services of an automated banking system which have the currency recognition as its key activity making automated currency recognition and classification of a key problem. Ample amount of the effort has been devoted for the same.

The paper money of the same or similar design are subjected the pollution and depreciation that discreteness in the same denomination and design becomes very large. The least variable features the Geometric measure becomes unreliable due the variance created by the running instability of conveying equipments. Hence most of the paper currency recognition methods involve image processing and some classifier mainly neural networks. Besides moving towards the universal economy shall make the task of paper currency recognition even more challenging as the use of the overt monetary characterization might be difficult. Hence we must look for some intrinsic characterization for the currency recognition.

The problem of the currency recognition is multipronged machine vision issue. The work being presented here only deals with capturing the meaningful features of the currency image having high interclass discrimination. Searching out the meaningful feature being described by the pictures for machine vision, we followed the approach adopted by human being in interpreting the pictorial information. In human pictorial interpretation there are three fundamental picture elements taken into consideration: spectral, textural and contextual. The spectral feature is the visible band of the spectrum manifesting as color. Color is the most discriminating feature in human vision process. But the high discrimination is derived from the huge number of sensors (cones) placed near fovea instead of any innate property of the image element. It is obvious that the efforts of currency classification failed to deliver promising result using color histogram feature.

International Journal of Novel Research in Electronics and Communication
Vol. 3, Issue 1, pp: (1-8), Month: March 2016 - August 2016, Available at: www.noveltyjournals.com

Texture is the variation of data at the scales smaller than the scale of interest. The textural feature contains the special distribution of tonal variation within the band. The tone is saturation level of various hues in the image. Texture and tone are not independent concepts. They bear an inextricable relationship. Texture is an innate property of all surfaces. It contains important information about the spatial arrangement at the surface.

AUTOMATIC machines capable of recognizing banknotes are highly used in automatic dispensers of a number of various products, that are ranging from cigarette to bus tickets, and also in many automatic banking operations.

The wide range of applications of these machines places severe constraints on their cost, performance, and, consequently, architectural solutions. For instance, most machines that are operating in automatic dispensers are not very efficient in terms of performance, but they are available at very low cost, whereas machines used in banking operations usually have to apply severe tests, but they are available only at a higher cost.

Recently, the problem of paper currency recognition has been dealt with very effectively by using neural networks at Glory Ltd. jointly with the University Of Tokushima, Japan (see [2]*).* On the basis of a comparison with a conventional manual method based on discriminative inequalities, which engineers are used to applying, they have shown the effectiveness of neural technologies. They propose using multilayer perceptrons for both the classification and verification steps. In particular, they suggest evaluating the reliability of the recognition by means of a standard statistical parameter, referred to as ES_2; which can be regarded as a measure of the distance between the purposive node and the rejected one. Moreover, they also propose using special random masks to limit the dimensions of the neural network and consequently the amount of data required for training.

An interesting and effective solution for reducing the number banknotes is given in, where special masks, properly optimized by using genetic algorithms, are used .for input preprocessing.

II. RELATED WORK

Over the years a lot of researches have been done in this field of Currency note recognition. The authors have done recognition based on Color, texture, security features etc.

Here in this section we mention a few related works in this field.

Hanish and Padam has done currency note recognition by using the color feature of the currency note. Parminder Singh Reel employed a method to recognize currency note based on heuristic analysis of characters and digits of serial number of Indian currency note. The main advantages of using heuristic analysis are increase computational performance, exclude different properties which are invalid and reduced time for solving problems. In another work made a comparative study on various currency recognition technique. Here the authors proposed a method for currency recognition using ensemble neural network (ENN) particularly for Bangladesh currency.

Ensemble neural network consist of number of neural network and each neural network is trained independently.

Vipin Kumar Jain et al.(2013) employed a method for currency denomination identification by using Neural network matching technique and pattern recognition.

KishanChakraborty made a review on the recent developments in currency recognition system. Here they have found that the most common method for currency note recognition is by using Artificial Neural Network (ANN).

In most of the color based recognition methods, the RGB color model is employed. However the authors developed a method for recognition wherein they converted. The image from RGB color space to HSV color space before feature extraction. They used HSV color space because it is close to human conceptual understanding of color. In [6], the authors proposed a method for currency note recognition by using ANN. Here a special linear transformation function is adapted to wipe out the noise pattern from background without affecting the note original feature. The edge detection feature along with linear transformation is a better feature extraction technique and helps to keep notes look similar in varying conditions.

Faiz M. Hasanuzzaman et al. proposed a component based framework for banknote recognition using a method called Speeded Up Robust Features (SURF). SURF feature divides the image into components and then matches test image with original image component. The SURF features are invariant to conditions of image occlusion, image rotation, changes of scaling, illumination and the viewpoint. In [7] also the authors have employed neural network for recognition of the currency notes. They have used Ensemble Neural Network ENN for this they have used three characteristics size, color and texture characteristics. Image histogram is used for calculating the plentitude of different color in currency note and Markov chain concept to model texture of paper currency as random process.

Ms. TruptiPathrabe et al.(2011) developed an embedded system for currency note recognition. In this method they have used HSV(Hue, Saturation, Value) color space instead of RGB color space because HSV color space is more closer to human conceptual understanding of colors.

FaridGarcía-Lamont et al.(2012) introduced a currency recognition method for Mexican currency note. In this method they have used two feature i.e color and texture using RGB model and Local Binary Pattern (LBP) respectively to recognize the note. The classification is done using LVQ (Linear Vector Quantization) network which is a supervised version of vector quantization[5]. Since the color and texture feature is combined the recognition rate is improved as compared to single color and texture analysis.

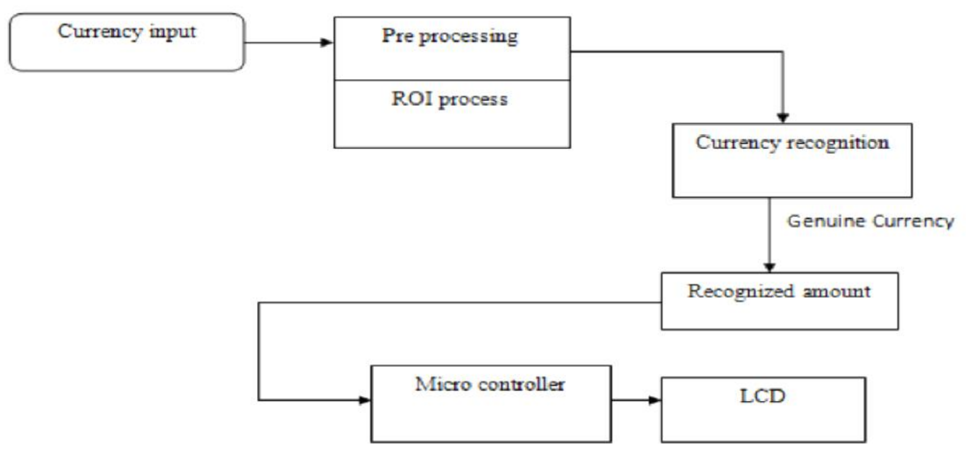
They have got 97.50% recognition performance.

Suriya Singh etal presented an application for Indian currency recognition on mobile. For this they have used visual Bag of Words (BoW) recognition method. Here they have used GrabCut algorithm to segment the foreground from background. This process of segmentation work so well that it can segment image from the cluttered background. After testing 2584 images they have got 96.7% accuracy.

III. PROPOSED METHODOLOGY

The various steps involved are explained below:

• **Image Acquisition**: It is the process of capturing an image from any object using a digital camera. The image is stored for further processing. Here the image is acquired with a digital camera of 14MP. A database of 50 images of each Indian Currency notes (Rs. 20, 50,100,500,1000) consisting of old, new, blurred, faded notes, etc are taken for experimentation and testing.



• **Image Pre-Processing:** Some image features are pre processed to enhance important features. It is used for additional processing and study. By preprocessing method image size is made compact and noise is removed which would have occurred in the image while transferring. Also the currency notes are being localized whereas the background is removed

• **Region of interest (ROI) and Texture Feature Extraction:** A *region of interest* (ROI) is a part of an image which you want to pass through a filter or perform some other process on. An ROI is defined by creating a *binary mask*, which is a binary image which is of the same size as the original image that you want to process with pixels. The ROI is set to one and all other pixels set to zero. More than one ROI can be defined in an image . The regions can be geographic in nature, such as polygons that includes contiguous pixels, or they can be defined by the level of intensities. In the latter case, the pixels are not necessarily contiguous. Based on input coin ROI region is automatically obtained. In order to classify the currency texture feature has been calculated.

• **Gray-Level Co-Occurrence Matrix:**

Image analysis techniques are comprised of The Gray Level Co-occurrence Matrix (GLCM) and calculations of associated texture feature. If an image is composed of pixels with an intensity (a specific gray level), the GLCM is an index of how fast a different combinations of gray levels co-occur in an image or in an image section. Texture feature calculations use the GLCM contents to give a measure of the intensity variation or image texture at the pixel of interest. Gray-level spatial dependence matrix is a statistical method of examining the texture that considers the spatial relationship between a pixels in the gray-level co-occurrence matrix (GLCM). The GLCM functions differentiates the texture of an image by calculating, how often the pairs of pixel with a specific values and in a mentioned spatial relationship occur in an image,which creates a GLCM, and then extracting statistical measures from this matrix. Information about shape or the spatial relationships of image pixels cannot be provided by the texture filter functions, described in texture analysis cannot provide an information about the shapes,ie..the spatial relationships of the pixel in an image.

A GLCM texture feature operator through which a virtual variable is produced is offered by Echoview which represents a specified texture calculation on a single beam echogram.

A record of how often various combinations of pixel brightness values that occur in an image according to a particular displacement vector is used in a matrix that shows the direction towards the occurrences. GLCM normalization which expresses the occurrence probability is used.

- Each Frame is divided into various Macro blocks (16x16 pixels).
- Each GLCM is computed as per to a displacement vector *d*.
- GLCM is computed for each Macro block.
- Different statistics are being calculated and placed into the feature vectors. These vectors are the inputs for the segmentation algorithm.
- 4 main directions have been used so as to compute the occurrences: *0° or (1,0); 45° or (1,1); 90° or (0,1); 135° or (-1,1).*

$$\begin{pmatrix} 0 & 0 & 1 & 2 \\ 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 0 \\ 1 & 1 & 0 & 2 \end{pmatrix} \longrightarrow P_{0^\circ} = \frac{1}{N_{pixels}} \begin{pmatrix} 1 & 1 & 1 \\ 2 & 4 & 1 \\ 0 & 1 & 1 \end{pmatrix} \longrightarrow \left\{ \begin{array}{l} \text{Dissimilarity} \\ \text{Entropy} \\ \text{Correlation} \\ \text{Contrast} \\ \text{Uniformity} \end{array} \right\} \longrightarrow \overset{\text{feature vector}}{\vec{v}}$$

Example of a GLCM matrix for a 4x4-pixel Macro block, using *d*=1 and direction 0°.

After you create the GLCMs, you can derive several informations from them using the graycoprops function. These provides information about the texture of an image.

a. Recognition based on Components:

SURF first locates the point of interest and generates equivalent descriptors for each and every query image.each reference region of SURF descriptors are used to match the detected points in the query image.With the query image certain reference region can be determine the point-level query. If the threshold of this region is larger than number of

International Journal of Novel Research in Electronics and Communication
Vol. 3, Issue 1, pp: (1-8), Month: March 2016 - August 2016, Available at: www.noveltyjournals.com

matching points of a certain reference region,this reference region will pass the point-level test. In the next step, the region level test is used to determine the final recognition class of the query image.In order to make recognition to occur for a reference image, its referenceregions (components) passing the point-level test must be equal to or greater than 2, the number of regions are needed in order to pass a region level test as a bill. The threshold levels are chosen from the empirical experiments by balancing a true positive rate and also a false positive rate.

1	1	2	2	5
3	2	4	5	1
0	1	5	0	1
3	2	4	0	1
2	1	5	4	3

(a)

Grey levels	0	1	2	3	4	5
0	0	3	0	0	0	0
1	0	1	1	0	0	1
2	0	1	1	0	2	1
3	0	0	2	0	0	0
4	1	0	0	1	0	1
5	1	1	0	0	1	0

(b)

(2, 0.8)	(2, 0.8)	(2, 0.6)	(2, 0.6)	(1, 1)
(1, 0.6)	(2, 0.6)	(1, 0.8)	(1, 1)	(2, 0.8)
(2,1)	(2, 0.8)	(1, 1)	(2, 1)	(2, 0.8)
(1,0.6)	(2, 0.6)	(1, 0.8)	(2, 1)	(2, 0.8)
(2, 0.6)	(2,0.8)	(1, 1)	(1, 0.8)	(1, 0.6)

(c)

Labels	1	2
1	2.2	3.8
2	3.4	5

(d)

III. PROPOSED METHOD

A. Component-Based Framework for Banknote Recognition:

The proposed method is based on component based model. It has four main advantages over the global model:

1) The class particular details are not equaly distributed on the banknote. Some regions cover many obvious class-particular features, while other regions are relatively small across different classes. It will be more effective to use more class specific components in the identification of the banknotes.

2) A component based model is able to focus on the local and constant parts, which vary less than that of the pattern of an entire banknote under the geometric and photometric changes.

3) Local image features that are generated from components are less than that of the entire image. This will help us to speed up the matching process and also it will reduce memory requirement.

4)This method is more suitable for handling the partial occlusions.It is practically impossible to take in account of all the conditions which cover the entire spectrum of possible variations that can result from occlusions. In the component-based model, individual components are identified by their corresponding detectors.

Partial occlusions only affect the outputs of a portion of component detectors. As long as a certain part of components are detected, the entire banknote is still able to be identified.

Component Generation: In a banknote recognition system, ground truth images for both the front side and back side of every category banknote are first collected under optimal conditions.

The marked regions in red are the components that are chosen as a reference regions for each category. The size of each reference region is manually cropped. For each component, SURF features are extracted and stored for later matching with the query images in the recognition process.

B. Local Image Parameter Detection and Representation:

The detection and representation of image features are essential to many applications, such as image retrieval and identification of an object, texture, and scene categories, since they are highly resistant to partial occlusion, background clutter and viewpoint modifications. This has helped in the development of several measurements and rotation invariant local image identifiers and descriptors.Generally, detectors localize interest points with constant regions in a measured space; descriptors build the representation of the support regions provided by detectors. The performance evaluation of local image features observed SURF were comparable with and often better than state-of-the-art systems, such as SIFT and gradient location and orientation histogram. Furthermore, SURF can be computed and compared much faster, which is expected in real-time applications. We choose SURF as the detection and representation of the local image features that are based on the following reasons:

1) Banknote images could be taken under the circumstances of rotation and scaling change. Interest points with support zones are identified by SURF are robust to rotation and scaling change.

2) Descriptors associated with support zone are distinct and also compact for feature matching process.

3) The low computational cost of SURF provides very fast interest point for localization and matching.

C. Verification Based on Pyramidal Multilayer Perceptrons:

Multilayer networks with pyramidal architectures have been massively and successfully employed in a number of different classification tasks. To the best of our knowledge, however, these networks have less used for pattern verification, that is in tasks where one wants to establish whether or not an unknown incoming pattern belongs to a given class. A straight forward approach to this problem is simply that of using verification criteria based on proper thresholds. The network had two hidden units and one output for coding the two classes. Unlike auto associators, for interesting problems of classification, the separation surfaces of these networks are likely to be open. They are likely to be met for true banknotes and not fair counterfeit ones. Basically, *t* is a true banknote provided that,

n(L). Idi(t) - ZZ(L)(t)l < 6,(4) where **Si** is the chosen *verification threshold.* A similar criterion has been used in a number of different applications, where the pattern classification includes the introduction of a “dummy class” for eliminating those patterns that do not belong to the classes.

As a matter of fact, depending on the specific application and on the actual pattern preprocessing, this criterion can work well in real world. In particular, we have applied successfully a various, but very much related criterion for the same problem faced in this paper. The perception of banknotes, however seems to be more sophisticated in terms of sensors and, therefore, the actual task assigned to the classification and verification engine is likely to be significantly different . No matter what kind of perceptual system is used, there is a clear theoretical argument for believing that the described thresholding criterion is not very well suited for general problems of pattern verification: the class discrimination takes place in feed forward networks by using a separation surfaces in the pattern area that are drawn by the learning algorithm under the *only* requirement of discriminating the given examples. It turns out that the resulting separation surfaces are likely to partition the input data properly, but these surfaces are not necessarily closed,which means they do not “envelope” the given examples by capturing their probability distribution.The separation surfaces created by a multilayer perceptron with pyramidal architecture, for the artificial take of discriminating two different classes of points. Because of the open separation surfaces that are created by these networks, false patterns that are far away from the distribution of the positive data can easily be found for which the assumed thresholding criterion gives a very low score, thus supporting evidence of a positive pattern.

IV. THE BANK RECOGNITION AND VERIFICATION MODEL

In this section we describe the model that has been used for banknote recognition and verification. First of all, a dimensional check is carried out using a simple optoelectronic sensors, that make it possible to establish the length on the basis of speed of the motor dragging the banknotes. This check turns out to be the first trivial verification of every banknote acceptor and, moreover, depending on the particular currency, it may be useful also for banknote classification. Certainly, this is not the case with U.S. currency, where all the banknotes have the same length, independently of the worth.For other currencies, however, the worth is partially, or even completely, related to the length of the banknote.’ As a result, the classification can obviously exploit the information on the banknote length very effectively. Since we are interested in the general process of accepting banknotes independently of the orientation and introduction side, we need, in any case, a classification phase is aimed at recognizing the banknote face.In general, the classifier which accomplishes this task combines its decisions with the information coming from the simple dimensional check. Obviously, the more the dimensional check provides information on the banknote classification the simpler the classification task becomes. For

International Journal of Novel Research in Electronics and Communication
Vol. 3, Issue 1, pp: (1-8), Month: March 2016 - August 2016, Available at: www.noveltyjournals.com

example, in the case of the Italian currency, the banknote classifier only has to detect the orientation and the introduction side. For U.S. currency the classification task is more difficult,because of the need to identify the banknote worth, orientation, and introduction side all at the same time.Some more details on the algorithm charged with scheduling the operations of the neural networks which shows the three verification steps based on the simple. For example, the Italian currency has now this property, since the old 1000 Rupee banknote, that has the same length of the new 1000 Rupee banknote, is no longer acceptable.

RBI Seal:

The RBI seal feature is found at the right bottom corner at the front face of a currency (refer Figure)

Reserve Bank of India (RBI) is solely authorized to print andcirculate Indian currency. The RBI seal also shows a slight difference for different denominations.

Micro Letter :

Micro letter is another security feature provided by

RBI for recognizing currency (refer Figure).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.

Latent Image:

The latent image can be located at the right center position of the currency (refer Figure). 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.

(i). Principal Component Analysis:

Principal component analysis method is employed in our study for currency recognition. Authors in [4] 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 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.

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 $N2$ x.

Results:

The system has been developed using Open CV 2.3. This system is tested with 100 currencies of different denominations.

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 values using these feature are generated by 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.

REFERENCES

[1] Faiz M. Hasanuzzaman, Xiaodong Yang and Ying Li Tian, "Robust and Effective Component-Based Banknote Recognition by SURF Features".

[2] F Takeda, S Omatu and I. Inoue, "Bill Money Recognition by a Small Size Neural Network",Univ.Tokushima, Japan, Tech. Rep. Bull. Faculty Eng.38, 1993

[3] H. Bay, T. Tuytellars and L. Gool, "SURF: Speeded Up Robust Features," in *Proc. 9th Eur.Conf. Comput Vis.*,2006, pp.404-417.

[4] A. Frosini, M. Gori and P.Priami, "A Neural Network Based Model for Paper Currency Recognition and Verification," IEEE Trans. Neural Netw. Vol. 7,no. 6, pp.1482-1490,Nov.1996.

[5] T.Kosaka, S. Omatsu and T.Fujinaka, "Bill Classification by using the LVQ Method," in Proc. IEEE Int.Conf. Syst., Man ,Cybern,2001,vol.3,pp. 1430-1435.

[6] D.K.A.S.Gunaratna, N.D.Kodikaraand H.L.Premaratne, "ANN Based Currency Recognition System using Compressed Gray Scale and Application for Sri Lankan Currency Notes-SLCRec", International Journal of Computer, Information, Systems and Control Engineering Vol:2 No:9, 2008

[7] A. Ms.TruptiPathrabe and B. Dr.N. G. Bawane, "Paper Currency Recognition System Using Characteristics Extraction and Negatively Correlated NN Ensemble," International Journal of Latest Trends in Computing, E-ISSN:2045-5364, vol1,Issue 2, Dec2010.