

# Indian currency recognition for visually disable people using image processing

Sonali P. Bhagat<sup>1</sup>, Sarika B. Patil<sup>2</sup>

PG Student (Digital systems), Department of ENTTC, SCOE, Pune, India<sup>1</sup>

Assistant Professor, Department of ENTTC, SCOE, Pune, India<sup>2</sup>

**Abstract:** Currency is the means for exchange of articles, goods, etc. Money related transaction is an important part of our day to day life. With the consideration of visually disabled people or blind people, it is somewhat difficult task to identify the paper currency as it has same feel without any brail marking on it. Even though denomination based on size may or may not be identified but it is almost difficult to identify whether the note is original or fake. It is the question on edge to develop such a system that will make sure for visually disabled or blind people that the currency they have is original or not. The currency recognition algorithm discussed in this paper using image processing is based on an ORB (Oriented fast and Rotated Brief). It is faster and also rotation invariant. The proposed algorithm shows 90% true recognition rate.

**Keywords:** Currency recognition, Denomination, ORB, visually disabled.

## I. INTRODUCTION

The recognition of currency is tedious task for blind or visually disabled people. The paper currency constitutes extrinsic as well as intrinsic properties. The extrinsic properties deals with size, width, colour, etc. whereas intrinsic properties deals with security thread, I.D. mark, number panel, etc. Extrinsic properties are not enough to recognize whether note is original or fake. Also currency may get damaged during transportation or exchange. The change in nature of an image can be well understood and improved with the help of image processing techniques. It enhances pictorial information embedded in the image for human interpretation. Currency recognition algorithm using image processing for Indian banknotes is developed with the help of ORB (Oriented fast and Rotated Brief). It is faster as compared to other descriptors like SURF (Speeded up Robust Features), SIFT (Scale Invariant Feature Transform), etc. ORB has an important feature that it is orientation invariant that's why it will be more helpful for visually disabled people.

The paper is organized as chapter I deals with the introduction, chapter II consists of literature survey, chapter III methodology of proposed algorithm, chapter IV experimental results, chapter V concludes the proposed algorithm.

## II. LITERATURE SURVEY

Zahid Ahmed, et.al. [3] proposed a software system for currency detection developed for Bangladeshi currency. The fake currency can be detected with the extraction of existing features of banknotes. These features vary in accordance with the currency of corresponding country. Here features considered are micro-printing, optically variable ink (OVI), water-marking, security thread and ultraviolet lines, etc. Sample currency note has to go through optical character recognition. The success rate of

this software can be measured in terms of accuracy that has 100% recognition result for UV visible lines, OVI and iridescent ink, security threads recognition, etc.

Faiz M. Hasanuzzaman, et.al [7] proposed banknote recognition system by using SURF (Speeded Up Robust Features) in order to achieve high recognition accuracy. It can also handle different challenging conditions those are present in real-world environments. Initially monetary features of every image are extracted with the help of SURF. These features are then matched with the pre-computed SURF features of image in each banknote category. The numbers of matched features are compared with automatic thresholds of each reference region. Thus category of banknote can be determined.

Farid Lamont, et.al [6] proposed a method of artificial vision to recognize Mexican banknotes. Images captured are supposed to be taken under no illumination changes i.e. the input images of notes are illumination invariant. Here features like colour and texture of the banknotes are extracted. On the basis of RGB space to extract colour and the Local Binary Patterns to extract texture, respectively these features of banknotes are classified. Similar method proposed here can be applied to recognize banknotes of other countries which constitute different colours to distinguish denominations.

Hinwood, et.al [11] proposed a method for vision impaired people. A money talker device is introduced that recognizes note electronically with the consideration of transmission and reflection property of light. The system is developed for Australian banknotes. A light is allowed to pass through the banknote taken as sample. The note has different colour for different denomination. When light passes through the sample note, the sensors detects a certain and distinct range of values which is stored and later it is compared with already classified banknotes. For best match found, the device announces denomination.

III.METHODOLOGY

An overview of the proposed currency recognition system can be given as follows:

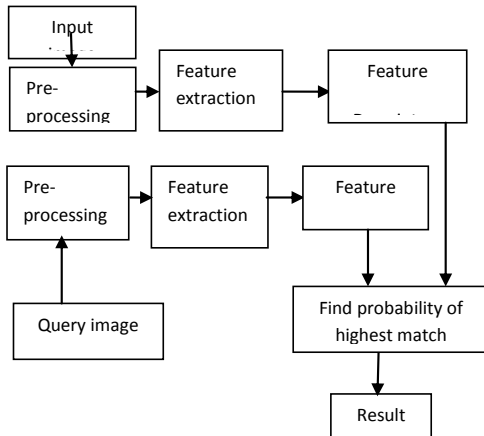


Fig.1.Proposed recognition system

In preprocessing, different images of banknotes are taken. These banknote images constitute images of different denominations. To make feature extraction easier, image resizing can be done. Image enhancement technique helps to increase the contrast among bright as well as dark points. This makes the image clear and so it will be further helps feature extraction. It produces feature points which are nothing but feature descriptors. Feature descriptors of both sample input image and query image are calculated and are compared to find probability of highest match points to generate final result.

A) Extraction of feature points

Detection of fast corner

Feature points extraction via ORB depends on detection of fast corner. If there are certain number of pixels, in a circular ring about the corner candidate pixel say p with its intensity as  $I_p$ , then a pixel can be considered as the fast corner if candidate pixel is brighter than  $I_{p+t}$  or it may be darker than  $I_{p-t}$  where t indicates threshold value[12]. Gray images consist of larger difference among the intensity values. The corners detected via fast are considered as feature points. It is simple to implement and also requires very low cost for computation. It is rotation invariant.

Orientation by intensity centroid

ORB has a little scale invariance but it is rotation invariant that's why it can be employed for intensity centroid. Intensity of the corner pixel can be considered from the center. Here corner's intensity is assumed as an offset. When a patch is taken into consideration it has its center as one of the feature point as considered in case of fast corner detection.

The moments of such a patch can be given as follows:

$$m_{x,y} = \sum_{(p,q) \in S} p^x q^y \mathcal{F}(p,q) \quad (1)$$

the intensity centroid can be :

$$c = \left( \frac{m_{1,0}}{m_{0,0}}, \frac{m_{0,1}}{m_{0,0}} \right) \quad (2)$$

A vector is constructed from the centroid to the feature point. The orientation of the features can be:

$$\phi = \arctan(m_{0,1}/m_{1,0}) \quad (3)$$

B) Rotation Invariance of ORB

The rotation invariance of a descriptor ORB is a bit string description of an image. This image is nothing but a patch which is constructed from a set of tests of binary intensity. Consider an image patch x of one feature point. A binary test  $\mathcal{T}$  is:

$$\mathcal{T}(x; p, q) = \begin{cases} 1, & x(p) < x(q) \\ 0, & x(p) \geq x(q) \end{cases} \quad (4)$$

where  $x(p)$  is the intensity of x at a test point  $p = (u, v)^T$ . For  $\mathcal{N}$  test point pairs selected, one can define the feature point descriptor with no rotation invariance as a vector of  $\mathcal{N}$  binary tests:

$$\mathcal{F}_{\mathcal{N}}(x) = \sum_{1 \leq i \leq \mathcal{N}} 2^{i-1} \mathcal{T}(x; p_i, q_i) \quad (5)$$

Above equation represents a descriptor with no rotation invariance. That's why it is efficient to steer it according to the feature orientation in (3). Feature set of  $\mathcal{N}$  binary tests at location  $(p_i, q_i)$  the  $2 \times n$  matrix can be:

$$Q = \begin{pmatrix} p_1, p_2, \dots, p_n \\ q_1, q_2, \dots, q_n \end{pmatrix} \quad (6)$$

Feature point orientation  $\phi$  in (3) and the corresponding rotation matrix  $R_{\phi}$ , ORB construct a steered version  $Q_{\phi}$  of  $Q : Q_{\phi} = R_{\phi} Q$ , then the rotation invariant feature points descriptor of ORB can be:

$$\mathcal{G}_{\mathcal{N}}(x, \phi) = \mathcal{F}_{\mathcal{N}}(x) | (p_i, q_i) \in Q_{\phi} \quad (7)$$

The correlation in above equation (7) is larger, it decreases the matching accuracy. In order to reduce correlation between binary tests, a learning method is developed with the help of ORB.

It helps to choose a better set of binary tests by testing all possible binary tests with high variance and with no correlation.

C) Feature matching with hamming distance

Similarity among the descriptors can be computed using the Hamming distance. It is a number which indicates the difference between two binary strings. It is used for information analysis.

To make matching possible, the binary strings should be of equal length. Comparing the strings bit per bit generates the result. If the bit compared is same, record 0 else record 1. Finally add these bits to obtain Hamming distance.

IV. RESULT

Performance of the proposed recognition algorithm can be well evaluated with the help of experimental results. Preprocessing can be done on the input image of Rs.100. Fig.2 and fig.3 shows preprocessing result indicating resized input image and histogram equalized image respectively. The Fast points marked on the sample note are shown in fig.4. Orientation of these fast points can be seen in fig.5. The accuracy can be calculated as:

$$\%Accuracy = \frac{\text{Number of correctly recognized notes}}{\text{Total number of notes}} \times 100$$



Fig.2 -Resized input image for Rs.100

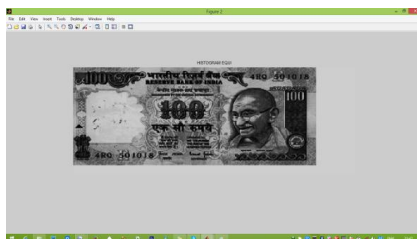


Fig.3 -Histogram equalization for Rs.100

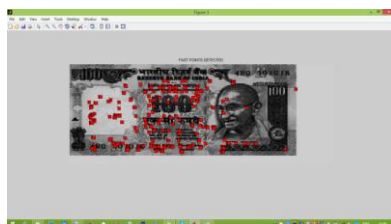


Fig.4 -Calculation of fast corner points for Rs.100



Fig.5-Orientation of feature points for Rs.100



Fig.6 -GUI representation of the result

Fig.6 shows graphical user interface representation of the result constitutes both input and output sections. Result is displayed for its denomination and a voice sample is generated for visually disabled person.

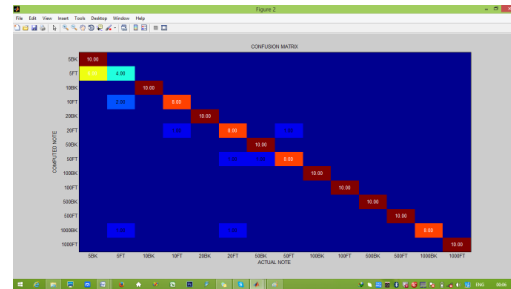


Fig.7 -Confusion matrix plotted for all notes

Table I- Representation of correctly and incorrectly recognized notes

Denomination	Samples	Correct	Incorrect	Missed
5	Front	4	6	--
	Back	10	--	--
10	Front	8	2	--
	Back	10	--	--
20	Front	8	2	--
	Back	10	--	--
50	Front	8	2	--
	Back	10	--	--
100	Front	10	--	--
	Back	10	--	--
500	Front	10	--	--
	Back	10	--	--
1000	Front	10	--	--
	Back	8	2	--

The confusion matrix plotted among computed note versus actual note shows the recognition rate fig.7. Table I represents correctly as well as incorrectly recognized denominations. The samples considered are from front side as well as from back side. The obtained accuracy is 90%.

V. CONCLUSIONS

The currency recognition algorithm is implemented with the help of MATLAB. The currency recognition system algorithm shows the appropriate preprocessing, feature extraction via ORB & feature matching. Classification can be done with the help of hamming distance.

Confusion matrix indicates number of correctly recognized notes also it indicates the notes which are not correctly recognized. With the help of confusion matrix, accuracy can be calculated. The result is integrated with the help of graphical user interface (GUI).

This system can be implemented where money related transactions are involved and found to be reliable for visually disabled people.

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