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A Robust Side Invariant Technique of Indian Paper Currency Recognition

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Abstract

An image based approach which detects Indian paper currencies (Notes) of different denomination has been proposed in this work. This consists of matching an input note image with a database of note images (templates) in two phases. The first phase involves, identifying matching dimension database notes. In the second phase, template matching is performed by correlating the edges of input and matching dimension database note images. The proposed template matching technique provides side invariance and does away with the requirement of placing the front face of the note up. If the correlation coefficient obtained by template matching satisfies the threshold, then input note stands recognised. The entire algorithm is developed in MATLAB and the obtained results are recorded. The proposed technique of paper currency (note) recognition is compared with existing recognition methods like LBP, Image Subtraction, Gabor Wavelet. The comparison results obtained from MATLAB have also been recorded.

1. Introduction

With development of modern banking services, automatic methods for paper currency recognition become important in many applications such as in automated teller machines and automatic goods seller machines. The needs for automatic banknote recognition systems encouraged many researchers to develop corresponding robust and reliable techniques [1-8]. Processing speed and recognition accuracy are generally two important targets in such systems. The technology of currency recognition aims to search and extract the visible and hidden marks on paper currency for efficient classification. Until now, there are many methods proposed for paper currency recognition. The simplest way is to make use of the visible features of the paper currency, for example, the size and texture of the paper currency [1]. However, this kind of methods has great limitations as currencies of different values may have the same size in some countries, and the visible marks may be contaminated by noise.

Junfang Guo et al. [1] proposed a method for paper currency based on the traditional local binary pattern method for feature extraction and template matching is performed in this method. Neural networks (NN) are widely used in the field of paper currency recognition. Fumiaki Takeda et al. [2] proposed a paper currency recognition method using neural networks. Two types of data sets, time series data and Fourier power spectra, are used. Er-Hu Zhang et al. [3] presented a method using linear transform of gray image and carried out sorting recognition by three layers BP NN. Sigeru Omatu et al. [4] proposed a local principal component analysis (PCA) method, which is applied to remove non-linear dependencies among variables and extract the main principal features of data. Fumiaki Takeda et al. [5] proposed a Neuro-Paper Currency recognition method using optimized masks by Genetic Algorithm. Trupti Pathrabe et al. [6] proposed a paper currency recognition system using characteristics extraction and negatively correlated NN ensemble. Three characteristics of paper currencies are considered here including size, colour and texture. Parminder Singh Reel et al. [7] proposed a paper currency recognition method, involving the heuristic analysis of characters and digits of serial number of Indian currency notes to recognition of currency notes. CAO Bu-Qing et al. [8] proposed a method based on uncertain network model structure and indeterminate initial weights and slow convergence speed for Back Propagation Neural Networks, then form GA-BP model was applied for currency recognition.

Although the NN technology has the ability of self-organization, generalization and parallel processing, and has been a good fit for pattern recognition, it also has some weakness. First, it needs a large number of training samples, which are used to avoid over-fitting and poor generalization. Second, if the distribution of training sample is not uniform, the result will probably converge to a local optimal or will even diverge unreasonably.

In currency circulation, the original information on paper currency may have a loss because paper currency may be worn, blurry, or even damaged. Figure 1 illustrates this problem. Figure 1 shows three notes of five rupee Indian currency. Texture of each note is different from other. The above image based methods [1-8] of paper currency recognition would not yield proper result in this case, as the intensity values change from image to image of same denomination/pattern paper currency.

To counter this problem the proposed method makes use of edge detection and correlating the edge detected images during template matching. After edge detection the image matrix consists of 1s or 0s, instead of 0-255 values. Hence, the proposed method becomes independent of the intensity values of each pixels of note (paper currency) image. This gives better recognition results for the proposed method.

Figure 1. Three paper currencies of same denomination

2. Assumptions

Following parameters are kept constant during image acquisition:

- Lighting condition
- Distance and Position
- Perpendicular image acquisition

Also, care is taken so that the surface of the paper currency is clean.

3. Proposed Side Invariant Paper Currency Recognition Method

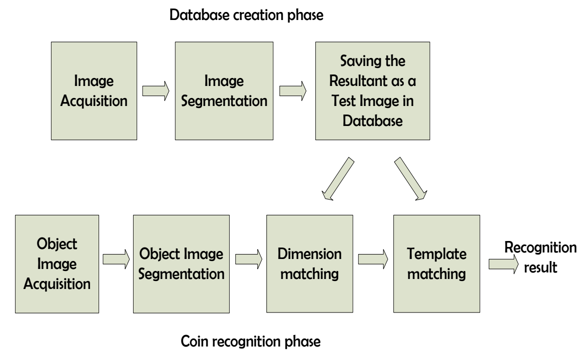

Figure 2. Block diagram of the recognition process

Fig. 2 shows the block diagram of overall recognition process. First a database of coin images is created and then recognition is carried out. The different stages involved in the overall process are described one by one.

3.1. Image Acquisition and Segmentation

A digital camera is used for image acquisition. Since each note has two faces (sides), there are four possible ways of placing a note for image acquisition. These four possible ways are shown in figure 3. The proposed method is side invariant and hence, is capable of recognising the paper currency in all four cases shown in figure 3.

Figure 3. Four possible ways of placing a note for image acquisition

The next step of the paper currency recognition system would be image segmentation, i.e. separating the note image from the background. In first step of segmentation, the edges of input image are detected, making use of 'sobel' operator. In second step, filtering of noisy edges other note's edges is performed. In third step, the boundary coordinates of the note part in the input image are noted down. With the help of the boundary coordinates the note part in cut out of the original input image. Thus, the note is segmented for future processes. Figure 4 shows an example of segmentation, employed in this work.

Figure 4. Paper currency segmentation result

3.2. Dimension Matching

After paper currency segmentation, the numbers of pixels row-wise and number of pixels column-wise in the segmented image are noted. These pixel counts (row-wise and column-wise) give the dimensions of the paper currency in terms of pixels.

After finding the dimensions of the input note, its dimensions are matched with the dimensions of all database notes. The matching dimension database notes are noted down. Hence, during template matching only these matching dimension database notes are matched with input note for recognition of input note.

3.3. Template Matching

The matching is performed by correlating the edges of input and database notes. The correlation coefficient is given by,

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right)\left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}} \quad (1)$$

where, r is correlation coefficient, A & B are two image matrices, m & n are number of rows & columns respectively in both A & B, $\bar{A}$ & $\bar{B}$ are the means of matrices A & B respectively.
Equation 1 is used to obtain the matching score (MS) of the template matching process. Figure 5 shows the entire process of template matching.

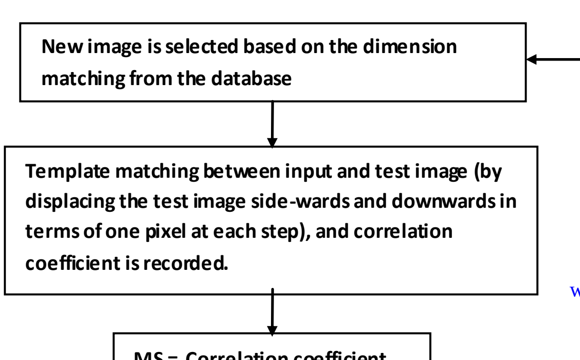

Figure 5. Flow chart of the template matching algorithm

3.3.1. Edge Detection. It is the preliminary step of template matching. Edge detection of the input note and database note, which is about to be matched is performed. Figure 6 shows an example result of edge detection method which is employed in this work. The edges of input and database notes are correlated to obtain a correlation coefficient. This coefficient is the matching score obtained by matching input and database notes.

Figure 6. Edge detection result

3.3.2. Template matching by displacement of database note. To obtain accurate matching results, displacement of database note is performed during matching process. Each matching dimension database note is displaced in two shifts. In first shift, the database note is displaced side-wards in terms of one pixel at each step, from 1 to 5 pixels. At each step, database note edges are correlated with edges of input note. The maximum correlation coefficient out of these steps is noted. In second shift, the database note is displaced downwards in terms of one pixel at each step, from 1 to 5 pixels. The second shift is performed at the first shift position where maximum correlation coefficient is recorded. The maximum correlation coefficient obtained after second shift becomes the final matching score between input note and particular database note.

3.3.3. Threshold comparison. The matching score obtained from each matching dimension database note is compared with a predefined threshold value. If the matching score is greater than threshold, the particular database note stands matched with the input note. Otherwise, the particular database note stands unmatched.

3.4. Decision Making

During threshold comparison, there is a chance of more than one note yielding matching score greater than threshold. So, there is a need of decision making. The database note yielding the maximum matching score is taken as final match of the input note. From the final match database note the denomination of input note is concluded. Hence, the input note stands recognized.

4. Experiments and Results

To test the accuracy of recognition of the proposed paper currency recognition method various experiments have been performed. The results of various experiments have been recorded in this section.

4.1. Recognition Results

4.1.1. Recognition of noisy (contaminated) paper currencies (notes). The proposed method works well even if the surfaces of the notes are contaminated by noise. This contamination is due to frequent usage of notes as shown figure 1. To prove this capacity of the proposed method, a 5 rupee Indian note (contaminated) has been placed in all possible ways as shown in figure 3 and subjected to recognition test. The recognition results of all cases are shown in figure 7.
Figure 7 shows that the proposed method effectively recognizes contaminated notes. Similar tests can be done by adding ‘Gaussian’ and ‘salt & pepper’ noises to input note by means of simulation. A 5 rupee Indian note added with simulated noise has been subjected to recognition tests.

Figure 7. Recognition results of contaminated notes of all four cases

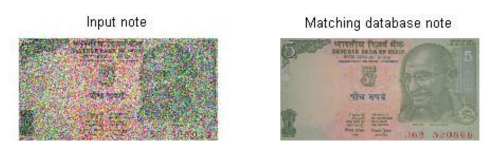

Figure 8. Recognition result of input note with gaussian noise (mean = 0 and variance = 0.05)

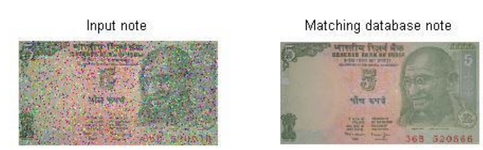

Figure 9. Recognition result of input note with salt and pepper noise (noise density = 0.1)

Figure 8 shows the recognition result of input note with ‘Gaussian’ noise and figure 9 shows the recognition result of input note with ‘salt and pepper’ noise.

4.1.2. Recognition capacity of the proposed method. To determine the recognition capacity of the proposed method an experiment is performed. Two sets of notes (paper currencies) containing 28 patterns have been formed. Pattern is nothing but one of the two faces/sides of a note. Each set consists of a mix of new and old/contaminated notes having denominations five, ten, twenty, fifty, hundred, five hundred and thousand rupees. Each note of one set is matched with all matching dimension notes of the other set. Therefore, a note of one set has to be matched with same pattern of other set and also with different patterns of same dimension. Hence matching and non-matching scores are obtained for each note. By obtaining these scores for all notes, a recognition capacity has been plotted, as shown in figure 10.

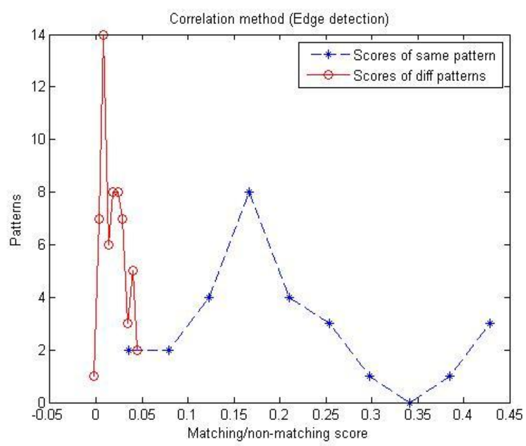

Figure 10. Recognition capacity graph of the proposed method

Figure 10 shows that the scores of different pattern curve (red) overlaps only a small portion of the scores of same pattern curve (blue-discontinuous curve). This means that the proposed method has good recognition capacity. It can successfully reject different patterns and accept similar patterns. From this graph the threshold value can also be decided, which can be used in threshold comparison step. The following parameters can be obtained from this graph:

- Threshold: 0.040105
- True Acceptance Ratio (TAR): 0.928571
- True Rejection Ratio (TRR): 0.967213
- False Acceptance Ratio (FAR): 0.032787
- False Rejection Ratio (FRR): 0.071429

Here, TAR and TRR give the measure of recognition accuracy of the proposed method. FAR and FRR give the measure of error. By observing these values, it can be concluded that the proposed method gives more than 90% recognition accuracy.

4.2. Comparison with other existing paper currency recognition methods

Four input sets have been formed, each containing 28 patterns (new/old/contaminated) for testing the recognition accuracy of the proposed method. These four sets of notes have also been subjected to recognition by means of Local Binary Pattern (LBP) based method, Image Subtraction method and Gabor wavelet based method. The results have been tabulated in table 1.

Table 1. Comparison of accuracy of proposed method with other methods

Method	Accuracy obtained for Input sets (in terms of percentage)				Overall accuracy
	Input set 1	Input set 2	Input set 3	Input set 4	
Proposed	100	100	99	98	99.5%
Gabor wavelet	65	70	50	75	65%
Image Subtraction	60	40	50	55	51.25%
LBP	60	55	50	45	52.5%

From the above table it can be concluded that the proposed method is better than other recognition methods.

Further, for much better comparison, the recognition capacity graphs have been plotted for all three methods. Same procedure is followed to obtain them, as discussed while plotting the recognition capacity graph of proposed method.

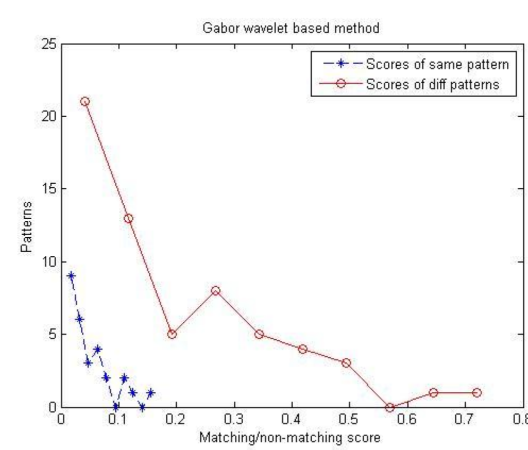

Figure 11. Recognition capacity graph for Gabor wavelet based method

Figure 11 shows that there is about 75% accuracy of recognition and about 25% error, in Gabor wavelet based recognition method. Figure 12 shows the recognition graph of Image Subtraction method. Figure 12 shows that there is about 60% accuracy of recognition and about 40% of recognition error. Figure 13 shows the recognition capacity graph of LBP based recognition method. Figure 13 shows that there is about 50% recognition accuracy only and about 50% of error.

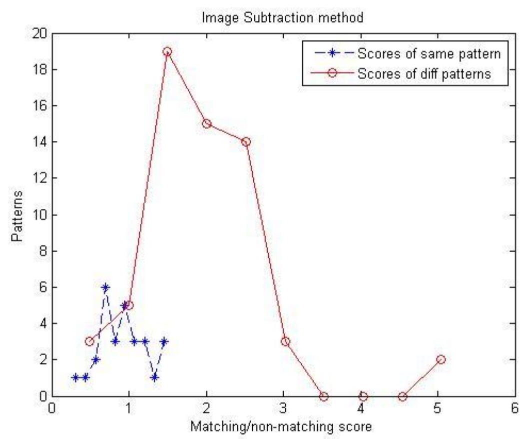

Figure 12. Recognition capacity graph for Image Subtraction method

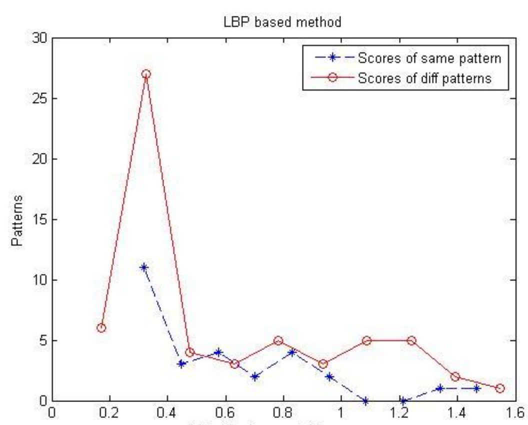

Figure 13. Recognition capacity graph for LBP based method

From figures 10, 11, 12 and 13, it can be concluded that the proposed method has better recognition capacity than other methods in consideration.

5. Conclusion

The proposed method for paper currency recognition has been found to be simple and accurate. This method yields an accuracy of more than 90%, which is much greater than accuracies of other methods. This method provides side invariance for recognition process. The method also avoids the dependence on constant light factor during image acquisition up to certain extent. Also two subsequent phases, dimension matching and template matching have been provided to give precise results.

Future works will include modifications of the present technique to recognize paper currencies. The work will include merging of other image processing techniques, such as, neural networks training using edge detection which would completely extricate the process from the dependency over standard light intensity and standard distance between the note and the camera during image acquisition, adding on to the accuracy of the process.

Acknowledgments

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Authors' Profile

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