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A Review: Paper Currency Recognition

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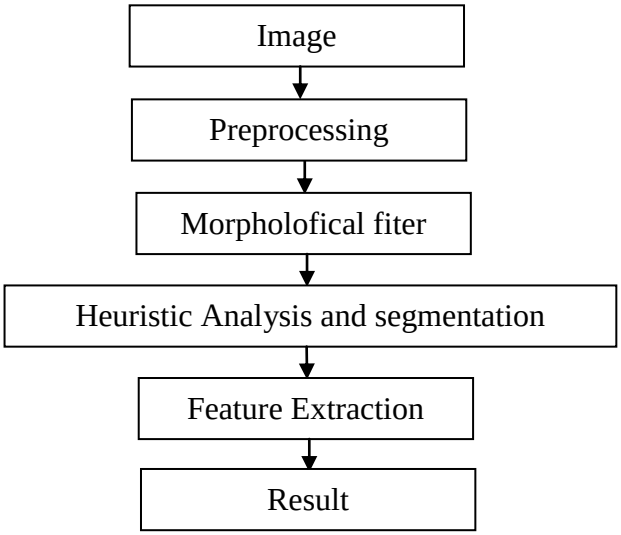
Abstract:

Currency has great importance in day to day life and may be because the currency recognition is a great area of interest for researchers. Different methods have been proposed by researchers for both coin and paper currency recognition. On the basic of vigorous literature survey, we can conclude that image processing is the most popular and effective method of currency recognition. Image processing based currency recognition technique consists of few basic steps like image acquisition, its pre-processing and finally recognition of the currency. Normally camera or scanner is used for image acquisition. Then these images are processed by using various techniques of image processing and various features are extracted from the images which are the key concept behind currency classification. In this paper we have discussed a variety of different currency recognition system.

Keywords:

I. INTRODUCTION

Paper money is still a widely accepted mode of money transaction besides so many alternates. The attractive features of the paper currency include privacy, simplicity, durability and complete control. But as a means of value transaction it lacks intrinsic value, and mechanism of reversal in case of repudiation, except the credential support by the state. Recent phenomena of financial self service being supported by the banks and other financial institutions have started various services of automated banking systems which have the currency recognition as its key activity making automated currency recognition and classification a key problem. Ample amount of the effort has been devoted for the same [1, 2, 3, 4, 5, and 6]. Neural networks (NN) are widely used in the field of currency recognition. Takeda et al. [2] have used a random mask for preprocessing the data and used a multi-layer neural network as the classifier for recognition of paper currency. ER-HU Zhang et al. [3] have extracted the edge information on paper currency and then used a three-layer BP NN for recognition. Although the NN technology has the ability of self-organization, generalization and parallel processing, and has 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. Therefore, the selection of the training set is a crucial issue for the NN. In currency circulation, the original information on paper currency may have a loss because paper currency may be worn, blurry, or even damaged. Furthermore the complex designs of different kinds of paper currencies make automatic currency recognition difficult to work well. So it is important how to extract the characteristic information from currency image and select proper pattern recognition algorithms to improve the accuracy of currency recognition. The method we present here
has an excellent performance.



Design flow of Indian paper currency[2]

II. RELATED STUDY

Supporting literature exists focusing on banknote recognition software intended for a variety of applications such as assisting the visually impaired [2], banknote sorting and Automatic Teller Machine (ATM) software [3], and banknote fatigue detection [4]. A trend observed is that an image is acquired, it is pre-processed then classified and finally the result is output. Various methods are employed at each stage, the correct combination to use is subjective to the currency in question. The same workflow is employed by our system to classify the note. Image acquisition and image pre-processing techniques are employed, either the entire note or distinct Regions of Interest (ROI) are acquired and compared independently. The serial number uniquely identifies an individual banknote, in some cases the location of manufacture can be pinpointed [1]. Therefore this adds a layer of security and can be computed [5]. If a note is found to have an incorrect or duplicate serial number, it is not authentic. Image acquisition techniques are explored, the aggregation of RGB color is with ultra-violet information [6]. Under ultraviolet light a different visual appearance is observed, specific areas of the note glow displaying otherwise hidden information, this places extra complexity on the casual counterfeiter. The fluorescence lifetime is investigated [7], it is found using a two-photon laser excitation and time-correlated single photon counting (TCSPC) method, significant differences in the duration of fluorescence are observed when comparing genuine and counterfeit notes. This approach is an alternative to the image processing and classification model used by this study, yet due to the requirement for specialized equipment may not be a practical solution. Image processing techniques are employed to extract key characteristics, key characteristics are numerical measures
computationally describing a banknote image. There are two primary categories of key characteristics used. Color measurements describe the level of color by creation of an intensity or gray-level histogram, shape descriptors are key color characteristics. Texture describes the pattern of pixel color and their relationship with one another [8]. It is found that vector spaces composed of both texture and color features improve classification accuracy [9]. The feature vector is input into a classifier where it is essentially compared against known good values. In the literature, many classification techniques are employed on a wide array of currencies, the classification method chosen is subjective to the currency in question and characteristics extracted. Many variants of the classical Artificial Neural Network (ANN) are proposed, using the Back Propagation (BP) learning model with Genetic Algorithm (GA) improves in learning performance [10]. In order to determine banknote authenticity, a measurement is calculated upon comparison of the suspect note and template image. The measurement is used as the determining factor of similarity, the distance measurement is used specifically on ROIs [4] to determine the fatigue of banknotes. It is anticipated, synonymous to fatigue determination, discrepancies occurring during counterfeit production will provide dissimilarity measures which substantially deviate from known good templates.

III. PAPER CURRENCY RECOGNITION METHOD

In 2003, Masato Aoba[18] et al. proposed paper currency recognition system for euro. Here three layer perception and radial Basis function (RBF) is used for paper currency recognition.
Salient features of the method:
1) Author has used three layer perception for classification and RBF for validation.
2) Three layer perception is used for pattern recognition which is very effective tool for classifying paper currency.
3) RBF network has a potential to reject invalid data because it estimates probability distribution of sample data effectively.

In 2003, Ali Ahmadi et al[15] postulated method to remove non-linear dependencies among variables and extract the main principal features of data. Initially the data space is partitioned into regions by using a self-organizing map (SOM) model and then the PCA is performed in each region. A learning vector quantization (LVQ) network is employed as the main classifier of the system.
Salient features of the method:
1) Complexity of data and correlation between variables is modeled by using a simple linear mode.
2) Accuracy of system can be extended to 100%.

In 2008, D. A. K. S. Gunaratna et al.[16] proposed system "SLCRec" with special linear transformation function which is adapted to wipe out noise patterns from backgrounds without affecting the characteristic images of paper currency note and repair images of interest. The transformation maps the original gray scale range into a smaller range of 0 to 125 then by applying edge detection, better robustness for noise and fair representation of edges for new and old damaged notes can be achieved. The proposed system comprises of two components namely image processing component and neural network component. In image processing component, first of all scanned currency notes are converted into gray scale. That means the image is converted from file format to pixel values. Then new set of values is generated from original gray scale pixel values with a linear combination of the former values. After the transformation, Edge detection is performed to extract the image identity. Then this detected edge information is extracted and arranged in a format required by the neural network. Neural Network Component consists of four classes like 100, 500, 1000 and 2000 rupee notes. The neural network is trained with notes representing different operational conditions in terms of color brightness, noise, dust, effect, etc. for these four classes. Since it is supervised learning, neural network is expected to give expected results when notes with similar or slight differences are presented for classification.
Salient features of the method:

1) Canny algorithm is used for edge detection because of its low error rate and good ability to localized edge points properly.
2) Three layer back propagation neural network is used for currency classification.
3) The experiments carried out by author showed good classification results and proved that the proposed methodology has the capability of separating classes properly in varying image conditions.

In 2010, Kalyan Kumar Debnath et al.[19] present a currency recognition system using ensemble neural network (ENN) particularly for TAKA (Bangladeshi currency). The individual neural networks (NNs) in an ensemble neural network (ENN) which in fact is a classifier and trained via negative correlation learning. The negative correlation learning (NCL) is to expertise the individuals on different parts or portion of input patterns in an ensemble. The image of different types note is converted in gray scale and compressed in the desired range. Each pixel of the compressed image is given as an input to the network. This system is able to recognize highly noisy or old image of TAKA.[7] Ensemble network is very useful for the classification of different types of currencies. It reduces the chances of misclassification than a single network and ensemble network with independent training. To prove the efficiency of proposed ENN method author has compared it with the other methods like Hidden Markov Model (HMM), radial basis function (RBF) and Feature Extraction method called SLCRec.
Salient features of the method:
1) Negative correlation learning is for training.
2) System can recognize the currency even though input pattern is noisy.

In 2010, Junfang Guo et al.[20] used block-LBP algorithm for characteristic extraction from paper currency. Block-LBP is improved version of traditional local binary pattern (LBP) method. The proposed currency recognition system works in two phases. The first phase is the model creating phase which consist of preparing template for paper currencies and feature extraction using block-LBP algorithm. The feature vectors of template images are obtained as an output of first phase and will be used as input for second phase. The second phase is the verification phase. In verification phase template matching is done by calculating the similarity between the sample image and template image.
Salient features of the method:
1) High recognition speed.
2) Robustness to noise and illumination change.
3) Higher classification accuracy can be achieved by Block LBP algorithm as compared with traditional LBP algorithm.

In 2011, Hai-dong Wang et al.[21] proposed paper currency number recognition method called fast Adaboost weak classifier training algorithm which sort the Eigen values to an array from small to large, and then traverse the sorted array once to find the best threshold and bias.
Salient features of the method:
1) Training speed can be increased to great extent.

In 2012, Chetan B. V. et al.[22] proposed side invariance paper currency recognition method which is two phase approach based on matching an input note image with a database of note image. The two phases are as follows:
1. Identifying matching dimension database notes.
2. Secondly, template matching is performed by correlating the edges of input and matching dimension database note images.

The different stages involved in the overall process are described one by one. The different stages involved in the overall process are described one by one.

Step 1. Image Acquisition and Segmentation
A digital camera is used for image acquisition. The next step of the paper currency recognition system is image segmentation. Segmentation is also three step process. In first step of segmentation, sobel operator is used to detect the edges of input image. Filtering of noisy edges is done in second step. In third step, the boundary coordinates of the currency note are noted down. With the help of the boundary coordinates, the currency note part is cut out of the original input image. Thus, the note is segmented.

Step 2. Dimension Matching
After paper currency segmentation, the numbers of pixels row-wise and column-wise are noted down. A dimension of the paper currency in terms of pixels is obtained from these pixel counts. 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.

Step 3. Template Matching
The template matching is performed by correlating the edges of input and database notes. Entire process of template matching process consists of edge Detection, template matching by displacement of database note and threshold comparison.

Step 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. Hence, the input note stands recognized.[10]

IV. METHODOLOGY

In this section, we explain the ensemble neural network structure and the methodological procedure so that one can visualize the architecture and its training together with its procedure.

A. Ensemble Neural Network Structure

The structure of ensemble neural network is shown in fig. 2 so that one can visualize. Each individual neural network in an ensemble in fact is a classifier. Each classifier minimizes the same objective or cost function. The number of inputs should be the same for all the individual classifier and outputs of all the individual NNs should also be same and this is according to the number of classes. However, the number of hidden units may be different for different individual NN. In the NCL, the objective function is composed of two terms, one for sum square error function and another is the penalty function. Therefore the update rules for the entire ensemble become the eqn (5). The number of hidden unit in an individual NN remains the same in the experiment. We do not optimize the number of hidden units. However, the number of hidden units is varied all together in an experiment and check the performance. An image of currency TAKA after preprocessing is applied to the inputs of all individual NN. The number of inputs to a classifier is the number of all pixel values of a particular currency.

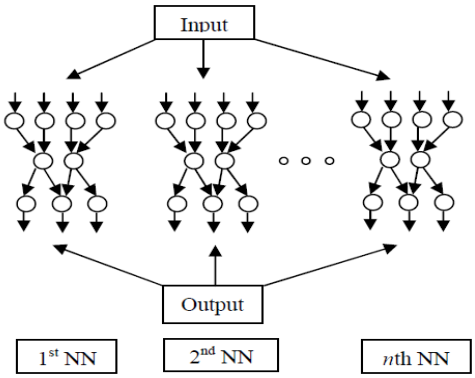


Figure 2. Architecture of ensemble neural network.

B. Procedure

We perform our experiment for seven types of TAKA (2, 5, 10, 20, 50, 100, and 500). To increase the accuracy of the NN ensemble, we applied one new & another older or noisy TAKA for each different type. The total number of input patterns is 28 since the both sides are trained. We consider an ENN where every network is a three layer feed-forward network. Each network contains 7 neurons in output layer, 70 hidden units and 10,000 (125*80=10000, according to the compressed image) input units. Each neuron in output layer is responsible for a definite class of TAKA such as the 1st neuron for the 2 TAKA, the 2nd neuron for the 5 TAKA and so on. We performed our experiment for single network and an ensemble with 3, 4 & 5 individual networks. In the hidden and output layer, we have applied a bias unit. The output of the bias unit is +1. The weights of the neural network are first assigned randomly then the network is trained according to NCL [7]. We choose the values of λ (strength of penalty term) and η (learning rate) are 0.75 and 0.15 respectively. The sigmoid function is used as an activation function both in the hidden and output layer. The images are applied one after another. After the application of the first image, we apply the second image and update the weights of the network. But we need to be conscious about the output for that particular image. Such as, when we apply the image of TAKA 2 the desired output of each network should be 1 0 0 0 0 0 0 (i.e. output of 1st neuron will be 1 and other will 0). For all the images of TAKA 2 the desired output should be same. Similarly for all images of TAKA 5 the desired output should be 0 1 0 0 0 0 0. The decision of ensemble is computed using voting scheme i.e., the ensemble classifies the class when the maximum votes for the class are detected from the individual classifiers. The entire methodology can be summarized in the following steps:

1) Determine the size of the currency image using preprocessing steps.
2) Select ensemble neural network size and their learning parameters.
3) Train the ensemble NN according to the setup parameters.
4) Test the ensemble NN with testing patterns and/or artificially added noisy patterns.

V. CONCLUSION

This paper focused on existing techniques and systems for currency recognition based on image processing. We have discussed paper currency recognition methods. Even though there is lot of research work done on this topic, still there are some issues related to the accuracy and efficiency of the method. Thus achieving maximum efficiency and getting 100% accuracy for heterogeneous currency, when physical state of currency is not that much good, will always be a challenge for researchers.

REFERENCES

[1] Dipti Pawade, Pranchal Chaudhari, Harshada Sonkamble, "Comparative Study of Different Paper Currency and Coin Currency Recognition Method", International Journal of Computer Applications (0975 – 8887) Volume 66– No.23, March 2013

[2] F. Grijalva, J. C. Rodriguez, J. Larco, and L. Orozco, "Smartphone recognition of the U.S. banknotes' denomination, for visually impaired people," in IEEE ANDESCON 2010, pp.1–6.

[3] H. Gou, X. Li, X. Li, and J. Yi, "A Reliable Classification Method for Paper Currency Based on LVQ Neural Network," in Advances in Computer Science and Education Applications. Springer Berlin Heidelberg, 2011, vol.202, pp.243–247.

[4] F. Daraee and S. Mozaffari, "Eroded money notes recognition using wavelet transform," in 6th Iranian Machine Vision and Image Processing (MVIP'10), 2010, pp. 1–5.

[5] L. Li, Y. Yu-tang, X. Yu, and P. Liang, "Serial Number Extracting and Recognizing Applied in Paper Currency Sorting System Based on RBF Network," in International Conference on Computational Intelligence and Software Engineering (CiSE'10), 2010, pp. 1–4.

[6] S.-H. Chae, J. K. Kim, and S. B. Pan, "A Study on the Korean Banknote Recognition Using RGB and UV Information," in Communication and Networking, Series of Communications in Computer and Information Science. Springer Berlin Heidelberg, 2009, vol.56, pp.477–484.

[7] T. H. Chia and M. J. Levene, "Detection of counterfeit U.S. paper money using intrinsic fluorescence lifetime," Optics Express, vol.17, no.24, pp.22 054–22 061, 2009.

[8] K. Verma, B. K. Singh, and A. Agarwal, "Indian currency recognition based on texture analysis," in International Conference on Current Trends in Technology, 2011, pp.1–5.

[9] F. G. Lamont, J. Cervantes, and A. Lopez, "Recognition of Mexican banknotes via their color and texture features," Expert Systems with Applications, vol.39, pp.9651–9660, 2011.

[10] C. Bu-Qing and L. Jian-Xun, "Currency Recognition Modeling Research Based on BP Neural Network Improved by Gene Algorithm," in Second International Conference on Computer Modeling and Simulation. ICCMS'10, vol.2, 2010, pp.246–250.

[11] Manuel Lang, Oliver Wang, Tunc Aydin, Aljoscha Smolic, Markus Gross, "Practical Temporal Consistency for Image-Based Graphics Applications"

[12] Bhausaheb Shinde, Dnyandeo Mhaske, Machindra Patare, A.R. Dani, "APPLY DIFFERENT FILTERING TECHNIQUES TO REMOVE THE SPECKLE NOISE USING MEDICAL IMAGES", International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue 1,Jan-Feb 2012, pp.1071-1079

[13] Kaiming He, Jian Sun, and Xiaoou Tang, "Guided Image Filtering"

[14] CC.W.G. Clifford, K. Langley, D.J. Fleet, "CENTRAL FREQUENCY ADAPTIVE IIR TEMPORAL FILTERS FOR PHASE BASED IMAGE VELOCITY ESTIMATION"

[15] Ali Ahmadi, Sigeru Omatu, Toshihisa Kosaka, "A Reliable Method for Recognition of Paper Currency by Approach to Local PCA) used local principal component analysis PCA", in IEEE proceedings of the International Joint Conference on Neural Networks, 20-24 July 2003,Vol. 2, Pp. 1258 – 1262.

[16] D. A. K. S. Gunaratna, N. D. Kodikara and H. L. Premaratne, "ANN Based Currency Recognition System using Compressed Gray Scale and Application for Sri Lankan Currency Notes-SLCRec", in proceedings of world academy of science, engineering and technology, Nov 2008,vol. 35,ISSN 2070-3740, Pp. 235-240.

[17] Masato Aoba, Tetsuo Kikuchi, Yoshiyasu Takefuji, "Euro banknote recognition system using a three layer perceptron and RBF networks", IPSJ Transaction on Mathematical Modeling and Its Application, Vol 44, No. SIG 7 (TOM 8), May 2003, Pp. 99-109.

[18] Kalyan Kumar Debnath, Sultan Uddin Ahmed, Md. Shahjahan, "A Paper Currency Recognition System Using Negatively Correlated Neural Network Ensemble", Journal Of Multimedia, December 2010, Vol. 5, No. 6, Pp. 560-567.

[19] Junfang Guo, Yanyun Zhao, Anni Cai, "A reliable method for paper currency recognition based on LBP" in proceeding of 2nd IEEE International Conference on Network Infrastructure and Digital Content, 24-26 Sept. 2010, Pp. 359 – 363.

[20] Hai-dong Wang, Leye Gu, Linping Du, "A paper currency number recognition based on fast Adaboost training algorithm", in IEEE proceedings of International Conference on Multimedia Technology (ICMT), Pp. 4772 – 4775.

[21] Chetan B. V., Dr. P. A. Vijaya, "A Robust Side Invariant Technique of Indian Paper Currency Recognition", International Journal of Engineering Research & Technology (IJERT), May – 2012, Vol. 1 Issue 3, Pp. 1-7.

