AN EXTENSIVE STUDY ON CURRENCY RECOGNITION SYSTEM USING IMAGE PROCESSING

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ABSTRACT

The need for currency recognition system is more relevant due to the advent of technology and machinery used to counterfeit the banknotes. There are many features to identify an authentic currency note physically. Although it may not be practical to accurately identify a counterfeit from an authentic currency note for a person. Several special features are included for strong security against counterfeit in the paper currency which only an intelligent machine can identify. We make use of this special visual properties and patterns to identify the original currency from a counterfeit. A system is applicable globally for the authentication of paper currency. Institutions like banks spend for expensive hardware and for their installation to resolve this issue of currency recognition. Image processing techniques are exploited for a better cost-effective and highly efficient currency recognition system. Although image analysis is not sufficient for authentication, it makes the process easier and faster than the existing system and has easy availability.

INTRODUCTION:

Currency recognition has been widely used in real life such as inventing machines, banks, supermarkets, charity organizations and ancient relics. Based on various recognition methods, three types of currency recognition systems are available in market: 1) Mechanical based 2) Electromagnetic based and 3) Image Processing based systems. Currency are differentiated with various patterns such as shape, size, surface design, weight etc. Currency Recognition is a difficult process because of its various rotations and widely change input patterns, noisy and cluttered images, which are the great challenges. Different algorithms used to detect, recognize and count currency, then produce their associated value. The mechanical method based systems use various parameters like diameter or radius, thickness, weight and magnetism of the currency to differentiate between the currency. But these parameters cannot be used to detect the different materials of the currency. It means that if we provide two currency-original and fake having same diameter, thickness, weight and magnetism but with different materials to me chanical method based currency recognition system then it will treat both the currency as original currency so these systems can be fooled easily. In the recent years currency recognition systems based on images. In these systems first, the currency image to be recognized is taken either by camera or by some scanning devices. After that these images are processed by using various image processing techniques like FFT, Gabor Wavelets, DCT, edge detection, segmentation, image subtraction , decision trees, ANN,SIFT etc .Based on various extracted features, different currency are recognized. Here we have a new approach to improve the performance of currency recognition system which is Rotation and Flipping Robust Region Binary Patterns using Gradient Magnitudes. RFR- GM was

extracted from gradients magnitudes in currency images by local difference magnitude transform. RFR - GM provides much better accuracy compared to the original RFR. The comparative experiments showed that the RFR-GM approach had a better accuracy, faster feature extraction time, and smaller feature dimension. Therefore, RFR-GM is very suitable for image-based currency recognition. There is a basic need of highly accurate and efficient automatic currency recognition systems in our daily life. Currency recognition systems and currency sorting machines have become a vital part of our life. They are used in banks, supermarkets, grocery stores, vending machines etc. In -spite of daily uses currency recognition systems can also be used for the research purpose by the institutes or organizations that deal with the ancient currency. There are three types of currency recognition systems based on different methods used by them

available in the market:

• Mechanical method-based systems

• Electromagnetic method-based systems

• Image processing-based systems

The mechanical method based systems use parameters like diameter or radius, thickness, weight and magnetism of the currency to differentiate between the currency. But these parameters can not be used to differentiate between the different materials of the currency. It means if we provide two currency one original and other fake having same diameter, thickness, weight and magnetism but with different materials to mechanical method based currency recognition system then it will treat both the currency as original currency so these systems can be fooled easily. The electromagnetic method based systems can

differentiate between different materials because in these systems the currency are passed through an oscillating coil at a certain frequency and different materials bring different changes in the amplitude and direction of frequency. So these changes and the other parameters like diameter, thickness, weight an magnetism can be used to differentiate between currency. The electromagnetic based currency recognition systems improve the accuracy of recognition but still they can be fooled by some game currency. In the recent years currency recognition systems based on images have also come into picture. In these systems first of all the image of the currency to be recognized is taken either by camera or by some scanning. Then these images are processed by using various techniques of image processing like FFT, DCT, edge detection, segmentation etc. and further various features are extracted from the images. Based on these features different currency are recognized. This paper presents existing systems and techniques proposed by various researchers on image based currency recognition.

LITERATURE SURVEY

Most of the approaches proposed till now can be applied for recognition of modern currency. A rotational invariant neural pattern recognition system for currency recognition. They have used 500 yen currency and 500 won currency to perform the experiment. In this work they have created a multilayered neural network and a preprocessor consists of many slabs of neurons. This preprocessor was used to get a rotational invariant input for the multilayered neural network. For the weights of neurons in preprocessor, concept of circular array was used instead of square array. The results show that 25 slabs with 72 neurons in each slab give the best recognition. They have used 500 yen currency and 500 won currency. In this work they have used Back Propagation (BP) and Genetic Algorithm (GA) to design neural network for currency recognition. BP is used to train the network. Then after training, GA is used to reduce the size of network by varying the architecture to achieve 100% recognition accuracy rate. an approach for currency classification using learning characteristic decision trees by controlling the degree of generalization. Decision trees constructed by ID3-like algorithms were unable to detect instances of categories not present in the set of training examples. Instead of being rejected, such instances get assigned to one of the classes actually present in the training set. To solve this problem the algorithm with learning characteristic, rather than discriminative, category descriptions was proposed. In addition, the ability to control the degree of generalization was identified as an essential property of such algorithms. Experiments were performed on Canadian and Hong-Kong currency and accuracy of 99.7% for Canadian and98.3% for Hong-Kong currency was achieved. the ARC Seibersdorf research centre in 2003 developed a currency recognition and sorting system called Dagobert. This system was designed for fast classification of large number of modern currency from 30 different countries. Currency classification was accomplished by correlating the edge image of the currency with a pre-selected subset of master currency and finding the master currency with lowest distance. Pre-selection of master currency was done based on three rotation-invariant features (edge angle distribution, edge distance distribution, occurrences of different rotation- invariant patterns on circles centered at edge pixels), currency diameter and thickness. Experiments on 12,949 currency were performed and 99.24% recognition rate was achieved. A currency recognition system to recognize US currency using vector quantization and histogram modeling. The system mainly focuses on the texture of various images imprinted on the currency tail. Based on different image texture the system differentiate between Bald eagle on the quarter, the Torch of liberty on the dime, Thomas Jefferson's house on the nickel, and the Lincoln Memorial on the penny. Experiments show that out of 200 currency images 188 were correctly classified. Thus,94% recognition accuracy rate was achieved. a multistage approach for currency classification using Eigen space and Bayesian fusion. In the first stage, a translational and rotational invariant description is computed. In a second stage, an illumination-invariant eigen space is selected and probabilities for currency classes are derived for both sides of each currency. In the final stage, currency class probabilities for both currency sides are combined through Bayesian fusion including a rejection mechanism. Experiments show that 93.23% of 11,949 currency from thirty different countries were correctly classified. an approach using neural network for currency recognition. In this work they have concentrated on the recognition of the numerals on the currency rather than other images. For this they extract a sub image of numeral from currency then this sub image is used for character recognition. To achieve rotation invariance Gabor filters and Back Propagation neural network are used. Experiments are performed on 1-rupee, 2-rupee and 5-rupee currency. The experiments show 92.43% recognition accuracy rate. a fast system for reliable currency classification called CURRENCY-O-MATIC. In this system currency classification is done based on edge-based statistical features (edge angle distributions, edge distance distributions, edge angle-distance distributions). The system consists of four

subsystems:

(1) a segmentation subsystem.

(2) a feature extraction subsystem.

(3) a classification subsystem.

(4) a verification subsystem.

Experiments were performed on MUSCLE-CIS dataset and 72% classification accuracy was achieved. an Intelligent Currency Identification System (ICIS) in 2006. ICIS uses neural network and pattern averaging for recognizing rotated currency at various degrees. ICIS consists of two phases. First is image processing in which currency images are mode converted, cropped, compressed, trimmed, pattern averaged etc. This is the pre processing phase. In second phase a back propagation neural network is trained. Once neural network converges and learns then only one forward pass is used that yields the identification results ICIS shows very encouraging results. It shows 96.3% correct identification i.e. 77 out of 80 variably rotated currency images were correctly identified. ICIS is very effective in reducing time costs because it reduces the processing data by pre processing images. a robust method for currency recognition with rotation invariance. In this method the rotation invariance feature is represented by the absolute value of Fourier coefficients of polar image of currency on circles with different radii. In this paper the variations on surface of currency such as light reflection effect are also considered. These effects can be reduced by Fourier approximation of the currency image.

PROPOSED SYSTEM

In recent years, a lot of illegal counterfeiting rings manufacture and sell fake currency, which have caused great loss and damage to the society. Thus, it is imperative to be able to detect fake currency. This is also an important concern in the field of numismatics. Forensic experts may be employed to examine the suspected currency, yet it is unrealistic considering the large quantities of currency that have to be examined. Therefore, an automatic fake currency detection system is highly desired. In recent years, the local keypoint detectors and descriptors have been widely employed to describe an image. The common pipeline is to first detect some key points in the image using detectors like Difference-of-Gaussian (DOG), Harris-Laplace, Harris-Affine, Hessian-Laplace or Hessian-Affine. Subsequently, the image region within a certain radius around the key point is described using descriptors such as Scale Invariant Feature Transform (SIFT), PCA-SIFT, gradient location and orientation histogram (GLOH) and shape context (SC). The local key point detectors and descriptors are distinguished by their great discriminative power and robustness to image distortions such as illumination, resolution and viewpoint transformations. Besides, the number of key points varies across images according to their characteristics. However, representing an image in terms of a set of key points cannot fit in the vector-based machine learning tools. To deal with this problem, the Bag-

Of-Visual- Words (BOVW) model may be employed. Analogous to the Bag-Of-Words (BOW) model in the text domain, a visual word vocabulary is built through clustering the local descriptors obtained from a training set. Hence an arbitrary descriptor can be represented by its nearest visual word in the vocabulary. Consequently, an image is represented by a vector, the dimension being equal to the size of the vocabulary.

Currency Recognition System Using ANN

A robust method for Automated Recognition System for Currency using Artificial Neural Network and is used for the recognition of Indian Currency with rotation invariance of various denominations such as `1', `2', `5' and `10'. For this, we have taken images from both sides. So this system is capable of recognizing currency from both sides. Features are extracted from images using various techniques such as Hough Transformation, Pattern Averaging etc. After passing the extracted features to a trained Neural Network., it has been achieved 97.74% recognition rate , which means only 2.26% miss recognition, which is quite encouraging.

Saudi Riyal Currency Detection and Recognition

A method to detect Saudi Riyal. In this paper a system is proposed, that accepts input images of Saudi riyal currency of the types quarter and half. Then, it recognizes Saudi Riyal currency through their radiuses. It starts by thresholding to produce binary image. Then, enhancing and detecting the edges. After that, using CHT to determine diameters of currency. Finally, recognize the currency and their associative value. It is applicable only to Saudi Riya currency to differentiate between its two divisions half and quarter.

Currency Recognition and Sum Counting System

An approach for Currency Recognition and Sum Counting System of Image Data Mining Using Artificial Neural Networks. The objective of this paper is to classify and recognize recently released Indian currency of different denominations, and count the total currency - value in terms of Indian National Rupees (INR). This system developed by combining Robert's edge detection method, Laplacian of Gaussian edge detection method,

canny edge detection method and Multi - Level Counter Propagation Neural Network (ML - CPNN) based on the currency. The proposed method used for realizing a simple automatic currency recognition system more effectively. The Robert's edge detection method achieved 93% of accuracy and Lap lacian of Gaussian method 95% of the result, the Canny edge detection method yields 97.25% result and the ML - CPNN approach yields 99.47% of recognition rate

SOFTWARE DESCRIPTION

Representing Currency in Dissimilarity Space The dissimilarity space is a vector space constructed by comparing an image with a set of pre-selected prototype images, with the dimension determined by the number of prototypes. Each dimension measures the dissimilarity between the image under consideration and one of the prototypes. Formally, given a set of prototype images P = fIp1 ; Ip2 ; _ _ _ ; IpK g chosen from the image domain I, where K is the number of prototypes, a mapping is defined from I to the K-dimensional real space: Consequently, an arbitrary image I 2 I can be represented by a K-dimensional vector x = fd(I; Ip1); d(I; Ip2); _ _ _ ; d(I; IpK)g, where d(_; _) measures the dissimilarity between two images. From the definition given above, two key issues are involved in constructing the dissimilarity space: the dissimilarity measure d(_; _) between two images and the selection of the prototypes. Different image dissimilarity measures can be defined to cater to different applications. We first detail the dissimilarity measure proposed in this study, which is followed by the prototype selection approach.

Currency Image Dissimilarity Measure

At first, a currency image is pre-processed to separate the currency from the background. Almost all the currency are circular except the ancient ones which are beyond the scope of this study. However, the currency may appear as an ellipse instead of a circle when it is not captured well. To address this issue, the Hough transform aiming at ellipse detection is first employed. Afterwards, the obtained ellipse is normalized as a circle. Because of the great descriptive power of local descriptors, they are employed to measure currency image dissimilarity. More specifically, we first detect key points on the currency image based on the DOG detector. Afterwards, the SIFT descriptor is chosen for key point description. The combination of DOG detector and SIFT descriptor has been shown to outperform other detector & descriptor combinations in many applications. Given two currency images, their dissimilarity can be derived from the number of matched key points. Generally speaking, the smaller the number of matched key points, the more dissimilar the two currency images are to find matched key points between two images, Lowe's methodology is adopted. So the descriptor associated with the key point on one currency is compared with the descriptors of all the key points on the other currency in terms of Euclidean distance, from which its closest and second-closest neighbours can be identified. Based on the distance ratio of closest to second-closest neighbours, a decision with respect to whether the key point under consideration and its closest neighbour key point on the other currency are matched or not can be made by comparing the ratio with a threshold.

Since there are usually hundreds or even thousands of key points on a currency image,

searching the closest neighbour for each key point is computationally expensive. However, this problem can be alleviated by taking into consideration the characteristics of the currency. Because the currency are circular, polar coordinates are preferred to the Cartesian coordinates when referring to the key points on the image. Thus the location of a keypoint is represented by (r; _) in polar coordinates, where r represents its normalized radius and is obtained by dividing its distance from the centroid of the currency by the currency radius. _ corresponds to its polar angle. Consequently, instead of comparing with all the key points on the other currency image when searching the closest neighbour for each key point, only those with similar normalized radius are considered, i.e. the difference between their r0 s is no greater than a threshold #, which greatly reduces the computational burden. Moreover, robustness to scale changes between the images can be obtained. In contrast to the methods that proposed different kinds of indexing techniques to speed up the closest neighbour search, we are guaranteed to find the exact closest neighbour. In our work, # is empirically set as 0:05, which is shown to be robust to currency segmentation and perform well according to the experiments in Section IV-B. Employing the method stated above, we can find the matched key points between two currency images. However, there are mismatched key points, several examples of which are shown in Fig 2. The circle superimposed on each of the two images represents the currency segmented from the

background.

Detecting Fake Currency Based on One-Class Learning

In real life, there is usually an imbalance with respect to the number of genuine and

fake currency. It is much easier to obtain genuine currency compared with the fake ones. The issue of imbalance hampers the generalization ability of the commonly used two-class classifiers which need both positive and negative samples for training. To address this issue, we conduct one-class learning, so that the classifier can be built from genuine currency only. Adopting one-class rather than the two-class learning is also justified by the fact that it is not reasonable to classify the fake currency into one single class. Since most of the existing anti- counterfeiting techniques aim at one particular type of counterfeiting, the malicious counterfeiters usually make fake currency that are different from each other, and thus can fool the anti-counterfeiting techniques. So the fake currency may belong to multiple classes. Yet, all the genuine currency can toughly be assumed to be alike. Thanks to one-class learning, we are able to focus on the genuine currency, and will not get distracted by the diversities of fake currency. Given a currency to be examined, if it bears great resemblance to its genuine counterparts, it will be classified as genuine; otherwise, it will be considered as fake. We employ one-class SVM for fake currency detection in this study. One-class SVM. and was considered a natural extension of the support vector algorithm to the case of unlabelled data. In general, the objects belonging to the class are termed as targets, while those outside the class are called outliers. With a set of training samples from the same class, the basic idea of one-class SVM is to learn a hyper sphere which can enclose most of the training samples while minimizing the volume of the sphere at the same time. As with SVM, the kernel trick is employed to map the input data to some feature space in which they can be linearly separable. In the mapped feature space, the origin is considered as the only sample from the

second class. Then a maximum margin hyper plane separating the training samples from the origin will be learned. Formally, given a set of training samples x1; x2; _ _ _ ; xl, where l is the size of the training set and each xi(i = 1; 2; _ _ _ ; l) is a K-dimensional real vector, namely, xi 2 RK, the optimization problem as shown in Eq. is solved. Note that since all the training samples are from one single class, no class labels are needed. For clarity, the symbol in bold font, e.g. _, is used to represent a vector or matrix, while its plain counterpart with a subscript, e.g. _i, represents each individual element in the vector or matrix.

Objective:

$$\min_{w,\xi,\rho} \frac{1}{2} w^T w - \rho + \frac{1}{\nu l} \sum_{i=1}^{l} \xi_i$$

subject to (for $i = 1, 2, \cdots, l$):

$$w^T \phi(x_i) \geq \rho - \xi_i$$

$$\xi_i \geq 0$$

Where w and _ are used to define the hyper plane, the superscript T represents the transpose operation, (xi); i = 1; 2; _ _ _ ; l; maps the input data xi to the feature space, and _i is the slack variable. _ represents the upper bound of the rate of outliers in the training set, i.e. the upper bound of the training error rate. It is used to avoid the issue of over fitting. Due to the heavy computational burden, the following dual problem is solved instead:

Objective:

$$\min_{\alpha} \frac{1}{2}\alpha^T \mathbf{Q}\alpha$$

subject to (for $i = 1, 2, \cdots, l$):

$$0 \leq \alpha_i \leq \frac{1}{\nu l}$$

$$\sum_{i=1}^{l} \alpha_i = 1$$

where each element Qi j(i; j = 1; 2; _ _ _ ; l) of the matrix Q is formally defined as the inner product of the input data xi and xj in the feature space:

$$Q_{ij} = \Psi(\mathbf{x}_i)^T \Psi(\mathbf{x}_j)$$

IMPLEMENTATION

OVERVIEW OF PROJECT MODULES

❖ Image Acquisition

Performing image acquisition in image processing is always the first step in the workflow sequence be- cause, without an image, no processing is possible. After the image has been obtained, various Methods of processing can be applied to the image to perform the many different vision tasks. There are various ways to acquire image such as with the help of camera or scanner. Acquired Image should retain all the features.

❖ Pre-Processing

The main goal of the pre-processing to enhance the visual appearance of images and improve the manipulation of data sets. Image preprocessing, also called image restoration, involves the correction of distortion, degradation, and noise introduced during the imaging process. Interpolation is the Technique mostly used for tasks such as zooming, rotating, shrinking, and for geometric corrections. Removing the noise is an important step when processing is being performed. However noise affects segmentation and pattern matching.

❖ Feature Extraction

Feature extraction is a special form of dimensional reduction. When the input data to an algorithm is too large to be processed and it is suspected to be very redundant then the input data will be trans- formed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full-size input.

Fig 1. Sample pairs of mismatched key points connected by

RESULTS

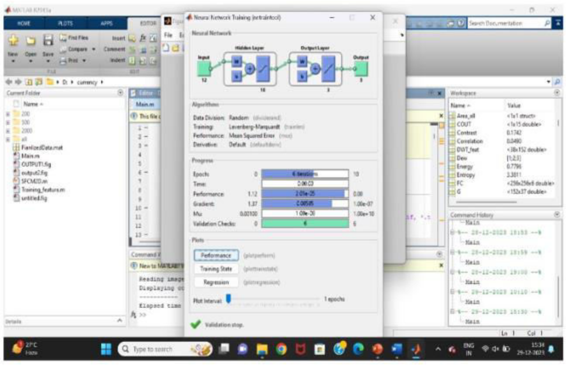

Fig 2.Output of Nueral network

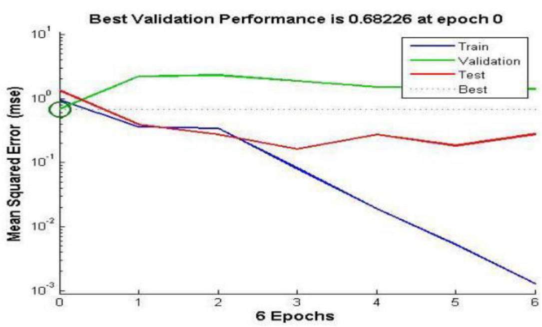

Fig 3.performance state

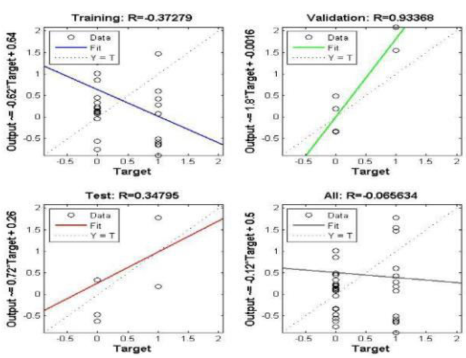

Fig 4.Training state

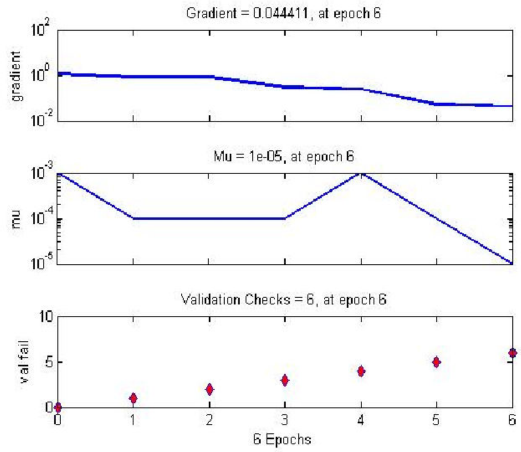

Fig 5.Rergerssion state

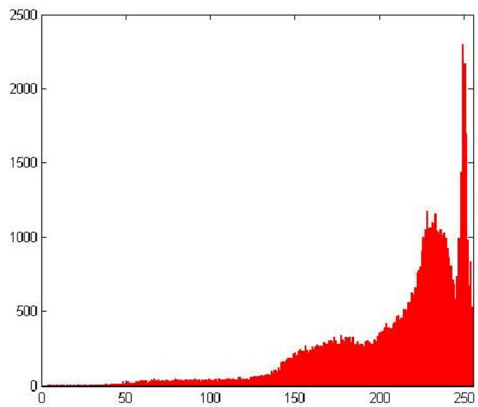

Fig 6.Output of Histogram

ADVANTAGES & APPLICATIONS

Advantages

- Accessibility
- Automation
- Accuracy
- Speed
- Security

Applications

- ATM machines

- ❖ Banking
- ❖ Transactions
- ❖ Public transportation
- ❖ Financial institutions

CONCLUSION

A fake currency detection method exploiting the characteristics of currency image is proposed in this paper. The currency image is represented in the dissimilarity space, whose dimension is determined by the number of prototypes. Each dimension corresponds to the dissimilarity between the currency image under consideration and a prototype. In order to compute the dissimilarity between two currency images, the local key points on each image are detected using the DOG detector and then described by the SIFT descriptor. Afterwards, the matched key points between the two images can be identified efficiently based on the characteristics of the currency. We also propose a post processing method to remove mismatched key points. Since the number of fake currency is very limited in real life, we conduct one-class learning. It is distinguished by the ability to train the classifier using genuine currency samples only. The proposed approach is evaluated on four different currency datasets and very encouraging results have been obtained. In spite of the promising results achieved, the proposed approach is not without shortcomings. As stated above, for each type of the currency, some genuine currency images are needed for training. Yet, for some rare currency, it may not be easy to obtain enough genuine images for training. How to address this issue deserves a closer look and will be the focus of our future work.

Future Scope

- ❖ Speaker attachments
- ❖ Denomination

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