Sample Coin Recognition System using Artificial Neural Network on Static Image Dataset

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Abstract—This paper presents a reliable coin recognition system that is based on a polar Fast Fourier Transform. Coins are frequently used in everyday life at various places like in banks, grocery stores, supermarkets, automated weighing machines, vending machines etc. So, there is a basic need to automate the counting and sorting of coins. For this machines need to recognize the coins very fast and accurately, as further transaction processing depends on this recognition. However, currently available algorithms focus basically on the recognition of modern coins. To date, no optical recognition system for coins has been researched successfully. In this project, the recognition of coins will be based on new algorithms of Polar Fast Fourier Transform and image processing, in a field – classification and identification of coins.

Keywords—coin, feature extraction, neural network, recognition.

I. INTRODUCTION

Nowadays, ancient coins are becoming subject to a very large illicit trade. Thus, the interest in reliable automatic coin recognition systems within cultural heritage and law enforcement institutions raises rapidly. Traditional methods to fight the illicit traffic of ancient coins comprise manual, periodical search in auctions catalogues, field search by authority forces, periodical controls at specialist dealers, and a cumbersome and unrewarding internet search, followed by human investigation. Applied pattern recognition algorithms are manifold ranging from neural networks to eigenspaces, decision trees, edge detection and gradient directions, and contour and texture features. Tests performed on image collections both of medieval and modern coins show that algorithms performing good on modern coins do not necessarily meet the requirements for classification of medieval ones. Main difference between ancient and modern coins is that the ancient coins have no rotational symmetry and consequently their diameter is unknown. Since ancient coins are all too often in very poor conditions, common recognition algorithms can easily fail. The features that most influence the quality of recognition process are yet unexplored. The COINS project addresses this research gap and aims to provide an efficient image based algorithms for coin classification and identification. There is a basic need of highly accurate and efficient automatic coin recognition systems in our daily life. Coin recognition systems and coin 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 coin recognition systems can also be used for the research purpose by the institutes or organizations that deal with the ancient coins. There are three types of coin recognition systems based on different methods used by them available in the market:

1. Mechanical method based systems
2. Electromagnetic method based systems
3. Image processing based systems

The mechanical method based systems use parameters like diameter or radius, thickness, weight and magnetism of the coin to differentiate between the coins. But these parameters cannot be used to differentiate between the different materials of the coins. It means if we provide two coins one original and other fake having same diameter, thickness, weight and magnetism but with different materials to mechanical method based coin recognition system then it will treat both the coins as original coin so these systems can be fooled easily. The electromagnetic method based systems can differentiate between different materials because in these systems the coins 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 and magnetism can be used to differentiate between coins. The electromagnetic based coin recognition systems improve the accuracy of recognition but still they can be fooled by some game coins. In the recent years coin recognition systems based on images have also come into picture. In these systems first of all the image of the coin 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 coins are recognized. This paper presents existing systems and techniques proposed rotation invariance on image based coin recognition.
There is very less work done on recognition of ancient coins. The main reason for this is that the ancient coins do not have symmetrical boundaries like modern coins because ancient coins were hammered or casted during manufacturing whereas modern coins are minted. Also ancient coins are generally found in poor conditions due to wear or fouling. So due to irregular shape and poor condition, the general approaches of coin recognition easily fail for ancient coins.

The basic block diagram of the coin recognition is shown in the following figure. In this all the steps that have to be carried for the coin recognition is been shown below. Initially, the digital image of the coin in taken, and other steps have been performed on it. And at the end recognition is carried out.

![Diagram of coin recognition process]

**Figure 1. Basic block diagram of the coin recognition**

## II. LITERATURE SURVEY

1. In May 20112 IJECCCT paper represents algorithm for recognition of the coins of different denomination. The proposed system first uses a canny edge detection to generate an edge map, then uses CHT (Circular Hough transform) to recognize the coins and further find the radii of them. Based on the radius of the coin, the coins of different denomination are classified. The experimental result shows that the Hough transform is an effective tool for coin detection even in the presence of noise.

   In this system, CHT (Circular Hough transform) is used to detect the presence of circular shapes like coins from the input image because it has the robustness to deal with the noises in the image. CHT is a kind of HT (Hough transform) that can extract circular objects from an image. The Hough Transform was first introduced by Paul Hough in 1962 to detect straight lines in bubble chamber data, the transform consists of parametric description of a feature at any given location in the original image’s space. The HT essentially consists of two stages. In the first stage, edge map of the image is calculated then each edge point contributes a circle to an output accumulator space. In the second stage, the output accumulator space has a peak where these contributed circles overlap at the center of the original circle and then define the coordinates of the circle. The CHT has been used in several researches in detecting iris and pupil boundaries for face recognition, fingertips position detection and automatic ball recognition.
The main advantage of using HT is high reliability and it gives ideal result even in the presence of noises. Also the HT provides parameters to reduce the search time for finding Objects based on a set of edge points. In spite of its advantages, the HT has some disadvantages when it deals with large size image.

2. In IJCTIB Volume 1 tells that Coins are integral part of our day to day life. We use coins everywhere like grocery store, banks, buses, trains etc. So it becomes a basic need that coins can be sorted and counted automatically. For this it is necessary that coins can be recognized automatically. In this paper we have developed an ANN (Artificial Neural Network) based Automated Coin Recognition System for the recognition of Indian Coins of denomination `1, `2, `5 and `10 with rotation invariance. We have taken images from both sides of coin. So this system is capable of recognizing coins from both sides. Features are extracted from images using techniques of Hough Transformation, Pattern Averaging etc. Then, the extracted features are passed as input to a trained Neural Network. 97.74% recognition rate has been achieved during the experiments i.e. only 2.26% miss recognition, which is quite encouraging.

3. In 2011, Shatrughan Modi, presented the coin identification approach. In this, images of coin are taken from different angles, and create a databank. By using this databank, data is provide to the neural network and trained that network.

4. In 1992, Minoru Fukumi et al. presented a rotational invariant neural pattern recognition system for coin recognition. They performed experiments using 500 yen coin and 500 won coin. In this work they have created a multilayered neural network and a preprocessor consisting of many slabs of neurons to provide rotation invariance. They further extended their work in 1993 and tried to achieve 100% accuracy for coins. In this work they have used BP (Back Propagation) and GA (Genetic Algorithm) to design neural network for coin recognition.

5. Davidsson compares several strategies, namely induction of decision trees neural networks and Bayesian classifiers. He derives a variation of the decision tree algorithm that will reject coins if their defining attributes are outside an acceptance region. However, it is difficult to extend the approach to images. Finally, Adameck et al. presented an interesting method for a coin recognition system based on colour images. Similar approach translational invariance is achieved through segmentation, whereas rotational invariance is a result of a polar coordinate representation and correlation. Their system uses a special hardware to assure that no fraud coins are accepted by the system. In our case there is no risk that fraud images of coins will be presented to the system. Therefore, the use of colour seems to increase the computational costs unnecessarily.

III. PROPOSED COIN RECOGNITION SYSTEM

Step 1: Develop a RGB code for loading database of coin image in MATLAB. This is done by using mat file.

Step 2: After that we convert a RGB code into gray scale

Step 3: A code to recognize type of coin is developed i.e., which type of currency it is.

Step 4: After that we remove shadow of coin from image. Shadow of the coin from grey scale image is removed using Hough Transform.

Step 5: At last I apply Neural Network with rotation invariancy to analyze our proposed Algorithm. Neural Network consists mainly of two phase that is training and testing.

Coin Recognition Approaches

In this section we present recent approaches for coin recognition techniques, namely algorithms based on the eigenspace approach, gradient features, contour and texture features. Finally, we discuss some preliminary results of tests performed on the MUSCLE CIS coin dataset.

1. Coin Detection

Hough transform is based on feature points extracted from the original image and usually, edges are used as the feature points. Various edge detection methods have been used for different applications. If Sobel filter is used to a coin image, large number of edge points are obtained from texture of the coin can be regarded as noise, which will induce a huge overhead in the execution time of the Hough transform and most importantly will produce measurement errors, so technique to reduce the unwanted edge is sought. Result of applying Sobel filter to an image is shown in Fig. 3. The canny edge detector is very powerful tool for detecting edges in a noisy environment. Canny edge detector can remove most of the edge points. Canny gives thin edge compared to the Sobel. Hence, canny edge detector has used for eliminating the unwanted edges that can result from Sobel. Based on the smoothed image, derivatives in both the x and y direction are computed, these in turn are used to compute the gradient magnitude of the image. Once the gradient magnitude of the image has been computed, a process called “non maximum suppression” is performed, in which pixels are suppressed if they do not constitute a local maximum.
The final step in the canny edge detector is to use hysteresis operator, in which pixels are marked as either edges, non-edges and in-between, this is based on threshold values. The next step is to consider each of the pixels that are in-between, if they are connected to edge pixels these are marked as edge pixels as well. The result of this edge detector is a binary image in which the white pixels closely approximate the true edges of the original image as shown in Fig. 4.

In this system, CHT (Circular Hough transform) is used to detect the presence of circular shapes like coins from the input image because it has the robustness to deal with the noises in the image. CHT is a kind of HT (Hough transform) that can extract circular objects from an image. The Hough Transform was first introduced by Paul Hough in 1962 to detect straight lines in bubble chamber data, the transform consists of parametric description of a feature at any given location in the original image’s space. The HT essentially consists of two stages. In the first stage, edge map of the image is calculated then each edge point contributes a circle to an output accumulator space. In the second stage, the output accumulator space has a peak where these contributed circles overlap at the center of the original circle and then define the coordinates of the circle. The CHT has been used in several researches in detecting iris and pupil boundaries for face recognition, fingertips position detection and automatic ball recognition.

The main advantage of using HT is high reliability and it gives ideal result even in the presence of noises. Also the HT provides parameters to reduce the search time for finding objects based on a set of edge points. In spite of its advantages, the HT has some disadvantages when it deals with large size image.

Figure 2: Sample Coin image

Figure 3: Result of Sobel Filter

Figure 4: Result of Canny Edge Detection.
2. Coin Verification

In general the appearance of one coin pattern varies considerably with respect to its grey values. These variations frequently are inhomogeneous. This suggests that for recognition purposes grey values by themselves will not give us appropriate results.

On the other hand edge information remains more or less stable or at least degrades gracefully. Therefore, we based the coin recognition algorithms of Detection on edges. In principle any edge detector may be used for this purpose. But from our experience the Canny edge operator and the Laplacian of Gaussian method work satisfactorily. As a result of the edge operator we either get a binary (edge) image or a list of coordinates at edge pixel locations.

Let \( I: \mathbb{M} \times \mathbb{N} \rightarrow \mathbb{R}[0,1] \) be an intensity image. \( \mathbb{M} \times \mathbb{N} \) gives the index space and \( \mathbb{R}[0,1] \) the intensity values taken from the closed interval [0, 1].
\[
E(x, y) = \begin{cases} 
1, & \text{if } I(x, y) \text{ is an edge point} \\
0, & \text{else} 
\end{cases}
\]

3. Features Extraction

The proposed coin recognition system is equipped with two additional sensors measuring the thickness as well as the rough diameter of the current coin. At the same time they are used to trigger the imaging process. For the main results in this paper we did not use these measurements, but they deliver valuable information for the pre-selection process as well. The production system uses these measurements for a coarse pre-selection of potential master coins into the short list. In this section we derive features that help us to refine this first pre-selection. Solely based on the edge information we derive three additional types of features that in turn are invariant against rotations of the coin.

4. Recognition

Neural networks give effective results for solving multiple class classification problems. Chau [11] notes that neural network facilitate gate recognition because of their highly flexible and non linear modeling ability. Neural network has three types of layers: input layer, output layers and hidden layers. Hidden layer does intermediate computation before directing the input to output layer. Back propagation can also be considered as a generalization of delta rule. When back propagation network is cycled, an input pattern is propagated forward to the output units through the intervening input to hidden and hidden to output weights. Neural network have been widely used in image and signal processing.

![Figure 5: The basic layout of the proposed system.](image)

the following are the snapshots of the outcomes of the proposed coin recognition system used for identifying the coin by using the neural networks.

![Image showing coin recognition system](image)
Figure 6: the input coin image is loaded.

Figure 7: in this the input image is further converted into the grayscale and the detection techniques are applied on it.

Figure 8: the pre-processing is carried out.
Figure 9: the calculations carried out for the recognition of the coin by neural networks.

Figure 10: After the pre-processing we obtained the desired image.
Figure 11: the database set is created.

Figure 12: the final outcome of the proposed coin recognition system.

Figure 13: the matching accuracy is been calculated.
IV. CONCLUSIONS

This paper presents various systems developed and existing techniques for coin recognition based on image processing. In this paper we basically provide various methods of recognition of the coins and as to get the best accuracy. It was shown that the described project contributes to image based coin recognition and classification. We presented an overview of the work-packages and project partners. Thereby, coins from more than 30 countries can be recognised and separated. Unknown coins are rejected. Further research will be carried out to improve the recognition result and speed. These results are very encouraging when considering the time costs with the neural network.

The implementation to a real system ensures the following important points:

a) The Recognition rate is close to 100 percent.

b) It is a low cost system.

c) Recognition time is very less.

REFERENCES


