Volume 3, Issue 11, November 2013 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Coin Recognition System using Artificial Neural Network on Static Image Dataset-A Review

Suchika Malik*, Parveen Bajaj, Mukhwinder Kaur

ECE &M.M U Sadopur Ambala

India

Abstract— This paper presents a reliable coin recognition system that is based on a registration approach. 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.

Keywords— background subtraction, 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.

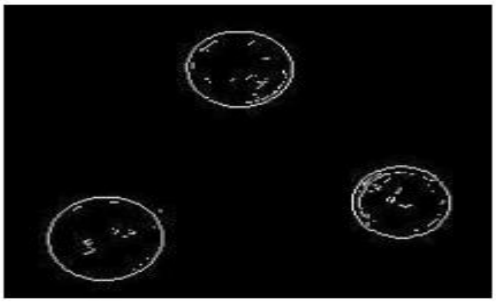


Figure 3. Result of Sobel Filter

II. 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.

2.1 Eigenspace approach

Huber et al. present in a multistage classifier based on eigenspaces that is able to discriminate between hundreds of coin classes. The first step is the preprocessing performed to obtain translationally and rotationally invariant description. Due to the controlled setup of the system presented coin detection becomes a trivial task. Rotational invariance is obtained by estimation of the rotational angle. This involves cross-correlation of the coin presented to the system with reference images. Each reference image is associated with a coin class depending on thickness (estimated from additional thickness sensor measurement) and diameter. In the second stage an appropriate eigenspace is selected. Again, based on the diameter and thickness measurements multiple eigenspaces are constructed. Thus, each eigenspace spans only a portion of the thickness/diameter plane and a moderate number of coin classes. In the last stage Bayesian fusion is applied to reach the final decision. Bayesian fusion incorporates probabilities for both obverse and reverse sides of the coin and knowledge about its orientation coherence.

2.2 Contour based algorithms

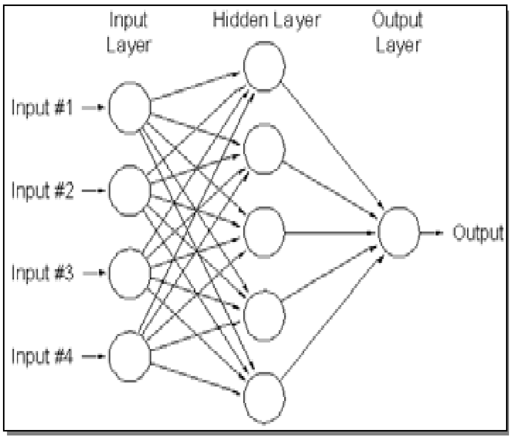
In Maaten et al. present a coin classification system based on edge-based statistical features, called COIN-O-MATIC. It was developed for the MUSCLE CIS Coin Competition 2006 focusing on reliability and speed. The system is subdivided into five stages: in the segmentation step (1) the coin is separated from the coin photograph. Next a feature extraction process measures edge-based statistical distributions (2). In order to give a good description of the distribution of edge pixels over a coin, they combine angular and distance information: edge distance measures the distance of edge pixels from the center of the coin and angular distance measures distribution of edge pixels in a coarsely discretized polar space. In the third step (3) – preselection – area and thickness measurement are used in order to obtain a reliable decision on the class of a coin. A 3-nearest neighbor approach on the two sides of the coin is applied (4). The last step (5) – verification – is only performed for coins for which the two coin sides were classified differently. It is based on mutual information of a test sample and an average coin image that corresponds to the classification assigned to the test sample. At the MUSCLE CIS Coin Competition the method achieved a recognition rate of 67.31% on a benchmark set of 10,000 coins. The Dagobert coin recognition system presented by N¨olle et al. aims at the fast classification of a large number of modern coins from more than 30 different currencies. In their system coin classification is accomplished by correlating the edge image of the coin with a preselected subset of master coins and finding the master coin with lowest distance. For the preselection of possible master coins three rotation-invariant visual features, besides sensor information of coin diameter and thickness, are used: edge-angle and edge-distance distributions similar to and a third feature counting the occurrences of different rotation-invariant patterns on circles centered at edge pixels.

2.3 Gradient based algorithm

The coin classification method proposed by Reisert et al. and presented at the MUSCLE CIS Coin competition 2006 is based on gradient information. Similar to the work of N¨olle et. al coins are classified by registering and comparing the coin with a preselected subset of all reference coins. In the preselection step the radius of the segmented coin is determined and only coins with a similar radius are taken for comparison. The registration and similarity computation of coin images is done by means of a Fast Fourier Transformation on binary images of discretized gradient directions. The final classification of a coin image is accomplished by a nearest neighbor scheme. The proposed method won the MUSCLE CIS.

2.4Neural Network

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.



Edge 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.

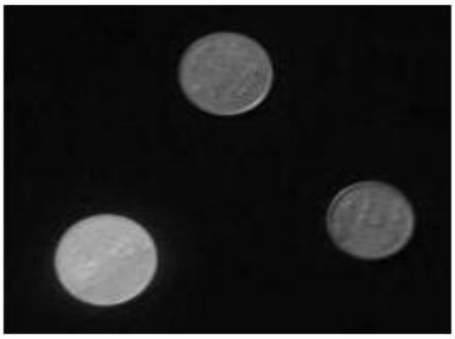


Figure 2. Sample image (Coins.jpg)

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.

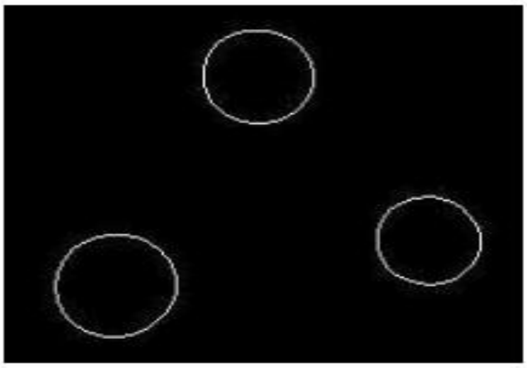


Figure 4. Result of Canny Edge detector

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.

III. CONCLUSION

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.

REFERENCES

[1] Gupta, V., Puri, R., Verma, M., "Prompt Indian Coin Recognition with Rotation Invariance using Image Subtraction Technique", International Conference on Devices and Communications (ICDeCom), 2011.

[2] Chen, H. "Chinese Coin Recognition Based on Unwrapped Image and Rotation Invariant Template Matching", Third International Conference on Intelligent Networks and Intelligent Systems, 2010

[3] Bremananth.R, B.Balaji, M.Sankari, A.Chitra, (2005), „A New approach to Coin recognition using Neural Pattern Analysis‟, IEEE Indicon Conference, pp 366-370.

[4] Huber Reinhold., Herbert Ramoser, Konrad Mayer, HaraldPenz, Michael Rubik, (2005), Pattern Recognition Letters, 26, pp 61-75.

[5] Adameck. M, Hossfeld.M, and M. Eich, (2003), *Three color selective stereo gradient method for fast topography recognition of metallic surfaces*, Proceedings of Electronic Imaging, Science and Technology (Martin A. Hunt and Jeffery R. Price, eds.), Machine Vision Applications in Industrial Inspection XI, vol. SPIE 5011, pp. 128–139.

[6] Petra Perner, (2002), „Are case-based reasoning and dissimilarity-based classification two sides of the same coin?‟, Artificial Intelligence, pp 193-203.

[7] Fukumi.M, Mitsukura.Y, Norio Akamatsu, (2000), „Design and Evaluation of neural Networks for Coin Recognition by using GA and SA‟, IEEE, pp 178-183.

[8] Sivanandam, S. N., Sumathi, S. and Deepa, S. N. (2000), "Introduction to Neural networks using MATLAB 6.0", Mc-Graw Hill, Computer Engineering Series.

[9] Gonzalez.R.C and Richard E. Woods, (1999), *Digital image processing*, Addison-Wesley Publishing Company.

[10] Earl Gose, Richard Johnson Baugh, Steve Jost, (1999), „Pattern Recognition and Image Analysis‟, PHI.

[11] Milan Sonka, Vaclav Hlavac, Roger Boyle, (1999), „Image Processing, Analysis, and Machine Vision‟, PWS Publishing Company.

[12] Davidsson.P, (1996), *Coin classification using a novel technique for learning characteristic decision trees by controlling the degree of generalization*, Ninth International Conference on Industrial and Engineering Applications of Artificial Intelligence & Expert Systems (IEA/AIE-96), Gordon and Breach Science Publishers, pp. 403–412.

