A SURVEY : COIN RECOGNITION TECHNIQUES USING ANN

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Abstract: The objective of this paper is to classify recently released Indian coins of different denomination. The objective is to recognize the coins and count the total value of the coin in terms of Indian National Rupees (INR).

Keywords: Neural networks, ICIS, Edge detection, Pattern recognition, and Threshhold.

I. INTRODUCTION

Pattern recognition researches and applications attempt to install in computers some of the cognitive capabilities of humans where one of the hallmarks of the human pattern recognition system is its extreme flexibility. How the visual system represents the appearance of objects to enable these recognition capacities has not been resolved yet [1]. However, we are able to simulate our perception of objects and pattern recognition in intelligent machines using mathematical representation and acquisition of patterns or objects by the neural network mechanisms. Coin identification using these mathematical representation and acquisition phases in pattern recognition system has an advantage over the conventional identification methods that are used commonly in slot machines. Most of the coin testers in slot machines, work by testing physical properties of coins such as size, weight and materials using dimensioned slots, gates and electromagnets. However, if physical similarities exist between coins of different currencies, then the traditional coin testers would fail to distinguish the different coins. One such case is the identification of the 2 Euro (EURO) and the new Turkish 1 Lira (TL) coins [2]. The 1 TL coin resembles very much the 2 EURO coin in both weight and size and both coins seem to be recognized and accepted by slot machines as being a 2 Euro coin, which is roughly worth 4 times more than a 1 TL coin [3], [4].

Several coin recognition systems were previously developed and showed encouraging results. Fukumi et al [5] described a system based on a rotation-invariant neural network that is capable of identifying Japanese coins. Rotational invariance is achieved by explicitly generating the rotational group for a coarse model of the coin in a preprocessing step and feeding the results into a neural network. The generated segments contain pixels which are presented onto various slabs that are presented as the neural network inputs. This approach has the advantage of identifying rotated coins at any degree, however, the use of slabs is time consuming [6]. Other methods for coin identification include the use of coin surface colour [7] and the use of edge detection of coin patterns [8]. The use of colour seems to increase the computational costs unnecessarily, whereas edge based pattern recognition has noise sensitivity problem.

This paper presents the development and implementation of an intelligent coin identification system (ICIS) that uses coin patterns for classification. This system is intended to be used as a support tool to standard physical measurements in slot machines. ICIS uses pattern averaging of coin images prior to training a back propagation neural network using the processed images. ICIS is a rotation-invariant system that identifies both sides of a coin rotated by 150 degrees. A real life application will be presented by implementing ICIS to correctly identify the 2 EURO and 1 TL coins.

II. COIN REPRESENTATION AND TRAINING

Mathematical representations of coin patterns in the proposed Intelligent Coin Identification System (ICIS) are gained by applying compression, segmentation and pattern averaging to the coin images prior to training the neural network.

The original captured coin image is in RGB color and with the dimensions of 352x288 pixels. First, the mode of the pattern is converted into grayscale. Second, the grey coin image is cropped to an even size image of 250x250 pixels. Third, the cropped grey coin image undergoes thresholding using a threshold value of 135, thus converting the image into black and white image. Finally, the thresholded image is compressed to 125x125 pixels and then trimmed to 100x100 pixels image that contains the patterns of the coin side. The 100x100 pixel image will provide the input data for the neural network training and testing. However, in order to provide a faster identification system, the 100x100 pixel image is further reduced to a 20x20 bitmap that represents the original coin image. This is achieved by segmenting the image using segments of size 5x5 pixels, and then taking the average pixel value within the segment, as shown in the following equations.

$$Segi = ((Sumi)/D)/256 \tag{1}$$

$$D = (TPx.TPy)/S \tag{2}$$

where **Segi** is the segments number,
Sumi is the summation of the defined segments and
D is the total number of each pixel,
TP denotes the x and y pixel size of image and S is the total segment number.

Various preprocessing techniques have been used to make the input image suitable for the algorithm. In order to reduce the noise from the image, Gaussian filter has been used to

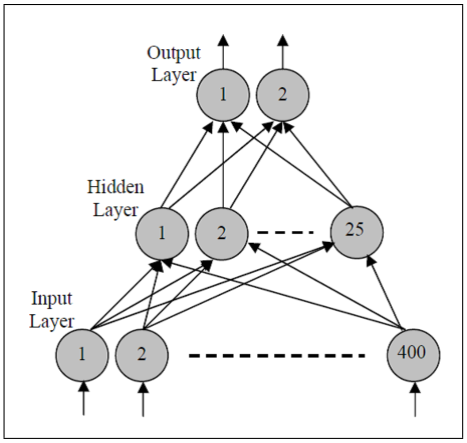

Figure 1: Neural Network Topology of ICIS

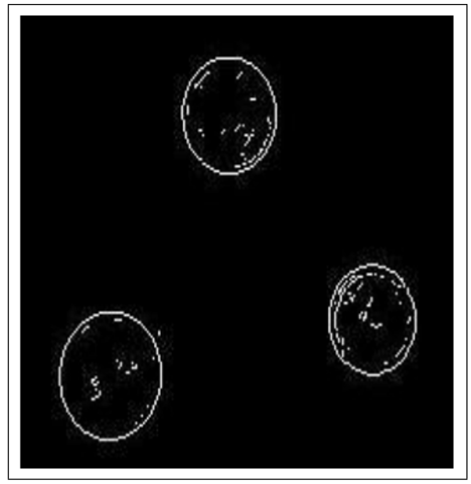

Figure 3: Result of Filtration

smooth the image, and then an appropriate gray level thresholding is done to obtain a binary image.

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.

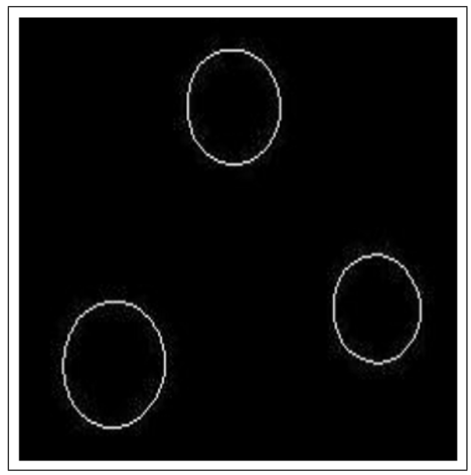

Figure 4: Result of Edge Detection

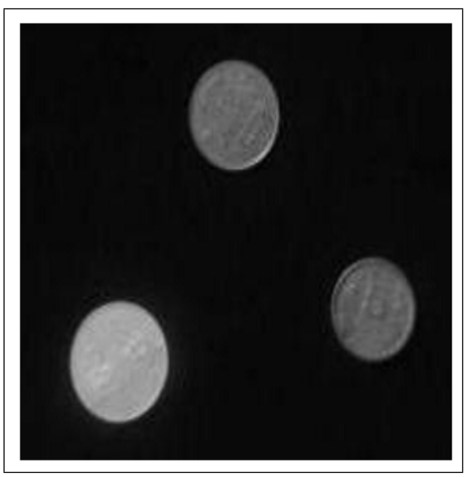

Figure 2: Sample Images

III. RELATED STUDY

Several coin recognition approaches are mentioned in the literature.

In 1992 [10] 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 [11] 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. Adnan Khashman et al. [12] presented an Intelligent Coin Identification System (ICIS) in 2006. ICIS uses neural network and pattern averaging for recognizing rotated coins at various degrees. It shows 96.3% correct identification i.e. 77 out of 80 variably rotated coin images were correctly identified. Mohamed Roushdy [13] had used Generalized Hough Transform to detect coins in image. In our work we have combined Hough Transform and Pattern Averaging to extract features from image. Then, these features are used to recognize the coins. Robinson and McIlroy [14] apply genetic programming techniques to the problem of eye location in grey-level face images. The input data from the images is restricted to a 3000-pixel block around the location of the eyes in the face image. This approach produced promising results over a very small training set, up to 100% true positive detection with no false positives, on a three-image training set. Over larger sets, the genetic programming approach performed less well however, and could not match the performance of neural network techniques. Winkler and Manjunath [5] produce genetic programmes to locate faces in images. Face samples are cut out and scaled, then preprocessed for feature extraction. The statistics gleaned from these segments are used as terminals in genetic programming which evolves an expression returning how likely a pixel is to be part of a face image. Separate experiments process the grey scale image directly, using low-level image processing primitives and scale-space filters. Zhang et al. [8] uses genetic programming for a number of object classification and detection problems. Typically, low-level pixel statistics are used to form the terminal set, the four arithmetic operators are used to construct the function set, and the fitness functions are based on either classification accuracy or error rate for object classification problems, and detection rate and false alarm rate for object localization and detection problems. Good results have been achieved on classification and detection of regular objects against a relatively uncluttered background. Since the work to be presented in this paper focuses on the use of genetic programming techniques for object recognition.

IV. IMPLEMENTATION DETAILS

Coin recognition process has been divided into seven steps. The architecture of Automated Coin Recognition System is shown in Fig.

Pattern Recognition :

There are two basic approaches in pattern recognition. They are statistical approach and structural approach. In the first approach, the pattern is represented as a vector in a feature space. Then a decision algorithm, which is mainly based on the statistical concept, is used to decide to which class the pattern belongs. In the structural method, the pattern is represented by its structure. For example, a string of symbols, a graph connecting the primary elements, etc. The statistical method can be broadly classified into classical and Artificial Neural Networks (ANN) approaches [10,11]. No single technique or model is suited for all Pattern Recognition (PR) problems. Hence, different types of PR approaches are to be adopted [7]. The coin classification technique is based on the following assumptions and computations :

1) The coins should move on a conveyor belt.
2) Proper lighting is to be focused on the coin.
3) Each coin is separated and fed to the system for recognition.
4) Coins are weighed accurately.
5) Both sides of the coin are to be collected.
6) The side view of the coin image can be captured.
7) The coin image can be rotated by any degree.
8) The Circular, Hexagon, Octagon, Polygon shape of coin's radius are measurable.
9) The coin Circumference/Perimeter and area are to be computed.
10) The thickness of each coin can be computed by the system.

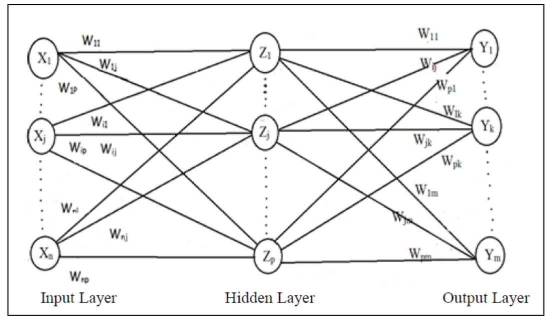

Figure 5: pre-Processing Image

11) The coin images with 256 gray values are to be computed.
12) The coin average gray values are computable.

Coin Counting System :

The coin baskets are mounted on the outside of the cabinet and are positioned at the most convenient height. They are fabricated from a durable plastic with the properties of flexibility and strength. Within the basket, is a flexible shock-absorbing back sheet, designed to dissipate energy and reduce the velocity of the coins as they are moved in. The system is modified for sorting Indian Coins. The standard features of coin recognition system are as follows:

1) Electromagnetic sampling coin detection.
2) Rejection of unauthorized coins.
3) Automatic removal of other objects.
4) Extensive self-diagnostics.
5) Unique anti-jamming facility on coin pickup wheel.
6) Local and remote alarm indications.
7) Modular design for ease of maintenance and repair.
8) Surge protection filters.

Pre-Processing :

The Zooming and de-zooming are the important processes by which a coin image is increased or decreased in size. The zooming helps us to make the size of the coin image bigger, by which recognition rate is increased.

Data Acquisition :

Usually the ordinary Cartesian coordinate system is used to represent a pixel of an image. In this system, g(x, y) is the gray level at the pixel (x, y). Images can alternatively be thought of as ordinary matrices in which the gray level of a pixel is represented as g1(i, j). The Table 1 stores values for parameters of each coin and fed to the system [15].

V. CONCLUSION

We have presented methods for coin classification and identification applicable to coin collections comprising either a large number of coin classes, e.g. modern coins, or high intra-class variation, e.g. ancient coins. In order to facilitate prevention

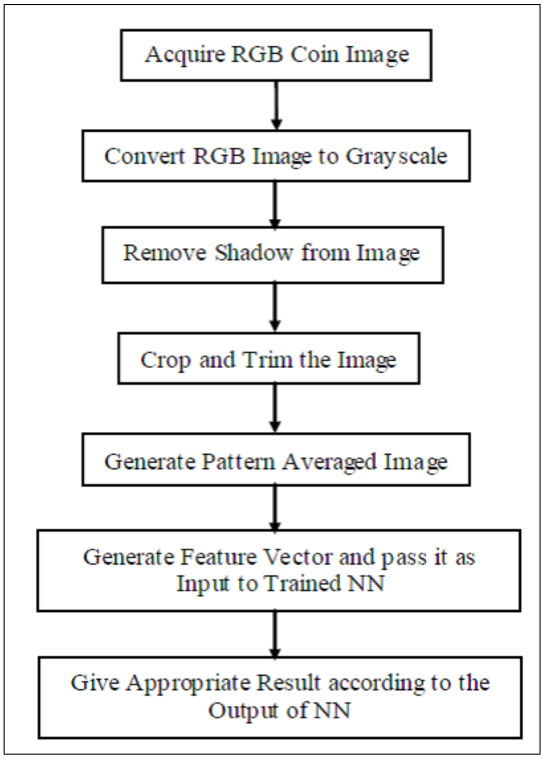

Figure 6: Architecture for Automatic Coin Recognition

and repression of illicit trade of stolen ancient coins technologies aimed at allowing permanent identification and traceability of coins become of interest. The results for classification of modern coins and identification of ancient coins are regarded to be almost perfect. Due to large intra-class variance, the classification of ancient coins is still a challenging task, especially if attempted from single 2D images. An ANN based automated coin recognition system has been developed using MATLAB. In this system, firstly reprocessing of the images is done and then these preprocessed images are fed to the trained neural network.

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