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Coin Identification Using Neural Networks

ADNAN KHASHMAN, BORAN SEKEROGLU, KAMIL DIMILILER
Electrical & Electronic Engineering Department
Near East University
Nicosia, Dikmen Road
CYPRUS

Abstract: - Neural networks have been used in the development of intelligent systems that simulate pattern recognition and object identification. Coin identification by machines relies currently on the assessment of the physical parameters of a coin. An intelligent coin identification system that uses coin patterns for identification helps preventing confusion between different coins of similar physical dimensions. This paper proposes a rotation-invariant intelligent coin identification system (ICIS) that uses a neural network and pattern averaging to recognize rotated coins by 15 degrees. Slot machines in Europe accept the new Turkish 1 Lira coin as a 2 Euro coin due to physical similarities; however, the 2 Euro coin is roughly worth 4 times the new Turkish 1 Lira. ICIS was implemented to identify the 2 EURO and the 1 TL coins and the results were found to be encouraging.

Key-Words: - Intelligent System, Coin Recognition, Pattern Averaging, Neural Networks

1 Introduction

Pattern recognition researches and applications attempt to instill 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 15^o degrees. A real life application will be presented by implementing ICIS to correctly identify the 2 EURO and 1 TL coins.

2 The Coins

There are 12 European countries that use the Euro as the official currency. All 2-EURO coins have the same design on the obverse side but different designs for each European country on the reverse side [9]. The implementation of ICIS involves distinguishing the 2 EURO coins from the 1-TL coin. Three coins are used for this purpose: two 2-EURO coins of Finland and Italy, and one 1-TL coin of Turkey.

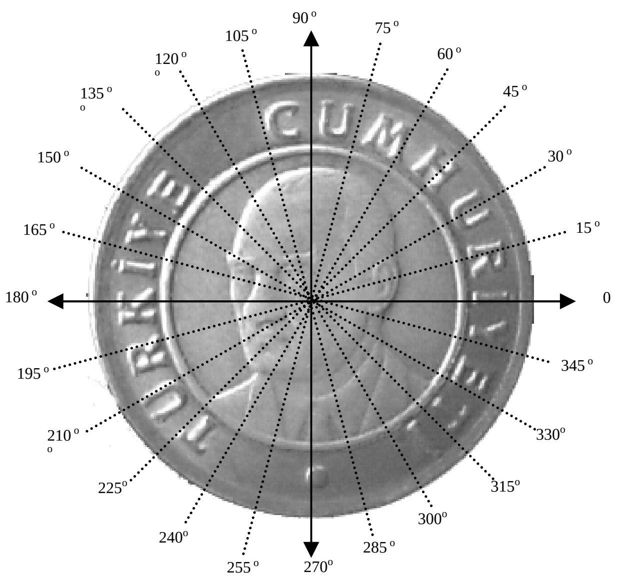
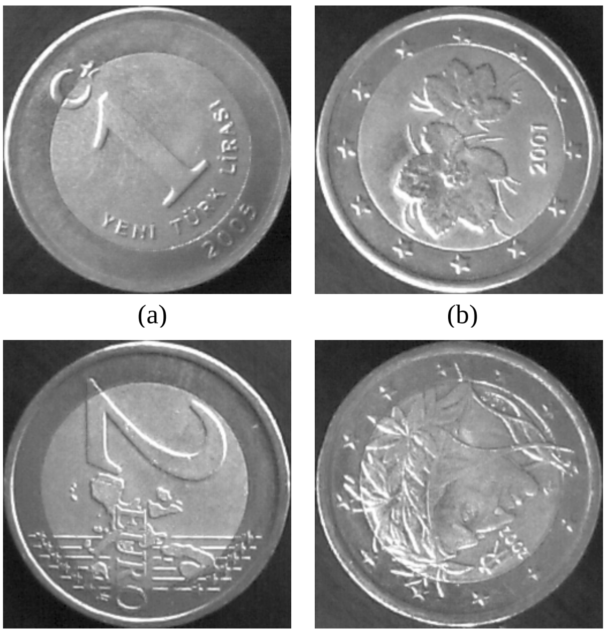


Fig.1 Rotation Degrees of 1-TL coin reverse side.



(a) (b) (c) (d)

Fig.2 Examples of Rotated Coin Patterns (a) 45° Rotated 1 TL (b) 90° Rotated 2 Euro of Finland (c) 270° Rotated 2 Euro Common (d)135° Rotated 2 Euro of Italy.

Table 1. Number of coin patterns at 15 ° rotations

Patterns	Obverse	Reverse	Total
2-EURO images	24	48	72
1-TL images	24	24	48
Total	48	72	120

Images of the obverse and reverse sides of the three coins were captured using a Creative WebCam (Vista Plus). The coins were rotated at intervals of (15°) degrees as shown in Figure 1, and images of rotated coins were captured. For example, rotation by 15° results in 48 images of the 1-TL coin (24 obverse sides and 24 reverse sides) and 72 images of the 2-EURO coins (24 obverse sides, 24 reverse sides of Finland and 24 reverse sides of Italy). 20 of the captured images (at 0°, 90°, 180° and 270° degrees rotations) were used for training the neural network within ICIS. This method of rotation using 15° degree interval is considered sufficient for all possible rotations of a coin in a slot machine, thus providing rotation invariance for ICIS and sufficient image database for training and testing the neural network. Table 1 shows the number of coin images obtained using rotation interval of 15° degree. Figure 2 shows examples of rotated coins.

3 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.

$$Seg_i = \left(\left(Sum_i\right)/D\right)/256 \quad (1)$$

$$D = \left(TP_x . TP_y\right)/S \quad (2)$$

where Seg_i is the segments number, Sum_i 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.

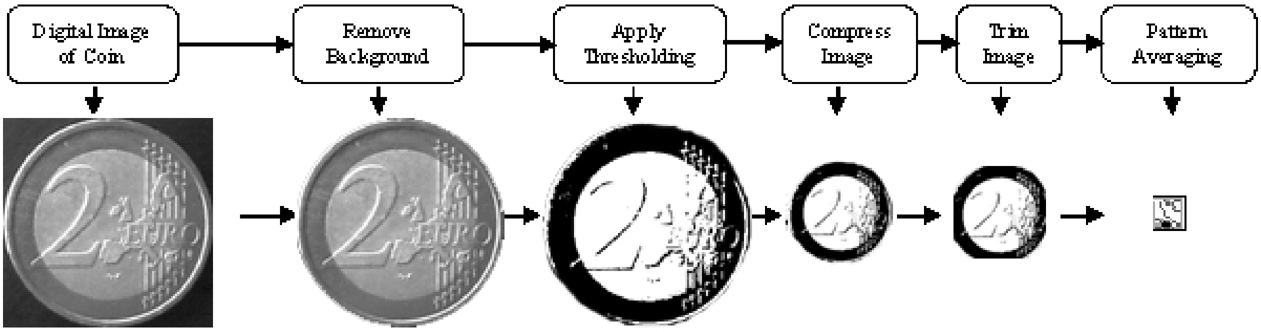


Fig.3 Coin pattern averaging process

This pattern averaging method which is shown in Figure 3 for reducing image data prior to presentation to a neural network provides meaningful learning and marginally reduces the processing time [10]. For the work presented within this paper, pattern averaging overcomes the problem of varying pixel values within the segments as a result of rotation, thus, providing a rotation invariant system. Using a segment size of 5x5 pixels, results in a 20x20 bitmap of averaged pixel values that will be used as the input for the second phase which is neural network training and testing.

ICIS uses a 3-layer back propagation neural network with 400 input neurons, 25 hidden neurons and 2 output neuron; classifying the 1 TL and the 2 EURO coins. Figure 4 shows the topology of the neural network.

The neural network is trained using only 20 coin images of the available 120 coin images. The 20 training images are of rotated coins at (0^o, 90^o, 180^o and 270^o degrees) resulting in 8 (4 obverse and 4 reverse) 1-TL coin images and 12 (4 obverse, 4 reverse of Italy and 4 reverse of Finland) 2-EURO coin images. The remaining 100 coin images are the testing images which are not exposed to the network during training and shall be used to test the robustness of the trained neural network in identifying the coins despite the rotations.

During the learning phase, initial random weights of values between –0.6 and 0.6 were used. The learning rate and the momentum rate; were adjusted during various experiments in order to achieve the required minimum error value and meaningful learning. An error value of 0.001 was considered as sufficient for this application. Table 2 shows the final parameters of the trained neural network.

Table 2**.** Trained neural network final parameters

Input Layer Nodes	400
Hidden Layer Nodes	25
Output Layer Nodes	2
Learning Rate	0.009
Momentum Rate	0.68
Minimum Error	0.001
Iterations	835
Training Time	18 seconds*

*****using a 2.4 GHz PC with 256 MB of RAM, Windows XP OS and Borland C^{++} compiler

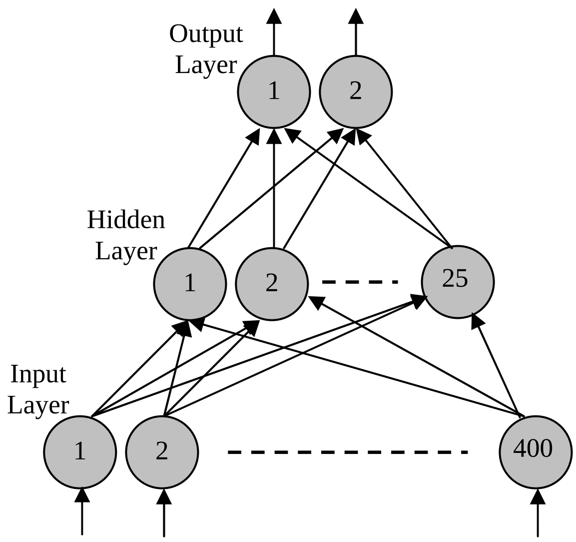


Fig. 4 Neural Network Topology of ICIS

4 Simulation Results

The Intelligent Coin Identification System (ICIS) was implemented using the C-programming language. The neural network learnt and converged after 835 iterations and within 18 seconds of training. The processing time for the generalized neural network after training and using one forward pass, in addition to the image preprocessing phase was a fast 0.03 seconds. These results were obtained using a 2.4 GHz PC with 256 MB of RAM, Windows XP OS and Borland C^{++} compiler. The robustness, flexibility and speed of this novel intelligent coin identification system have been demonstrated through this application.

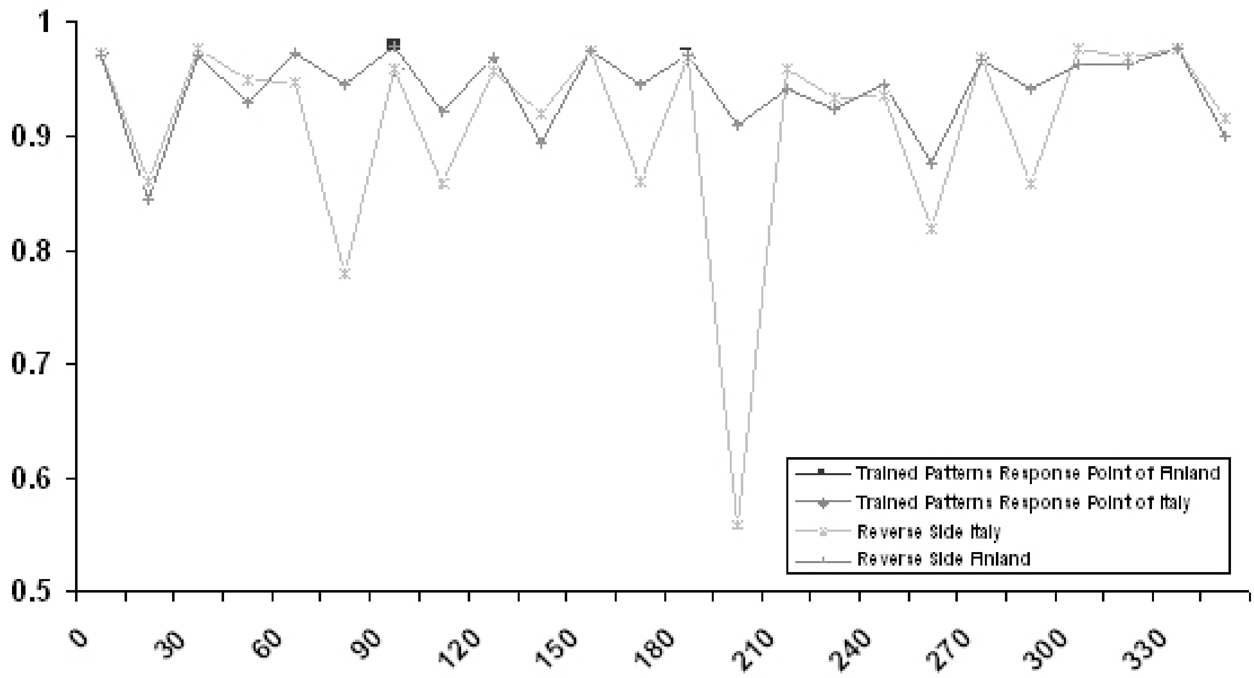


Fig. 5 Output response for trained and tested patterns of 2-Euro coins- Finland and Italy reverse side

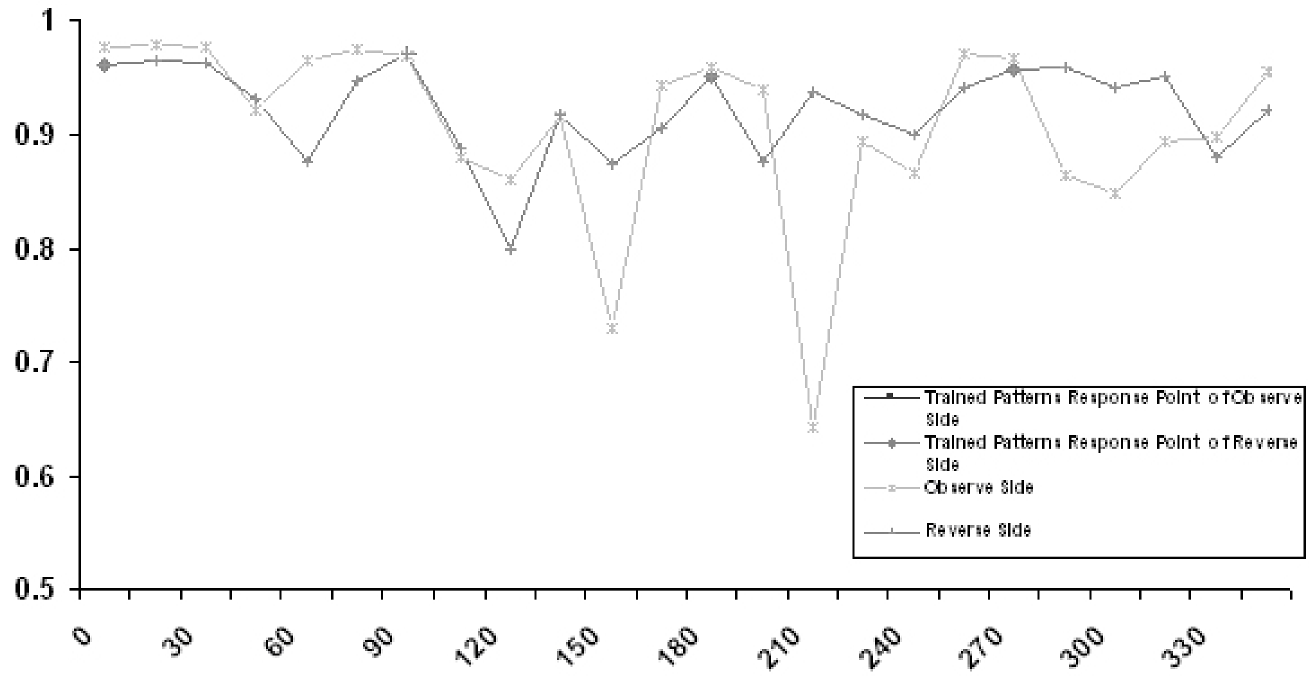


Fig. 6 Output response for trained and tested observe – reverse sides of 1-TL coin

Coin identification results using the training image set yielded 100% recognition as would be expected. ICIS identification results using the testing image sets were successful and encouraging.

The results of implementing ICIS using 40 testing images of the 1-TL coin yielded a 92.5% recognition rate where 37 out of the 40 testing images were identified. The total recognition rate for the 1-TL coin using both training and testing images was 93.75% with 45 out of the available 48 1-TL coins being correctly identified.

The results of applying ICIS using 60 testing images of the 2-EURO coins yielded a 96.67% recognition rate where 58 out of the 60 testing images were successfully identified.

Table 3. ICIS implementation results

Coin	Coin Image Set	Recognition Rate
2-EURO	Training	12/12 (100 %)
	Testing	58/60 (96.67 %)
	Combined	70/72 (97.22 %)
1-TL	Training	8/8 (100%)
	Testing	37/40 (92.5 %)
	Combined	45/48 (93.75 %)
Total		115/120 (95.83%)

The total recognition rate for the 2-Euro coins using both training and testing images was 97.22% with 70 out of the available 72 2-EURO coins being correctly identified.

In summary, the recognition rate for all testing images that were not previously exposed to the neural network was a successful 95% with 95 out of 100 testing images correctly recognized. The overall recognition rate using testing and training coin images of both TL and EURO coins was 95.83%. Table 3 shows the coin identification results in details. Figures 5 and 6 show the output responses for different rotated patterns

5 Conclusions

This paper presented a novel coin identification system that uses coin surface patterns and a neural network for identification of rotated coins at intervals of 15^o degrees. This rotation invariant **I**ntelligent **C**oin **I**dentification **S**ystem, abbreviated as ICIS, uses image preprocessing as its first phase, where meaningful representations of coin patterns are provided while reducing the amount of data within the result images. A back propagation neural network receives the optimized data representing the coin images and learns the coin patterns in the second phase. ICIS has been successfully implemented as shown in this paper to identify the 2-EURO and 1-TL coins. This solves a real life problem where physical similarities between these coins led to slot machine abuse in Europe. However, ICIS can also be trained to recognize other coins providing it is trained using the additional coins prior to use. ICIS can be used as a support tool to standard physical measurements in slot machines.

An overall 95.83% correct identification of both the EURO and the TL coins has been achieved, where 115 out of 120 rotated coin images, were correctly identified. Rotation by intervals of 15^o degrees provides sufficient coin image database for a robust learning of the neural network within ICIS.

These results are very encouraging when considering the time costs. The neural network training time was 18 seconds, whereas the ICIS run time for both phases (image preprocessing and neural network generalization) was 0.03 seconds.

Future work will focus on training ICIS to recognize all varieties of Euro coins in addition to those of Finland and Italy.

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