Review Article *ISSN: 2319-507X*
Ashwini Dakhode, IJPRET, 2013; Volume 1(8): 640-651 *IJPRET*

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

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COIN RECOGNIZATION USING GENETIC ALGORITHM: A REVIEW

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Accepted Date:

27/02/2013

Publish Date:

01/04/2013

Keywords

Artificial Neural Network,

Genetic algorithm,

Pattern Matching,

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Abstract

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 Genetic algorithm. 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.

Introduction

We cannot imagine our life without coins. We use coins in our daily life almost everywhere like in banks, supermarkets, grocery stores etc. They have been the integral part of our day to day life. So there is basic need of highly accurate and efficient automatic coin recognition system. 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 available in the market based on different methods:

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 dia meter, 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 method 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 [1, 2], Gabor Wavelets [3], DCT, edge detection, segmentation, image subtraction [4], decision trees [5] etc and various features are extracted from the images. Then based on these features different coins are recognized.

Automatic machines are used for Coins classification and recognition to find the sum of the coin is quite complicate. In this paper, it is proposed a coin recognition method by Genetic algorithm. The effectiveness of the coins classification is ensured based on the parameters of the coin. Moreover, the variations in images obtained from new and old coins are also discussed. The polar coordinate image of coin on circles with different radii is used as the feature for coin recognition. Finally, the knowledge base of the coin is fed to the recognition system to classify the coin easily. For a given coin, image is scanned and stored as gray values in a matrix. The intensity of the pixel is maximized. The Genetic algorithm is adapted to classify the coin after pre-processing of the image. We present a coin classification which is able to discriminate between many coin classes. The approach described is a multistage procedure. In the first stage a translational and rotationally invariant description is computed. Correct decision into one of the different coin classes and the rejection class, i.e., correct classification or rejection, was achieved for 99.23% of coins in a test sample containing 10,000 coins. False decisions, i.e., false classification, false rejection or false acceptance, were obtained for 0.67% of the test coins. The classification of these coins according to their denomination in the field of application for the method is presented in this paper. The basic idea of the method can be seen from the coin image of detecting a straight line in coin image [Duda and Hart 72]. The criteria for coin classification can be based on gray-level, color, texture, shape, model, etc, are discussed by R. Bremananth [1]. The method which specifically addresses coin segmentation based on color or gray value is reported by P. Thumwarin and Petra Perner [2, 6]. Many serious problems like shape, peak detection in surface of the coins are reported by Reinhold Huber [3]. An attempt has been made to use genetic algorithm techniques to recognize most of the coin images.

Classification tasks arise in a very wide range of applications, such as detecting faces from video images, recognizing words in streams of speech, diagnosing medical conditions from the output of medical tests, and detecting fraudulent credit card fraud transactions [11, 15]. In many cases, people (possibly highly trained experts) are able to perform the classification task well, but there is either a short-age of such experts, or the cost of people is too high. Given the amount of data that needs to be classified, automatic computer-based classification programmes/systems are of immense social and economic value. A classification programme must correctly map an input vector describing an instance (such as an object image) to one of a small set of class labels. Writing classification programmes that have sufficient accuracy and reliability are usually very difficult and often infeasible: human programmers often cannot identify all the subtle conditions needed to distinguish between all instances of different classes. Genetic programming (GP) is a relatively recent and fast developing approach to automatic programming [4, 23, and 24]. In GP, solutions to a problem can be rep-resented in different forms but are usually interpreted as computer programmes. Darwinian principles of natural selection and recombination are used to evolve a population of programmes towards an effective solution to specific problems. The flexibility and expressiveness of computer programme representation, combined with the powerful capabilities of evolutionary search, make GP an exciting new method to solve a great variety of problems. Strength of this approach is that evolved programmes can be much more flexible than the highly constrained, parameterized models used in other techniques such as neural networks and support vector machines. GP has been applied to a range of object recognition tasks such as shape classification, face identification, and medical diagnosis with some success.GP research has considered a variety of kinds of classifier programmes, using different programme representations, including tree or tree-like classifiers, decision tree classifiers, classification rule sets [24], and linear and graph classifiers[4]. Recently, tree-like numeric expression representation classifiers have been developed using GP [3, 8]. In these years, this form has been successfully applied to some real-world classification problems such as detecting and recognizing particular classes of objects in images [22] demonstrating the potential of GP as a general method for classification problems. Tree-like numeric expression GP classifiers model a solution to a classification problem in the form of a mathematical expression, using a set of arithmetic and mathematical operators, possibly combined with conditional/logic operators such as the "if-then-else" structures commonly used in computer programmes. The output of a tree-like numeric expression GP classifier is a numeric value that is typically translated into a class label. For the simple binary classification case, this translation can be based on the sign of the numeric value [17]; for multiclass problems, finding the appropriate boundary values to separate the different classes is more difficult. The simplest approach—fixing the boundary values at manually chosen points—often results in unnecessarily complex programmes and could lead to poor performance and very long training times [3,5,9]

2. Literature review

In 1992 [6] 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 [7] 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. [8] 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 [9] 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. In section 3 implementation details are given. In section 4 we have presented training and testing data. Then, in section 5 the experimental results are provided. Then, in section 6 we have concluded the work.

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.

3.Our Proposed Method

Training Phase

1. Select Indian Coin images of front & back side.
2. Crop images so that only an effective

area should remains.

3. Detect Edges on Images using Edge Detector filter.
4. Find centroid of Images & save it into data file.
5. Train edges Image using Neural Network with genetic algorithm.
6. Save Neural Network file.

Testing Phase

1. Select Test Image.
2. Detect Edge using Edge Detector filter.
3. Find centoid of an Image
4. Input an Image to ANN.
5. ANN will locate patterns from train images directory into input coin image.
6. Detect area of coin in an input image.
7. Show Result.
8. Stop

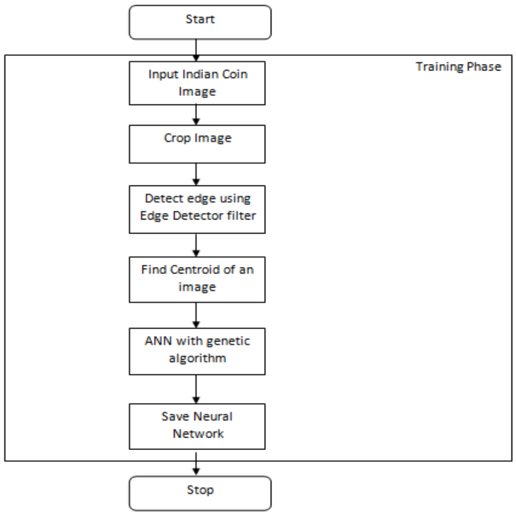

Figure 3.1 training Phase of Coin Recognization Method

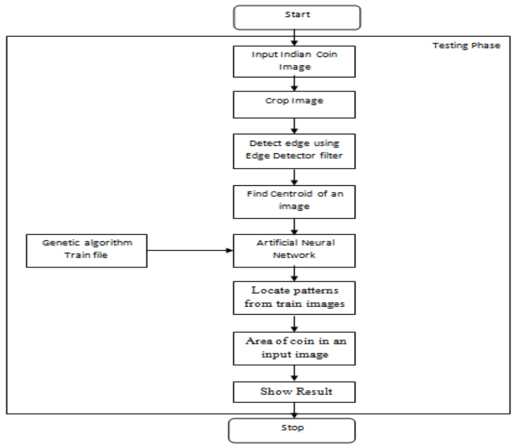

Figure 3.2 training Phase of Coin Recognization Method

For object classification problems, terminals generally correspond to image features. Some conventional approaches to image recognition usually use high-level, Domain specific features of images as inputs to a learning/classification system, which generally involves a time consuming feature selection and a hand crafting of feature extraction programmes. In this approach, we used pixel level, domain-independent statistical features (referred to as pixel statistics) as terminals. We expect that the GP evolutionary process can automatically select features that are relevant to a particular domain to construct good genetic programmes. Four pixel statistics are used in this approach: the average intensity of the whole object image, the variance of intensity of the whole object image, the average intensity of the central local region, and the variance of intensity of the central local region.

Problems	Applications
Object Classification	Tank detection
	Letter recognition
	Face recognition
	Small target classification
	Shape recognition
	Eye recognition
	Texture classification
	Medical object classification
	Shape and coin recognition
Object Detection	Orthodontic landmark detection
	Ship detection
	Mouth detection
	Small target detection
	Vehicle detection
	Medical object detection
Other Vision Problems	Edge detection
	San Mateo trail problem
	Image analysis
	Model Interpretation
	Stereoscopic Vision
	Image compression

Figure 3.3 *Object recognition related work based on genetic programming.*

4.Summary & discussion

In summary, the results suggest that the SCBD method could perform well on relatively easy object classification problems if the classes were arranged in their ordinary order (such as Shape1), but would perform badly when the classes were out of this order (as in Shape2) or when the classification problems became more difficult (such as Coin1, Coin2, and Face datasets). This is mainly because a high degree of nonlinearity is required to map the class regions on the programme out-put to the object features in these situations. The performances of all the three methods on Coin1, Coin2, and the Face datasets were worse than the two shape datasets, reflecting the fact that the classification problems in these datasets are more difficult than in the two shape datasets. Because these problems were harder, more features might need to be selected, extracted and added to the terminal set. Also more powerful functions might also need to be applied in order to obtain good performance. However, the investigation of these developments is beyond the goal and the scope of this chapter. We leave this for the future work. In terms of the classification performance, the CDCBD method performed better than the SDCBD method for all of the datasets investigated here. In particular, the CDCBD method achieved over 90% of accuracy for the difficult problems in Coin2 and Face datasets, which was significantly better than the other two methods. Also notice that this method resulted in the least standard deviation over 50 runs among all the three methods investigated here. For training generations, it seems that the computational cost of the CDCBD method is also lower than the SDCBD method for the two shape datasets, but slightly higher for the three difficult problems in the coin and the face datasets. However, if a slightly higher computational cost can lead to clear improvement in classification performance, this will be a small price to pay in most situations.

5.Conclusion

The goal of this chapter was to investigate and explore dynamic class boundary determination methods as class translation rules in genetic programming for multiclass object classification problems, and to determine whether the new dynamic methods could outperform the static method. Two classification methods, CDCBD and SDCBD, were developed and implemented where the class boundaries were dynamically determined during the evolutionary process. The two dynamic methods were examined on five datasets in three object image groups providing object classification problems of varying difficulty. The results showed that the static method, SCBD, performed very well on the relatively easy, linearly separable object classification problems where the classes were arranged in their ordinary order, but performed less well when the classes were arranged in an arbitrary order. The two dynamic methods, CDCBD and SDCBD, always outperformed the static method on all the object classification problems in the five datasets in terms of both classification performance and the training convergence. The centered dynamic method achieved better classification performance than the slotted dynamic method for all cases. Although developed for object image classification problems, these two dynamic methods are also expected to be applied to other classification problems. For future work, we will investigate whether the performance on the relatively difficult coin and face datasets can be improved if more features are added to the terminal set. We will also compare the performance with other long-term established methods such as decision trees and neural networks

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