A Robust Rotation Invariant Coin Recognition System

Thesis submitted in partial fulfillment of the requirements for the award of degree of

Master of Technology

in

Computer Science and Applications

Submitted By

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled "*A Robust Rotation Invariant Coin Recognition System*" in partial fulfillment of the requirements for the award of degree of Master of Technology in *Computer Science and Application* submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Mr. Shatrughan Modi* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

Coins have been the integral part of our day to day life since the ancient civilizations. In comparison to paper currency coin are easy to carry, requires less maintenance and can be used for a longer period of time. Moreover, commemorative coins issued by the governments were a common practice to mark important events and personalities. The coins are used frequently in places like grocery stores, banks, trains, buses, etc. With increase in coins usage and introduction of new automated machines that can use coin as a token to provide services, the need for coins to be recognized, counted, sorted automatically arises. In this thesis A Robust Rotation Invariant Coin Recognition System is proposed that takes into consideration various features of the coins (radius, color, rotation and texture) for the recognition.

The system can recognize Indian coins of denominations of Rs.1, 2, 5 and 10. The system takes as input a RGB coin image of single side i.e. tail. The image is then pre-processed to remove the unwanted part to find out the radius using Hough transform. Then the color comparison is performed by comparing the RGB channels. After that rotation of the input coin is checked to find out whether it is rotated by using multi-level image subtraction technique. If the coin is rotated then it is rotated back to our desired position. In the end texture comparison is done using the LBP operator. If coin passes all the tests, then it will be recognized among one of the database coins. The system provides high recognition rate on the Indian coins as specified in given experimental results.

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Chapter 1
Introduction

1.1 Indian Coins

India got its independence from Britain on 15 August 1947 but the old coins from pre-independence were still in trend as a frozen currency till India became Republic in 1950. The initial post-independence currencies used in Republic of India are Rupee coins that were minted in 1950. From the past, Indian coins have been evolved through various series as follows.

- The Frozen Series 1947-1950
- The Anna Series 1950-1957
- The Decimal Series
    - Naya Paisa Series 1957-1964
    - Aluminium Series 1964 onwards

Figure 1.1: Indian Coins of different Denominations

Currently the coins in circulation are made up of Ferratic Stainless Steel. Various new coins commonly used now days are shown in Figure 1.1. Various commemorative coins or symbolic coins to mark various important events and personalities were issued by Indian government since independence. An example of commemorative coin is shown in Figure 1.2. These coins have a distinct design that provides a reference to the various important occasions. Mostly these coins serve as collector's items only, although some of the commemorative coins are in regular circulation. These coins mark many important events and scenarios like Political Leadership, War and Peace, Independence Struggle, Great Personalities etc.

We cannot imagine our daily life without the use of coins. The usage of coins in our daily life is very common in places like bus tickets, supermarkets, banks, vending machines, post offices etc. Coins have been a necessity of our daily life's currency usage.

Figure 1.2: An example of commemorative coin

Therefore the need of efficient and highly accurate automatic coin recognition system arises. In addition to the daily usage, coin recognition systems were also a necessity for the research of ancient coins by various organizations. There are various systems for coin recognition in the market which can be subdivided into three types based on the method they used for the recognition:

- Mechanical method based systems
- Electromagnetic method based systems
- Image processing based systems

The systems based on mechanical method takes into account features like thickness, radius, and magnetic properties of coin material and weight of the coin for the recognition purpose. But shortcoming of these parameters is that they were unable to compare between the different materials used in the coins. This means if two coins one counterfeit and one original coin, both having same properties (thickness, diameter, weight and magnetism) but with different composition of materials were fed to the coin recognition system then it won't be able to differentiate between the two and treat both were treated as same coin. Therefore these systems may not provide accurate recognition.

The systems based on electromagnetic method takes into account the magnetic property of the coins. Due to different magnetic properties when coins made of different material were fed at a certain frequency to an oscillating coil they made different changes or alterations in direction and amplitude of the frequencies. By combining these alterations with the other features like weight, diameter, and thickness the system can be used to differentiate among various coins. The electromagnetic method based coin recognition systems helps in improving the accuracy of coin recognition but they can still be fooled to make false recognition by the use of some game coins.

In the recent years image processing based systems were also emerges as an option for coin recognition. These systems use camera or some scanning device for the input coin image. Then images are processed by using various techniques (FFT, segmentation, DCT, neural network, edge detection, full subtraction etc.) of image processing and various features from the coin images are extracted based on which the recognition among different coins are done. We will mainly focus on image processing based coin recognition systems. Our project uses techniques like image subtraction, LBP and Circular Hough Transform, which we are going to use in our system for implementation.

1.2 Digital Image Processing

Processing of images that are digital in nature by a digital computer is known as Digital Image Processing [1]. A digital image can be viewed as a 2-D function $f(a, b)$, where a and b are plane coordinates and the amplitude of the function at any point a and b is called the intensity of the image at that point. A digital image is composed of finite number of elements called pixels, each having a particular value and location. The process of digital image acquisition is shown in Figure 1.3. The need of digital image processing is motivated by following major applications

- Improvement of pictorial information for human perception.
- Image processing for autonomous machine application.
- Efficient storage and transmission

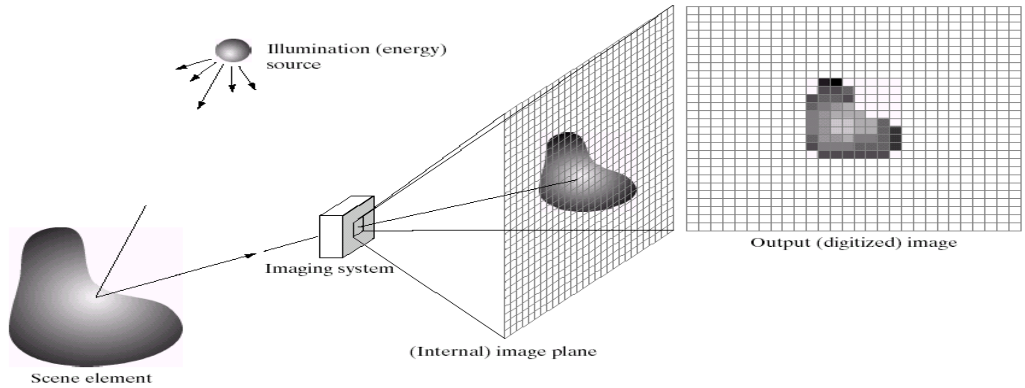
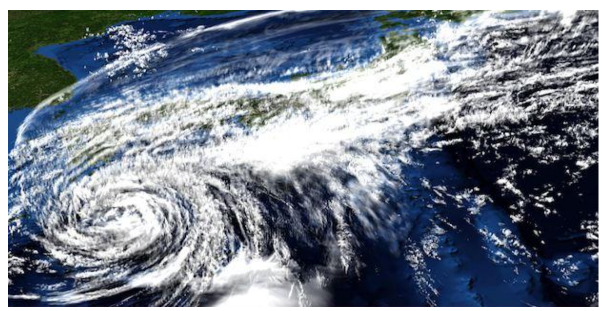


Figure 1.3: A digital image acquisition process[1]

1.2.1 Improvement of pictorial information for human perception

This application employs methods which are capable for enhancement of the pictorial information that is used for human perception and analysis so that the information can be understood in a better way by humans and to help them extract information from the image. This application is mainly used for Noise filtering, Remote Sensing, Content enhancement etc. Some of the uses of the application are shown in Figure 1.4.

A



B

Figure 1.4: An example of (A) noise filtering (B) remote sensing

In industries the machine vision is used for computer vision. The main focus of computer vision in the image processing field is at the level of hardware. But in case of machine vision there's always a requirement of additional computer networks and hardware input/output that can be used for the transformation of information which is generated by the components of other processes, like as a robot foot. Machine vision is a subdivision of machine engineering, dealing with issues related to industrial automation, optics, information technology and mechanics. A frequent application of machine vision is in case of products inspection such as in packaging, in quantity measurement, in assembly lines of automobile industry, pharmaceuticals etc. Extensive use of machine vision systems for problem solving in industries helps in complete automation in various processes which leads to better efficiency, accuracy and reduced costs.

1.2.3 Efficient storage and transmission

For Efficient storage and transmission image must take less space in storage as well as in the bandwidth during transmission. This application deals with the compression of the image. An image commonly have a lot of repetitive data that can be eliminated to achieve compression like coding redundancy, psycho-visual redundancy etc. [1]. Image contains 2 types of entities

- Information content
- Redundancy

We try to remove redundancy and try to retain only the information part. Benefits of compression are reduced space, reduction in required bandwidth.

1.3 Image Types

There are primarily categorized into three types as described below [2]:

- **Binary Image**: A binary image can be defined as a logical array that contains only 0s and 1s as values. The value 0 indicates for black color and pixels the value 1 indicates white color as shown in Figure 1.5.

- **Gray scale image**: It is also known as an gray level image or intensity image. The intensity value range for the gray scale depends on the type of array class (e.g. uint8, uint16, int16, single, or double etc.) The range for single arrays or double arrays is from [0, 1], in uint8 range is from [0,255], in uint16 range is between [0, 65535], in int16 values range is between [-32768, 32767]. Figure 1.6 shows an example of a grayscale image.

- **True color image**: Commonly known as an RGB image, a true color image is made up of pixels in which each pixel have a scalar value which is specified by the combination of three basic RGB (Red-Blue-Green) values. An example is shown in Figure 1.6. A true color image can be viewed as a 3-D array in which each dimension is of a specific color channel. It can have different range values, depending upon the type of class of the image i.e. uint8 [0,255], uint16 [0, 65535], single or double [0, 1] etc.

1	1	1	1	1	1	1	1	1	1
1	0	0	0	1	1	0	0	0	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	0	0	0	0	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	0	0	0	1	1	0	0	0	1
1	1	1	1	1	1	1	1	1	1

Figure 1.5: Binary Image [3]

A B

Figure 1.6: An Example of (A) True color image and (B) grayscale image [2]

1.4 Image Subtraction

Image subtraction (or pixel subtraction) is a process in which the pixel values of one image is subtracted with respect to the pixel values of another image at the same location. Image Subtraction is primarily done with two aims – to level uneven parts of an image (*e.g*. half image having shadow and half having the object), or for detecting difference between two images. This change detection is useful in determining whether something in the image is altered or moved. This is commonly used in fields such as in surveillance systems to detect intrusion, in astrophotography to assist with the computerized search for asteroids etc.

Figure 1.7: Example of image subtraction (A) image 1 (B) image 2 (C) result image

For subtraction images must be of same size and of same type. If the resultant image after subtraction is black then it indicates that both the images are similar else there's won't be a complete black image. The Figure 1.7 shows an example of image subtraction. In this subtraction is performed between image 'A' and image 'B' which is formed by rotating image 'A' by few degrees. The resultant image 'C' is not completely black which shows that both the images are not identical.

1.5 Color Space

The color space can be viewed as a model in which the colors are represented in terms of their intensity values. It defines a 1d to 4d space in which one of the dimensions is the color channel or a color component. Gray-scale space is represented by one color dimensional space (*i.e.* one dimension per pixel).

1.5.1 RGB Color Model

The RGB (Red-Green-Blue) color model is formed of the additive primary colors Red, Green, and Blue. It is an additive color model where the three primary colors were added to form a large array of colors. It is the basis that is commonly used in color CRT monitors and raster graphics. The Cartesian coordinate system used in the RGB model is as shown in Figure 1.8. The diagonal from (0, 0, 0) black to (1, 1, 1) white represents the gray-scale. Figure 1.9 is a view of the RGB color model [3] looking down from "White" to origin. After carefully studying the RGB model various channel based comparisons were formulated to perform color comparison among the various coin types.

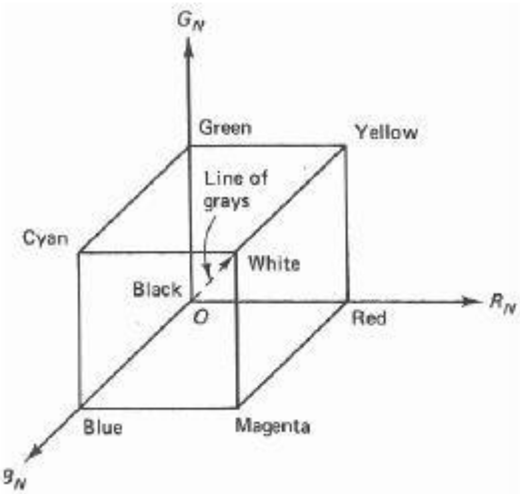


Figure 1.8: RGB Color Model [4]

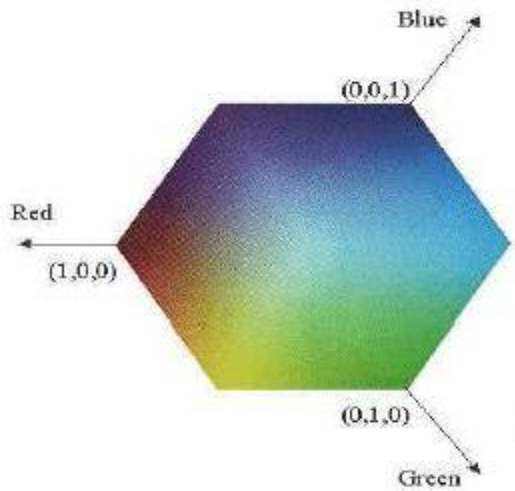


Figure 1.9: RGB Coordinates System[4]

1.6 Local Binary Patterns

The local binary pattern operator [5] uses the surrounding neighbors of a pixel to provide its texture information. It is usually used to find out the texture information of an gray scale image. Local binary pattern can be applied using 4-neighbour, 8 neighbors, 16 neighbor etc. with increase in number of neighbors the texture information becomes more accurate but the works get more complicated. In our system we used the 8-neighbor concept, where we take a 3×3 surrounding of a pixel matrix. A binary 1 is assigned to the neighbor if the neighbor of the center pixel has larger value than the center pixel and a binary 0 if the neighbor pixel holds a value that is less than the central pixel value. The eight neighbors of the center are then represented as an 8-bit number and the decimal conversion of the number is done to find out the texture value. An example to show the working flow of the local binary pattern is shown in Figure 1.10.

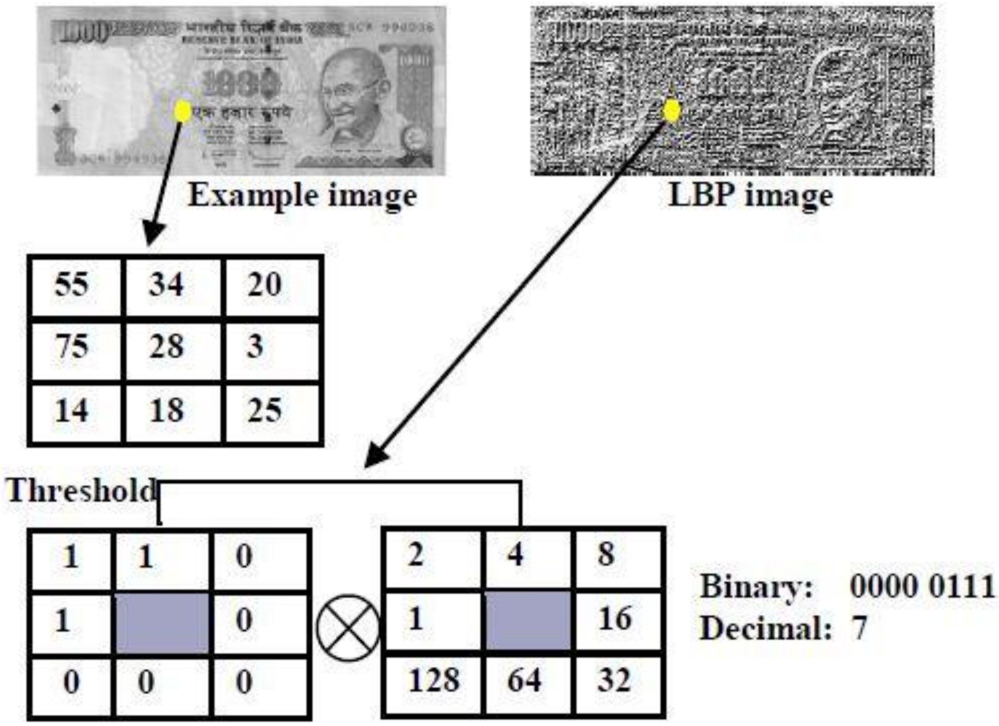


Figure 1.10: An example of LBP [5]

1.7 Rotational Invariance

It is used to found out if the image is rotated by a certain angle compared to an initial state. A zero value indicates no rotation and otherwise a rotation is there. An example showing rotation is shown in Figure 1.11. Finding rotational invariance is an important step because for the texture comparison our system requires the input image to be aligned at a specific angle. For rotational invariance multi-level image subtraction technique is used in our system.

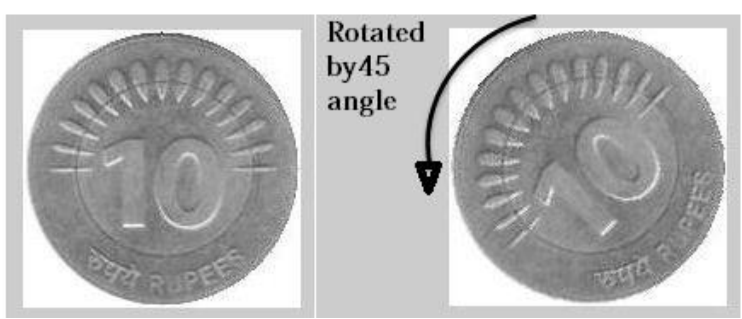


Figure 1.11: Coin images indicating rotation invariance

1.8 Resolution

The images simply can be viewed as a matrix of N rows and M columns where each matrix element is known as a pixel. Each pixel is assigned a value that is the average brightness of its surrounding. Each pixel position can be given by a pair of coordinates (x, y). The resolution of a digital image is simply represented as the product of number of columns × number of rows. E.g. an image having a resolution of 800×600 indicated that it have 800 columns with each column having 600 pixels. Some other frequently used resolutions are 640×480 and 1024×728.

Resolution is a parameter commonly used to describe the quality of an image capturing device like digital camera. The resolution is described by the unit dots per inch. E.g. A display system having a resolution of 120 dots per inch (dpi). In our proposed system coin images of 200 dpi were used for the experiments.

Chapter 2
Literature Survey

A lot of progress has been done in the field of Coin Recognition. Creation of a coin recognition system means solving a variety of problems like, multidimensional indexing, design of user interface, data visualization, analysis of texture and construction of feature vectors.

In 1992 [6]Minoru Fukumi et al. presented an approach for yen and won coins based on neural pattern that is insensitive to the rotation of the coin fed into the system. The coins of 500 yen and 500 won are used in the experiment. The system is made up a preprocessor which is a fixed invariance network having multiple slabs called preprocessor and a trainable multilayered network named a-CONE network. The preprocessor have the neurons whose weights were assigned by using the concept of circular array. The output of the preprocessor is the input for the a-CONE network which performs the final recognition. Experiment shows that the best results were obtained using 25 slabs with each slab containing 72 neurons.

In 1993 [7] Minoru Fukumi et al. presented an approach for coin recognition system based on a smaller neural network that can be implemented on a hardware and try to achieve 100% accuracy. The experiment is performed on coins of 500 yen and 500 won. For the approach the Genetic Algorithm (GA) and Back Propagation (BP) methods were used to design the final system. The proposed method can make a smaller sized neural network for the rotation-invariant system thus reducing the complexity of the neural network. The training of the network is done by Back Propagation method and its architecture is modified by Genetic Algorithm to fit the environment.

In 1994 [8] Paul Davidsson successfully used the method a learning tree's i.e. ID3-SD algorithm to solve the problem of learning the decision mechanism of coin-sorting machines. The main reason of algorithm success for the problem solving is due to its ability to manage the degree of generalization. Experiments were performed on two databases; one database of Canadian coins that is made up of 7 coins (1 and 2 dollar, cent coins of 1, 5, 10, 25 and 50) and another of Hong Kong coins that also compromises of 7 coin types (1, 2, and 5 dollar coins, cent coins of 5, 10, 20, 50). The system gives an accuracy of 98.3% for Hong-Kong coins and 99.7% for Canadian coins.

In 1996 [9,10] Ojala et al. evaluated the performance of different texture measures that were already in use in various applications and also some recently proposed new promising approaches e.g. Gray level difference method, Law's texture measures etc. For classification the method used is Kullback discrimination of sample and prototype distributions. The classification is evaluated based on single feature or pair of complementary features, as single texture measure is unable to provide information that is enough to tell about the amount and spatial structure of local texture performances. Two types of data sets were used for the experiments: a set of Brodatz's images and a set of images used by Ohanian and Dubes.

In 2003 [11] Michael Nolle et al. developed coin recognition and sorting system called Dagobert in wake up of merging of various European countries merging into Eurozone. This system is based on pattern recognition for speedy recognition of huge number of modern coins from thirty different nations. The master sample for each currency type is collected for recognition pattern set (RPS). The process is divided into 3 steps- coins detection, pre-selection and verification. Coin detection involves finding the coin in the image and preprocessing to remove unwanted part. For pre selection of master coins three parameters were considered: coin diameter, thickness and rotation-invariant features. Furthermore, the rotation invariance features were categorized into three parts: edge angle, edge distance and different rotation invariant patterns that occur on circles centered at edge pixels. The verification of coin was done by correlating the edge image of the input coin with a preselected subset of master coins and then finding the master coin that have the lowest distance with the edge image of input coin. Accuracy of 99.24% is achieved after performing experiment on 12,949 coins.

McNeill et al. in 2004 [12] presented an approach to recognize US coins from a single side (Tail side). The system focuses on imprinted images on the tail side of the US coins like, the Lincoln Memorial on the penny, Thomas Jefferson's house on the nickel etc. for the texture of each coin to perform recognition. To prevent size dependent classification the size of image coin is normalized. The resultant system recognizes single coins using vector quantization and histogram modeling with an accuracy of 94% on the test data.

In 2005 [13] Bremanathan et al. presented an approach for Indian coins that focuses on the numerals on the coin faces for the identification. Statistical color threshold method is used for the process of coin recognition. First the Cartesian co-ordinates of numeric print in the coin is found, then the sub image of the numeric print is extracted and used for character recognition process. During final stage rotation-invariant character recognition is done by using two methods multi-channel Gabor filter and back propagation network. Coins of denomination 1, 2 and 5 are used in the experiment and approach gives an accuracy of 92.43% on the dataset.

In 2005 [14] Huber et al. presented an approach to coin classification based on eigenspace. The multistage procedure is divided into three stages. In first stage processing for translation, rotational invariance and hypotheses generation is done. The second stage is for Eigenspace selection and classification after which probabilities for coin classes is derived using coin’s both sides. The third stage is Bayesian fusion and rejection in which class probabilities of both sides of coin are merged using Bayesian fusion with a mechanism for rejection. An accuracy of 93.23% is achieved after working on 11,949 samples.

In 2006 [15] Khashman et al. developed a system ICIS (Intelligent coin identification system) that uses neural network and pattern averaging to recognize coins rotated at various degrees. The system helps in avoiding confusion in identification between coins which have similar physical characteristics. For the experiment samples of 2 EURO coin and Turkish 1-Lira coins were used as slot machines in Europe fails to differentiate between the two due to their similar physical characteristics.

In 2006 [16] Maaten et al. presented a computationally efficient system named COIN-O-MATIC to perform reliable classification of different coins. The system uses coin images and information from sensor for classification of the coin. The coin image is preprocessed and then a class is assign to it on the basis of edge-based statistical features. Then class verification is done by using rejection threshold based mutual information. The experiment is performed on data set supplied by the MUSCLE CIS benchmark. The system classifies approximately 72% of the coins from the dataset with only 2% misclassification.

Thumwarin et al. in 2006 [17] gives a robust method for coin recognition based on rotation invariance. The absolute value of Fourier coefficients of polar image of coins having different radius were derived and used to represent rotational invariance. They consider the absolute value of Fourier coefficients as a individual feature for a particular coin and perform recognition on the basis of distance between the absolute value of Fourier coefficients of the reference coin and the input coin. Two experiments were performed, first on similar sized Thai 5 baht coin and US 25 cent coin and in the second experiment, similar sized Thai amulet coins were used for coin recognition.

In 2007 [18] A. Chalechale gives a coin recognition method Spiral Decomposition of Abstract Image (SDAI) which uses image abstraction and spiral decomposition. The approach measures the similarity among colored coin images having multi-components on their surface. Using coin image strong edges an abstract image is produced. Then the spiral decomposition of pixels of this image is done. This spiral decomposition is used to extract a set of features. Experimental on the COIN BANK dataset shows major improvement in the recall ratio over three other similar approaches.

In 2007 [19] Wei et al. presented an approach for ancient coins which extract textual information embedded on the coins for the classification. In the approach tree-structured wavelet transform is combined with ant-colony optimization algorithm to get the texture information of the ancient coin. For segmentation ACO algorithm is combined with information entropy to search an optimal threshold for texture segmentation of coin images in absence of noise. Unlike other traditional methods which focuses on low frequency channels for the texture information this approach obtain texture information from all the channels by using tree-structured wavelet transform (TWT).

In 2007 [20,21] Zaharieva et al. gives an overview of EU granted project COINS (COmbatting Illicit Numismatic Sales) which works for avoiding illegal ancient coins theft, selling etc. in illegal antiques market. The project focuses on ancient coins identification and their traceability to avoid their illegal trading. The project has following main activities: standardizing of numismatic data structures and web search tool and image based recognition tool for the coins of ancient times. The overview includes initial test results of various experiments performed and a discussion of work that has already been performed in field of coin recognition.

In 2007 *[22] Marco Reisert et al.* presents a coin recognition based on the registration approach that proves to be a fast and reliable system. The system completely neglect gradient magnitude feature and considers only the gradient direction of the coin images.
The classification process is a sequence of tests in which initially coins are classified based on the nearest neighbor classifier scheme, after that a series of rejection criteria's were used to satisfy the low false positive rate demand. The system is capable of withstanding the contrast and illumination changes which adds to its reliability. System was tested by using CIS benchmark dataset in the experiment.

In 2009 [23] Shen et al. presented an approach of coin recognition based on Gabor features. To get the features of local texture Gabor wavelets were used. The coin is divided into small sections using the concentric ring structures to find out the rotation invariance. For each section Gabor coefficients are calculated and were concatenated into a feature vector to represent a complete image. Comparison between two images is based on Euclidean distance property and the nearest neighbor classification technique. The proposed approach gives an accuracy of 74.27% comparatively much improved than similar type's approaches like EDHD (Edge Distance Histogram Distribution), EAHD (Edge Angle Histogram Distribution) etc.

In 2010, [24] Hussein R. Al-Zoubi et al. proposes a coin recognition system for Jordanian coins based on a statistical approach. The method works on two features: the color of the coin, and the area of the coin. The coin is firstly converted into gray scale divided into two regions: coin and background, after that pre-processing is done to remove the noise. Then the four required parameters: area, average red, blue and green colors are calculated and based on values the category of the coin is decided. The experimental results shows that high recognition rates of more than 97% could be achieved using statistical approach.

In 2010 [25] Chen et al. introduced a coin recognition method based on rotation invariance. In this approach Fourier coefficients of polar images of coins of different radius is computed. Moreover, by using the Fourier approximation of the coin image they try to reduce coins image surface variations on due to light reflection effect. The comparison is done by feeding these features of the input coin into a multi-layered BP neural network. The method is initially used to recognize coins of China, but it works well on other currency coins as well. The approach is tested on a dataset of size 900 with each coin image having dimension 1000×800, resulting in an accuracy of 83.3%.

In 2010 [26] Huahua Chen presents a method for Chinese coins that unwrap the coin image and perform rotation invariant template matching. The approach is divided into two parts: Unwrap the coin image and Rotation invariant template matching. In Unwrapping, both the specimen coin image and reference coin image is unwrapped and lengthened. Template matching is done for every allowed position of the template in the specimen image. To make template matching capable of differentiating residual coins their images were refined by using local template matching, YCbCr and detection of inclination of two close line segments. An accuracy of 80.6% is achieved on the dataset of 144 coins.

In 2011[27] Vaibhav Gupta et al. proposed a rotation invariant coin recognition system to detects Indian coins of different denomination. Three checks (radius, coarse and fine) were performed on the input image for the recognition by the system. The technique requires placing the front face of the coin up. First radius is determined by circular Hough transform and based on the radius type the dataset image is selected for further processing to found out the rotation invariance. Rotation invariance is found out by doing the coarse and fine subtraction. First coarse subtraction is done by subtracting the input coin and database coin and rotating the database coin by an interval of 5^o. The range which gives the minimum value is used for the fine subtraction in which the database image is rotated by 1^o after each subtraction and results were stored. Results of MATLAB based simulations were provided in the research paper.

In 2011 [28] Shatrughan Modi et al. presented a system based on ANN (Artificial Neural Network) methodology that recognize Indian Coins of denomination Rs. 1, 2, 5 and 10. This system considers both sides of the coins during the recognition process, thus it is capable of recognizing the coins from either side. Features extraction from the input coin images is done using techniques of CHT (Circular Hough Transformation), Pattern Averaging etc. Then, the recognition is done by feeding the extracted features as input to a trained Neural Network. The accuracy of approximately 97.74% is achieved by the presented system.

In 2012 [5] Sharma et al. presented an approach based on texture to recognize the Indian paper currency using Local Binary Pattern (LBP) technique. In the LBP 8-neighbour approach is used to calculate the LBP of a pixel in currency image. First a 9×9 matrix is selected, in which the central pixel act as threshold. All the neighboring pixels were assigned value 0 or 1 based on whether their value is greater than threshold or not. After that LBP operator is applied and LBP value for the central pixel is found. In the proposed approach Euclidian distance between LBP image of currency from the data base and the input image is calculated to find out the result. An accuracy of 100% is achieved on the dataset of new paper currency. Although, this accuracy is only for the identification of currency notes and not for distinguishing between original and counterfeit notes. This discrimination can be detected by using techniques [29, 30] which use infrared or ultraviolet spectra.

2.1 Comparison

A structured layout of each technique is shown in Table 2.1.

Table 2.1: Comparison of various existing techniques

Sr. No.	Year	Technique Used	Dataset of coins used	Type of coins	Accuracy
1	1992	Neural Patteren	500 yen (Japan) and 500 won (Korea)	Modern	
2	1993	Neural network using Genetic Algorithm	500 yen (Japan) and 500 won (Korea)	Modern	
3	1994	Decision trees	Canadian and Hong Kong coins	Modern	99.7% for Canadian, 98.3% for Hong Kong coins
4	1996	Gray level difference method, Law’s texture measures	a set of Brodatz's images and a set of images used by Ohanian and Dubes.	Modern	
5	2003	Edge angle distribution, Edge distance	Coins from 30 countries	Modern	99.24%

		distribution			
6	2004	Vector Quantization and Histogram modeling	US coins	Modern	94%
7	2005	Statistical color threshold method	Indian Coins	Modern Coins	92.43%
8	2005	Eigen space, Bayesian fusion	Coins from 30 countries	Modern Coins	93.23%
9	2006	Neural Network and Pattern Averaging	Turkish 1 Lira and 2 Euro coin	Modern Coins	96.3%
10	2006	Edge angle distribution, edge distance distribution, edge angle-distance distribution	MUSCLE CIS dataset	Modern Coins	72%
11	2006	Fourier approximation of polar image	Thai amulet and Thai baht coins	Modern Coins	
12	2007	Image abstraction and spiral decomposition	COIN BANK	Modern Coins	
13	2007	Tree structured Wavelet transform, Ant colony optimization algorithm		Ancient Coins	
14	2007	standardizing of numismatic data structures and web search tool and image based recognition tool		Ancient Coins	
15	2007	registration approach , gradient direction	CIS benchmark dataset	Modern Coins	

16	2009	Gabor wavelet, Euclidean distance and nearest neighbor classifier	MUSCLE dataset	Modern Coins	74.27%
17	2010	Statistical approach	Jordanian Coins	Modern Coins	97%
18	2010	Fourier approximation of polar image, neural network	Chinese Coins	Modern and Ancient Coins	83.3%
19	2010	Rotation invariant template matching	Chinese Coins	Modern Coins	80.6%
20	2011	Image Subtraction, rotational invariance	Indian Coins	Modern Coins	
21	2011	Artificial neural network	Indian Coins	Modern Coins	100%
22	2012	Local Binary Pattern	Indian paper currency	Modern Currency	100%

Chapter 3
Problem Statement

In this chapter, gaps in the existing work, problem statement, objectives to achieve and methodology to achieve the objectives are discussed.

3.1 Gap Analysis

In the previous chapter of Literature Survey, various image processing techniques are discussed for the recognition of coins. Various gaps that were found are given below:

1. Processing time in existing techniques is large enough and could be improved so as to recognize the coin in the real time.
2. There is very less work done for recognizing the coins based on all its collective features like radius, texture, color, rotation invariance.
3. Most of the systems perform the recognition based on the physical properties and rotating angles only which can be fooled easily.
4. Very less work is done for the recognition of new Indian coin series in which various coins of different denomination have very similar physical characteristics like radius, color thickness etc. which makes the recognition a complex problem.

3.2 Problem Statement

The various existing techniques performs the recognition based on features like weight, thickness and diameter etc. which can be fooled by fake coins which have similar physical properties as of the original coins as they don’t take into consideration other features like color, texture etc. for the recognition. Therefore, to remove such discrepancies features such as color, radius, texture and rotation angle of the coin could be used so that more accuracy could be achieved in the recognition results.

3.3 Objectives

1. To study the existing techniques for coin recognition.

2. To propose a technique for coin recognition using the four features: radius, color, rotation invariance and texture.
3. To implement the proposed technique.
4. To test and validate the implemented technique.

3.4 Methodology

1. Literature Survey
2. Purpose the technique using concepts of image processing and neural networks.
3. Implementation process is as follow:
   3.1. Perform experiment on various coin samples to determine the radius, color and texture properties of various denominations to find out the threshold range or exact test value for testing in the system.
   3.2. Pre-process the input coin image using Hough transform.
   3.3. Classify the coin using radius, color and texture in MATLAB.
4. Test the system against other input samples and observe the results.

Chapter 4
Implementation Details

This chapter includes the implementation details for the automated coin recognition system. MATLAB 8.1.0.604 R2013a is used for implementation. It integrates computation, visualization and programming in easy to use environment. In our implementation we have used image subtraction and LBP for coin recognition. This section gives a brief introduction to the MATLAB and coin recognition system based on these techniques.

4.1 Overview of MATLAB

The name MATLAB [31] stands for MATrix LABoratory. Chief scientist of MathWorks Inc. Dr. Cleve Moler write the MATLAB program to provide easy usage of matrix software developed in the projects of LINPACK and EISPACK. The initial version was written in the late 1970s preliminary for the use in courses in matrix theory, numerical analysis and linear algebra. The foundation of MATLAB is sophisticated matrix software, whose basic data element is a matrix and this matrix does not require pre-dimensioning.

MATLAB is an advanced software package specially designed for engineering and scientific computation. It is product of the Math Works, Inc. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. This allows us to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRAN. MATLAB has evolved over a range of years with the help of feedback from many users. In many university curriculums, it is the standard instructional tool for introductory and advanced courses in engineering, mathematics and science.

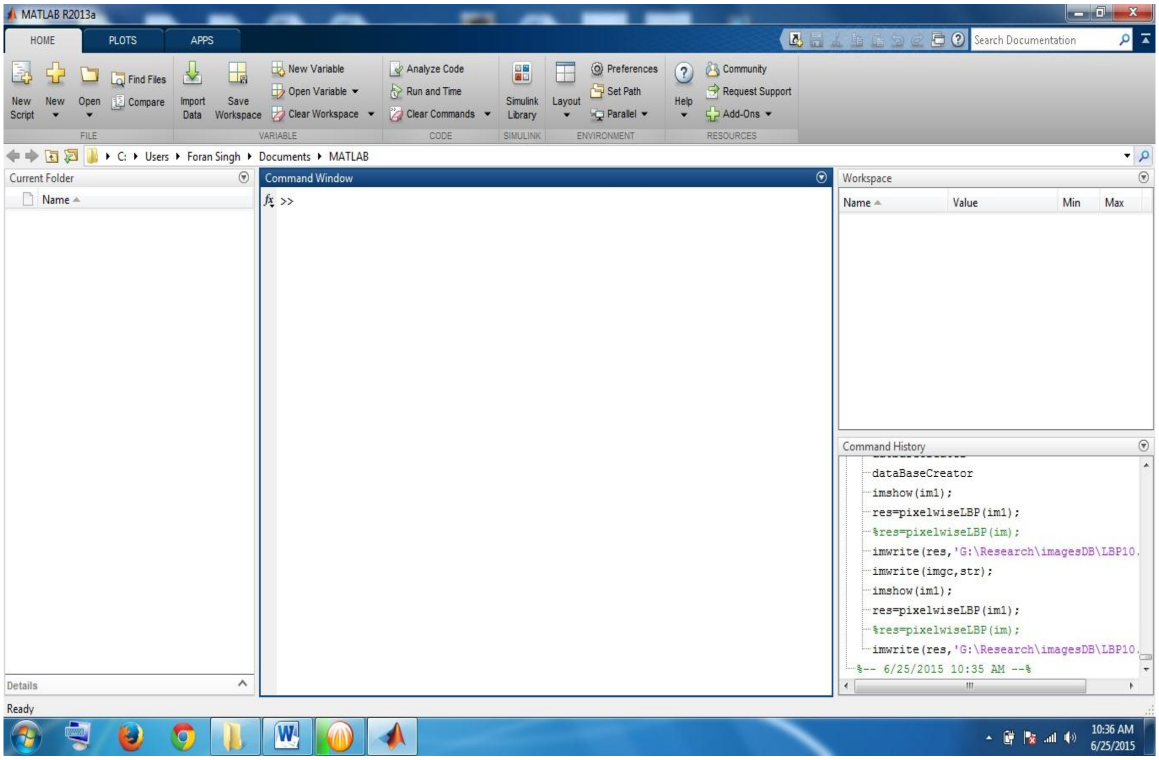


Figure 4.1: Snapshot of Matlab R2013a

The graphical user interface of Matlab R2013a is shown in Figure 4.1. In industry, MATLAB is the tool that is used for high-productive research, development, and analysis. MATLAB provides various types of toolboxes like Image Processing Toolbox, Neural Network Toolbox and Signal Processing Toolbox etc. These allow us to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions also known as M-files that extend the MATLAB environment to solve particular problems of different classes.

4.2 Architecture of Rotation Invariant Coin Recognition System

The coin recognition is divided into seven steps. The architecture of rotation invariant coin recognition system is as shown in Figure 4.2.

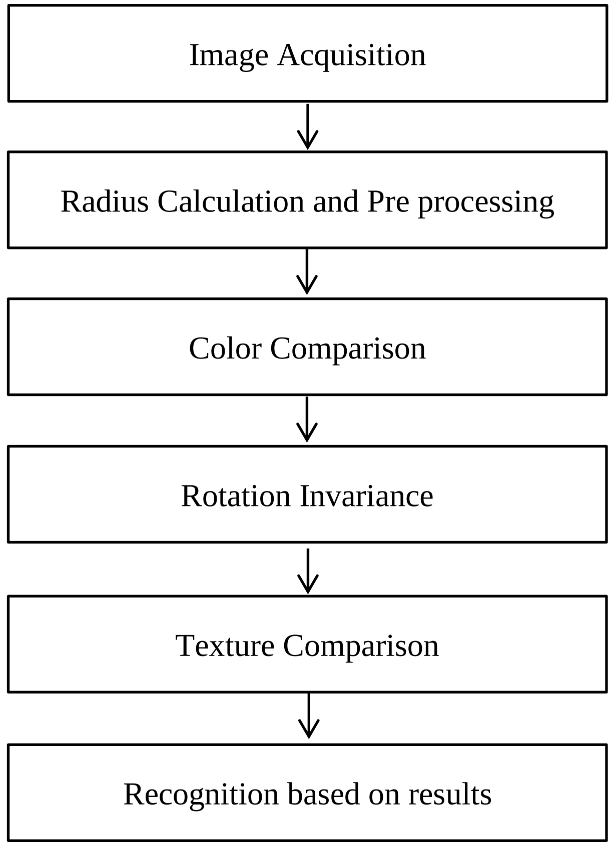


Figure 4.2: Architecture of the proposed system

The different coins used in the experiments are shown in Figure 4.3. Now the detailed description of each part is discussed in the subsequent sections.

Figure 4.3: Various coins used during the process (A) Rs.1 Type(i); (B) Rs.1 Type(ii); (C) Rs.1 Type(iii); (D) Rs.2 Type(i); (E) Rs.2 Type(ii); (F) Rs.2 Type(iii); (G) Rs.5 Type(i); (H) Rs.5 Type(ii); (I)Rs.10

4.2.1 Image Acquisition

The images were acquired using a good quality scanner. The image is of 320×320 dimensions as shown in Figure 4.4, which is large enough to hold the largest coin used with 200 ppi pixel density. The acquired image is converted into gray scale using the formula described in Equation (1)

$$\text{Grayscale} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \tag{1}$$

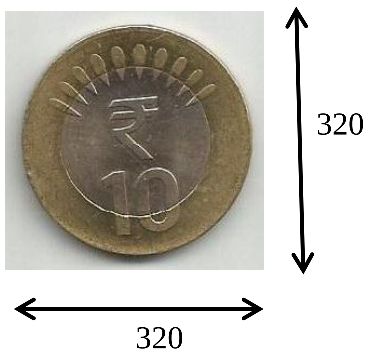


Figure 4.4: Required Dimensions for input

4.2.2 Radius Calculation and Pre-processing

After grayscale conversion, radius and center of the coin is calculated using Hough transform [32].

Step 1. Define a 3-dimensional Hough Matrix of dimension M×N×R, where M, N is the height and width of the Grayscale image and R is the no. of radii for which we want to search.

Step 2. For each edge pixel (x, y) and for particular radius r, search circle centre coordinates (u, v) that satisfy the equation $(x-u)^2+(y-v)^2=r^2$ and increase count in Hough Matrix at (u, v, r) by 1.

Step 3. Repeat step 2 for other radii.

Step 4. Find the maximum value from the Hough Matrix. The corresponding indices give the centre coordinates and radius of coin.

After finding the radius and center of the coin the image is segmented out and the unwanted background is removed. This is done using the formula described in the Equation. 2.

$$\text{Segmented image} = [X_c - r, Y_c - r, (2 \times r),\ (2 \times r)] \tag{2}$$

Where, r is radius, X_c, Y_c are co-ordinates of coin center. All the remaining pixels of the segmented image outside the radius of the coin were turned black to get the exact coin from the image.

To find out the exact radius for each coin we take 5 samples initially of each coin. After the preprocessing we calculate the exact radius for each sample. We found out that the coins radius of multiple samples of a single denomination does not have exactly similar radius. E.g. for 5 different coins samples for Rs.5 the values of radius are 89.8225, 89.1291, 88.9832, 89.016 and 88.993. Although the difference is in decimal places, the radius should be chosen in a way that the sample we obtain after the preprocessing should be of a specific size that could match our database images. So, we took the average of the samples and took the seal value as a radius.

Now, if a coin of Rs.5 having a radius 88.87 is fed then first our system classifies the range in which it falls and crop out the coin after preprocessing with a radius 89. Thus, crop out a specific sized template for further processing. There might be some data loss due to rounding off the radius but its quiet minimal for consideration.

4.2.3 Color Comparison

For color comparison we store the copy of initial colored image that is converted into a gray-scale image for radius calculation. Color Comparison is done by comparing the RGB color channels. Indian coins have mostly 2 colors i.e. gray and golden. Based on radius we can categorize the Indian coins in 4 types, but based on color only golden and gray classes can be distinguish. After finding the radius in the previous step we will check if there is a golden color in that radius category. If the category doesn't have the golden color then we check for the gray color. Among the 4 radius category we have the golden color in 2 categories and different gray shades in all the categories.

The golden color is a combination of R and G channels with B values for different shades of golden color. The gray color is made by combining R, G and B values in equal proportions with darker gray shades with higher RGB values. The point of distinguish is the difference in the channels values. First we check the category of the radius of the input sample. If the coin belongs to radius type R_1 or R_3 then it means that it should not have the presence of golden color, therefore we only perform the check for the suitable gray shade. If the coin belongs to radius type R_2 and R_4 then we check for both suitable golden and gray shade. The three comparisons used to find the color are

1. Difference of R and G with B channel values (R-B, G-B).
2. Individual threshold values for R,G and B channels
3. A final comparison in which we add up all the RGB channel values and subtract it with the sum of RGB channels of the database coins from the radius type selected.

The input coin will be identified by the coin type if it gives a true result for all possible comparisons for its category.

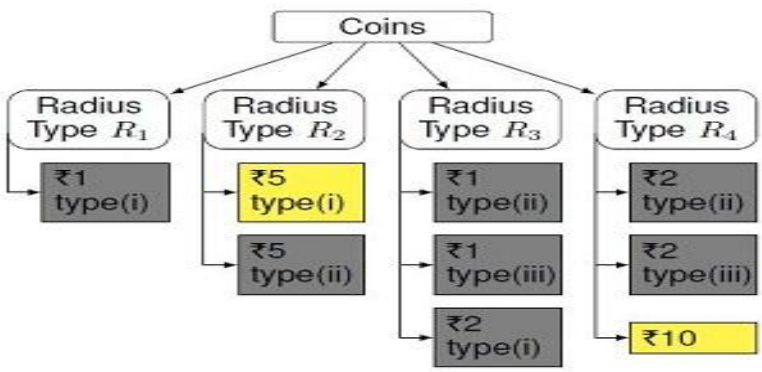


Figure 4.5: Categorization of coins based on their dominant color

For color comparison RGB channel values were used. The basis of the comparison is difference in the channel values in case of gray and golden. In case of gray the sum of Red-channel, Green-Channel and Blue-Channel were very close. But in case of golden color the Blue-Channel sum values were less as compared to the other two channels. After working with our color comparison on the coins we provide a range of ±10% of the exact values. The categorization if coins based on their dominant color is shown in the Figure 4.5.

4.2.4 Rotation Invariance

For rotation invariance we use multi-level image subtraction technique. During our experiments we found out that simple image subtraction process is not efficient in finding the rotation invariance. Then instead of performing a complete subtraction, the region which remains common on an axis were found out for each coin. First the subtraction using these common regions were carried out depending upon the radius type and the full subtraction is performed. This technique is divided into 2 parts

4.2.4.1 Partial Subtraction

In partial subtraction instead of making the complete subtraction we select a smaller region keeping the center of the coin as the locus we try to find out a square region from the center which remains into a square box during rotation. We find out the common region for all the coins we used and store there region values to be used on input image. The reason for using this common central region is because in some coins the values of pixels in various regions are same this leads to multiple smaller values at different rotation angles due to which we can’t approximate the exact rotation invariance. Moreover it results in less data generation during the process as the common region of all the coins used was within the 20-30% of the radius. An example of common region of coins is shown in Figure 4.6.

The pseudo code for partial subtraction is as follows:

- Step 1. Create an array say *Par* of size 360 and initialize variable count to 1.
- Step 2. Select the database image based on the radius of input image.
- Step 3. Repeat steps from 4 to 6 till count<=360.
- Step 4. Select the common square region of the input image and the database image and perform partial subtraction.
- Step 5. Store the sum of pixel values of the resultant image at *Par[count]*.
- Step 6. Increment count by 1, rotate the input image by 1°.
- Step 7. Repeat from Step 1 if more than one coin in database with same radius and generate multiple resultant arrays *Par1*, *Par2*, *Par3*... etc.

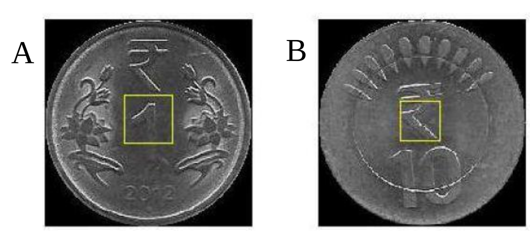


Figure 4.6: Common region for coin of (A) Rs.1 and (B) Rs.10

4.2.4.2 Full Subtraction

In full subtraction we use only 5 samples with minimum values in partial subtraction. The pseudo code for partial subtraction is as follows:

Step 1. From the array *Par* we find out the minimum 5 values and store it in a new array temp of size 5.

Step 2. We select a value from this array, found out its index value from *Par*.

Step 3. Now we rotate our input image with the index value and perform a full subtraction and store the sum of pixel values of the resultant image to the corresponding index in our new array *final*.

Step 4. Repeat steps 2 and 3 for the remaining values of *temp*.

Step 5. Now find the minimum value in the *final* and its corresponding index value. For this index values find out the respective value in *temp*. For that value find the respective index value from the *Par* to get the resultant angle to rotate out input image.

Step 6. Rotate the input coin with the index value to get into our desired position.

4.2.5 Texture Comparison

For texture comparison we use Local Binary Pattern technique. LBP operator is first introduced by Ojala T. et al.[9] LBP is used for texture description and widely used in fields like fingerprint recognition, face recognition, medical and satellite imaging etc.

In LBP the central pixel act as a threshold using which all the neighboring pixels were assigned values 0 or 1 using the Equation 3 given below.

$$S(x)=\begin{cases} 1 & \text{for } x \geq p \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Here S(x) is the threshold function, p is the center pixel and x is the neighbouring pixel whose values is to be determined. The Local Binary Pattern image of different coins is shown in Figure 4.7.

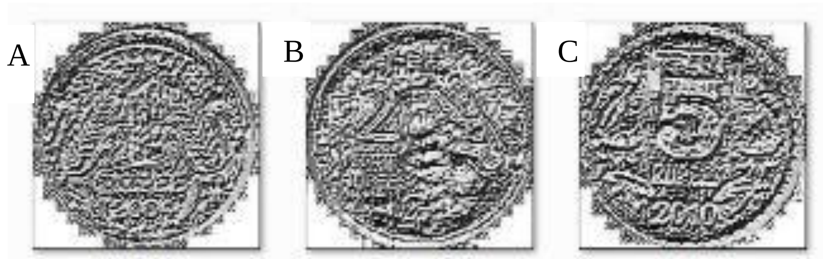


Figure 4.7: LBP images of coins of (A) Rs.1 and (B) Rs.2 and (C) Rs.5

After that the binary code is generated by forming an ordered pattern depending upon the relative position of the pixel from the central pixel. Equation for relative positioning in case of 8 neighbors is given below in Equation (4)

$$LBP_p = \sum_{i=0}^{7} 2^i \times S(z_i - z_c) \tag{4}$$

z_c be the gray value of the center pixel p, and z_i be the gray value of the i^{th} pixel in clockwise order at the 8-neighborhood of pixel i, where $i = 0, 1, \ldots 7$. The working of LBP operator is shown in a simplified way in Figure 4.8.

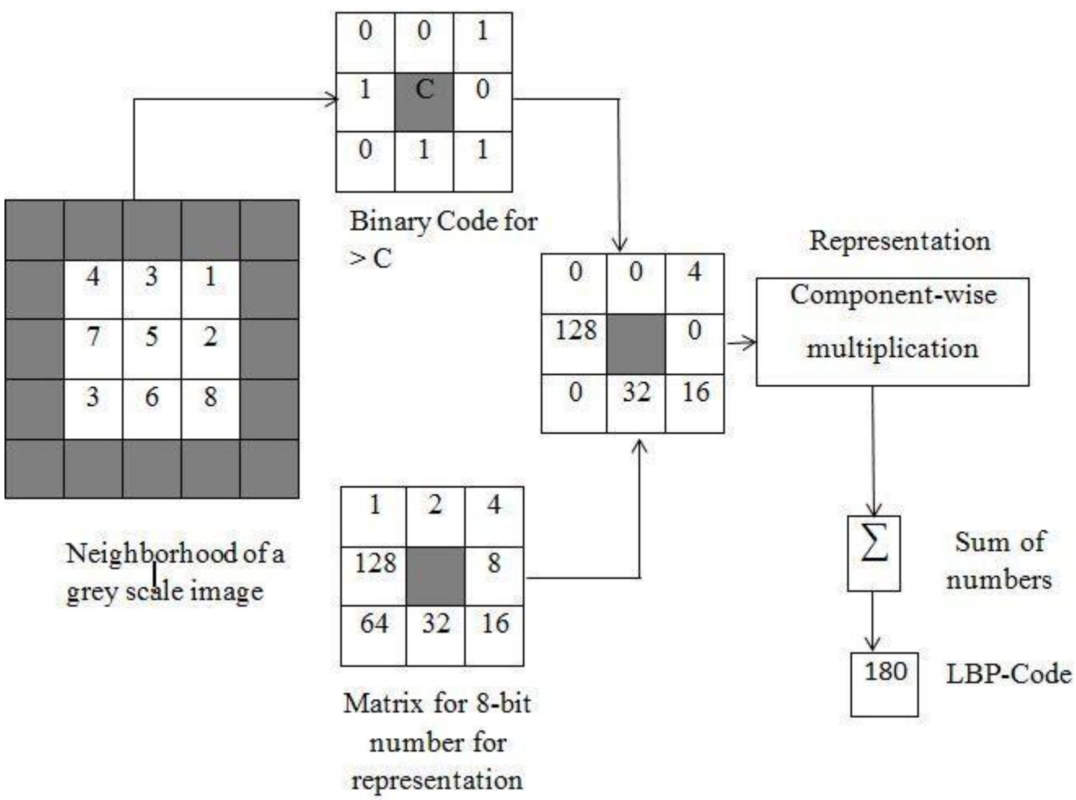


Figure 4.8: An example of LBP working

Texture comparison is done by adding pixel values of the resultant image obtained by subtracting the Local binary pattern image of the database image with the LBP of input image which is brought at desired rotation angle by using the multi-level image subtraction technique. To give the threshold value range for texture comparison the range is provided from 0-10% of the actual LBP sum of the database image.

4.2.6 Recognition based on results

The recognition is done by using the results of all the three properties comparisons i.e. the coin radius, coin color and coin texture. If the input coin image satisfies the value or threshold range of all the properties then coin will be recognized.

Chapter 5
Experimental Results

The system has been designed to perform the coin recognition based on multiple features like: radius, color, rotation invariance and texture.

5.1 Result for a Coin of Rs.10

The coin image of Rs.10 is taken as input. The dimensions of the input were 320×320. The sequence of results that produced by the system to provide our final recognition is as follows.

5.1.1 RGB to Grayscale conversion

The input image is a true-color image. For processing we take a copy of the image and convert it to the grayscale image as shown in Figure 5.1

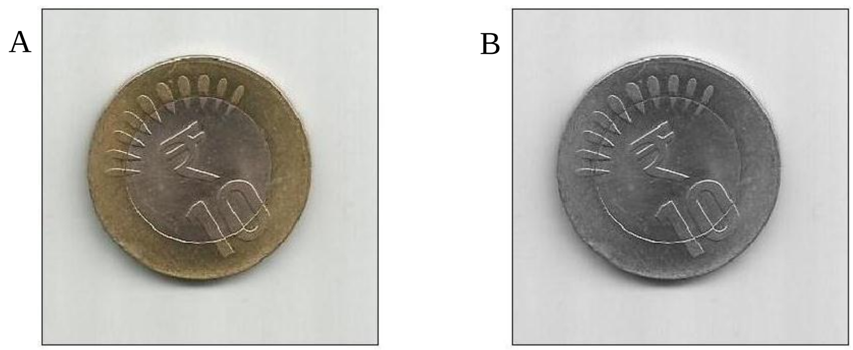


Figure 5.1: (A) colored image and its (B) gray-scale version

5.1.2 Preprocessing and Radius Calculation results

The grayscale image is further preprocessed using the Hough transform to remove the unwanted background from the image and to know the radius of the coin. After the removal rest of the background is converted black as shown in Figure 5.2.

Figure 5.2: Image after pre-processing

Radius of the coin type is found out to be 106. Radius for all coins type used are as shown in Table 5.1.

Table 5.1: Radius of different coin types

Coin Type		Radius
1	Type(i)	86
	Type(ii)	95
	Type(iii)	95
2	Type(i)	95
	Type(ii)	106
	Type(iii)	106
5	Type(i)	89
	Type(ii)	89
10		106

5.1.3 Color comparison results

For the color comparison we use the initial input colored image. According to the radius class R-B, G-B, R-Channel, G-Channel, and B-Channel comparisons were performed. The results values satisfy all the tests that indicates the presence of golden color in the image. The table indicating the test thresholds and the sequence of tests required for each coin type is as given in Table 5.2.

Table 5.2: Threshold values for the color comparisons.

Coin Type		R-B	G-B	R-channel	G-channel	B-channel	RGB subtraction
1	Type(i)	Not Required	Not Required	$5.1\text{-}5.6\times10^6$	$5.2\text{-}5.7\times10^6$	$5.1\ 5.6\times10^6$	Not Required
	Type(ii)	Not Required	Not Required	$6.1\text{-}6.7\times10^6$	$6.1\text{-}6.8\times10^6$	$5.9\text{-}6.5\times10^6$	$1.8\text{-}2.0\times10^7$
	Type(iii)	Not Required	Not Required	$6.8\text{-}7.6\times10^6$	$6.9\text{-}7.6\times10^6$	$6.7\text{-}7.4\times10^6$	$2.0\text{-}2.2\times10^7$
2	Type(i)	Not Required	Not Required	$6.9\text{-}7.7\times10^6$	$7.0\text{-}7.8\times10^6$	$6.8\text{-}7.6\times10^6$	$2.0\text{-}2.3\times10^7$
	Type(ii)	$<1.1\times10^6$	$<7.9\times10^5$	$6.0\text{-}6.7\times10^6$	$6.1\text{-}6.8\times10^6$	$5.9\text{-}6.6\times10^6$	$1.8\text{-}2.0\times10^7$
	Type(iii)	$<1.1\times10^6$	$<7.9\times10^5$	$6.0\text{-}6.7\times10^6$	$6.1\text{-}6.7\times10^6$	$5.9\text{-}6.6\times10^6$	$1.8\text{-}2.0\times10^7$
5	Type(i)	$\geq3.2\times10^5$	$\geq2.7\times10^5$	$5.9\text{-}6.6\times10^6$	$5.6\text{-}6.2\times10^6$	$4.9\text{-}5.4\times10^6$	Not Required
	Type(ii)	$<3.2\times10^5$	$<2.7\times10^5$	$5.2\text{-}5.7\times10^6$	$5.1\text{-}5.7\times10^6$	$4.9\text{-}5.4\times10^6$	Not Required
10		$\geq1.1\times10^6$	$\geq7.9\times10^5$	$7.1\text{-}7.9\times10^6$	$6.8\text{-}7.6\times10^6$	$6.1\text{-}6.8\times10^6$	Not Required

5.1.4 Rotation invariance results

For the rotation invariance multi-level image subtraction technique is applied and the input is found out to be rotated by 26 degrees. The image after finding out the rotation invariance is rotated back to be in a desired position as shown in Figure 5.3

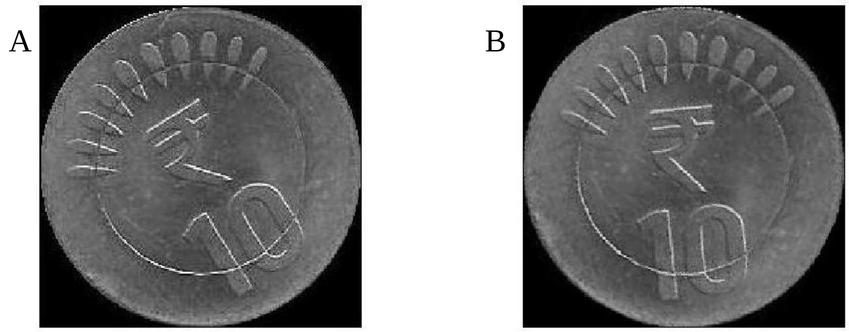


Figure 5.3: (A) Image before rotation (B) Image after rotation

5.1.5 Texture comparison results

After rotating the image to our desired position we apply LBP on the image to perform our texture comparison. The LBP output of the image is shown in the Figure 5.4

Figure 5.4: LBP output of the input image

The coin satisfies the threshold values for the Rs.10 coin. The table with various threshold values for LBP comparisons were shown in Table 5.3

Table 5.3: Threshold values for the texture comparisons

Coin Type		$LBP_{database}$-LBP_{input}
1	Type(i)	$\leq 5.69\times10^5$
	Type(ii)	$\leq 6.73\times10^5$
	Type(iii)	$\leq 7.62\times10^5$
2	Type(i)	$\leq 7.74\times10^5$
	Type(ii)	$\leq 6.74\times10^5$
	Type(iii)	$\leq 6.70\times10^5$
5	Type(i)	$\leq 6.63\times10^5$
	Type(ii)	$\leq 5.7\times10^5$
10		$\leq 7.9\times10^5$

5.1.6 Recognition based on results

As the coin satisfies all the parameters for the coin of Rs.10, therefore it is a coin of Rs.10.

5.2 Overall Recognition results

We have used 5 samples of each type i.e. 5 samples of Rs.1 type(i), 5 samples of Rs.1 type(ii) and similarly for other coin types. Then we have rotated each sample coin by 1^o, so the total samples were 9×5×360=16200. All the coins used in the experiment are new with clear surface. The results are summarized in Table 5.4. The reason for less accuracy in case of Rs.2 Type (ii) coin is due to less accuracy in case of our rotational invariance due to which our texture comparison result values don't satisfy our threshold values.

Table 2.4: Final results showing accuracy achieved

Coin Type		Recognition
1	Type(i)	97.74%
	Type(ii)	96.53%
	Type(iii)	93.37%
2	Type(i)	94.43%
	Type(ii)	78.89%
	Type(iii)	95.54%
5	Type(i)	96.81%
	Type(ii)	95.76%
10		98.56%
Avg. Accuracy		94.18%

Coin recognition using our approach shows positive signs for coin recognition. As all the three properties i.e. radius, color and texture are under consideration when we perform our experiments, the experiment results in an promising approach for coin recognition Future works will include modifications of the technique and also merging of other image processing techniques, such as, Neural Networks training for rotational invariance and using our approach on old coins. The snapshot of the graphical user interface of our system is shown in Figure 5.5.

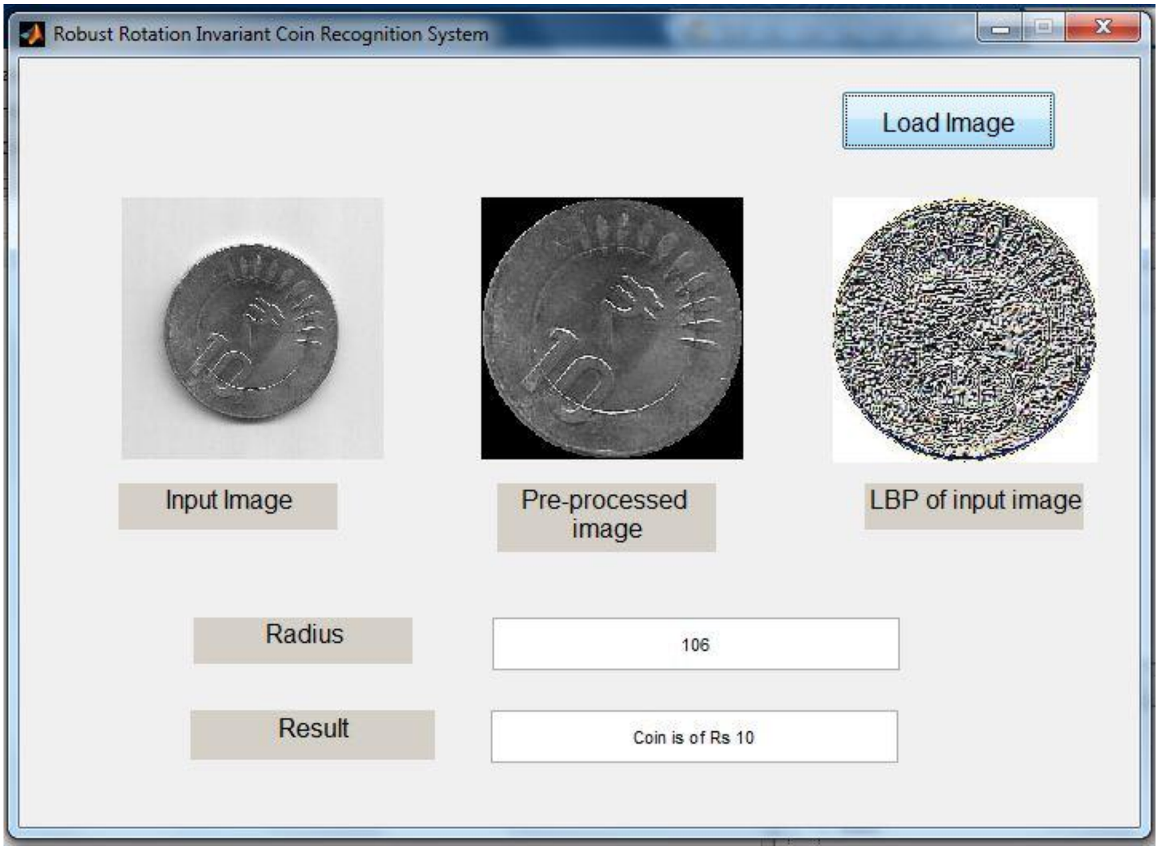


Figure 5.5: Snapshot of GUI of the Coin Recognition System

Chapter 6
Conclusion and Future work

6.1 Conclusion

In this thesis a Robust Rotation Invariant Coin Recognition System is implemented using MATLAB that considers various features of the coin image to perform the recognition. The process of coin recognition covers all the necessary feature by using various techniques, e.g. for radius Hough transform is used, for color comparison RGB channel values were compared, for rotation multi-level image subtraction is used and texture comparison is done by using the LBP operator. The recognition is based on the results of all the features. If the coin satisfies all feature tests, then only it stands recognized. The multi-level image subtraction technique used is better and a faster alternative for finding the rotation of the coin. The recognition rate of 94.18% is achieved during the experiment that proves the better quality of the system.

6.2 Future work

The system covers the features of an image only, by combining it with an electromagnetic system will further increase its capabilities. Also the existing techniques like neural network, spiral decomposition, Fourier coefficients etc. can be merged into the system to improve results. A dataset of coin images of other countries can be used to check the effectiveness of the system methodology.

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List of Publications

1. Foran Singh and Shatrughan Modi, "Rotation Invariant Coin Recognition System using Multi Level Image Subtraction", communicated at Computer Graphics, Vision and Information Security (IEEE CGVIS 2015), KIIT University, Bhubaneswar, Odisha, India.
2. Foran Singh and Shatrughan Modi, "A Robust Rotation Invariant Coin Recognition System", communicated at IEEE INDICON 2015, Jamai Millia Islamia, New Delhi, India.

Video Presentation

1. https://www.youtube.com/watch?v=w4X9lqq7ObA&feature=youtu.be