

Palmprint Image Identification Using PCA, LBP and HOG Features

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ABSTRACT

Biometrics considered as the science which is playing an important role of person recognition. User identification mainly based on the physiological characteristics of an individual. Palmprint is an example of physiological characteristics of an individual which can be easily captured by using some types of sensors and cameras. The palmprint has many nature compositions which contain rich features that mainly used for distinguishing such as, wrinkles, ridges, principal lines, singular and minutiae points, these make a palmprint as one of a unique biometric and reliable for human recognition. In this work different features extraction algorithms were used such as a texture based method (LBP, HOG), and appearance based method (PCA). Also K-Cross Validation algorithm was implemented. The accuracy rates of recognition results of implemented algorithms were acquired and compared.

Keywords: Biometric, Palmprint, Accuracy rates and Recognition algorithms.

ÖZ

Bir bilim dalı olarak Biyometri kişiyi tanımada önemli bir rol oynamaktadır. Biyometri, kişisel belirlemeler esas olarak bir bireyin fizyolojik özelliklerini esas almaktadır. Bireyin fizyolojik özelliklerine bir örnek olarak Palmprint (Avuç İçi) bazı sensörler ve kameralar kullanılarak kolayca yakalanabilir. Palmprint’de birçok doğal özellik bileşenleri varolmakla birlikte, belirgin özellikler içeren kırışıklıklar, kabarıklar, ana hatlar ve tekil ayrıntı noktaları insan tanımlamasında eşsiz güvenilir biyometrik ölçütleri oluştururlar. Bu çalışmada farklı özellik çıkarma algoritmaları kullanılarak doku tabanlı (LBP,HOG) ve görünüşe dayalı (PCA) özelliklerin çıkarılması çalışılmıştır. Bunlarla birlikte k-çapraz doğrulama algoritması da öğrenme sürecinde uygulandı. Tanıma sonuçlarının doğruluk oranları kullanılarak uygulanmış algoritmalar karşılaştırıldı.

Anahtar Kelimeler: Biyometri, palmprint, doğruluk oranları ve algoritmaları tanımlama.

DEDICATION

To my beloved family

&

My best friends

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Chapter 1

INTRODUCTION

1.1 Biometrics– An Overview

Biometrics is the science of establishing the identity of an individual based on a vector of features derived from a behavioral characteristic or specific physical attribute that the person holds. The behavioral characteristic includes how the person interacts and moves, such as: their speaking style, hand gestures, and signature, etc. (Figure 1.1). The physiological category includes the physical human traits such as: fingerprints, iris, face, veins, eyes, hand shape, palmprint and many more. Evaluating these traits assists the recognition process using the biometric systems [1].

1.2 Biometric Requirements

Some requirements must exist in any physiological or behavioral characteristic in order to officially be used as a biometric characteristic. Absence of any of the following requirements will lead to a poor biometric system: [2]

- Universality: any person who may join the system must have that characteristic;
- Distinctiveness: different people should not have the same features of that trait characteristic;
- Permanence: over a period of time, the characteristic should be stable or have minimum change as possible.

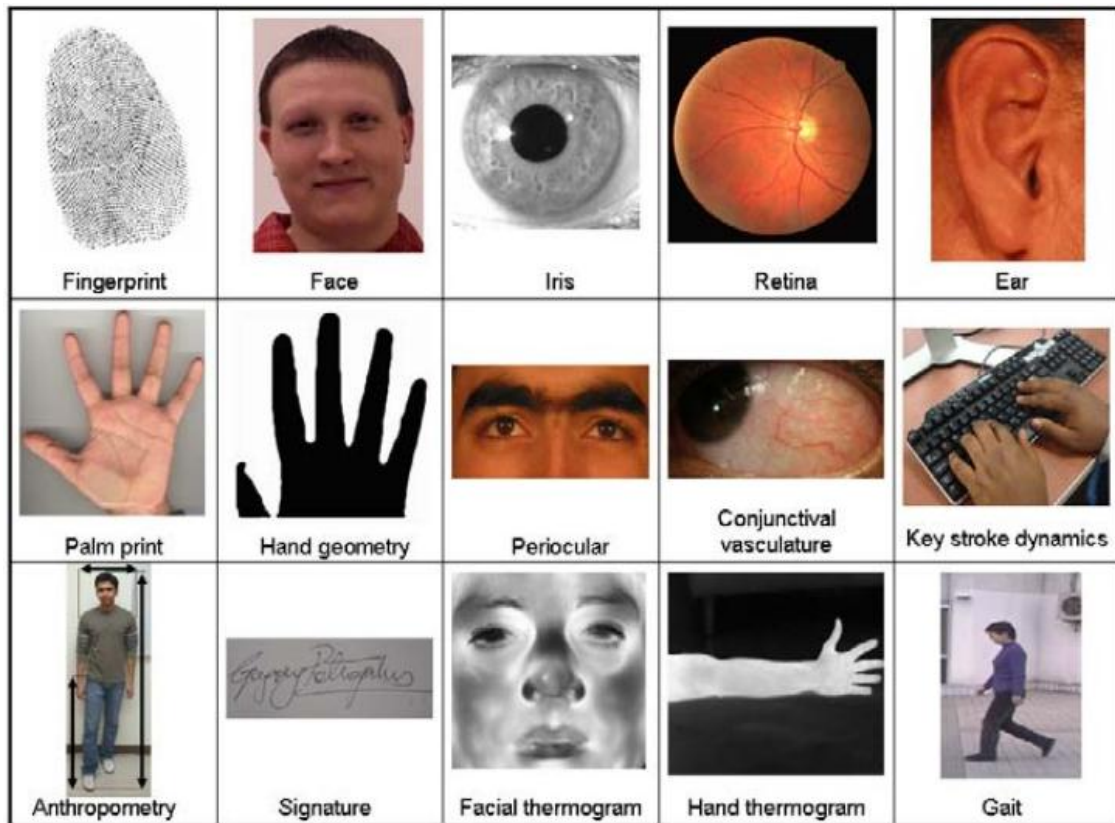


Figure 1.1: Commonly Used of Biometric Traits. [1]

- Collectability: ability of the system to measure the characteristic quantitatively.
- Performance: refers to the achievable recognition speed and accuracy, the resources required to achieve the desired recognition speed and accuracy, as well as the environmental and operational factors that affect the speed and accuracy
- Acceptability: people should easily able to use that biometric trait in their daily lives;
- Circumvention: Being able to enter the system by a person whose access is not permissible.

1.3 Biometric– Step by Step

Any biometric system should implement the following (Figure 1.2):

- 1- Sensor: the first step is to get the raw data such as (voice or image) from the user in order to use it later for recognition process.
- 2- Pre-processing operations: some operations may be needed before processing biometric data:
 - a- Quality assessment: check if the quality of the raw data is suitable for other processing steps.
 - b- Segmentation: remove the unnecessary part from the raw data, such as noise and background.
 - c- Quality enhancement: applying some enhancement algorithms in order to increase the quality of the segmented data.
- 3- Feature extractor: process of generating digital information from the raw data that is acquired by the sensor; the digital information may be called features which form a template. The template contains only discriminatory information that is used for recognizing the person.
- 4- Database: templates should be stored in a database in order to retrieve them for matching; some other information may be stored besides the templates (name, address and passwords).
- 5- Matcher: aim of the matcher process in biometrics is to estimate the differences between the stored templates with query features to find the match scores. Hence, a smaller difference indicates greater similarity between the template and the query.

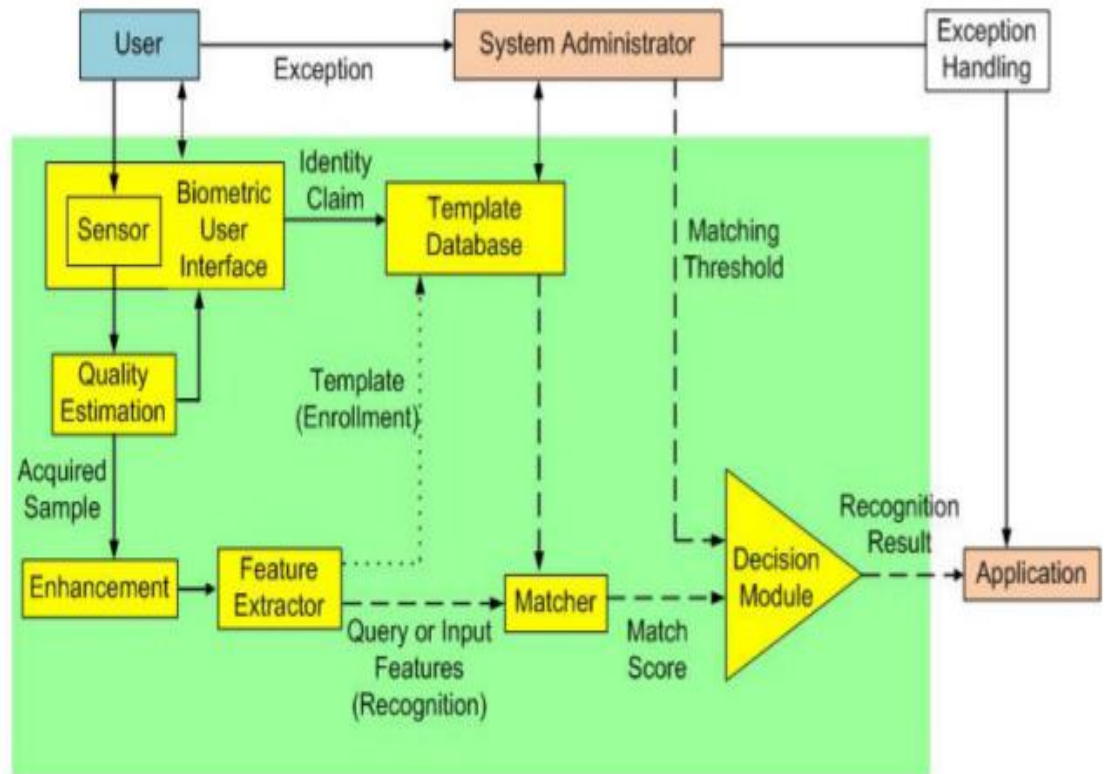


Figure 1.2: Summary of Biometric Steps [1]

1.4 Modes of Biometrics

Verification and identification (Figure 1.3) are the main modes of biometrics. Based on how the system works and how to search in the database, the modes of biometrics are classified to:

- 1- **Verification Mode:** identity of the person is recognized by comparing the input image with stored templates of the claimed ID. In such a system, users should claim his identity to be recognized, usually via magnetic cards, such as a user name, password, etc. The recognition system implements a one-to-one comparison to check if the claimed identity is genuine or an imposter. Positive recognition is mainly based on verification; the purpose is not to allow many users to use the same identity.

2- **Identification Mode:** by searching all the saved templates of the users in the database, the recognition system recognizes an individual. So, the system applies a one-to-many comparison to find an individual's identity (if the subject is available in the database or cannot be recognized otherwise) and there is no need for claimed identity to be submitted by the user. *Negative recognition* applications are considered as a critical component for identification systems, where the identification system reports the user who (explicitly or implicitly) denied being. Preventing the same person to use multiple identities is the aim of negative recognition.

Identification can be used in positive recognition in order to achieve the convenience for the user; the user does not need to claim his identity). Positive recognition in traditional methods of personal recognition may need a PIN, password, token, and key.

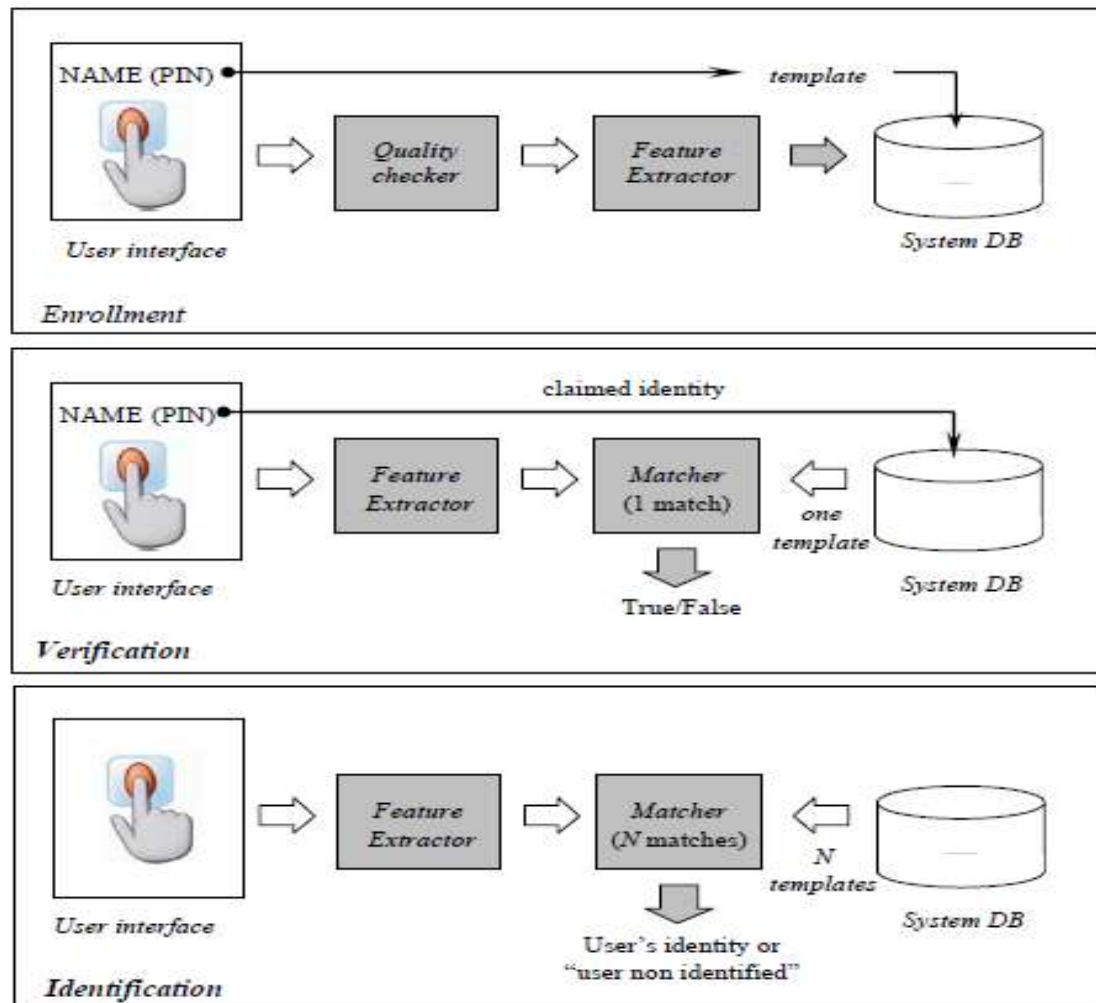


Figure 1.3: Recognition Steps of Biometric [1]

1.5 Errors of Biometrics

If two samples from the same user are captured of the same biometric trait-two images of your right eye, they are not exactly the same. This is because of some problem that may occur during the capturing process (like sensor noise and partially closed eyelashes). Some physical characteristics of users may change over time such as cuts on the fingers. Changes in surrounding conditions (light and humidity), and interaction of users with the sensors (finger placement). Figure 1.4, 1.5 and 1.6 show some possible limitations of biometrics.



Figure 1.4: Variation in The Image of Iris due to Differences in Dilation [1]



Figure 1.5: Variance in The Fingerprint Images of Same Finger due to Different Positions [1].

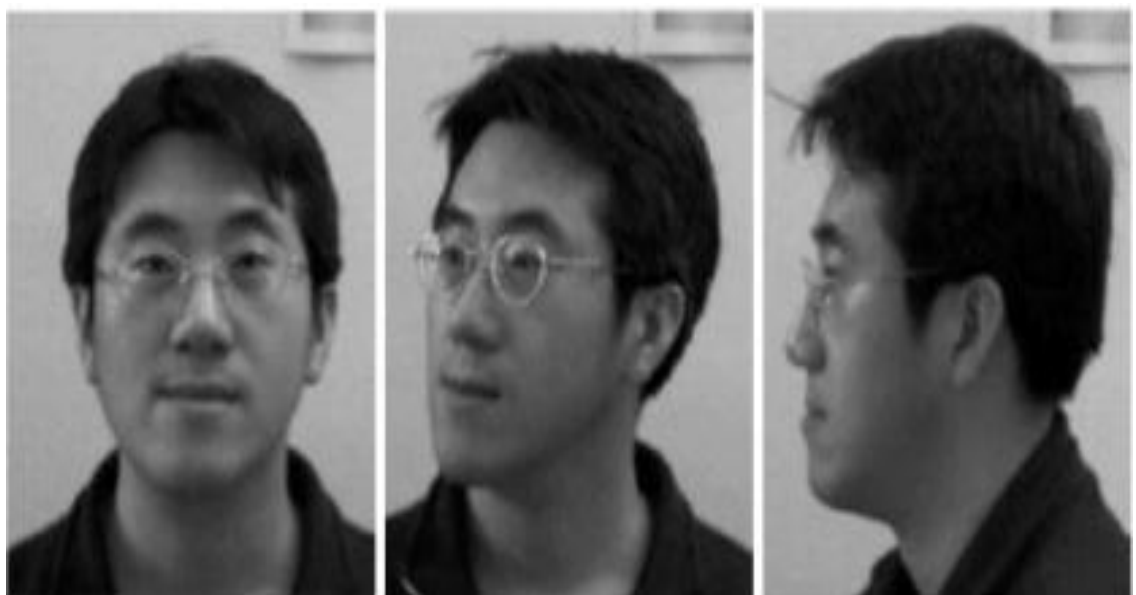


Figure 1.6: Pose Variation of Face Image [1]

In general, the recognition process in a biometric system is typically based on a matching score, which decides the degree of difference between the template that is stored in the database and input. If the difference between two biometric samples is low, the match score will be high, and a high match score means that the input and stored template come from the same person.

System decision is also regulated by a threshold. Logically, if two biometric samples belong to the same user, the score will be equal or greater than a threshold (mate pairs). Consequently, if pairs of biometric samples belong to different people, the generated scores will be lower than a threshold (non-mate pairs). The score distribution which is the result of two samples from the same person is called a genuine distribution, while the distribution of scores that result of two samples which are not from the same person is called an impostor distribution. (See Figure 1.7) [3].

A biometric verification system may produce two types of errors:

- Two different samples from two different persons will be recognized as they will belong to the same person (false accept rate) (FAR).
- Two samples from the same person will be falsely recognized as they are not from the same person (false reject rate) (FRR).

Some other errors may also occur:

- Fail to Enroll (FTE): A rate of unsuccessful tries to produce a template which is captured by the sensor. This can be caused by using low quality sensors or inputs. [4]
- Fail to Capture (FTC): The rate where the system fails to capture the input sample, when the sample is correctly presented. [4]

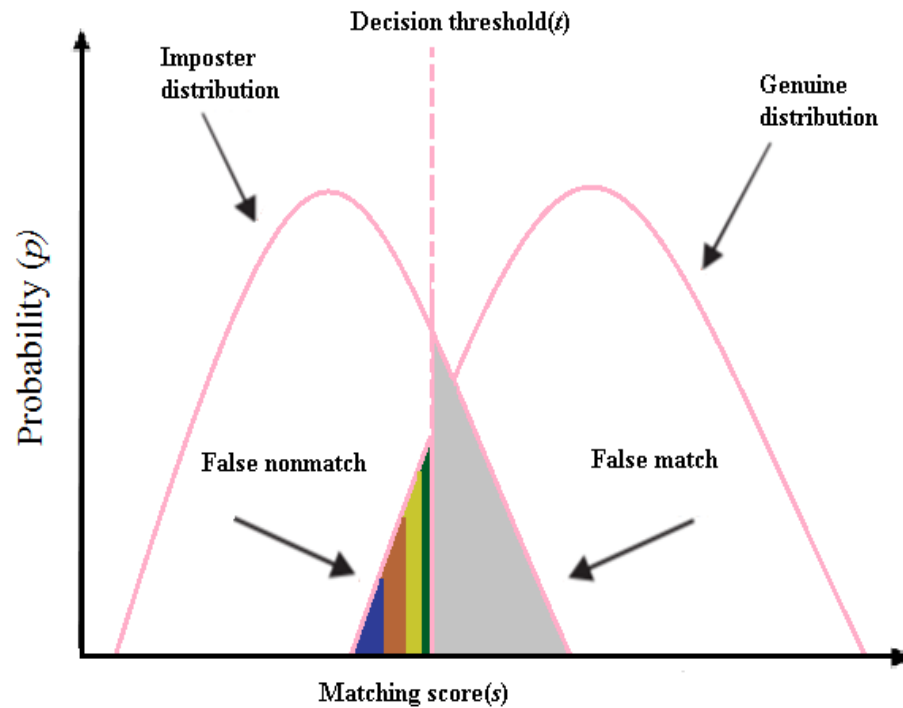


Figure 1.7: Genuine and Imposter Distribution [3]

1.6 Biometric Cycle

In order to achieve successful biometric systems, a cycle of steps should be implemented as follows:

1. Understand the nature of the system: the aim of the system must be identified.
2. Choose a biometric trait: a suitable and efficient biometric trait must be chosen.
3. Collect biometric data: samples of the chosen biometric trait should be collected in order to construct the system.
4. Choose features and matching algorithm: discriminant features of the chosen trait should be extracted.
5. Evaluate the biometric system: check if the accuracy rates of the constructed biometric system are high enough to meet the requirements of the nature of the system.

Steps of biometric cycle are shown in Figure 1.8.

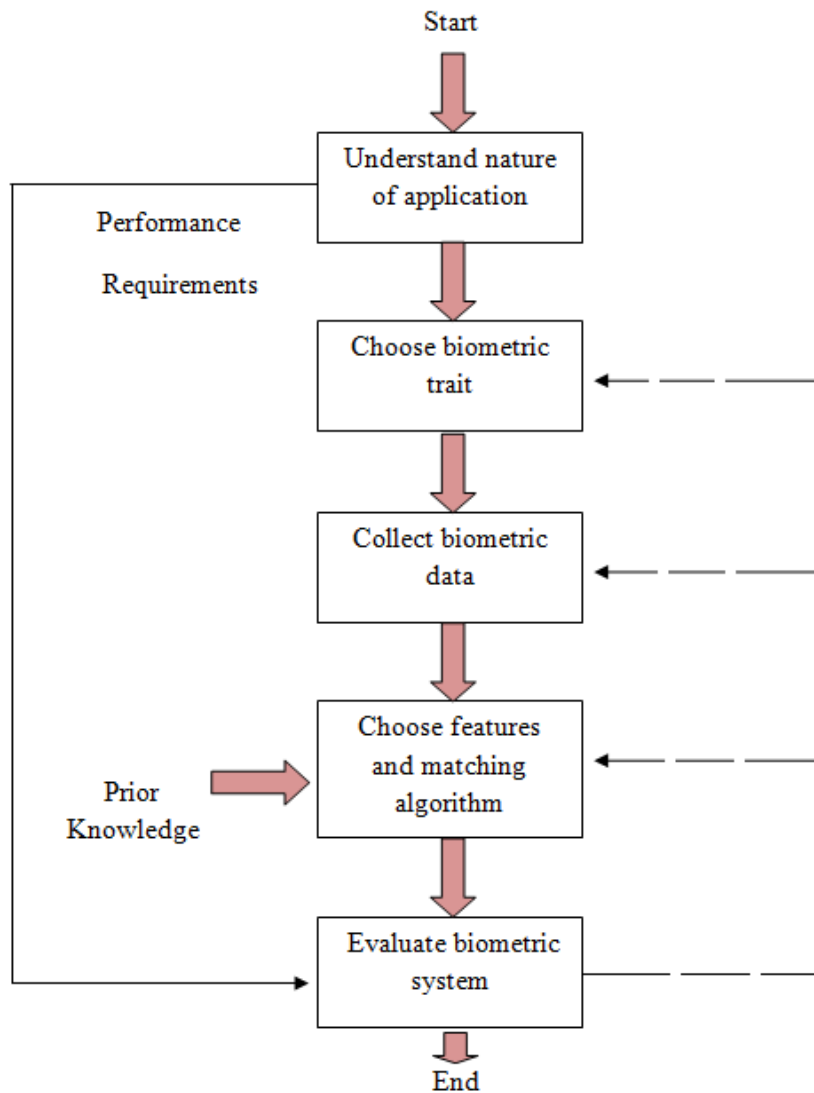


Figure 1.8: Biometric Cycle [1]

1.7 Applications of Biometric Systems

The need for the applications of biometric systems is increasing more and more. People use biometric applications in their daily and frequent activities, such as opening car doors, or front house doors, accessing accounts of the bank, online shopping from the internet, starting the engine of their car, mobile phone, laptops, etc.

The biometric applications are categorized into five main groups, depending on where the biometrics is used: government, forensic, healthcare, commercial and traveling and immigration.

1.7.1 Forensic

Biometric was used since long time for the purpose of law enforcement and forensic identification of criminals. Particularly, the fingerprint was used for forensic purposes. Now, besides fingerprints, face recognition is being also used for identification of criminals. The typical applications are:

- Identification of criminals
- Surveillance

1.7.2 Commercial

Financial services and banking represent massive growth areas of biometric technology. Some commercial applications used in this section are:

- Account Access: By using biometrics, the employees can log into their workstations and customers can access their accounts. The biometric is used to access the user accounts in the bank.
- ATMs.
- Online Banking.
- E-Commerce

1.7.3 Government

Biometrics can be used in electronic voting for both local and national elections, locating duplicates enrolled in benefits systems such as social security, issuance of driver's license, etc.

1.7.4 Immigration and Travel

The aim of the biometric application in this field is to check if the claimed identity of the user refers to the same person who is about to leave or enter a specific country.

1.7.5 Healthcare

The main use of the biometric application in the healthcare sector is to prevent an imposter by identifying or verifying the ID of users who interact with a health care entity, and to protect the information of patient and control the selling of medicine.

Chapter 2

PALMPRINT AS BIOMETRIC TRAIT

2.1 Introduction to Palmprint

The palmprint recognition system is considered one of the most successful biometric systems that is reliable and effective. This system identifies the person based on his palmprint. Studies and research have proven that a palmprint acquired from any person is unique, so it can be reliable as a biometric trait.

The interesting feature of palmprint is that the ridge structure is fixed and invariant. At the third month of the embryonic growing, the ridge structure is formed and completed by the eighteenth week.

2.2 Advantages of Palmprints

Some of the advantages of the palmprint recognition compared with other biometric traits systems are:

- Invariant line structure.
- Low intrusiveness.
- The low cost of capturing device.
- Require low resolution image.

A lot of work has already been done about palmprint recognition, since it is a very interesting research area. But, still more needs to be researched and more effort given to make the systems more efficient. [5]

Due to low cost, user friendly, high speed, and high accuracy, based on the previous merits of palmprint recognition, it can be considered as one of the most reliable and suitable biometric recognition system.

2.3 Palmprint Identification Techniques

There are three groups of marks, which are used, in palmprint identification: [6]

1. Geometric features, such as the width, length and area of the palm. Geometric features are a coarse measurement and are relatively easily duplicated.
2. Line features, principal lines and wrinkles. Line features identify the length, position, depth and size of the various lines and wrinkles on a palm. While wrinkles are highly distinctive and are not easily duplicated, principal lines may not be sufficiently distinctive to be a reliable identifier in themselves.
3. Point features or minutiae point features are similar to fingerprint minutiae (Figure 2.1) and identify, amongst other features, ridges, ridge endings, bifurcation and dots.

In order to understand the previous recognition concept, first, physiology of the valleys and ridges of a palm or fingerprint must be understood.

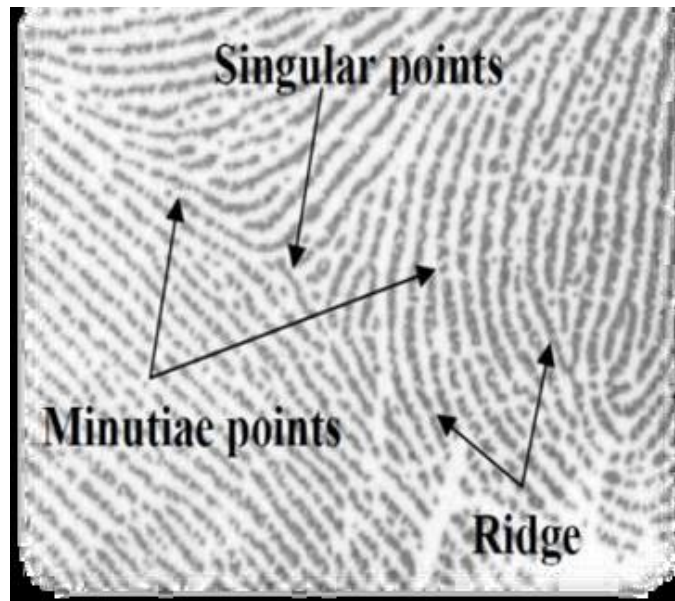


Figure 2.1: Palmprint Features [6]

The captured palmprint or fingerprint appears as a black line, which represents the peaking, the valley among the dark lines appears as a white line and is the shallow, low portion of the friction ridged skin. See Figure 2.2.



Figure 2.2: Ridges and Valleys of Fingerprint. [7]

Minutiae are limited to the direction, orientation, and location of the endings of ridge and bifurcations along a ridge path.

The images in Figure 2.3 presents a pictorial representation of the regions of the palm, examples of other detailed characteristics, and two types of minutiae used during the minutiae extraction and automatic classification processes. [7]

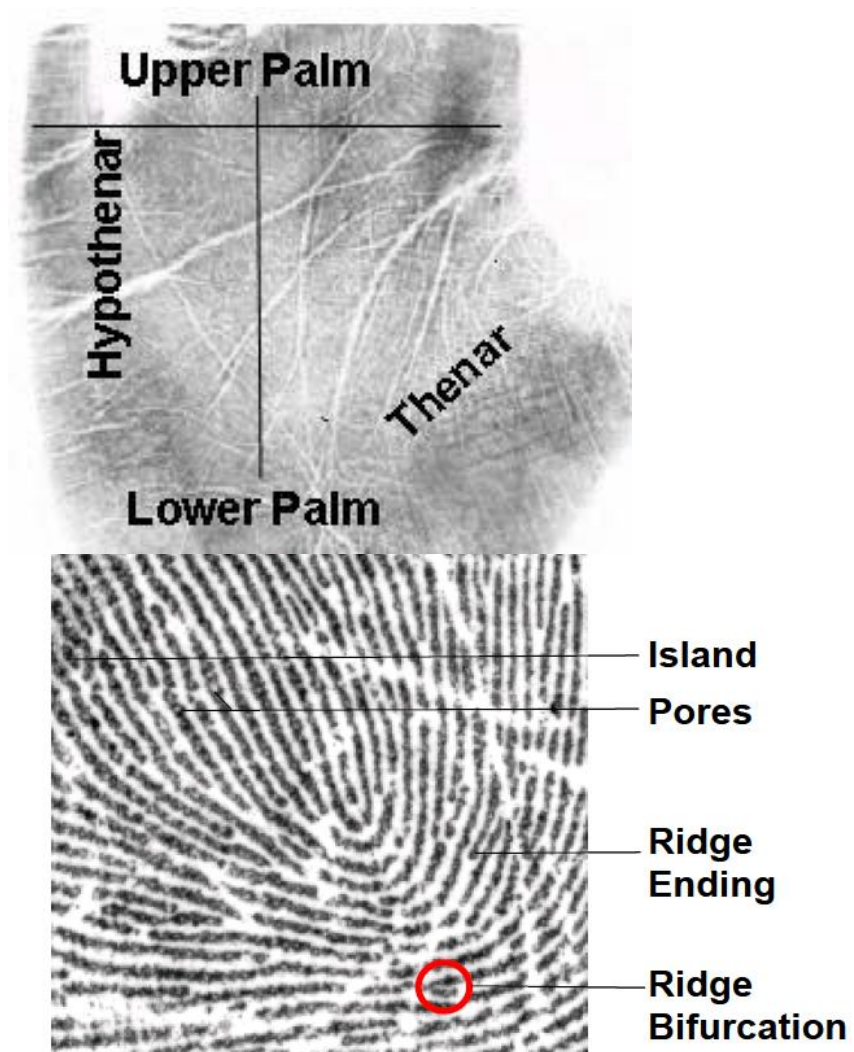


Figure 2.3: Close-up Showing of Minutiae for Palmprint [7]

2.3.1 Palmprint Acquisition

Many methods are available to capture the palmprint image, digital scanners; Researchers use video camera, CCD-based scanners, and tripod to capture palmprint images.

A high resolution image of palmprint can be captured by using a CCD-based scanner, also a palm image can be easily aligned accurately because CCD-based scanner has pegs for guiding the user where to put his hand. A CCD-based scanner is shown in Figure 2.4. [8]



Figure 2.4: CCD Based Scanner [8]

2.3.2 Preprocessing Operations

Correction distortions, aligning different palmprints, and cropping the Region Of Interest (ROI) for feature extraction are important steps before applying the feature extraction and matching process, these steps are implemented as pre-processing operations. The most commonly pre-processing steps that researches focuses on are:

1. Palm images binarizing.
2. Boundary tracking.
3. Key point identification.
4. Constructing a coordination system.
5. Extracting the middle part.

Two approaches are used to accomplish the third step:

- 1- Tangent based approach.
- 2- Finger based approach.

As shown in Figures 2.5& 2.6 the tangent based method considers the edges of the two holes of the finger to be traced. The common tangent of the both holes of the finger represents the axis. The main points in the coordination system are considered as the center point of the two points on the tangent. This approach is the best comparing with finger based approach. [8]

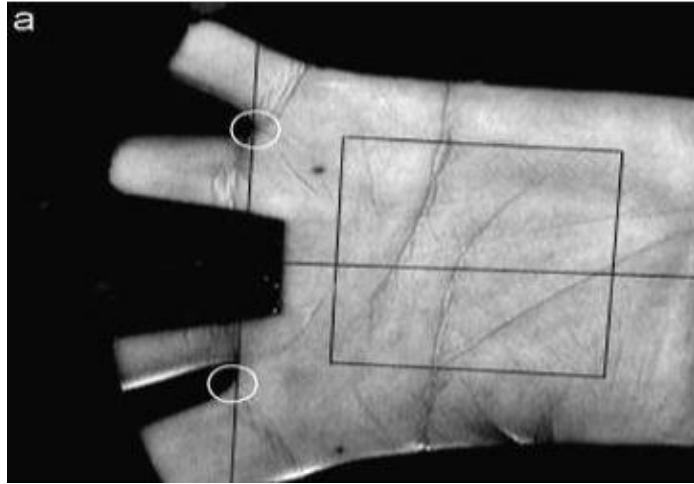


Figure 2.5: Key Points and Coordinate System [8]

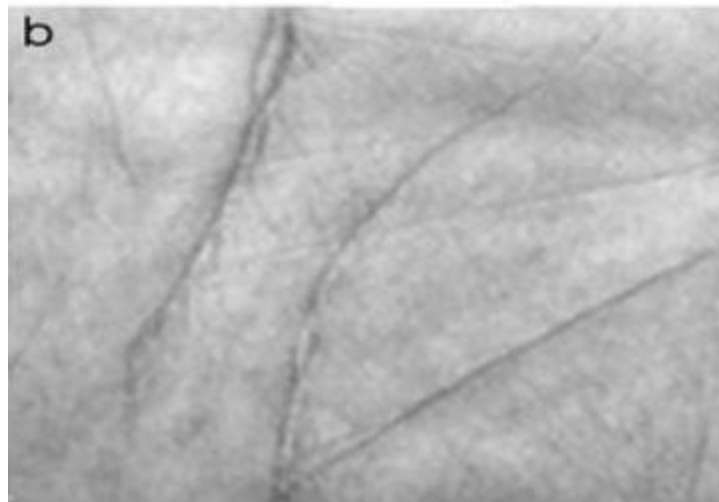


Figure 2.6: ROI Extraction [8]

2.3.3 Region of Interest (ROI) Extraction

During pre-processing operations, a segmentation process to detect the central region of the palm image should be implemented. For feature extraction, different algorithms such as square regions, half elliptical or segment circular. The easiest and most widely used is a square region. Then, a low pass filter applied to the cropped image, in order to blur the image. The secondary lines get suppressed in the blurred image, and the basic lines are also affected, but they are distinguished. Then, they can be used for process of feature extraction [8].

2.3.4 Region of Interest (ROI) Location:

P1, P2, P3, and P4 which represents the holes must be obtained (Figure 2.7), and then a line is connected between P2 and P4. After that, as shown in Figure 2.7, a square is drawn below the line. The drawn square represents (ROI) the region of interest of the palm. Depending on the experiment results, the required time (average time) for locating and identifying the ROI was less than 1ms [9].

ROI segmentation of palmprint is to reliably and automatically divide a small portion from the palmprint image, and palmprint extraction is to separate the palmprint from a ROI. This is one of the important steps in these four steps because it greatly influences the overall verification accuracy and processing speed of the complete system. It is important that to take the ROI at the same position for distinct palmprint images to guarantee the stability of the segmented palmprint features to provide fast processing speed and genuine recognition rate. In fact, a palmprint is frequently surrounded by noise; a novel palmprint segmentation scheme must separate the palmprint by removing all of these features that classified as noise [9].

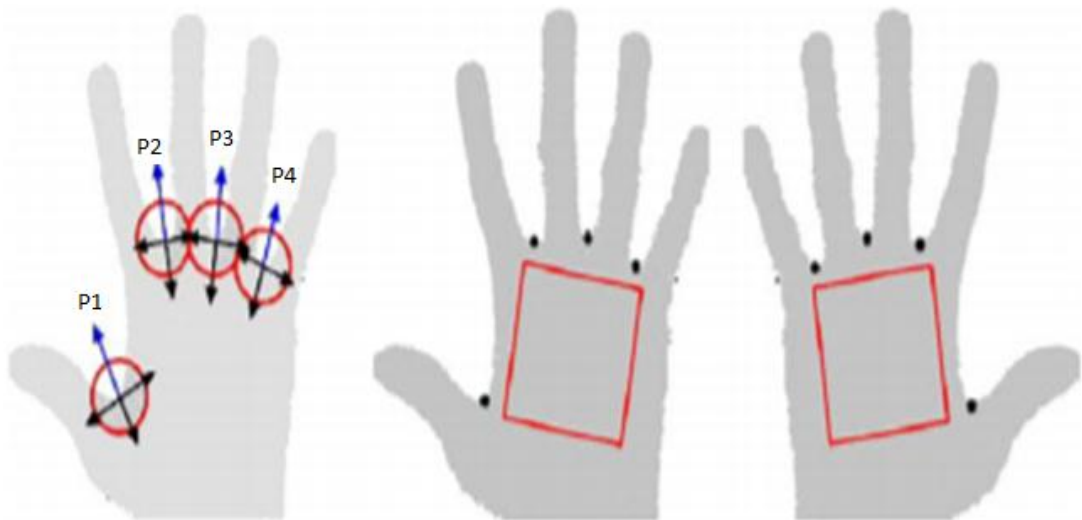


Figure 2.7: The ROI Detection Technique

2.4 Features Extraction and Matching

The purpose of these steps is to allow for the correct user to recognize and to prevent another who is not authorized from using the privileges of other people. In identification mode, the system recognizes the users by checking the all the stored samples of individuals in the DB for matching [8].

Palmprint Acquisition, Preprocessing, Feature Extraction and Matching are summarized in Figure 2.8.

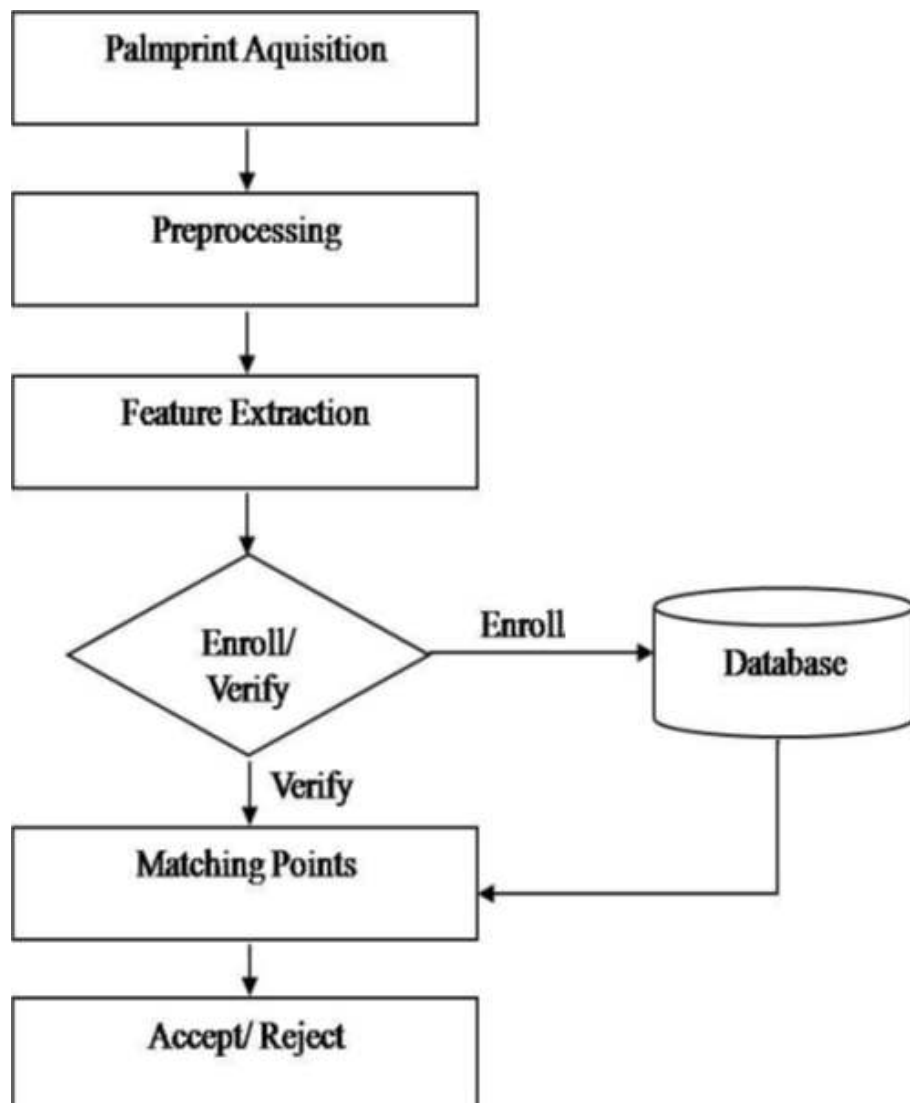


Figure 2.8: Flowchart of Palmprint Recognition [8]

2.5 Problems in Palm Recognition

Following problems considered as the main reasons that lead to shortage of the accuracy rate of [9]:

- 1- Skin distortion: since the size of the palmprint is large and contains many joints comparing with the finger tip, the distortion is quite famous when comparing between different impressions that are captured from the same palm, so skin distortion of the fingerprint is less crucial than the distortion of palmprints.

Figure 2.9 shows an example of distortion of palmprints.

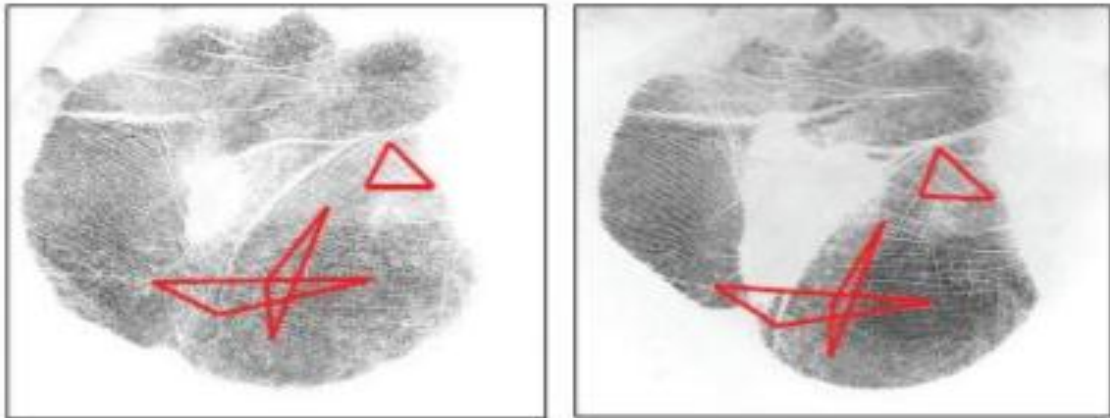


Figure 2.9: Example of Skin Distortion of Palmprint [9]

- 2- Diversity of different palm regions: Capturing of palmprint may produce different regions of palmprints; different region of the same palm may cause varying quality and distinctiveness.
- 3- Computational complexity: Algorithms that are used for fingerprint recognition are not efficient to match palmprint, because of fingerprints have not minutiae as much as palmprint. And since the database of palmprints is not placed in a common coordinate system, matching algorithm that based on minutiae need to try all possible translations and spinning or correlation of minutiae.

Chapter 3

LITERATURE REVIEW OF THE RELEVANT RESEARCH

Jadhav, S. B, Raut, M. S. D, Humbe, V. T, and Kartheeswaran, T in 2016 [10] proposed a method to recognize a person based on texture measurement by using the low-cost contactless palmprint device. By using texture features of palms such as a filled area, a palmprint recognition system was formed. Furthermore, high resolution web camera was used. It was a low cost device as compared to other implemented biometric systems and also being contactless too. The texture measurements that were calculated of palmprint images were found to be distinct. The result and analysis performed 100% success rate of the experiment.

Dubey.P. and Kanumuri.T in 2015 [11] proposed a new Palmprint recognition method based on Anisotropic Filters (AFs) and Gabor Filters. Varying illuminations in image cause high complexity and need large storage requirement when using Gabor Filters extensively. After applying Anisotropic Filters, Local Binary Pattern (LBP) also must be applied, what is known as (OLdirBP) Optimal Local Direction Binary patterns to decrease feature size. Low complexity computation and robust to noise system were achieved by applying the proposed method.

Dai and Zhou in 2012 [12] proposed a novel technique for palmprint recognition based on extraction of multiple features. Such as density, minutiae, principal lines and orientation are considered extract features. Both, Radon-Transform-Based Orientation

Estimation and DFT were used for orientation estimation. For ridges enhancement according to the local ridge direction and density in minutiae extraction, Gabor filter is used. Using the composite algorithm, density map is calculated, Gabor filter, Hough transform. Also Hough transform is applied to extract the principal line features.

Kong and D. Zhang in 2011 [13] proposed a novel method for feature extraction. The information of orientation from palmprint lines are extracted and stored in the constructed code using this method. In order to compare Competitive Codes an angular match with an effective implementation is developed. It is suitable for real-time applications since the total run time for verification is near to 1s. A database from 386 different palms (7,752 images), was used to evaluate the proposed method. For verification, the results of this method: GAR= 98.4% and FAR = 3×10^{-6} %.

Jiaa.H and Zhang in 2008 [14] based on robust line orientation, they proposed method for verification of palmprint. For feature extraction, modified finite Radon transforms were used, that extracts orientation feature. Line matching technique was used in order to match the test sample with a training sample, which mainly depends on the algorithm of pixel-to-area.

D. Huang, W. Jia, and D. Zhang in 2008 [15] proposed a novel method for the automatic classification of low-resolution palmprints. First, based on the position and thickness of palm, principal lines of the palm are found. The proposed method recognizes these palmprints with accuracy rate 96.03%.

Jadhav, S. B., Raut, M. S. D., Humbe, V. T., & Kartheeswaran, T. In 2016 [16] proposed a system for Palmprint recognition based on a symmetric mask based on a

discrete wavelet transform method and kernel based approach. In order to authenticate the palm, the edge detection, feature extraction and matching steps were used. The edges of the palm were found by applying the Kernel and average based threshold methods. The probability density function was estimated by using the Kernel-based threshold method. By using (2DSMDWT) 2-D Symmetric Mask-based Discrete Wavelet Transform and a line based approach, the features of palm edges were extracted. By using the proposed method, the computing complexity increased, also recognition rate increased by extracting more features from a low-resolution image.

W. Li, J. You, and D. Zhang in 2009 [17] have proposed a novel method in order to retrieve the images of palmprint in case of a huge database by using effective indexing and searching scheme. Feature extraction, indexing, and matching are the main issues to be considered in this research.

Prasad, Govindan and Sathidevi in 2009 [18], by using Fusion of Wavelet Based Representations, Palmprint Authentication system was proposed. The features extracted are line features and Texture feature. For feature extraction, OWE was used. Pre-processing in the proposed system includes, location of invariant points, segmentation, alignment and extraction of Regions Of Interest (ROI). The match scores are generated for texture and line features individually and in combined modes. For score level matching, weighted sum rule and product rule are used.

Meraoumia, A., Chitroub, S., & Bouridane in 2012 [19] proposed identification system to identify Palmprint online. First, for feature extraction they used Gabor filter, and in order to achieve higher performance multiple classifiers were combined. Two methods

used for classification were, the Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM).

Chapter 4

IMPLEMENTED ALGORITHMS

The experiment is carried out by using MATLAB software image processing toolbox.

Three recognition algorithms are implemented and this chapter explains the technique that is used in each algorithm:

4.1 Principal Component Analysis (PCA)

The principal component analysis (PCA) is considered as one of the algorithms in biometrics. It is a technical, statistics and used orthogonal transformation to convert many observations of possibly correlated variables into a set of values of linear uncorrelated variables.

PCA is used also to reduce a high dimensional data to lower dimensions without changing most of the information. It covers covariance, standard deviation, and eigenvectors. This background knowledge is meant to make the PCA section very straightforward, The PCA method is an unsupervised technique of learning that is most suitable for databases that contain images with no class label.

4.1.1 PCA Algorithm Steps

Let $D = \{X_1, X_2, X_3, \dots, X_n\}$ denoted dimensional feature vectors belonging to two or more classes :

Step 1: Compute mean vector (μ):

$$\bar{\mu} = \frac{1}{N} \sum_{n=1}^N \bar{x}_n \quad (4.1)$$

Step2: Subtract the mean to obtain data matrix (Φ_n):

$$\phi = \bar{x}_n - \bar{\mu} \quad (4.2)$$

Step3: Compute the covariance matrix (Σ):

$$\Sigma = \frac{1}{N-1} \sum_{n=1}^N \phi_n \phi_n^T \quad (4.3)$$

Step4: Compute the eigenvalues (λ) of covariance matrix (Σ) and sort them as:

$$\lambda_1 > \lambda_2 > \dots > \lambda_d \quad (4.4)$$

Step5: Compute the corresponding eigenvector (u) of Σ as:

$$\bar{u}_1 > \bar{u}_2 > \dots > \bar{u}_d \quad (4.5)$$

Step6: Define the projection matrix (Z_n) as:

$$\bar{z}_n = W^T (\bar{x}_n - \bar{\mu}) \quad (4.6)$$

Where

$$W = [\bar{u}_1 \bar{u}_2 \dots \bar{u}_d]$$

4.2 Local Binary Patterns (LBP)

Several methods exist for extracting the most useful features from (pre-processed) images. One of these feature extraction methods is the Local Binary Pattern (LBP) method. This relatively new approach was introduced in 1996. Using LBP, the texture

and shape of a digital image can be described. This is implemented by dividing an image into multi smaller regions from which the features are extracted.

These features consist of binary patterns, which describe the surroundings of pixels in the regions. The extracted features from the regions are combined into a one feature histogram, which forms a representation of the image. Then, images can be compared by measuring the similarity between histograms [20].

4.2.1 Texture Descriptor

The operator assigns a label to each pixel of an image by thresholding a 3x3 neighborhood with the center pixel value and considering the result as a binary number.

The LBP operator compares the eight neighboring pixel intensity value to the intensity value of the central pixel. If a surround pixel has a higher value (Gray value) than the pixel located in the center, or has the same value as one is assigned to that pixel, else it gets a zero. The LBP code for the center pixel is then produced by concatenating the eight zeros or ones to a binary code [20]. (See Figure 4.1)

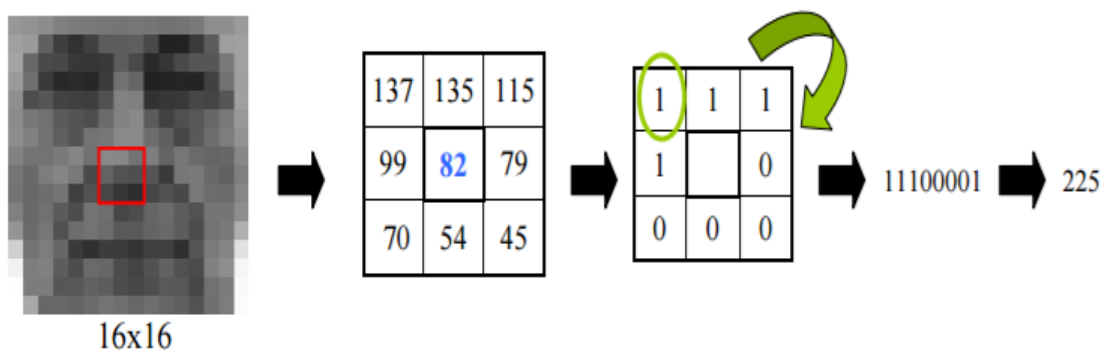


Figure 4.1: LBP Descriptor [21]

4.3 Histogram of Oriented Gradient (HOG)

HOG is one of the used algorithms for human recognition detection. HOG features can be extracted from all the locations of a dense grid on an image region and use linear SVM to classify the collected features. Although HOG gives an accurate description of the contour of the human trait, it needs a high computational time [22].

The main idea of HOG is that the shape and local appearance of objects in an image can be described by the intensity distribution of gradients or direction of the contours. By dividing the image into small connected parts, the implementation of these descriptors can be obtained, small parts called cells. Then, for each cell edge orientation or histogram of gradient directions for all pixels of the cell should be computed. The descriptor is the combination of these histograms [23].

4.3.1 HOG Descriptor

Calculation of the classic HOG descriptor begins by dividing an image under the detection window into a dense grid of rectangular cells. For each cell, a separate orientation of gradients is calculated. The histogram consists of evenly spaced orientation bins accumulating the weighted votes of gradient magnitude of each pixel belonging to the cell. For example, 8 x 8 pixel cell and 9 bins for the orientation range of 0–180 degrees have been used. Additionally, the cells are grouped into blocks and for each block all cell histograms are normalized. The blocks are overlapping, so the same cell can be differently normalized in several blocks. The descriptor is calculated using all overlapping blocks from the image detection window. From the detection window of size 64 x 128 pixels and for a block of 2 x 2 cells, shifted by 8 pixels, 3780 features per detection window are obtained. See Figure 4.2 [23].

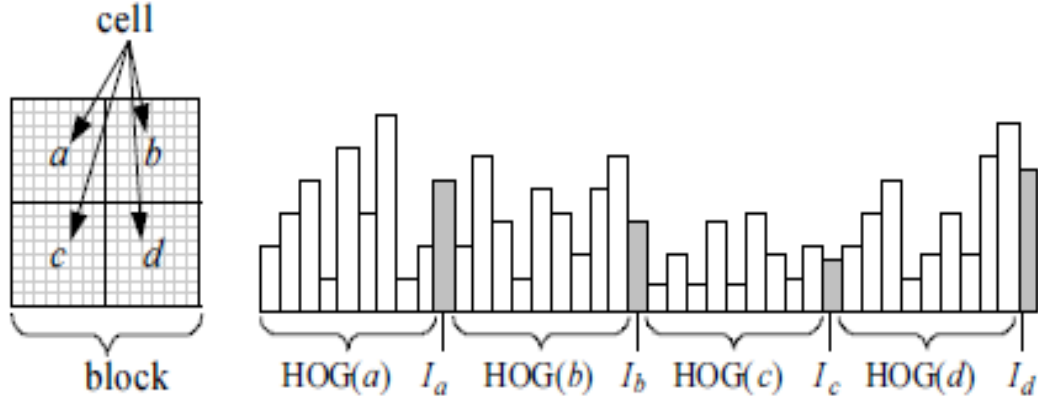


Figure 4.2: Example of HOG Descriptor[13].

4.3.2 HOG Algorithm Implementation

- 1- Gradient computation: the first step for producing the HOG descriptor is to calculate the I -D point derivatives G_x and G_y in x - and y direction by convolving the gradient masks M_x and M_y with the raw image I :

$$G_x = M_x * I \quad M_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \quad (4.7)$$

$$G_y = M_y * I \quad M_y = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}^T \quad (4.8)$$

On the basis of the derivatives G_x and G_y the gradient degree was calculated $|G(x,y)|$ and direction angle $\phi(x,y)$ for each pixel. The gradient degree shows the gradient strength at a pixel:

$$|G(x,y)| = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (4.9)$$

The gradient degree is simply employed as a weighting factor for the direction histogram. The gradient direction angle can be calculated straightforward as the following from:

$$\tan(\phi(x,y)) = \frac{G_y(x,y)}{G_x(x,y)} \quad (4.10)$$

- 2- Orientation binning, the calculation involves creating the cell histograms, each pixel within the cell casts a weighted vote for an orientation – based histogram

channel based on the values found in the gradient computation. The cells themselves are rectangular and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees.

- 3- To account for changes in illumination and contrast the gradient must be normalized. The HOG descriptor is then the vector of the components of the normalized cell histogram from the entire block region; these blocks typically overlap, meaning that each cell contributes more than once to the final descriptor.
- 4- Block normalization: four different methods for block normalization were explored. Let V be the non-normalized vector containing all histograms in a given block, $\|V\|_k$ be its k -norm for $k = 1, 2$ and e be some small constant (the exact value, hopefully, is unimportant). Then the normalization factor can be one of the following:

$$L2 - norm: f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}} \quad (4.11)$$

L2-hys: L2-norm followed by clipping (limiting the maximum values of v to 0.2) and renormalizing, as in

$$L1 - norm: f = \frac{v}{\sqrt{\|v\|_1 + e}} \quad (4.12)$$

$$L1 - sqrt: f = \sqrt{\frac{v}{\|v\|_1 + e}} \quad (4.13)$$

In addition, the scheme L2-hys can be computed by first taking the L2-norm, clipping the result, and then renormalizing. Experiments were found, the L2-hys, L2-norm, and L1-sqrt schemes provided similar performance, while the L1-norm provides slightly

less reliable performance; however, all four methods showed very significant improvement over the non-normalized data.

Chapter 5

RESULTS OF RECOGNITION AND DISCUSSION

This study mainly depends on recognition and identification of human based palmprints/ three different algorithms are implemented, each algorithm has a different scheme as explained in chapter 4, PCA, LBP and HOG were applied separately on PolyU multispectral palmprint Database.

5.1 Description of the PolyU Multispectral palmprint Database

250 volunteers were joined to collect the palm images of multispectral palmprint; participants in the DB were 55 females and 195 males. The range of volunteers' age started from 20 to 60 years old. They collected images in two different modes. In each mode, each user was provided 6 samples for each palm. Each sample was captured with four different illuminations: blue, green, red and NIR illumination (See Figure 5.1 -5.8). The ROI of the palmprint samples on PolyU multispectral palmprint Database are already detected [24].

For each user, 12 samples from each hand (Left and Right) were captured. In this study, left and right palms of the same user were considered as two separated users, which increases the challenge of recognition, since distinguishing between the right and left palmprints is harder from distinguishing different palm of different user. So, by constructing a system, which can distinguish between two palmprints (right and left) of the same user, the system will be more efficient in distinguishing between different users [24].

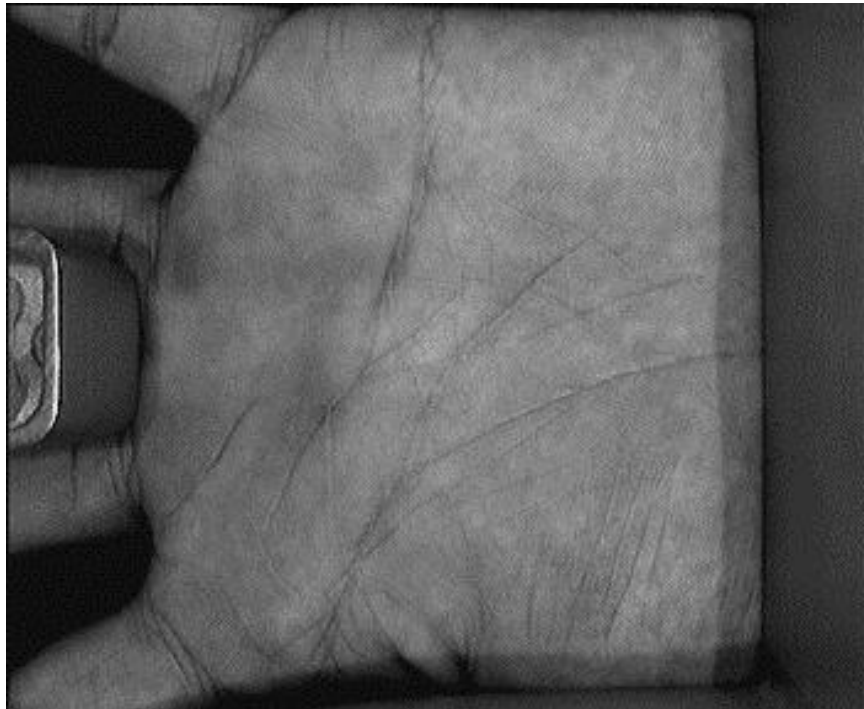


Figure 5.1: Sample of Palmprint (Blue Illumination)

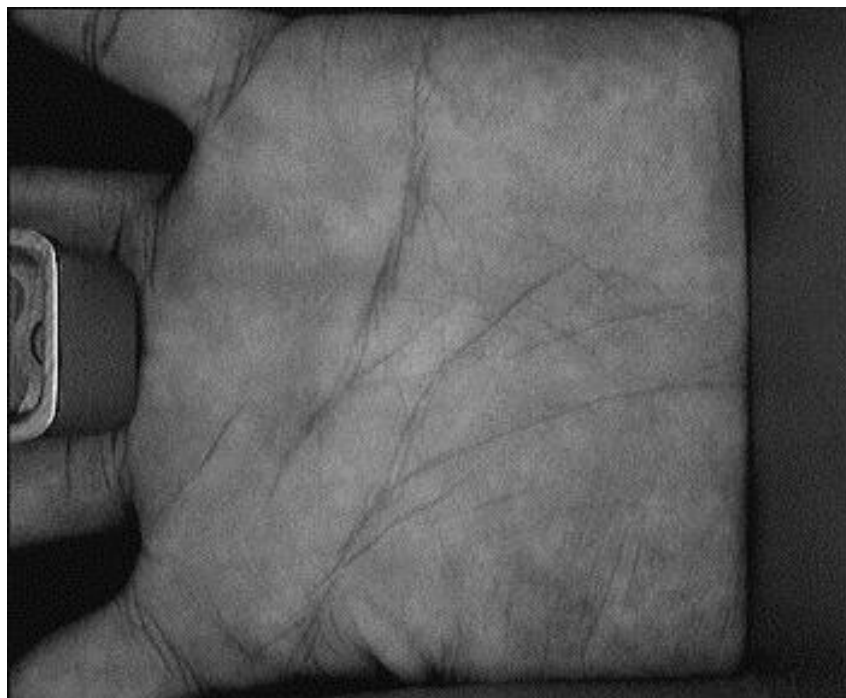


Figure 5.2: Sample of Palmprint (Green Illumination)

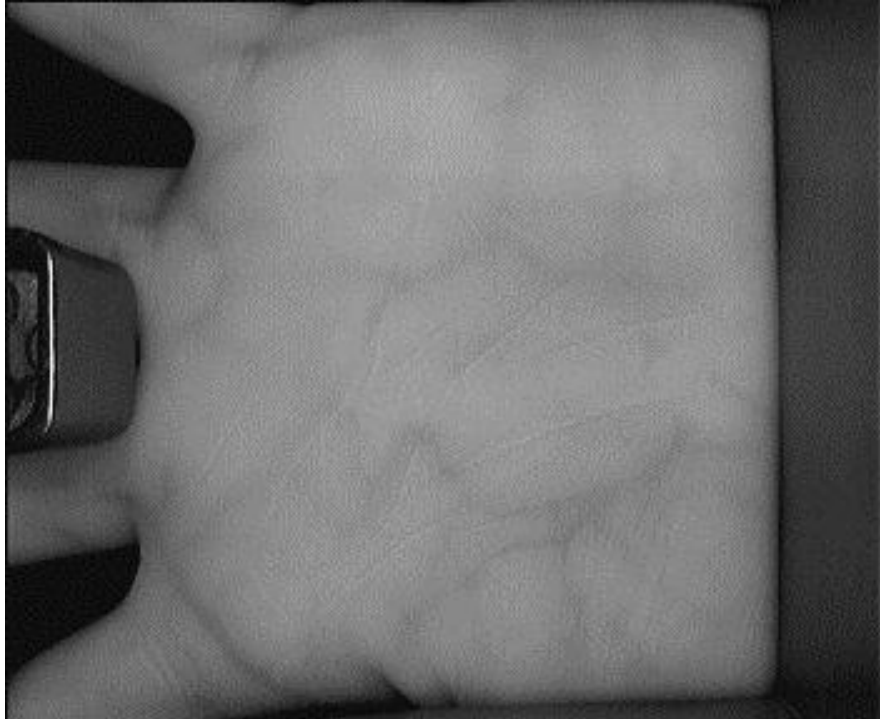


Figure 5.3: Sample of Palmprint (NIR Illumination)

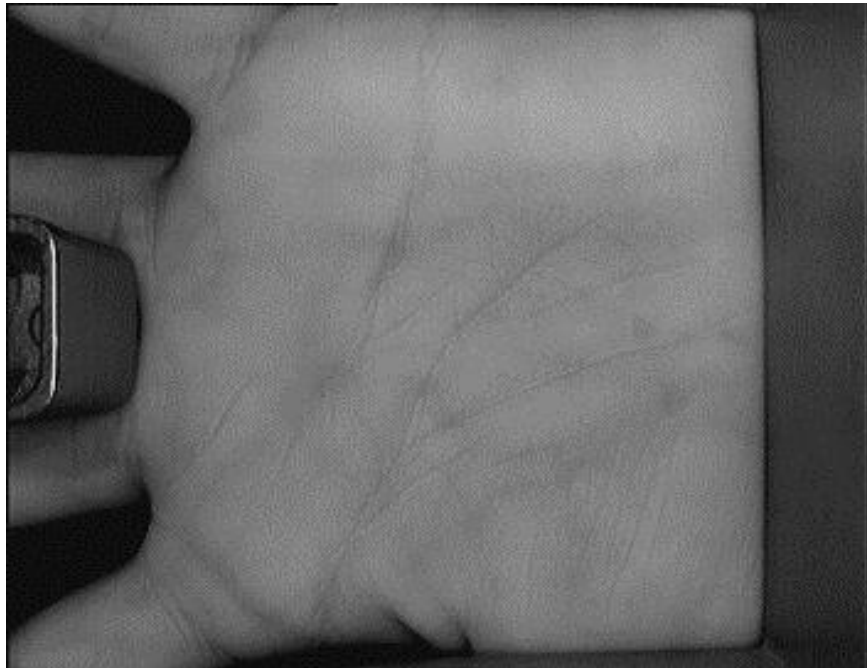


Figure 5.4: Sample of Palmprint (Red Illumination)

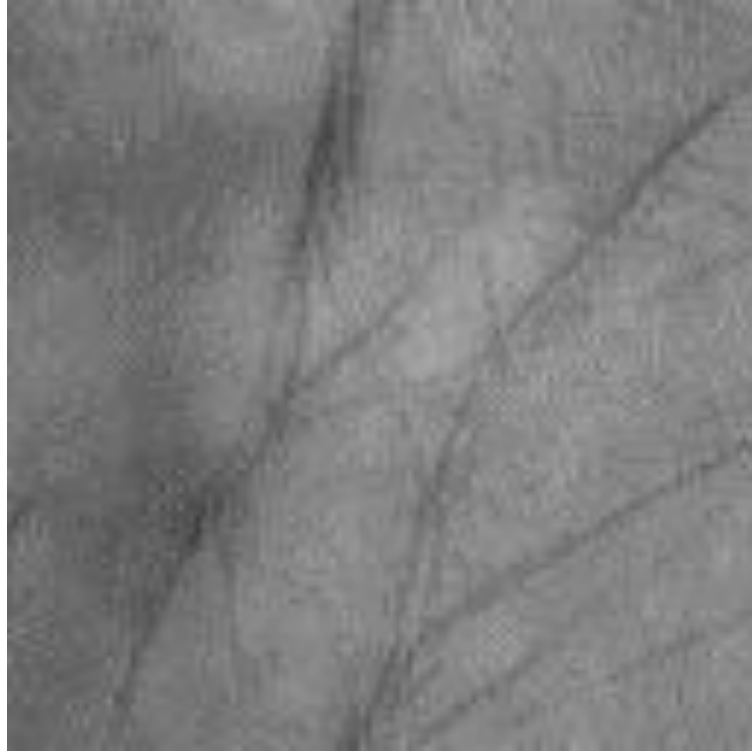


Figure 5.5:Region Of Interest (ROI), Blue Illumination

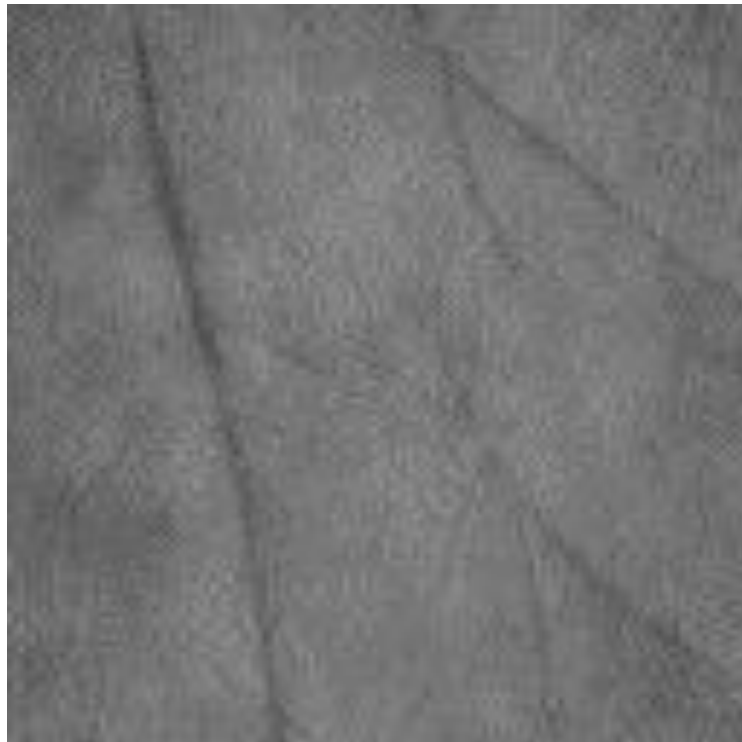


Figure 5.6: Region Of Interest (ROI), Green Illumination



Figure 5.7: Region Of Interest (ROI), NIR Illumination

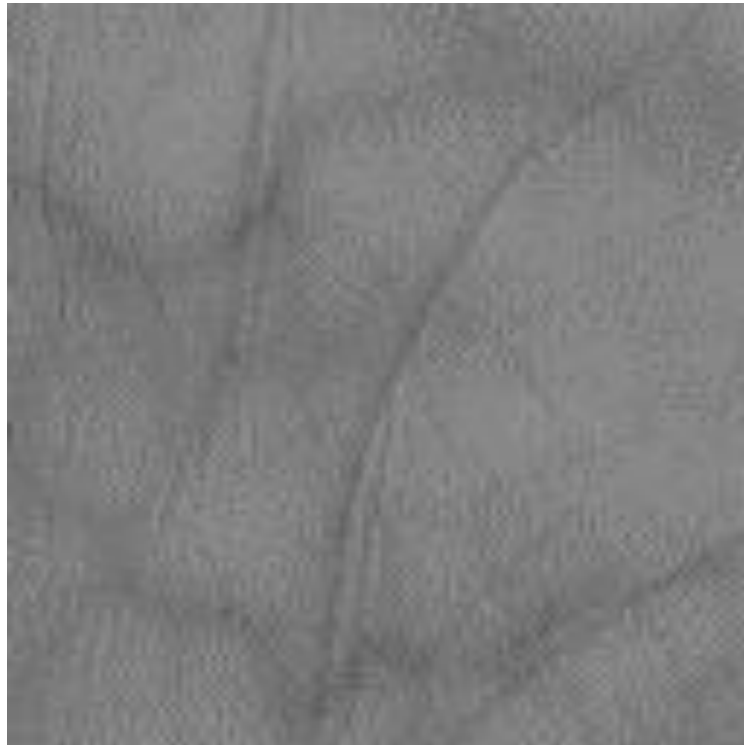


Figure 5.8: Region Of Interest (ROI), Red Illumination

5.2 Experiments and Results

5.2.1 Experiments with 1-out-of-6-Fold Cross Validation

Experiments in this study were implemented in 24 different modes. For each one of the four illuminations, PCA, HOG and LBP algorithms were implemented, each algorithm was applied with and without 1-out-of-6-Fold cross validation.

First, each user has 12 different samples; 6 random samples were taken and 1-out-of-6-Fold cross validation was applied. The first sample of palmprint was considered as test and the other five samples were considered as training samples, then second sample became the test while the other five samples became training samples etc.

For example, any user has 12 different samples, suppose the system randomly chooses six samples, which are (6,3,8,4,2 and 11). First step, sample 6 is a test sample while 3,8,4,2 and 11 are training samples. Second step, sample 3 is a test sample while 6,8,4,2 and 11 are training samples. Third step, sample 8 is a test sample while 6,3,4,2 and 11 are training samples... etc. Sixth step, sample 11 is a test sample while 6,3,8,4 and 2 are training samples.

By applying the previous steps, six different accuracy rates are acquired. For example, the accuracy rate by applying step 1. The final accuracy rate is equal to the average of all the acquired accuracy rates.

Each experiment (with all previous steps) was repeated 10 times, and the average accuracy rate was considered.

Tables from 5.1 to 5.5 show the accuracy rates of all implemented experiments by using 1-out-of-6-Fold cross validation:

Table 5.1: Accuracy Rates of Green Illumination with 1-out-of-6-Fold Cross Validation

	Accuracy Rate 1	Accuracy Rate 2	Accuracy Rate 3	Accuracy Rate 4	Accuracy Rate 5	Accuracy Rate 6	Final Accuracy
PCA	90 %	94.28%	95%	93.6%	99.8%	77%	91.7%
HOG	94.40%	99.60%	98.2%	99.8%	99.6%	99.8%	98.5%
LBP	99.8%	99.8%	98.4%	99.8%	99.8%	100%	99.6%

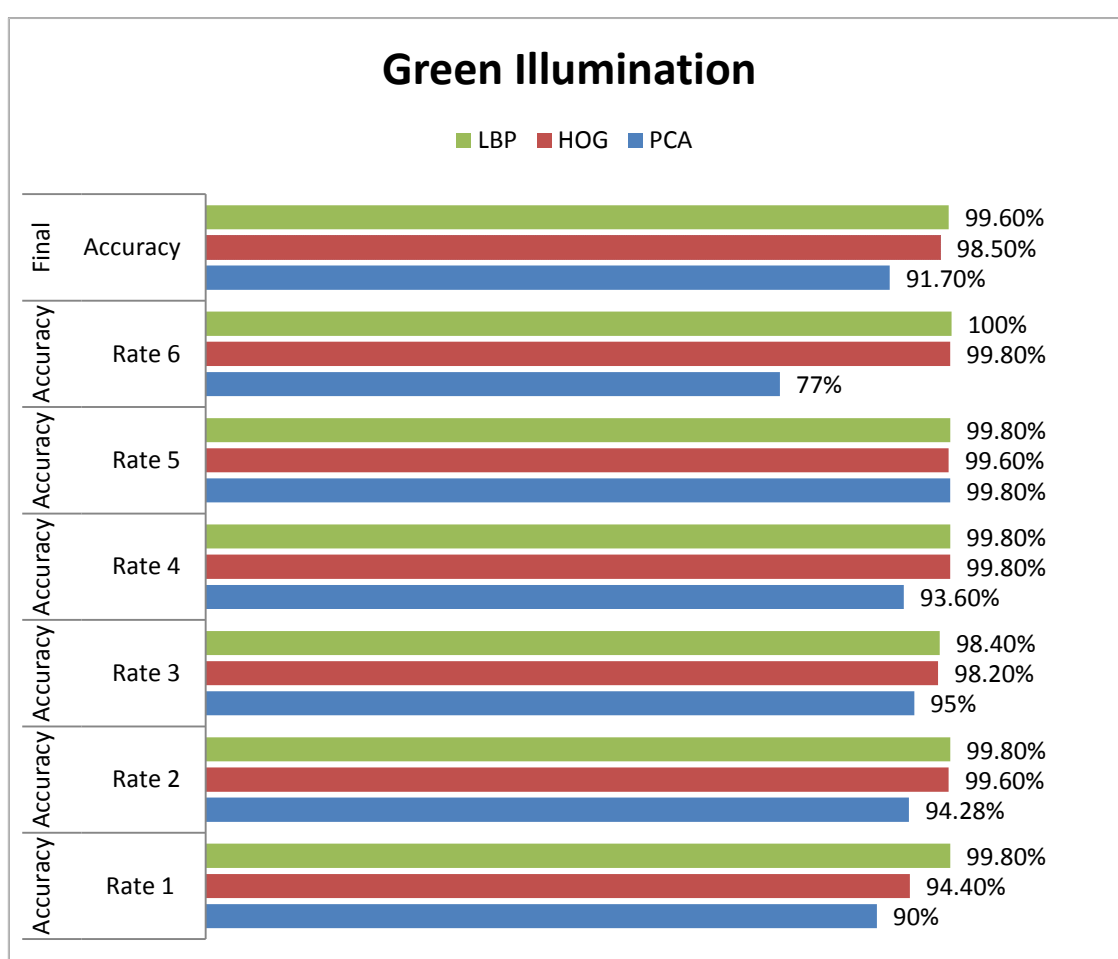


Figure 5.9: Accuracy Rates of Green Illumination with 1-out-of-6-Fold Cross Validation

Table 5.2: Accuracy Rates of NIR Illumination with 1-out-of-6-Fold Cross Validation

	Accuracy Rate 1	Accuracy Rate 2	Accuracy Rate 3	Accuracy Rate 4	Accuracy Rate 5	Accuracy Rate 6	Final Accuracy
PCA	98.6%	95.4%	68.8%	97.8%	99.8%	72.9%	88.8%
HOG	99.6%	99.8%	100%	99.8%	99.6%	99.6%	99.7%
LBP	99.8%	99.8%	99.6%	99.2%	100%	99.8%	99.7%

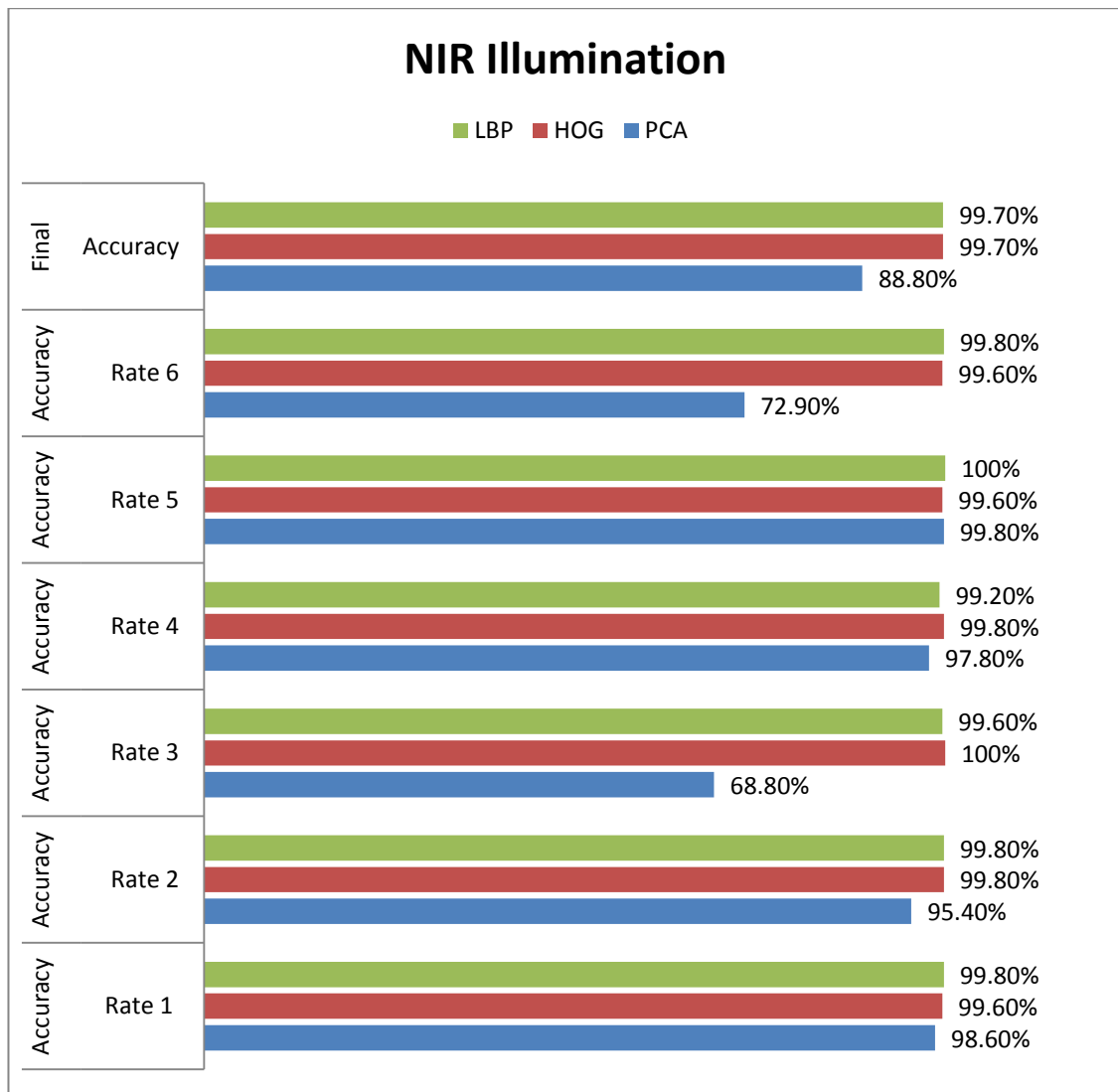


Figure 5.10: Accuracy Rates of NIR Illumination with 1-out-of-6-Fold Cross Validation

Table 5.3: Accuracy Rates of Red Illumination with 1-out-of-6-Fold Cross Validation

	Accuracy Rate 1	Accuracy Rate 2	Accuracy Rate 3	Accuracy Rate 4	Accuracy Rate 5	Accuracy Rate 6	Final Accuracy
PCA	90%	79%	94.2%	88%	88.8%	85.2%	87.53%
HOG	99.2%	99.8%	99.6%	99.4%	99.6%	99.4%	99.5%
LBP	99.8%	99.8%	100%	99.8%	99.8%	99.6%	99.8%

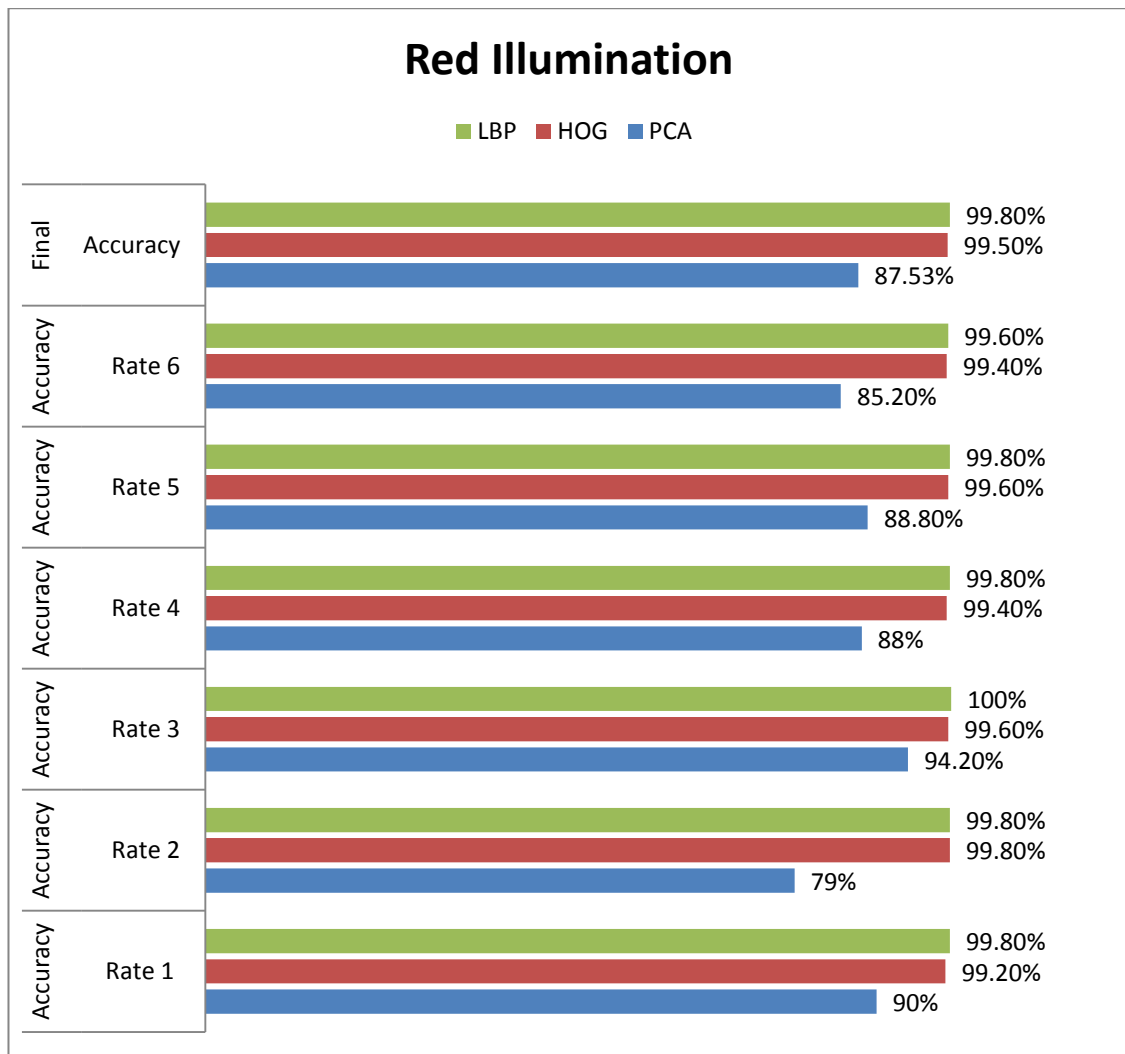


Figure 5.11: Accuracy Rates of Red Illumination with 1-out-of-6-Fold Cross Validation

Table 5.4: Accuracy Rates of Blue Illumination with 1-out-of-6-Fold Cross Validation

	Accuracy Rate 1	Accuracy Rate 2	Accuracy Rate 3	Accuracy Rate 4	Accuracy Rate 5	Accuracy Rate 6	Final Accuracy
PCA	95%	93.8%	84.2%	81%	93%	78.2%	87.5%
HOG	99.8%	100%	99.8%	99.8%	99.9%	99.8%	99.85%
LBP	99.8%	99.6%	99.2%	100%	99.8%	99.6%	99.6%

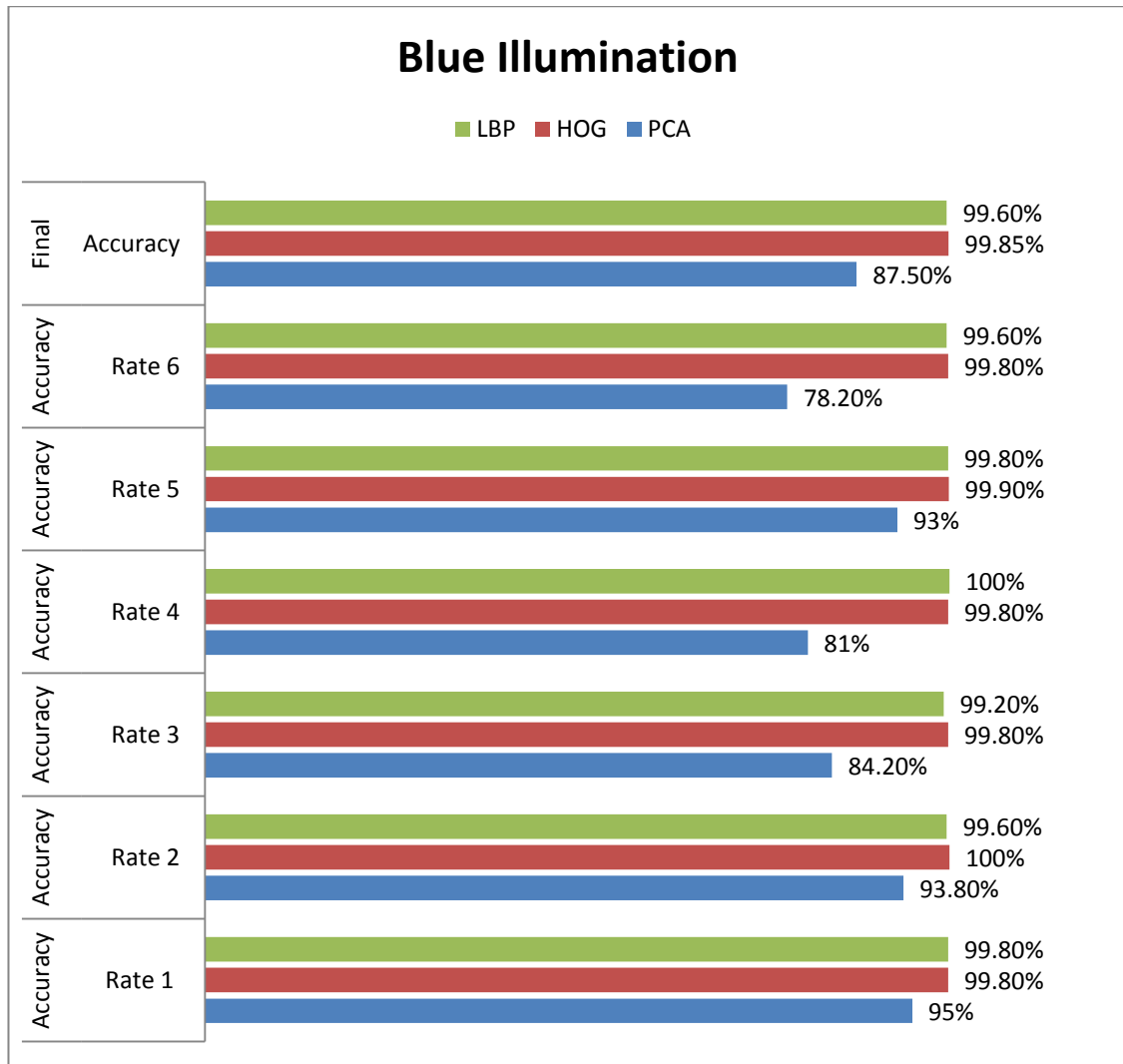


Figure 5.12: Accuracy Rates of Blue Illumination with 1-out-of-6-Fold Cross Validation

Table 5.5: Final Accuracy Rates of All Illumination with 1-out-of-6-Fold Cross Validation

	Green	NIR	Red	Blue
PCA	91.7%	88.8%	87.53%	87.5%
HOG	98.5%	99.7%	99.5%	99.85%
LBP	99.6%	99.7%	99.8%	99.6%

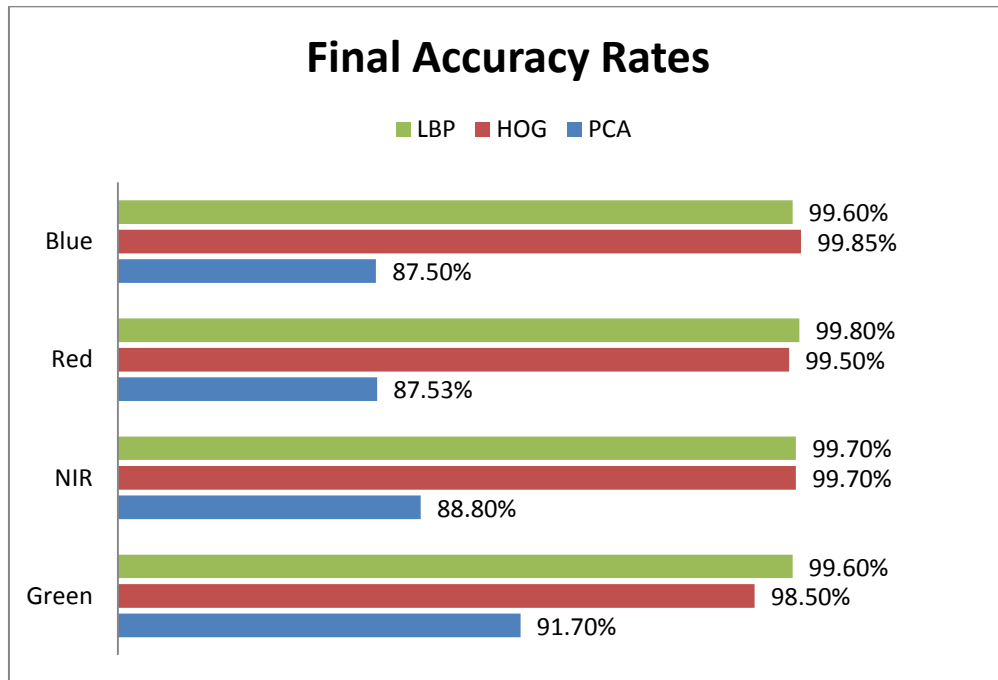


Figure 5.13: Final Accuracy Rates of All Illumination with 1-out-of-6-Fold Cross Validation.

5.2.2 Experiments without Applying K- F old Cross Validation

The second case of implemented experiments is to find the accuracy rates of the remaining of 12 palmprint samples which were randomly chosen, as supposed in the first case 6,3,8,4,2 and11 were chosen to implement the first case of experiments (1-out-of-6-Fold cross validation).

In this case 1,5,7,9,10 and 12, which were not chosen in the first case, were used as test samples, while sample 6 was as train sample.

Also, as in the 1-out-of-6-Fold cross validation experiment, this case was repeated 10 times and the average accuracy rate was considered.

Following table show the accuracy rates of recognition for the second case:

Table 5.6: Accuracy Rates of All Illumination (Second Case)

	Green	NIR	Red	Blue
PCA	83.36%	86.6%	84.2%	84.7%
HOG	92.26%	94.6%	93.7%	92.7%
LBP	96.3%	96.7%	97.3%	96.4%

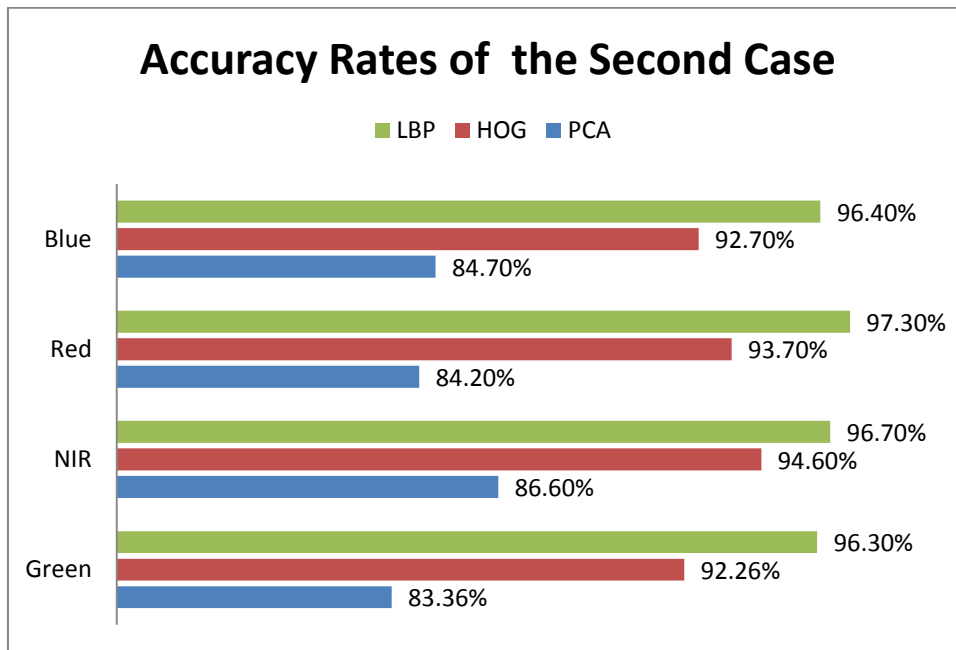


Figure 5.14: Accuracy Rates of All Illumination (Second Case)

All experiments and cases show that LBP and HOG produce the highest accuracy rates, while PCA is the worst. LBP and HOG are texture based, which uses the distribution of local pixel value for recognition, texture based is robust to light variation. While PCA is appearance based which use the raw pixel for recognition,

appearance based is sensitive to light variation. So, it is logically to acquire the highest accuracy rate by using LBP and HOG, and the lowest rates by PCA.

Experiments also show that accuracy rates are not significantly different when comparing between them based on illumination.

Finally, increasing the number training samples, will increase the accuracy rates, it easily can be noted, when comparing the accuracy rates of the first case when using five trainings, and accuracy rates of the second case when using one training sample.

Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusion

Human Recognition is one of the most challenging tasks in the field of image processing. Many existing techniques have been reviewed for palmprint recognition. In our approach, feature extraction algorithms in biometric field such as LBP, HOG, and PCA for feature extraction were used. KNN algorithm was used for matching. Applying these method leads to reduce the features (Unnecessary features), which helps to reduce the error rates and to increase the accuracy of the whole system. The aim of Proceeding with palmprint recognition is to try to construct a system with more speed and accuracy.

Highest accuracy rates were produced by LBP in all experiments and cases, while PCA produced the lowest accuracy rates compared with other algorithms.

6.2 Future Work

Some fusion method can be implemented among different parameters such as illumination (blue, green, red and NIR), or with other biometric traits like fingerprint in order to get higher accuracy rates. Other recognition algorithms may be applied with a view to compare with our study results.

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