Palmprint Recognition with Statistical, Wavelet and Local Feature Extraction Methods

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Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the Degree of

Master of Science
in
Computer Engineering

Eastern Mediterranean University
February 2015
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

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ABSTRACT

Palmprint recognition has gained significant importance in biometric and multi-biometric identification systems and it has been widely used in most of the security projects. The reason behind this is that a palmprint is a unique sample for each individual person. It is a biometric signature of fix shape; a born baby holds the same shape up to death.

Nowadays most of the studies focus on enhancing the recognition rate and determining the age and gender of palmprint images.

In this thesis, three different feature extraction techniques have been applied on images of a well know palmprint database. The three methods can be characterized as a statistical method namely principle component analysis (PCA), a transformation method namely Haar wavelets and a texture method namely local binary pattern (LBP). The aim of applying different feature extraction methods is to compare their relative performance and determine the best method for palmprint recognition.

Moreover, hybrid methods combining the algorithms mentioned above have been created in order to take the advantage of two or more feature extraction methods. Outputs individual method are fused using voting techniques.

Keywords: Palmprint recognition, Principal Component Analysis, Local Binary Patterns, Haar Wavelets.

ÖZ

Avuç içi tanıma biyometrik ve çoklu biyometrik tanıma sistemlerinde önem kazanmış ve pek çok güvenlik projesinde de yaygın olarak kullanılmıştır. Bu önem kazanmasının arkasında avuç içinin her bireye özel eşsiz bir özellik olmasıdır. Avuç içi değişmez bir biyometrik özelliktir ve doğumdan ölüme kadar aynı şeklini korur.

Şimdilerde, avuç içini tanımaya yönelik çalışmalar tanıma oranını iyileştirmeye ve avuç içi görüntüsünde yaş ve cinsiyetini belirlemeye odaklanmıştır.

Bu tezde bilinen bir avuç içi veritabanındaki görüntüler için üç farklı özellik çıkarma yöntemi uygulanmıştır. Bu üç farklı yöntem karakteristik olarak, bir istatistiksel algoritma olan Ana Bileşenler Analizi (PCA), bir dönüşüm gösterimi olan Haar Dalgacıkları, ve bir desen yöntemi olan Yerel İkili Örüntüler (LBP) olarak adlandırılır. Bu üç farklı özellik çıkarma yönteminin kullanılmasında, bu yöntemleri birbirleriyle karşılaştırarak başarımı en iyi olanı belirlemektir.

Ayrıca, bu üç yöntem kullanılarak hibrid algoritmalar da oluşturulmuş, sonuçlar oylama yoluyla birleştirilmiş ve avuç içi tanımaya yönelik sınanmışlardır.

Anahtar Kelimeler: Avuç İçi Tanıma, Ana Bileşenler Analizi, Yerel İkili Görüntüler, Haar Dalgacıkları.

Dedicated to my family and my wife

ACKNOWLEDGMENT

I would like to show a special thanks to my great supervisor Asst. Prof. Dr. Adnan Acan for his gratitude and encouragement. He has taught me to manage and write this thesis. Without his support, it was not possible to understand the topic and doing this research.

There is no way to show my appreciation and thank the professors in EMU, they enabled me to do more studies in the field of computer engineering as a result I became a self-motivated person. Their method of teaching is unforgettable and it was a good lesson in my life.

A very special thanks goes to my lovely wife, she was always encouraging me to continue on my studies. During my studies, the situation made us to be far away from each other, she tasked out to replace my space and growed our lovely daughter without me and they had suffered a lot.

Last but not least, there is no way to appreciate my parents support; they had supported me financially and morally.

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LBP	Local Binary Patterns
PCA	Principal Component Analysis
GAR	Genuine Acceptance Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
EER	Equal Error Rate
K-NN	K-Nearest-Neighbors

Chapter 1

INTRODUCTION

Palmprint recognition is available in many biometric systems that contain two modes of measurements that are used to authenticate the identity. In general, the physiological and/or behavioral are two main categories of biometrics. The first category contains the physical human traits like hand shape, palmprint, eyes, veins, etc. The second category covers physical movement of the human body, like speaking style, walking style, etc [**1**].

Palmprint recognition system is one of the important issues in the field of biometric systems, because it is unique from the birth to the death for every person even with twins, and also it has some advantages over the other signatures of biometrics like face recognition, iris recognition, voice recognition, etc. These advantages points can be listed as fixed line structure, easy and low cost, capturing and extracting of features even in low resolution imaging [**2**].

Palmprint images include several features but the most important ones are line features and texture features that we used in this thesis. The line features contain wrinkles, ridges, and principal lines, whereas the texture features are associated with patterns of the palmprint. Common methods for feature extraction are Fourier transform, wavelet transform, Discrete Cosin transform (DCT), Local binary patterns (LBP), etc [**2**].

In this thesis, three different feature extraction techniques have been applied. In order to investigate the recognition performance of individual methods and to make comparisons between them, all algorithms are implemented dedicates to palmprint recognition. Furthermore, two or more algorithms have been combined through using decision fusion techniques. Experimental results and detailed discussions on the performance of algorithms are presented in the following sections.

1.1 System Overview and the Structure

As shown in figure 1.1 [3], the base structure of a palmprint recognition system contains four main steps, namely image acquisition, preprocessing and/or detecting region of interest (ROI), feature extraction and classification for matching process.

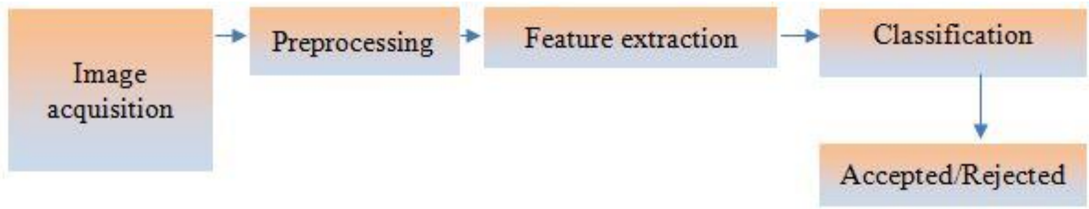

Figure 1.1: Components of a Palmprint Recognition System [3]

1.1.1 Image Acquisition

In this stage rewarded images are converts to images of particular or image format. An image format determines the precision, portability, data type, storage space, etc of an image. The images maybe 2-D gray scale or color images [2].

1.1.2 Pre-processing

The preprocessing stage implements noise removal and enhancements needed for efficient feature extraction. In addition, region of interest (ROI) is determining by cropping the image for the purpose of eliminating unnecessary parts. Noise in images usually comes from the bad lighting environments and degraded function of decoding denies [3] [2].

1.1.3 Feature Extraction

Extraction of features is the most important step before classification process. The important features that are necessary for classification are extracted and processed to make them ready for the matching process. The way the images are extracted and processed depend on the algorithms used in this stage. For example, the lines on the palmprint are very important features to be considered in extraction process. Figure 1.2 shows sample palmprint images and it is characteristic features [2] [3] [4].

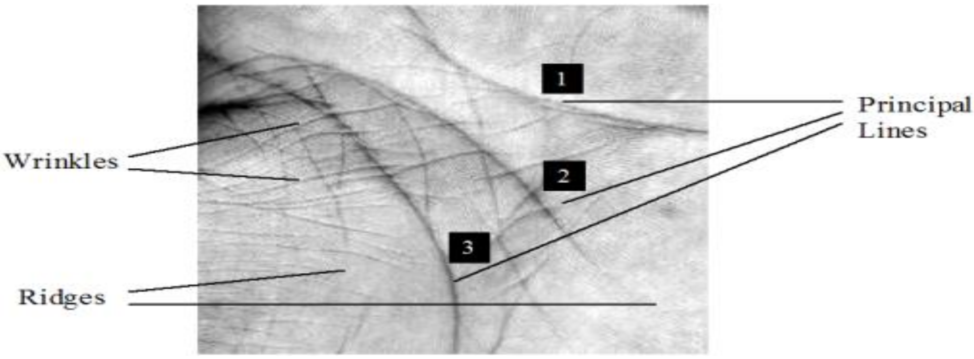

Figure 1.2: A Sample of Palmprint Image and its characteristic features [4].

1.1.4 Classification

This stage represents the conclusion processes that use the extracted features and determine the identity of input images [5]. Algorithms for this computational stage are described in the following sections. The rest of this thesis is organized as follows. The state-of-the-art for palmprint recognition will be reviewed in chapter 2. In chapter 3, the feature extraction techniques used in this study like Principle component analysis (PCA), Local Binary Patterns (LBP), and also Haar wavelet are described. In Chapter 4, results associated with each algorithm alone and results of their hybrids will be illustrated together with discussion on advantages and disadvantages for each of them. Conclusions and feature vote palms will be presented in chapter 5.

Chapter 2

PREVIOUS WORK ON PALMPRINT RECOGNITION

2.1 Review about History of Biometric Recognition

Nowadays biometrics is one of the most popular field in image processing. Many researchers are trying to develop or enhance algorithms for problems in this area, because of their use in security, industrial, enviromnets, E-government, E-commerce, and so on.

In the Greek language “bio” and “metric” are two merged words, the bio means life and the metric means measurement, so the biometric comes form these words and it means life measurement **[**6**]**.

In the twenty first century design and implementation of biometric systems became an important topic of research for researchers because of wide and indispensable use of digital technology. Some common examples of a biometric applications are recognition and identification of palmprint, face, fingerprint, and iris.

In the past centuries, the only verified method of identifying workforces was to take their handprints. For those who couldn’t write their names, hand imprints were taken by pressing onto back of papers after inking their hands.

Sir William Herschel in 1858 found to be the first one who used the recording of handprints on the rear side of papers while working in India [6]. He did this to identify the real workers from the false ones and his work is considered one of the very first systematic ways to record hands and fingers impressions for the purpose of identifying people. A Hungarian corporation for technology is known to be the first to build a known system for AFIS for palm supported recording and this was in the late 1994 **[**6**]** **[**7**]**.

Later on, some interested experts from USA contacted the Hungarian company and invited it to attend the IAI conference in 1995. Later in 1997, the company sold its palmprint identification system to a US company. In USA, starting from 2004, databases for palmprints are made available that facilitated the law enforcement to take, search and compare with criminals records.

The Australian government established the NAFIS which has more than 4.8 million records of palmprints and the method used complies with the international standards. The database is allowed to be exchanged with other agencies around the world such as the FBI and Interpol. In the recent few years some business and private companies started to involve in the process of recording finger and palmprints. They also upgraded the capabilities of their systems to include storage and search in a large database of prerecorded palm and fingerprints. For the current time, FBI has the largest archive of recorded information for justice and criminal purposes. This system allows identification services for many law and order agencies such as the FBI and other state users through the use of IAFIS. Other commercial companies have joined the field and developed their own methods for palm and fingerprints which lead to variety of choices for the government agencies to compare results with their systems **[**6**]**.

2.2 A Survey on Palmprint Recognition Methods

Brief explanations about Principle Component Analysis (PCA), Haar Wavelet, and Local binary patterns (LBP) techniques are given below.

Timo et al, applied LBP histogram for face recognition. They used fixed-size face images and they divided images into sub-windows. Then, LBP is used to extract the face features. In 2006, Xianji Wang et al, enhanced the work of Timo et al, in three ways by scanning palmprint images extract features by LBP histogram for each sub-window with six combinations. The last step is applying AdaBoost on the resulting images. They used UST_HK palmprint database and they reported 2% result for equal error rate **[**8**]**.

In 2009, Baochang Zhang et al, proposed a method named as Local Kernal Mapping (LKM) for extracting features and they showed. That its results are better than those of LBP. Their depends method on mathmaticaly issues like similarity between the testing images without the training images are saved. LKM use the kernal function to take the non-linear relations between neighorhoods. They also combined a Gabor wavelet with LBP features. The results show that success of LBP is close to 96% whereas LKM performance is close to 98% **[**9**]**.

One year later in 2010, Zhenhua Guo et al, proposed an hierarchical algorithm for multi-scale local binary patterns for both face and palmprint recognition. They used a small radius with non-uniform LBP, and a big radius with LBP for extracting the features. They used PolyU database for palmprint and AR database for face recognition problems. They reported 98.89% success for their expermental evaluations [10].

LI Yunfeng and ZHANG Yali, used a weighted fusion method of Discrete Multiwavelet Transform (DMWT) and LBP to extarct the features of palmprint images and also they used PCA for dimensionality reduction. They simplified this work in four steps: first LBP and DMWT are used for extracting features from the palmprint images. Then, the second step involves multiplication of LBP and DMWT features with different weight coefficients. The third step is dimensionality reduction for feature vectors by using PCA, and the last step is applying Euclidean distance measure for classification. They showed that the fusion method has a better recognition rate than the single methods. The best success rate for this work is 98.8% [11].

In 2006, Junwei Tao et al, proposed a combination method by combining 2DPCA and PCA for palmprint recognation. They applied 2DPCA first on the image matrix for the purpose of choosing components that are better for classification process, PCA is used for dimensionality reduction. Applications using the PolyU database showed that the combinattion method is better than the single methods and the best recognition record reported by authors is 98.4% **[**12**]**.

Chang-Zhi Wen and Jia-Shu Zhang proposed a method for palmprint recognation by using a Gabor wavelet with 2DPCA and PCA applied on the PolyU database. The Gabor wavelet is used for representing palmprint images and then the 2DPCA was used for extarcting features from Gabor wavelet representation. Where PCA is used for dimension reduction. In classification process, use of Euclidean distance measure resulted in 100% recognation rate **[**13**]**.

T. Nagarjuna Reddy and S. Karunakar Reddy presented a wavelet reconstruction algorithm together with local DCT and 2DPCA. Where the 2DPCA is used as a feature extraction algorihm and local DCT is used for the reconstructed palmprint images. They also used a nearest neighbor for classifecation process.

Muhammad Imran Ahmad et al, presented a method by using feature level fusion for multimodal biometrics like a face and palmprint recognition. They used PCA and LDA for dimensionality reduction that can significantly eliminate noise and redudant data. For feature extraction, Gabor filter has been used followed by a statical transformation technique for each orientation and scales. Their work on AR databese for face recognition and PolyU database for palmprint recognition exhibited 97% success **[**1**]**.

In 2008, Kozik Rafa et al, worked shape based recognition of palmprint images. They first detected and normalized palmprint images followed by a segmantation processes to determine different shapes like as polygons, rectangules and sequares. They used Haar wavelet and PCA algorithms for extracting features. Feature vectors are encoded for each shape using 15 elements. The goal in this paper is to identify which type of features is better for human identification by seperating the high frequency and low frequncy images. They used a Haar wavelet that gives good results for edge detection and PCA is used for dimensionality reduction **[**14**]**.

Edward Wong et al, have modified haar wavelet algorithm to extract features of the palmprint images. They have used the modified Haar Energy (MHE) for classification. Their recognition accuracy is reported as 94.3678% **[**15**]**.

Chapter 3

FEATURE EXTRACTION METHODS

Feature extraction process is one of the fundamental problems in pattern recognition. In this stage, the most important features for classification are computed. In image processing feature extraction is generally applied on two domains, namely spatial domain and frequency domain. For the spatial domain, features are directly extracted from the subject. However, for the frequency domain, the image should first be converted from spatial to frequency domain and then spectral features can be extracted.

In this thesis three-feature extraction algorithms namely, Principle component Analysis, Haar Wavelet and Local Binary Patterns are used.

3.1 Principal Component Analysis (PCA)

Principle component analysis is a statistical method that is used in the field of pattern recognition and/or image compression. PCA is a good technique for converting high dimensional data to low dimensional representation that is useful for finding patterns within input data. PCA is also a powerful technique for data compression since; it can reduce the number of dimensions significantly, particularly for high dimensional images [16] [17].

Basic steps for feature extraction from 2D images are as follows:

3.1.1 Select and Read the Images

In the first stage, palmprint images are taken from a dataset of L images. Each image has two dimensions which are N and M. Then the images are converted into a vector shape. As shown in figure 3.1, each palmprint image into a vector of length NxM. Each column vector Imi represents a palmprint image and the whole dataset is shown by X.

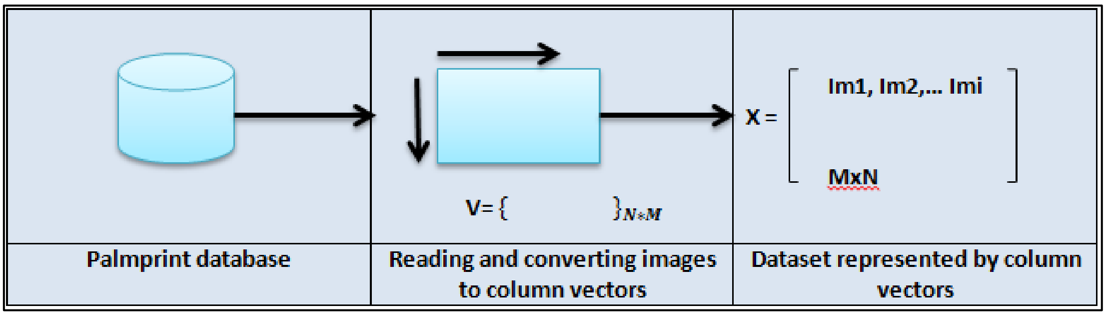

Figure 3.1: Tips of Reading and Converting Images in the Dataset

3.1.2 Calculating Mean Center of Dataset

In this stage, the mean of the input dataset is calculated using the equation 3.1.

$$m^T = \frac{1}{L}\sum_{i=1}^{L} X_i \tag{3.1}$$

3.1.3 Subtracting Mean From the Vectors

In this stage, the calculated mean is subtracted from each image in the dataset. The goal of this operation is to remove constant component and deal with the maximum directions of in variance in the database. Consequently, the computed mean is subtracted from each column of X:

$$B = X - m^T \tag{3.2}$$

In equation 3.2, B is the matrix of mean-subtracted vectors; X is representing the vectors in the dataset.

3.1.4 Compute the Covariance Matrix

Following the mean-subtracted dataset, the covariance matrix C is calculated by the following formula;

$$C = \frac{1}{n-1}\ B.B^T \tag{3.3}$$

3.1.5 Computation Eigenvalues and Eigenvectors of the Covariance Matrix

Eigenvectors of the covariance matrix are computed to find the principal bases of variation. Since the covariance is typically square, eigenvectors and eigenvalues can be computed from CV = λV, the solution of which can be obtained using the factorization of equation.

$$(\mathrm{C} - \lambda\mathrm{I}).\mathrm{V} = 0 \tag{3.4}$$

In equation 3.4, the diagonal matrix λ keeps the eigenvalues and V is the matrix of corresponding eigenvectors. If the dimensions of C is PxP, this procedure computes P eigenvalues and the same number of eigenvectors, one for each eigenvalue.

3.1.6 Sort the Eigenvectors in Decreasing Order of Their Eigenvalues

Eigenvectors are sorted in decreasing order of their eigenvalues.

3.1.7 Determining Principal Components

After sorting the eigenvalues, eigenvectors corresponding to the highest eigenvalues represent principal components of the dataset. Simply, a number, K, of eigenvectors corresponding to the largest eigenvalues are considered C to build the projection matrix of PCA.

$$W = Vs[1{:}K] \tag{3.5}$$

Where Vs is the sorted version of the eigenvector matrix V.

3.2 Haar Wavelet Transform

Wavelets are used in different areas such as: image processing, signal processing and data compression. Discrete Wavelet Transform (DWT) is a type of wavelet transform is appropriate for computer implementation and some commonly used type of wavelets used in DWT are Haar, Morlet, Mallat and Meyer, Daubechies, etc. Mathematically DWT can be described in the equations below:

$$W(j,k) = \sum_{j}\sum_{k} x(k)2^{-j/2\varphi(2^{-j}n-k)} \quad (3.6)$$

where j is index of frequency components and k is the index for time domain samples.

The simplest and oldest wavelet transform technique in signal processing is Haar wavelet; it is usually used to extract local features from the images. It has been widely used in many applications in biometric recognition such as face, iris, palm and fingerprint.

One of the prosperities of any frequency domains transformations techniques is that it's not localized in continuous form. This prosperity is considered as a disadvantage of frequency domains transformations techniques, it cannot always consider the difference of the coefficients, while Haar wavelet giving a good localization.

The first stage to extract features in signals using Haar wavelet is considering two values and taking the average and difference between two neighbor pixels. The output of this process is constructing low and high pass wavelet sub-bands.

The work of the DWT transform can be illustrated using the following sequence of equations:

$$\mathrm{H}\ (\omega) = \sum_{k} \mathrm{h}\ k^{\cdot e^{-j\,k\,\omega}} \quad (3.7)$$

$$\mathrm{G}\,(\omega) = \sum_{k} \mathrm{g}\,\mathrm{k}\cdot\mathrm{e}^{-\mathrm{j}\,\mathrm{k}\,\omega} \tag{3.8}$$

H (ω) is a low- pass, G (ω) is a high-pass filter, and h and g are the filter coefficients. The discrete signal F(n) for low and high frequency can be represented as

$$f\,j - 1^{low}\,(k) = \sum_{n} h_{n-2k}\;\; f\,j\,(n) \tag{3.9}$$

$$fj - 1^{high}\,(k) = \sum_{n} g_{n-2k}\;\; f\,j(n) \tag{3.10}$$

In this thesis, Haar filter has been implemented for which the Haar filter equations as follows:

$$H\,(w) = \frac{1}{2} + \frac{1}{2}\,e^{-\,jw} \tag{3.11}$$

$$G\,(w) = \frac{1}{2} - \frac{1}{2}\,e^{-jw} \tag{3.12}$$

3.3 Original LBP

In 1996, Ojala et al. has invented a new texture method algorithm for pattern recognition, his method was working by comparing eight neighbors of the central pixel to the central pixel. He had put the central pixel as a threshold and the pixel around it as a neighbor. The method was coding the pixels based on comparing the neighbor to the central pixel, in case the central pixel was higher than the neighbor it assigns zero to the neighbor position as a binary code, otherwise one assigned. To construct the new gray values, the neighbor codes are concatenated in clockwise order and converted to decimal representation. Figure 3.2 bellow shows the original LBP operation.

After constructing all new gray value codes, the histogram will extracted to represent the final feature set.

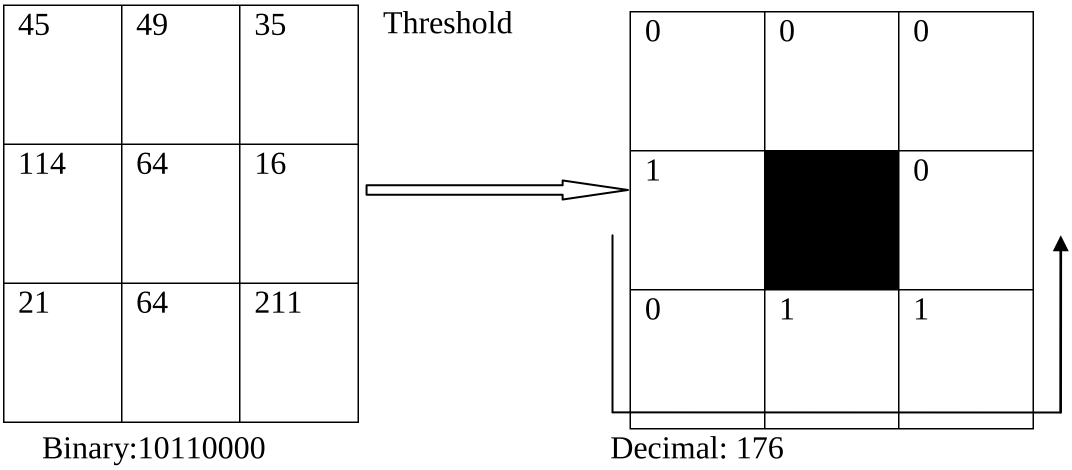

Figure 3.2: The Original LBP Operator

Since neighbors has significant affect on representing final features, different scales (radius) can be chosen for feature extraction. Figure 3.3 shows different scaling with choosing different number of neighbors.

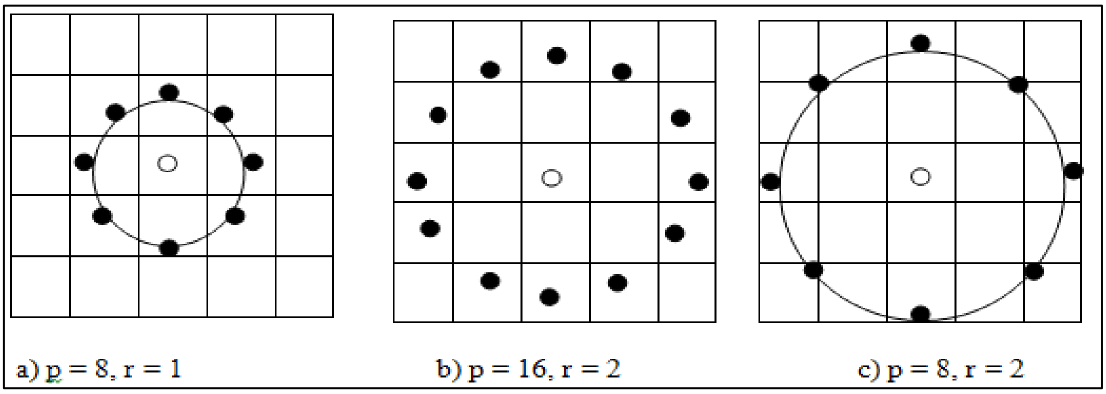

Figure 3.3: Circular Neighborhood in LBP [**18**]

The equation shows LBP calculation.

$$LBP_{(p,r)}(X_C) = \sum_{P=0}^{P=7} u\left(X_p - X_C\right)2p \qquad (3.13)$$

$$u_y = \begin{cases} 1, & y \geq 0 \\ 0, & y < 0 \end{cases} \tag{3.14}$$

Where (x_c) denotes the value of the centered pixel, (x_p) is the value of the sample (neighbor) pixel (p,r) is representing the pixels in neighborhoods, where p is the number of points on a circle of radius r.

Moreover, the method was strong enough to encourage and push researchers to become interested to make it a base for other improvements on this method.

3.3.1 Blocking LBP

In 2006, Ahonen et al. had improved the original LBP. The idea comes out from the fact that extracting histogram over all images in one package will not extract the local features that may images have. Therefore, the new idea will sub-divide the original image to sub-blocks then extract the histogram of each block from them after the LBP applied. Finally, all histograms extracted from sub-blocks are concatenate to represent final feature vector. The figure 3.4 shows the feature histogram for face image.

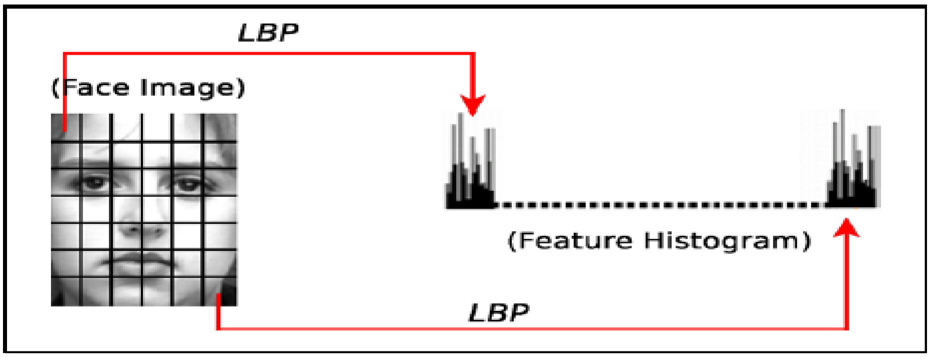

Figure 3.4: An Example of LBP Histogram [**19**]

3.3.2 Uniform LBP

In image representation using histogram, there are some bins that are more important than the others (i.e. more occur than the others), Ojala et al. names these bins as-uniform LBP and they noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8,1) neighborhood and for around 70 % in the (16,2) neighborhood. The LBP called uniform if there are at most 2-bit transitions from zero to one or from one to zero, such as (11001111) has 2 transition, (00000000) has zero transition and they are uniform LBP code, while (01011100) has 4 transition , (11101010) has 6 transition and they are non-uniform LBP codes. From the gray representation, which contains 256 histogram bins there are only 58 uniform LBP codes. Therefore, to represent an image using this method we will choose this 58 uniform bins and all other remaining bins will added together and the result puts to bin number 59. As a result, we will represent each block using only 59 bins instead of 256 bins using original LBP [9].

3.4 Decision Fusion Techniques

The fusion technique of biometric systems is a way of enhancing the performance rate of biometric algorithms. It is used in multi-biometric or single biometric systems, and nowadays researchers shows that feature fusion technique can improve the recognition rate performance.

A fusion technique can be implemented in different levels namely decision level, feature level, score level and sensor level **[**20**]**.

In this thesis feature decision level has been implemented by using majority voting. After extracting features for all algorithms separately, decision of individual classifiers are combined to reach one conclusion. Majority voting procedure is applied to combine individual decisions of all algorithms described above. Figure 3.5 show the process of decision level fusion by using majority voting technique.

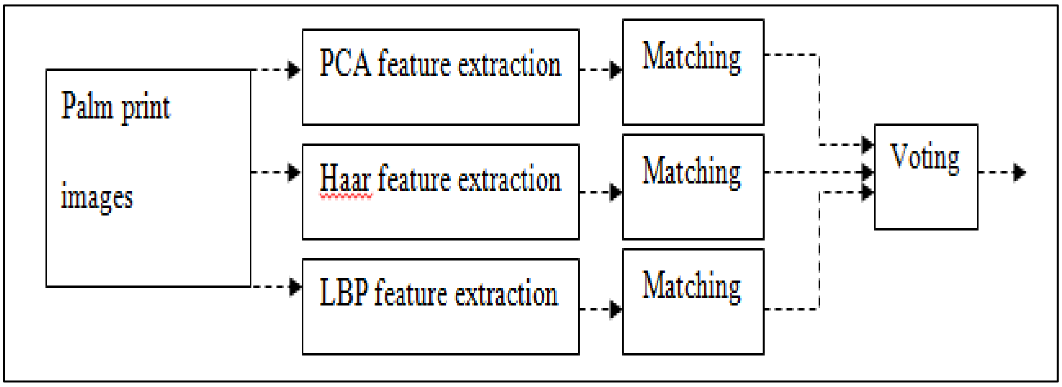

Figure 3.5: The Process of Feature Decision Level by Using majority Voting [20]

Chapter 4

EXPERIMENTAL EVALUTIONS

This chapter focuses on the experiments and results of three algorithms namely PCA, Haar Wavelet and LBP. Different conditions have been considered in implementation of these algorithms when they are applied on PolyU database.

4.1 Palmprint Database

The Polytechnic University in Delhi, India, created the PolyU database that contains hand images collected from the staff and student of this university. They used a digital CMOS camera to capture images and all images are saved in a bitmap format.

Nowadays, the PolyU dataset is a standard database that helps researchers in the field of biometric recognition. PolyU has been used for many researches and studies and it is a standard database for Palmprint recognition.

From July 2006 to June 2007, the PolyU database has been created for left and right hand images from 235 people. It consists of 2601 images; 1301 for left hand images and 1300 for right hand images. Images are captured from a group of 14-56 years old participants. Initially, the resolution was 800*600, but later they cropped the image or they selected region of interest, and the resolution became 150*150. Moreover, in the PolyU dataset each class contains five to seven hand images from left hand and the same for right hand.

4.2 Experimental Results

Experimental evaluations using PolyU database and PCA, Haar wavelet and LBP algorithms are presented in this chapter.

4.3 Results Using the PCA Algorithm

As mentioned in chapter three, PCA algorithm is implemented on palmprint images for feature extraction. As a first experiment, PCA is applied by increasing the number of training and testing images from 100 set to 470 images for the right hand and left hand.

Table 4.1: PCA Performance on Left Hand Palmprint Images in the Datasets.

No.	Training images	Testing images	PCA performance (%)
1	100	100	74.00
2	150	150	78.66
3	200	200	79.00
4	250	250	78.00
5	300	300	76.33
6	350	350	74.85
7	400	400	75.75
8	450	450	74.88
9	470	470	75.10

In Table 4.1 for the left hand palmprint datasets best result is 79% for 200 training images and 200 testing images.

Table 4.2: PCA Performance on Right Hand Palmprint Images in the Datasets

No.	Training images	Testing images	PCA performance (%)
1	100	100	73.00
2	150	150	76.66
3	200	200	75.00
4	250	250	70.00
5	300	300	72.33
6	350	350	74.28
7	400	400	74.00
8	450	450	73.33
9	470	470	74.46

The Table 4.2 shows the PCA performance results for the right hand palmprint images, it can be seen that the best result is 76.66% for 150 training and 150 testing palmprint images.

4.4 Evaluations Using of the Haar Wavelet

Haar wavelet is a type of DWT transform and it is applied on right and left hand plamprint images with normalization for first, second and third level sub-bands. Tables 4.3 and Table 4.4 shows the success of Haar wavelet with Knn and Hamming distance classifiers. Haar wavelets are used with a Hamming distance classifier with four sub bands namely, (CA CH CV CD) (or in some papers LL LH LV LD). These four sub-bands represent images in different resolution. The first sub-band or CA is close to the original image than the other sub-bands. Images in each size can take Kth level. For example, if the size of images is AxB we can take Kth levels where K= 1,2,3,4 etc. These four sub-bands within the image represents as CA for horizontal, CH for vertical, and CV for diagonal orientation, in the first level but CD sub-band is an approximation image [21].

As seen on the tables, the first sub-band CA or LL shows the best result over Haar wavelet because it is close to the original image. It can be seen that the result shows that the best result is 75.74% for left hand palmprint with K-NN classifier.

Table 4.3: Haar Wavelet Performance with KNN Classifier

Haar wavelet sub-bands	**Performance on right hand palmprints (%)**	**Performance on left hand palmprints (%)**
CA	74.25	75.74
CH	1.27	6.38
CV	3.40	10
CD	0.42	0.85

The Table 4.3 show the Haar wavelet performance with KNN classifier for both left and right hand palmprint iamges in the dataset and the best result for right hand is 74.25% in CA sub-band and best result for left hand is 75.74% in CA sub-band.

Table 4.4: Haar Wavelet Performance with Hamming Distance Classifier

Haar wavelet sub-bands	**Performance on right hand palmprints (%)**	**Performance on left hand palmprints (%)**
CA	52.76	51.48
CH	1.27	0.42
CV	4.46	1.27
CD	0.63	1.06

In the Table 4.4 show the results for both left and right hand palmprint images and the best result for right hand is 52.76% in CA sub-band and for the left hand best result is 51.48% in CA sub-band.

Moreover, Haar wavelets are used two combined sub-bands for the left palmprint images and right palmprint images.

Table 4.5: Haar Wavelet by Combining Two Sub-bands on Left Hand Palmprint

Number of sets	**Sub-band combination**	**Haar wavelet performance (%)**
1	CA+CH	71.91
2	CA+CV	71.27
3	CA+CD	73.19

Table 4.5 shows sub-band combination and the best result is 73.91% for left hand palmprint iamges in CA+CD combination.

Table 4.6: Haar Wavelet by Combining Two Sub-bands on Right Hand Palmprint

Number of sets	**Sub-band combination**	**Haar wavelet performance (%)**
1	CA+CH	73.19
2	CA+CV	72.76
3	CA+CD	73.61

Table 4.6 shows that the best result for right hand palmprint images is 73.61% in the CA+CD combination.

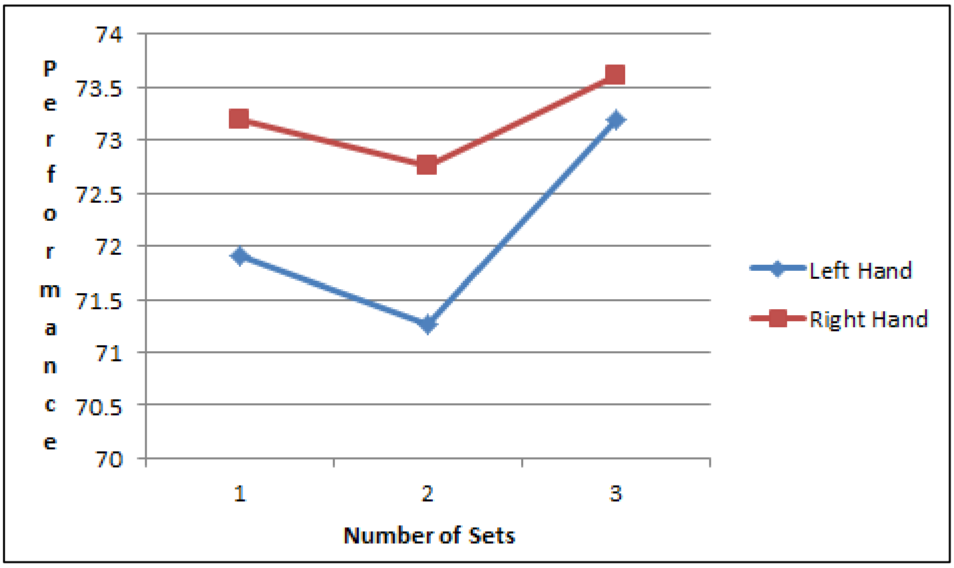

Figure 4.1: Haar Wavelet by Combining Two Sub-bands on Left and Right Hand

Figure 4.1 shows the Haar wavelet by combining two sub-bands for both left and right hand palmprint images and the best result is 73.61% for the right hand images in CA+CD combination.

However, we can take more levels over Haar wavelet, but we applied just three levels with combining sub-bands.

Table 4.7: Second Level Haar Wavelet Performance for Left Hand

Number of sets	Sub-bands combination	Haar performance (%)
1	CA+CCA	76.38
2	CH+CCA	42.12
3	CV+CCA	49.57
4	CD+CCA	44.82

The Table 4.7 shows the results for left hand palmprint images with second level of Haar wavelet by combing with the first level sub-bands, and the best result is 76.38% by combining CA and CCA.

Table 4.8: Second Level Haar Wavelet Performance for Right Hand

Number of sets	Sub-bands combination	Haar performance (%)
1	CA+CCA	75.53
2	CH+CCA	45.95
3	CV+CCA	53.82
4	CD+CCA	45.74

Table 4.8 shows the results for the right hand palmprint images and the best result is 75.53% by combining CA and CCA.

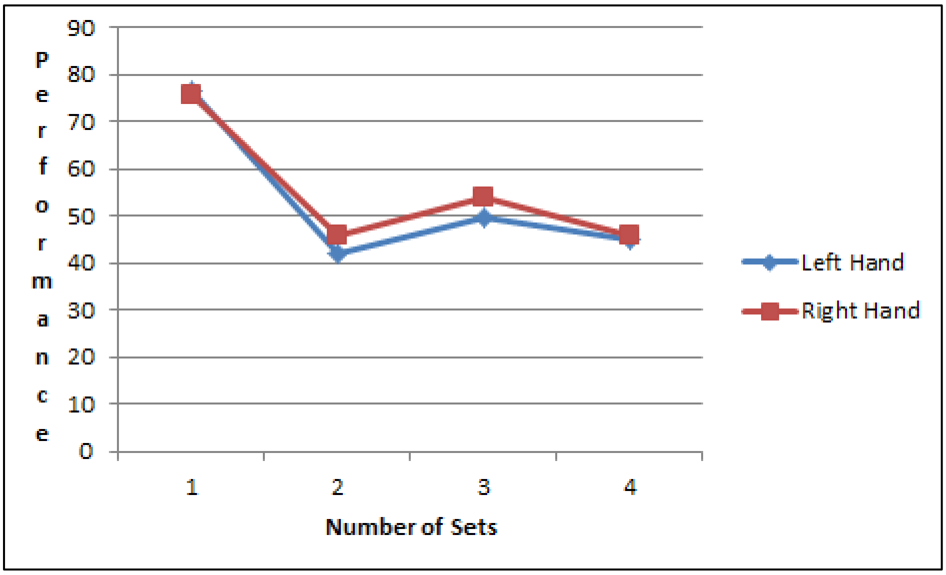

Figure 4.2: Second Level Haar Wavelet Performance for Right and Left Hand

Figure 4.2 shows the curve of combination first and second level Haar wavelet performance for both left and right hand palmprint images.

However, some of researchers believes that the number of levels has significant impact on the results, because of the differences of the original image with the number of levels, for example the CA in the first level is closest than the CCA in the second level and so on. Table 4.9 and 4.10 show that it cannot be generalized to all data. If we look Table 4.7 which shows that the best result is 76.38% for left hand by combining CA+CCA for second level, but Table 4.9 shows that the best result is 76.59% for the left hand also by combing CA+CCA+CCCA in the third level.

Table 4.9: Third Level of Haar Wavelet Performance on Left Hand

Number of sets	Sub-bands combination	Harr wavelet performance (%)
1	CA+CCA+CCCA	76.59
2	CA+CCA+CCCH	76.17
3	CA+CCA+CCCV	75.74
4	CA+CCA+CCCD	76.17

Table 4.9 shows the result for third level of Haar wavelet for the left hand palmprint images and the best result is 76.59% in CA+CCA+CCCA.

Table 4.10: Third Level of Haar Wavelet Performance on Right Hand

Number of sets	Sub-bands combination	Harr wavelet performance (%)
1	CA+CCA+CCCA	75.53
2	CA+CCA+CCCH	75.10
3	CA+CCA+CCCV	74.23
4	CA+CCA+CCCD	74.68

Table 4.10 shows the tird level of Haar wavelet for the right hand palmprint images and the best result is 75.53% in CA+CCA+CCCA.

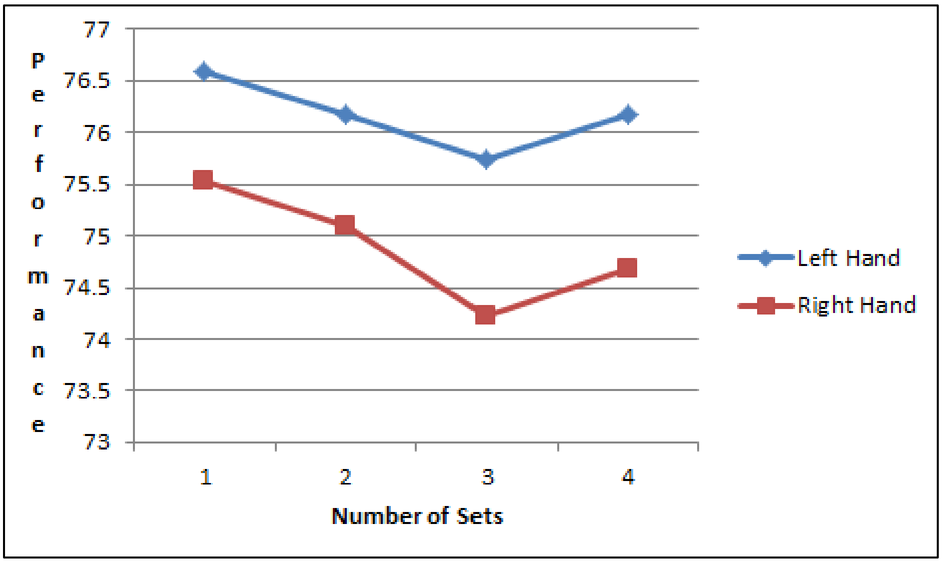

Figure 4.3: Third Level of Haar Wavelet Performance on Left and Right Hand

Figure 4.3 shows the curve of third level Haar wavelet performance for both left and right hand palmprint images.

4.5 The performance of Local Binary Pattern (LBP)

The performance of the uniform LBP is investigated by trying different experiments for 235 classes in left and right hand palmprint images. For each class, there are four images two of them are used for training set and the remaining two images are for the testing set. The uniform LBP takes 59 bins for each block. The Table 4.11 shows the results for left hand palmprint and right hand palmprint images from 4x4 blocks to 12x12 blocks over the size of 150*150 cropped images. The best recognition result is 82.97% for left hand and 83.40% for right hand using 8x8 blocks.

Table 4.11: The Performance of Uniform LBP for both Left and Right Hand

Pattern size	LBP performance for left hand palmprint (%)	LBP performance for right hand palmprint (%)
4X4	73.19	74.04
5X5	76.17	77.87
6X6	78.51	80.85
7X7	81.27	82.53
8X8	82.97	83.40
9X9	80.85	82.12
10X10	79.78	82.12
11X11	81.91	81.48
12X12	80.63	81.70

Table 4.11 shows the LBP performance results for both left and right hand palmprint images and the best result is 82.97% for right hand in 8x8 blocks and the best result for left hand is 82.53% again in 8x8 blocks.

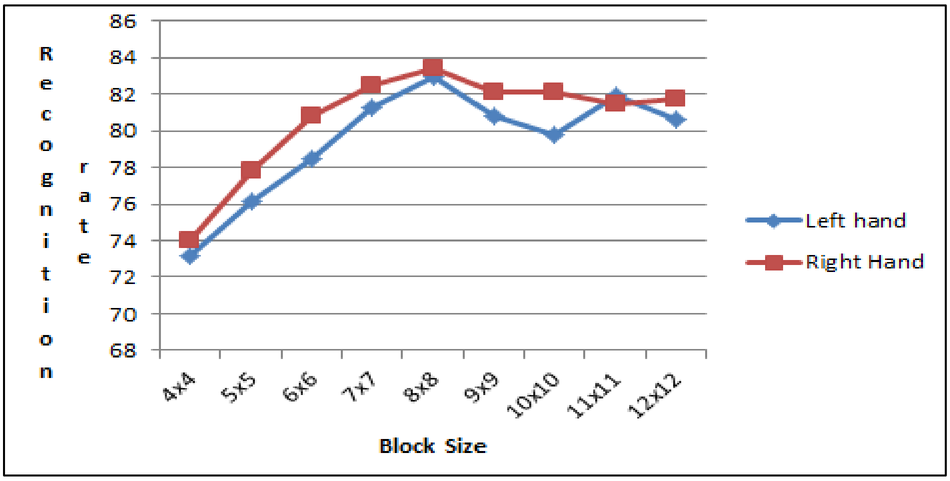

Figure 4.4: The Performance of Uniform LBP for both Left and Right Hand

Figure 4.4 shows the curve of uniform LBP for both left and right hand palmprint images in the dataset.

4.6 Decision Level Fusion of Classifiers

As seen Figure 4.5, show an example of majority voting procedure. A class that takes of votes is taken as the fused identity.

Algorithms	**Number of Classes**						
	1	2	3	4	5	….	470
PCA	1	1	1	1	0	….	1
Haar Wavelet	1	1	1	0	0	….	1
LBP	1	1	1	0	1	….	0
Voting	1	1	1	0	0	….	1

Figure 4.5: An Example of Majority Voting

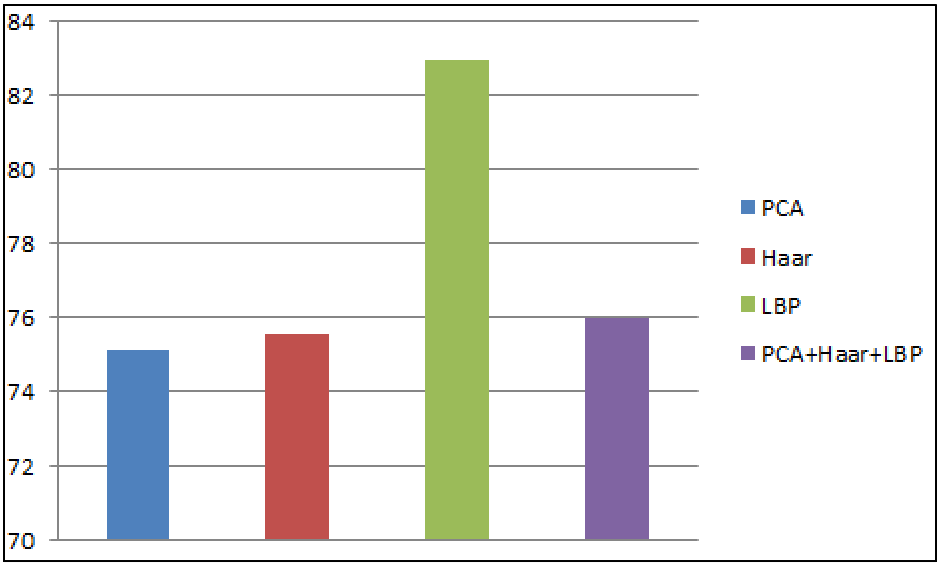

Figure 4.6: Feature Decision Level by Using Majority Voting for Left Hand

Figure 4.6 shows the performance of feature decision level by using majority voting for left hand palmprint images and the result is 75.95%.

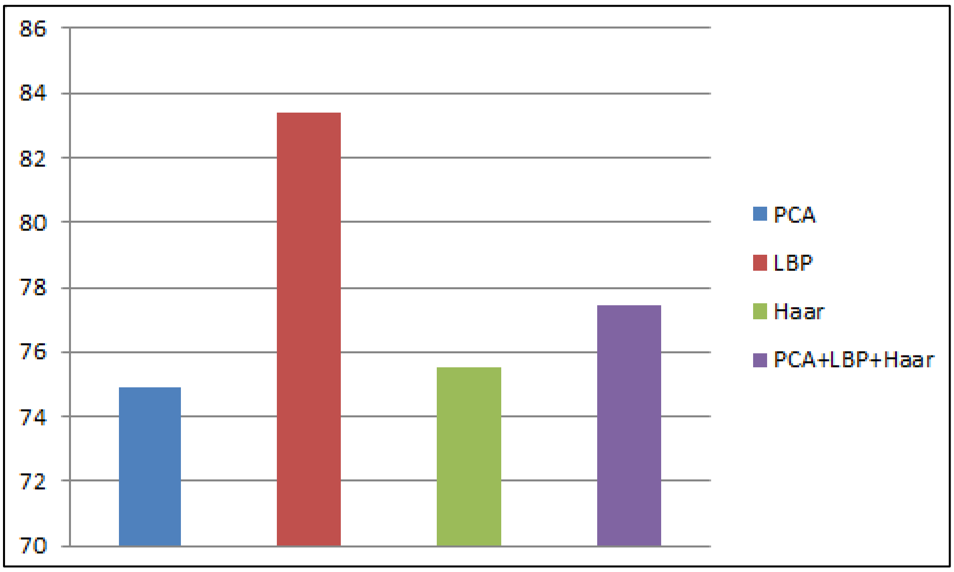

Figure 4.7: Feature Decision Level by Using Majority Voting for Right Hand

Figure 4.7 shows the performance of feature decision level by using majority voting for right hand palmprint images and the result of is 77.44%.

Figure 4.6 and 4.7 clearly show that the majority voting has the disadvantage of dominating weak classifiers. That is, when a strong classifier is combined with majority of weak classifiers, the advantage of strong classifiers may be lost.

4.7 Discussion on Experimental Results

In this thesis, matlab code has been used for the simulation. Two images for training and two images for testing set have been used for all algorithms namely Principle component analysis, Haar wavelet and Local binary patterns.

After trying different parameters value for all algorithms above, the results appears that Local binary patterns has a best recognition rate performance.

The local binary patterns obtaining 82.97% for the left hand images in the dataset and 83.40% for right hand images in the dataset but by using 8x8 blocking image. performance rate. After Local binary pattern, the Principle component analysis is the second highest performance that for the left hand images in the dataset is 79.00% by using 200 classes from 470 classes and the worst result is 74% by using 100 classes from 470 classes. For the right hand images in the dataset the best result is 76.66% by using 150 classes from 470 classes and the worst result is 72.33% by using 300 classes from 470 classes. Tables 4.1 and Table 4.2 for the left and right hand images performance rate show that PCA performance depending on the number of classes in the dataset.

After Principle component analysis, the Haar wavelet is the third highest performance rate that obtaining 76.59% by using 3 level and taking 3 sub-bands CA+CCA+CCCA. Moreover, Table 4.3 to Table 4.10 the results show in the first, the best results in the first sub-band because of the first sub-band in all levels is closest from the original image.

Furthermore, feature decision level had been used for all algorithms. Figure 4.6 show the results of left hand palmprint images by using majority voting and the result is 77.44%. Figure 4.7 show the results for right hand palmprint images by using majority voting and the result is 75.95%. For those techniques, the best results are selected for LBP and Haar wavelet but for PCA all 470 classes are selected.

Chapter 5

CONCLUSION

This thesis shows a different feature extraction approaches on palmprint recognition for Principle Component Analysis (PCA), Haar wavelets and Local binary patterns (LBP). The different parameters value has been tried for all algorithms above and they have different performance of recognition rate.

The PolyU database have been used for the simulation that contain left hand palprint images and right hand palmprint images, the experimental results appears that the LBP has a best performance accuracy of both left and right hand images that obtain 83.40% , so the reason for that is LBP is an texture method which selecting the most texture information and features in the palmprint images.

Feature decision level has been implemented by using majority voting for enhancing the performance accuracy of algorithms above.

In the future work we have a plan to create a standard database for twin's face, because it is abnormal case in the field of recognition. The different voting method can be applied for making a hybrid method and feature subset selection methods with the use of weighted decision combination methods.

REFERENCES

[1] Muhammad, I., Mohd, Z., Mohd, N., Ruzelita, N., & Abdul Majid, D. (2014) Information Fusion of Face and Palmprint Multimodal Biometrics. Kuala Lumpur. 635 - 639.

[2] Jaspreet, K., Shreyash, V., Nikhil, M., Gaurav, D., & Prateek, A. (2013) Palmprint Recognition System. International Journal of Innovative Research in Science, Engineering and Technology. 2,1006-1009.

[3] Abdallah, M., Salim Ch., & Ahmed B. (2011) Fusion of Multispectral Palmprint Images For Automatic Person Identification. in Electronic., Communications and Photonics Conference (SIECPCZ). 1-6.

[4] Zhang, D., Kong, W., You, J., & Wong, M. (2003) Online palmprint identification. Pattern Analysis and Machine Intelligence, IEEE Transactions. 25, 1041-1050.

[5] Maheswari, M., Ancy, S., & Suresh, G. (2013) Selecting Best Spectrum Using Multispectral Palm Texture. in Recent Trends in Information Technology (ICRTIT). 195-201.

[6] United State Federal Government. (2011) Biometric Center of Excellence. [Online]. http://www.biometrics.gov/default.aspx

[7] Sir William, J. (1917) Death Of Sir William Herschel. Author Of Finger-Print Identity System. Oxford University Press. 41618, 25.

[8] Xianji, W., Haifeng, G., Hao Zh., Bin, Li., & Zhenquan Zh. (2006) Palmprint Identification using Boosting Local Binary Pattern. in *ICPR*. 503-506.

[9] Baochang, Zh., Hong Zh., & Zhongli W. (2009) Local Kernel Mapping for object recognition. in ICNC. 573-576.

[10] Zhenhua, G., Lei Zh., David, Zh., & Xuanqin M. (2010) Hierarchical Multiscale Lbp For Face And Palmprint Recognition. in ICIP. 4521-4524.

[11] Yunfeng, LI., & Zhang Y. (2011) Palmprint Recognition Based on Weighted Fusion of DMWT and LBP. in CISP. 1531-1534.

[12] Junwei T., Wei J., Zan G., Shuang Ch., & Chao W. (2006) Palmprint Recognition Based on 2-Dimension PCA. in ICICIC. 326-330.

[13] Chang, Zh., & Jia, Zh. (2007) Palmprint Recognition based on Gabor Wavelets and 2-Dimensional PCA&PCA. in ICWAPR. 1518-1523.

[14] Kozik. R., Aleksandra, Z., & Michał, Ch. (2008) Palmprint Recognition Enhanced by the Shape Features. in CISIM. 214-215.

[15] Edward, Y., Sainarayanan, G., Ali Ch., & Narendra, G. (2008) Palmprint Identification Using Sequential Modified Haar Wavelet Energy. in IEEE-International Conference on Signal processing, Communications and Networking, Newdelhi. 411-416.

[16] Murat, E., & Murat A. (2008) Palmprint recognition using kernel PCA of Gabor features. in 23'rd International Symposium on Computer and Information Sciences. 106-111.

[17] El-Seddek, M., Morsy, S., & Zaki, W. (2014) Processing and classification of palmprint images. in Radio Science Conference (NRSC). 150-156.

[18] Onsen, T., Fatemah, M. (2011) Age Classification using Facial Feature Extraction. Computer Engineering.

[19] Caifeng, Sh., Shaogang G., & Peter, M. (2009) Facial expression recognition based on Local Binary Patterns: A comprehensive study. Image vision computingl. 27, 803–816.

[20] Abouelenien, M., Yiwen, W., & Saudagar, A. (2012) Feature and decision level fusion for action recognition. in Computing Communication & Networking Technologies (ICCCNT). 1-7.

[21] Rajbhoj, S., & Mane, P. (2013) Haar Wavelet Approach of Iris Texture Extraction for Personal Recognition. International Journal of Innovative

Technology and Exploring Engineering (IJITEE). 3, 22-25.

[22] Shaw, A., & Multivariate S.(2003) for the Environmental Sciences.

[23] Rao, N., Ahmed, T., & Natarajan. (1974) Discrete Cosine Transform. IEEE Transaction on Computers. 1, 90-93.

[24] Supachai, T., & Chaivatna S. (2008) Optical Character Recognition Techniques for Restoration of Thai Historical Documents. International Conference on Computer and Electrical Engineering, Phuket, Thailand. 531-535.

[25] Zhao, B., Gao, W., & Chan, K. (2002) Morphological Representation of DCT Coefficients for Image Compression. IEEE Transactions On Circuits And Systems For Video Technology. 12, 819-823.

[26] Jie, W., & Zhengding Q. (2006) A Hierarchical Palmprint Identification Method Using Hand Geometry and Grayscale Distribution Features. in 18th International Conference on Pattern Recognition (ICPR 2006). 409-412.

[27] Smoot, R., & Rowe, LA. (1996) Study of DCT Coefficient Distributions. in Conference on Human Vision and Electronic Imaging. 2657, 403-411.

[28] Cole, A. (2002) A History of Fingerprinting and Criminal Identification. Cambridge: Harvard University Press.

[29] Zhang, L., & Zhang, D. (2004) Characterization of palmprints by wavelet signatures via directional context modeling. IEEE Transactions on Systems Man and Cybrentics - part B : Cybrentics. 34, 1335-1347.

[30] Zhao, H., Cai, Y., Li, J., & Xu, H. (2005) Face recognition based on discrete cosine transform and support vector machine. in International Conference on Neural Networks and Brain (ICNN&B). 1248-1252.

[31] Gunatilaka, H., & Baertlein, A. (2001) Feature-level and decision-level fusion of noncoincidently sampled sensors for land mine detection. Pattern Analysis and Machine Intelligence. 23, 577-589.