A COMPARISON STUDY ON PCA, MODULAR PCA AND LDA FOR FACE RECOGNITION

CHEAH BOON WAH

UNIVERSITI SAINS MALAYSIA

2017

A COMPARISON STUDY ON PCA, MODULAR PCA AND LDA FOR FACE RECOGNITION

by

CHEAH BOON WAH

Thesis submitted in partial fulfillment of the

requirements for the degree of

Bachelor of Engineering (Electronic Engineering)

JUNE 2017

ACKNOWLEDGEMENTS

Firstly, I would like to express my deepest gratitude to my supervisor, Dr Shahrel Azmin Sundi, for his incessant support since the beginning of this final year project. He gives consistent motivation by spending the time to discuss with me about the project. His guidance helps me succeed in the implementation of this project.

Secondly, I would like to thank USM for involving me in this project. This triggered my interest in the image-processing field.

Last but not at least, I would like to thank my family and friends. They have given me the support in completing the project.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

A COMPARISON STUDY ON PCA, MODULAR PCA AND LDA FOR FACE RECOGNITION

ABSTRACT

Face recognition has been considered as a popular technique to recognise identity of a person. Many face recognition algorithms have been developed and modified by researchers. This paper will study the performance of three face recognition algorithms which are PCA, Modular PCA and LDA. These three face recognition algorithms will be implement to determine which algorithm has the best performance. The performance of these face recognition algorithms will be evaluated by 10-fold cross validation using ORL database. K-fold technique will divide the image database into k-fold that has the same size or segment. Nine-fold will be used for training sets and the remaining one-fold will be used as validation sets to calculate the accuracy of the system. PCA is known as eigenface projection to transfer the image space to low dimension feature space. Modular PCA is to divide an image into sub-image and then apply PCA on it. LDA is used to separate two or more class further and enclose population in the class. The recognition rate for PCA, Modular PCA and LDA is 96.25%, 85.75% and 89%, respectively.

KAJIAN PERBANDINGAN PADA PCA, PCA MODULAR DAN LDA UNTUK PENGIKTIRAFAN MUKA

ABSTRAK

Pengenalan muka telah dianggap sebagai teknik popular untuk mengenali identiti seseorang. Banyak algoritma pengecaman wajah telah dibangunkan dan diubahsuai oleh penyelidik. Kertas kerja ini akan mengkaji prestasi algoritma pengiktirafan tiga muka yang PCA, Modular PCA dan LDA. Algoritma ini pengiktirafan tiga muka akan melaksanakan untuk menentukan algoritma mempunyai prestasi yang terbaik. Prestasi ini algoritma pengecaman wajah akan dinilai oleh pengesahan silang 10 kali ganda menggunakan pangkalan data ORL. Teknik K-kali akan membahagikan pangkalan data imej ke dalam k kali ganda yang mempunyai saiz atau segmen yang sama. Sembilan kali ganda akan digunakan untuk set latihan dan baki satu kali ganda yang akan digunakan sebagai pengesahan menetapkan untuk mengira ketepatan sistem. PCA dikenali sebagai eigenface unjuran untuk memindahkan ruang imej untuk ruang ciri dimensi rendah. Modular PCA adalah untuk membahagikan imej ke dalam sub-imej dan kemudian memohon PCA di atasnya. LDA digunakan untuk memisahkan dua atau kelas lebih lanjut dan sertakan penduduk di dalam kelas. Kadar pengiktirafan PCA, Modular PCA dan LDA adalah 96.25%, 85.75% dan 89% masing-masing.

CHAPTER 1

INTRODUCTION

1.1 Research Background

An identity of a person becomes an important issue of our society. The identity of an individual can be identified by capturing the face image and then perform facial recognition. Facial recognition technique is one of the most effective biometric techniques that is used to identify people [1]. Facial recognition technique can be utilised in many fields to identify the identity of a person. It can be used to take student's attendance effectively. Furthermore, it can be used to identify a person as a security system.

There are many algorithms, and techniques have been developed by many researchers. The most well-known algorithms are the PCA, Modular PCA and LDA. These three algorithms have their advantages and disadvantages [2]. PCA is known as eigenface projection to transfer the image space to low dimension feature space [3]. It is used mainly for dimensional reduction. Eigenface image which has the most dominant feature will remain and those less dominant features will be discarded in the face recognition process to reduce the calculation of principal component. Modular PCA is an approach that divides an image into sub-image and followed by apply PCA on it [4]. LDA is a powerful technique that is used for feature extraction and dimension reduction. It is used to separate two or more class.

The main difference between PCA and LDA is that PCA requires more of data classification, and LDA involves more of feature classification [3]. Besides that, light illuminance will be one of the aspects that will be researched in this project because it may have an impact on the face recognition process. Modular PCA will have higher accuracy than PCA in a large variation of lighting conditions and face posture. These three algorithms will be evaluated by using cross validation technique under a standard database.

1.2 Problem Statement

Various face recognition algorithms and techniques have been developed by researchers to tackle the factors that affect the recognition accuracy. Face posture, face expression and light illuminance will be the main factors that need to be overcome in order to increase the accuracy of the face recognition algorithm. In this research, three face recognition algorithms will be implemented. The algorithms will be tested to figure out the best algorithm that has the highest accuracy.

1.3 Objectives of Research

The objectives of this project are:

I. To implement PCA, Modular PCA and LDA, Modular PCA and LDA as the face recognition algorithms

II. To study the performance of PCA, Modular PCA and LDA by applying cross-validation technique.

1.4 Scope of Research

In this research, various face recognition algorithms will be tested to estimate the accuracy of the algorithm. PCA, Modular PCA and LDA will be the algorithm than to be tested by applying the k-fold cross validation. ORL database is the only database that will be use in this project. Cross-validation accuracy is the sole result that will be considered in this project.

1.5 Thesis Outline

Thesis is organised by this logic. Chapter 1 provides the introduction to this project. The research background, problem statement and objectives of this project will be explained in this chapter. Chapter 2 summarises the research information from previous research that is related to face recognition algorithm. It explains the algorithms that have already been developed and modified by other researchers. The basic concepts of the face recognition algorithm will be explained in this chapter. Chapter 3 provides the methodology being applied in this project. The flow chart and design procedure of the face recognition algorithm will be explained in this chapter. Chapter 4 provides the results that get in this project. Discussion on the result will be explained in this chapter. Chapter 5 discusses the conclusion and future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter discusses the studies and researches done formerly about the development of the face recognition algorithm. The review is to gain information, ideas and concepts, which have been conducted previously. The studies on it are to make this research to be more effective and efficient. Applications of PCA, Modular PCA and LDA also have been discussed here.

2.2 PCA

Face poses, and image resolutions are the important factors that affect the performance of face recognition [5]. Three face recognition algorithms that have been studied in the research are adaptive boosting (Ada Boost) with linear discriminant analysis as weak learner, principal component analysis (PCA)-based approach and local binary pattern (LBP) – based approach. It is investigated by using face images under different pose and low resolution (LR) face images. Large range of variation in pose and image resolution has been tested in this research.

Recognition performance of each algorithm has been tested. Figure 2.1 shows the recognition accuracy of different face size. Label a, b and c represent 20x20 pixels, 10x10 pixels and 5x5 pixels, respectively. Pose 1, pose 2, pose 3 and pose 4 represent +45 degrees, +30 degrees, frontal and -35 degrees, respectively. LBP are not visible due to its ability to process and recognise face image size of 20x20 pixels and below. For a face size 20x20 pixels and 10x10 pixels, AdaBoost and PCA have 100% classification for pose

3. AdaBoost still has 100% classification on a 5x5 pixels, but PCA has extremely low rate (8%) for LR face images.

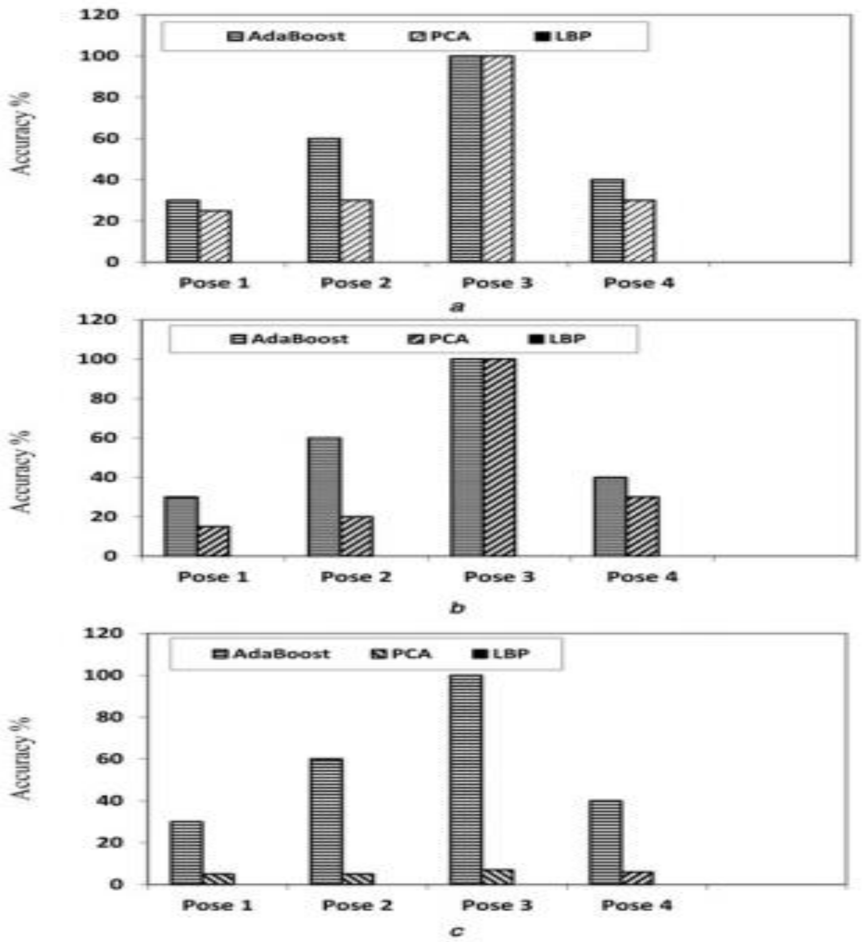

Figure 2.1: Recognition accuracy of different face size [5]

Many applications of PCA have been developed for face recognition propose. Smart multi-eye camera network by using unused mobile phones has been proposed [6]. This system is to improve the accuracy of stranger invasion detection. This system can be separated into three parts: smart key mobile clients, smart surveillance mobile clients and server clients. The smart key mobile clients are to control the switches and reset the parameters of surveillance clients. The smart surveillance mobile clients are activated by the sensors to give the alert when the surveillance system is working. The server clients are to enable users to control the key and surveillance clients.

New PCA-based facial recognition algorithm have been developed so that it is more comparable and faster than conventional PCA. Detection using sensor assisted facial recognition algorithm was implemented on Android platforms higher than 2.3 versions to achieve higher accuracy. The image resolution of the image detected is increased because the image resolution of the image detected from distant subject was lower than the image database. The pixel of the image will be scaled to the position with the factors from 0.1 to 0.3 to map the desired image resolution. MUCT face database were used in this experiment [7]. MUCT stands for Milborrow / University of Cape Town is the face database which was created to provide more variation of age and ethnicity. The recognition accuracy related to scaling factor is plotted. Red curve, green curve and blue curve represent nearest interpolation, bilinear interpolation and bicubic interpolation, respectively. Square curve, circle curve and star curve represent 10 number of subjects, 90 number of subjects and 275 number of subjects, respectively.

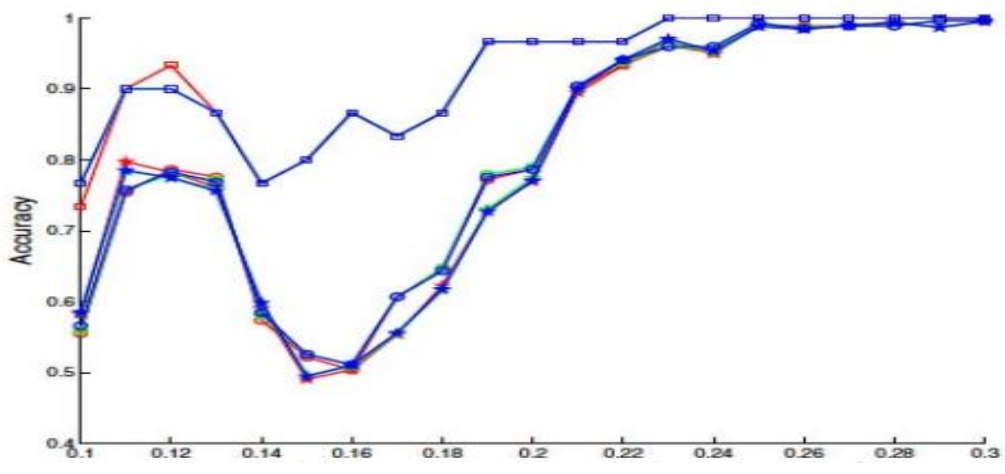

Figure 2.2: Recognition accuracy related to scale factor [6]

Furthermore, face recognition technique has been implemented to manage attendance of students in the attendance system by using Eigenface and PCA [8]. Illumination invariant, Viola and Jones algorithm and Principle Component Analysis are used in this system to overcome the intensity problem. Illumination invariant algorithm can be used to reduce the surrounding light intensity. Detection and recognition of face are the major steps in their proposed method. Table 1 shows the comparison of various algorithms for face recognition.

There are few steps for face recognition based attendance system.

i) Enrolment - Capture the image of all students and make the enhancement on all images. Database is created.
ii) Image Acquisition - Capture image of the whole classroom by camera devices.
iii) Grayscale transformation of image - Captured image is converted to grayscale for the enhancement.
iv) Histogram Normalization - The image is equalised to remove the contrast.
v) Noise Removal - The median filtering is used to remove the noise.
vi) Skin Classification - The pixels close to the skin are made white and other pixels are made black. This can improve face detection algorithm.
vii) Face Detection - Viola and Jones algorithm is used for the face detection
viii) Face recognition - Cropped face is compared with the face database by performing PCA face recognition. Face is verified by using eigenface method.
ix) Attendance - Attendance marked on the server.

Table 1 Comparison of various algorithms for face recognition [8]

Method	No. of Images	Success Rate
Principal Component Analysis (PCA)	400	79.65%
Principal Component Analysis + Relevant Component Analysis	400	92.34%
Independent Component Analysis	40	Gauss function 81.35%
Support Vector Machines	-	85-92.1%
Neural Networks	-	93.7%
Eigenfaces Method	70	92-100%
Eigenfaces with PCA method	-	92.30%

2.3 Modular PCA

Extended Modular Principal Component Analysis have been proposed to improve recognition rate against the light illuminance, post variation and facial expression [9]. This method locates two eyes from darker blobs and normalised to the size 60x60. It will also divide the input image into small blocks using Gaussians models which are created for blocks of mouth, nose and eye. PCA will be applied to each block. The training time of Extended Modular PCA is shorter than the conventional PCA. Figure 2.3 shows the comparison of experimental result. Global recognition pattern (GRP) is a recognition pattern that uses the entire face image. Region recognition pattern (RRP) is a recognition pattern that uses the facial part. RRP 1, 2, 3, 4, and 5 represent left and right eyes, nose, mouth, and glabella.

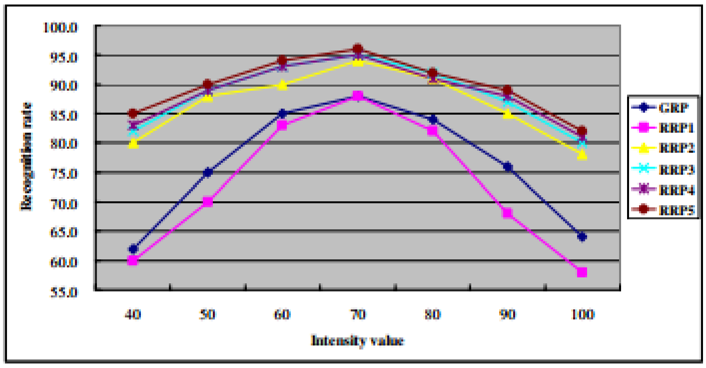

Figure 2.3: Comparison of experimental results [9]

In addition, the Modular PCA did not show much improvement under the variation of the pose when compared with Conventional PCA. A modified approach on Modular PCA has been proposed [10]. There are two methods for multi-view approach. One, which is separate views built from separate eigen space for training image. The input test image that is best described by eigenface will be selected. The other method is to separate training image to multi-view instead of training image.

2.4 LDA

The accuracy of traditional face recognition theorem will be affected hugely in the condition of variance Gaussian noise. A new algorithm has been proposed that combined the linear discriminant analysis (LDA) and Pulse Coupled Neural Network (PCNN) to overcome this problem [11]. PCNN is a simplified model of Eckhorn model that is developed from observation of the virtual cortex nerve cell. Synchronous oscillation and non-linear modulation are the good characteristics of Eckhorn model. Variance Gaussian noise will destroy the variance information of the image. PCNN which has a pleasant feature of good regional clustering around can be used for image smoothing.

Figure 2.4 shows the recognition in low variance Gaussian noise. The recognition rate of PCNN+LDA is higher than LDA when σ is greater than 0.05 in low variance

Gaussian Noise. Figure 2.5 shows the recognition in high variance Gaussian noise. The recognition rate of PCNN+LDA is higher than LDA and Median Filtering +LDA when σ is greater than 0.1 in high variance Gaussian Noise.

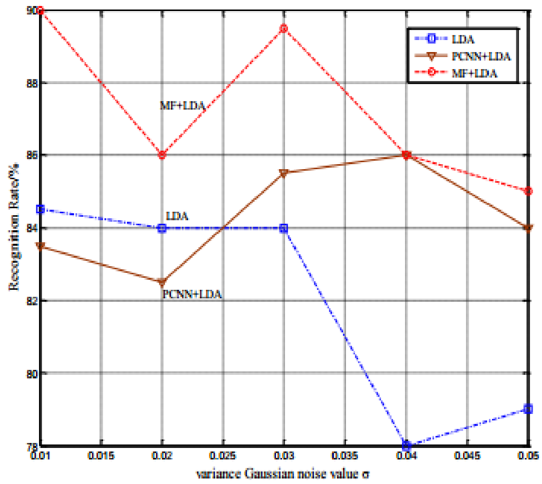

Figure 2.4: Recognition in low variance Gaussian noise [11]

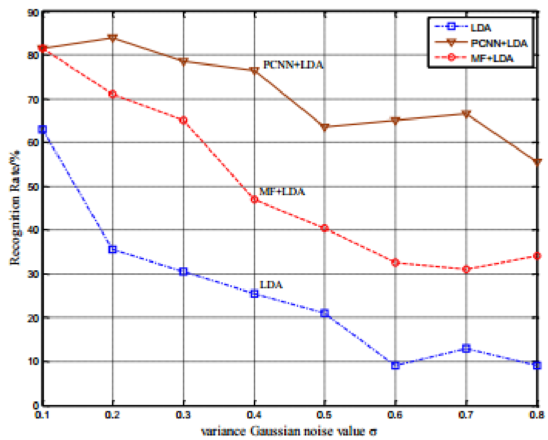

Figure 2.5: Recognition in high variance Gaussian noise [11]

Besides, Intelligent surveillance system which implemented the LDA-based face recognition algorithm has been proposed [12]. The proposed algorithm uses face feature extracted from 1 meter to 5 meter for training images. The face image that is extracted from distance 1 meter to 5 meter is normalised into the same size by using bilinear interpolation. Bilinear interpolation uses adjacent four pixels to create the pixel to be interpolated. Euclidean distance measure has been implemented in the matching.

Figure 2.6 shows the face recognition rate per training image. Case 1 and Case 2 represent Lanczos3 interpolation and bilinear interpolation, respectively. These interpolations are used to normalised the image. This result shows that bilinear interpolation has the higher accuracy to normalise the image from distance 1m to 5m.

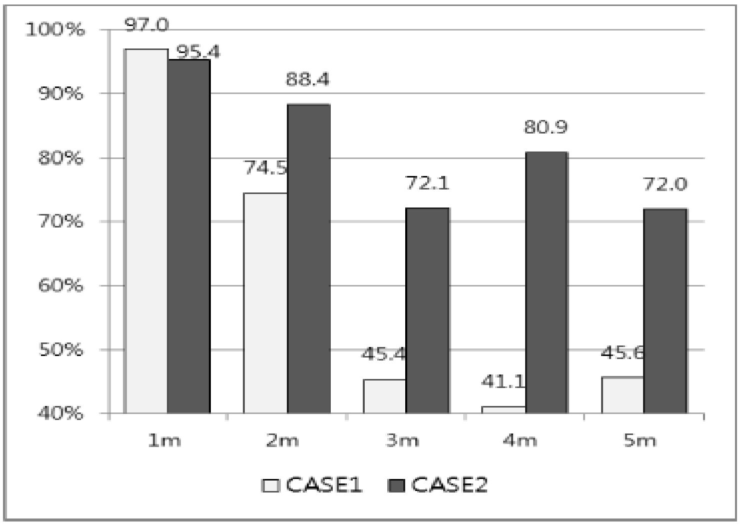

Figure 2.6: Face recognition rate per training image [12]

2.5 Chapter Summary

Investigations on applications that are formed by implementing PCA, Modular PCA and LDA have been conducted to understand more about how the development of face recognition algorithms can help to improve the existing system.

AdaBoost with LDA has 100% recognition rate for frontal pose on 20x20 pixels, 10x10 pixels and 5x5 pixels. PCA is not an effective face recognition algorithm on low resolution images. Frontal pose has a good recognition performance compared to another pose. Light illuminance can be reduced by using illumination invariant algorithm and PCA.These three face recognition algorithms have been implemented, and the design methodology will be explained in the next chapter

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the methodology of this project. Implementation of PCA, Modular PCA and LDA will be discussed and tested under ORL database. K-fold cross-validation has been used to find the face recognition accuracy of it.

3.2 Project Implementation Flow

The image is read from the database. The image is converted into a matrix. K-fold is applied to the image matrix to separate out the training image matrix and test image matrix. PCA, Modular PCA and LDA will be processed on training image and the test image. Euclidean distance is calculated between the training image and test image. Accuracy is calculated by determining the number of training image matched with test image from the Euclidean distance calculated. Mean of accuracy will be calculated if the number of the fold is reached 10 folds. Figure 3.1 shows the flowchart of project implementation flow.

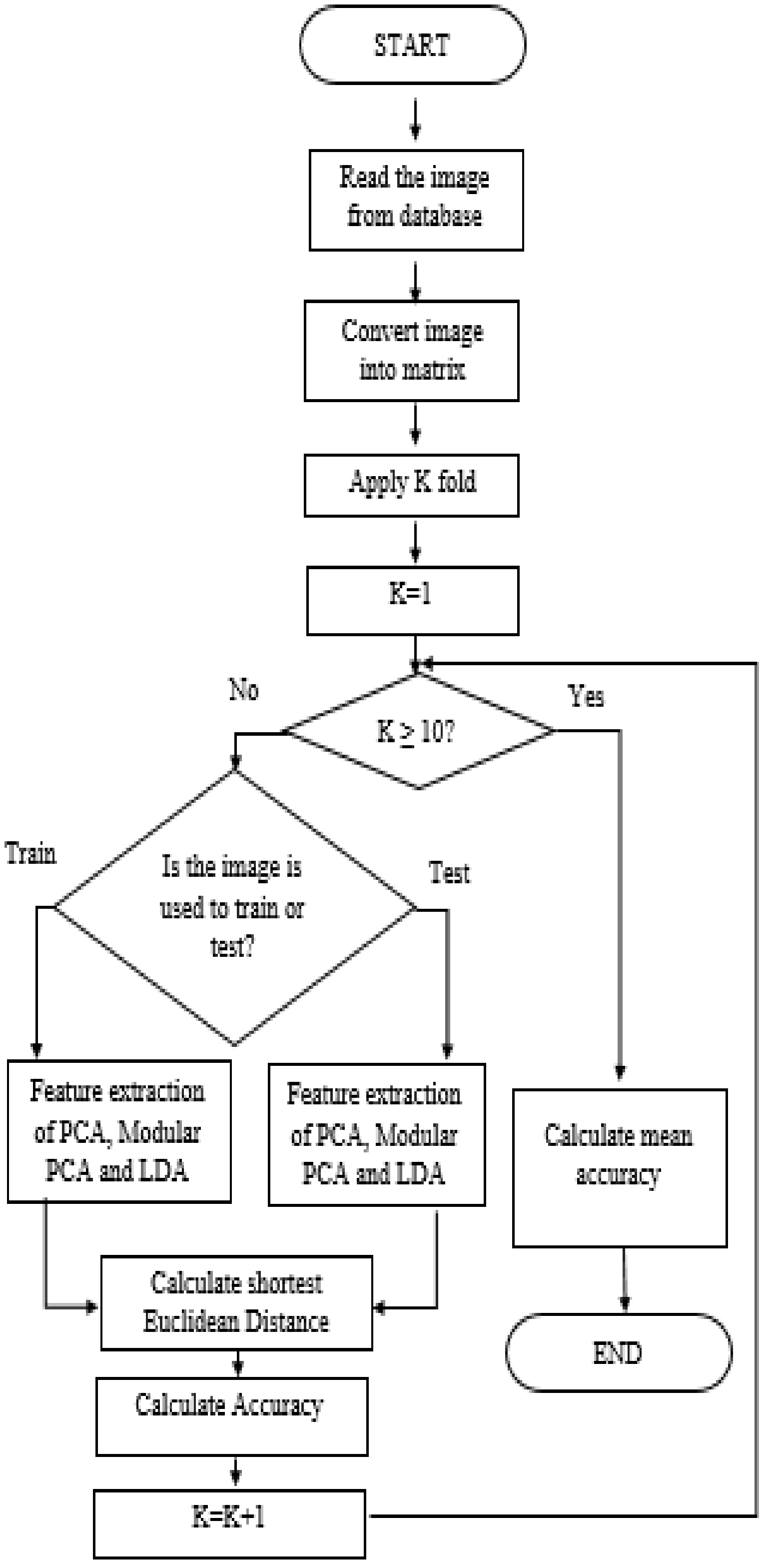

Figure 3.1: Flowchart of project implementation flow

3.3 Project Requirement

This project is fully software based. Matlab 2015b has been used to implement face recognition algorithm. This project operates on Windows 8.1.

3.4 K-Fold Cross Validation

Cross Validation is a model validation technique to estimate the accuracy of the classifier by using random sets of training samples and testing samples [13]. K-fold cross validation is a most common cross validation technique that can be applied to face recognition theorem to calculate the recognition rate.

K-fold technique will divide the image database into K-fold that have the same size or segment. K-1 fold will be used for training sets and the remaining one-fold will be used for test sets to estimate the accuracy of the system. It will be repeated k times to ensure each repetition will have different training sets and validation sets in the estimate of accuracy until all the sample haven been utilised as training sets and test sets in the K-fold. The mean of the accuracy of each fold will be calculated to estimate the performance of the system.

10-fold cross validation is used in the system. There are nine samples in the training sets and one sample in the test sets for one class in each fold by using ORL database. There will be 40 test image for each subject in each fold. Figure 3.2 shows the process of 10-fold cross validation.

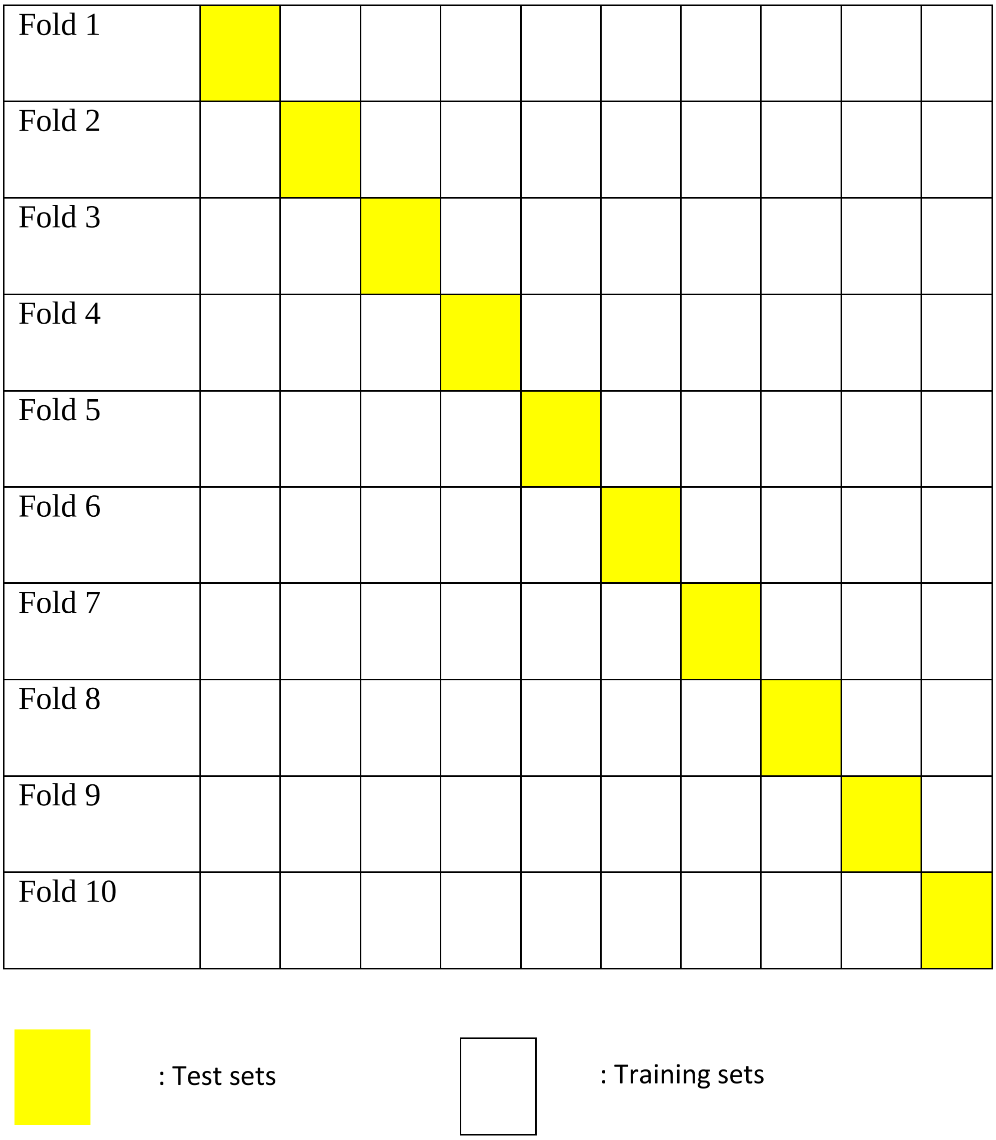

Figure 3.2: Process of 10-fold cross-validation

3.5 ORL Database

ORL database composed of 10 distinctive images for each of 40 distinct subjects [14]. The images were taken at different times, varying the facial details, facial expression and lighting for some subjects. All images were taken with the subjects in the frontal position against a dark background. The sizes of each image are 92x112 pixels with the grayscale in the PGM format. Figure 3.3 shows the ORL database.

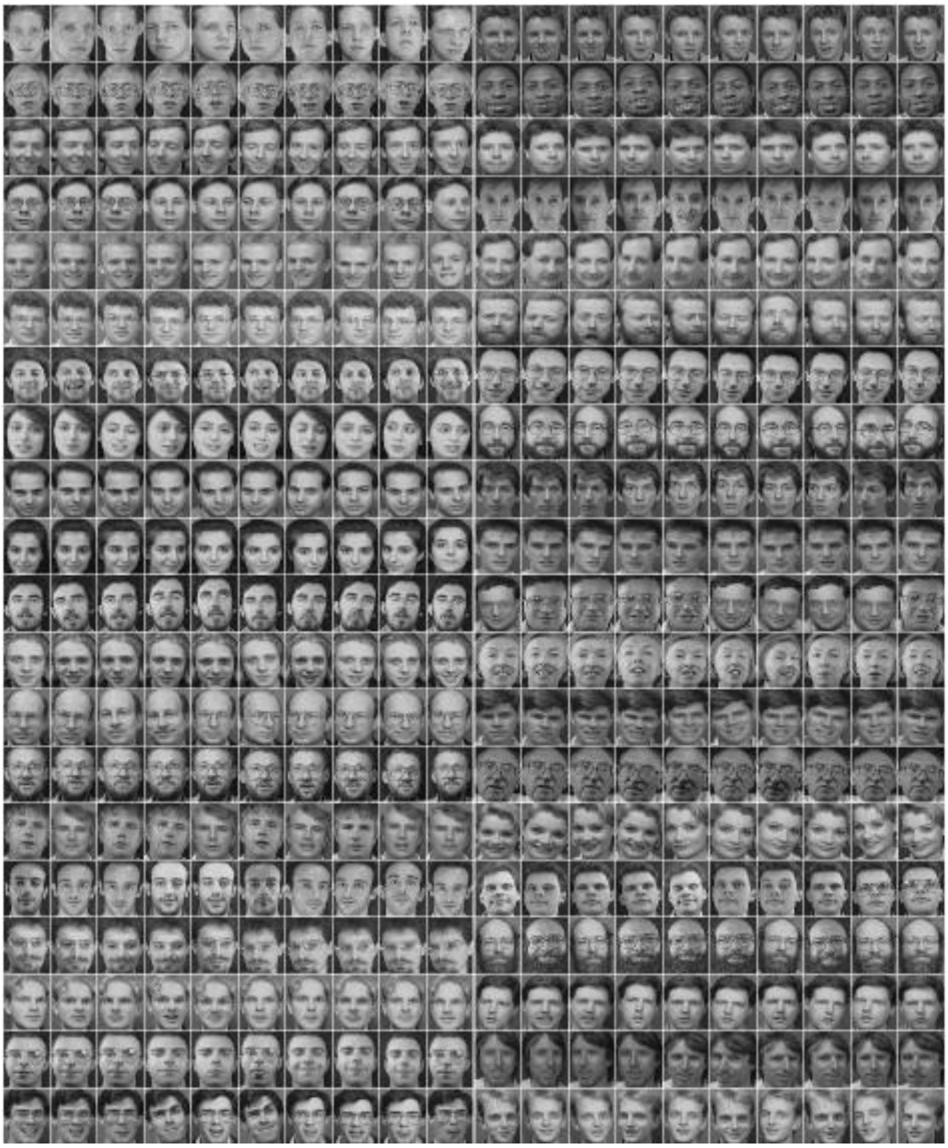

Figure 3.3: ORL Face Database

3.6 Project Design

3.6.1 Convert Image into Matrix

Image made of the pixels. The image can be divided into 3 categories which binary, grayscale and colour. The pixel value is 1 and 0 only when it is in the binary form and the pixel for grayscale is 0-255 value. The pixel for colour is the multiplication of the 0-255 value of red, yellow and blue.

The image needs to be converted into pixel value for the ease of calculation. Image from a database that will be using in this project is grayscale, which means that each pixel is 0-255 value. Matrix will be formed by using this pixel value. Row of the matrix represents the length of image size, *r* and the column of the matrix represents the width of image size, *c*. Image matrix, *I* formed from the image is shown in Equation (3.1). One column matrix, I_c formed from I is shown in Equation (3.2).

$$I = \begin{pmatrix} I_{11} & I_{12} & I_{13} & \cdots & I_{1c} \\ I_{21} & I_{22} & I_{23} & \cdots & I_{2c} \\ I_{31} & I_{32} & I_{33} & \cdots & I_{3c} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ I_{r1} & I_{r2} & I_{r3} & \cdots & I_{rc} \end{pmatrix} \tag{3.1}$$

$$I_c = \begin{pmatrix} I_{11} \\ I_{21} \\ \vdots \\ I_{r1} \\ I_{12} \\ I_{22} \\ \vdots \\ I_{r2} \\ \vdots \\ I_{rc} \end{pmatrix} \tag{3.2}$$

Equation (3.3) shows the final image matrix, I_f. It will be formed when the total number of image, N have been read and convert into column matrix. The size of the I_f will be *(r x c) x N* matrix.

$$I_f = \begin{pmatrix} I_{11} & \cdots & I_{11(N)} \\ I_{21} & \cdots & I_{21(N)} \\ \vdots & \cdots & \vdots \\ I_{r1} & \cdots & I_{r1(N)} \\ I_{12} & \cdots & I_{12(N)} \\ I_{22} & \cdots & I_{22(N)} \\ \vdots & \cdots & \vdots \\ I_{r2} & \cdots & I_{r2(N)} \\ \vdots & \cdots & \vdots \\ I_{rc} & \cdots & I_{rc(N)} \end{pmatrix} \tag{3.3}$$

I_f will divided into training image matrix, *trainmat* and test image matrix, *testmat* according to k-fold that apply which is 10-fold. There are total of 360 training image and 40 test image for *trainmat* and *testmat*, respectively, in each fold. Total number of training image is represented by *numtrain* and total number of test image is represented by *numtest*. Label of the class of subject will also give to training image matrix, *labeltrain* and test image matrix, *labeltest.*

3.6.2 PCA

3.6.2(a) Flowchart of Feature Extraction of PCA

Figure 3.4 shows the flowchart of feature extraction of PCA.

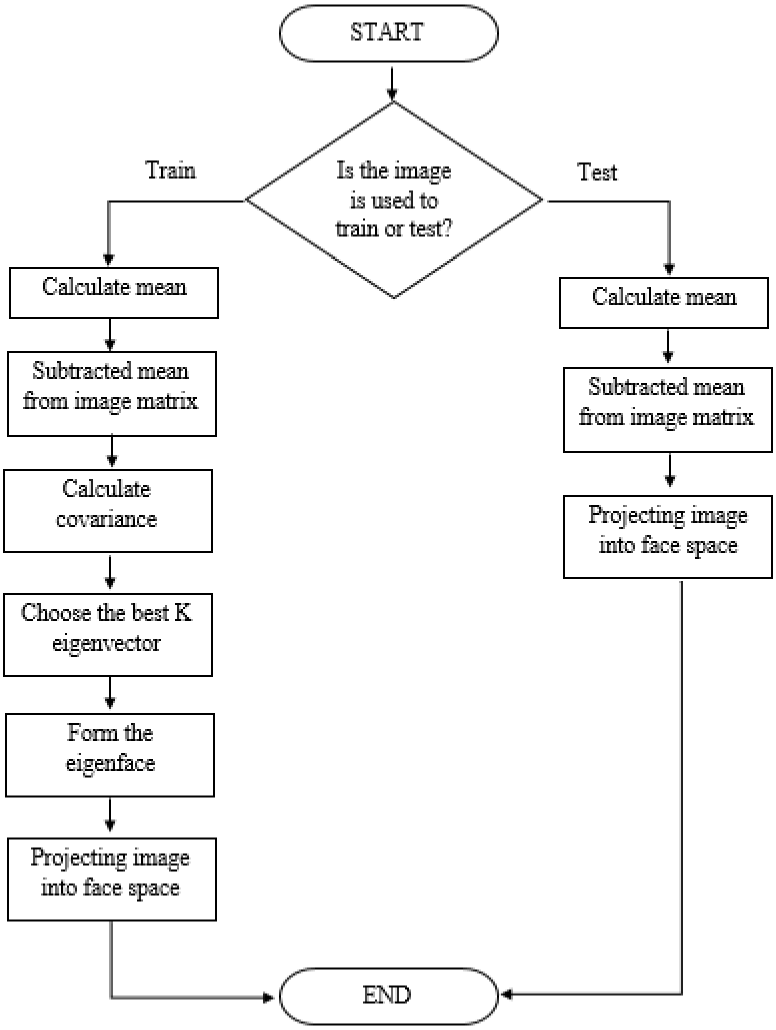

Figure 3.4: Flowchart of feature extraction of PCA

3.6.2(b) Calculate Mean

Common feature of all the image was find out by calculate the mean of it. Mean of each row, u from I_f is calculated in Equation (3.4) [15].

$$u = \frac{1}{N}\sum_{i=1}^{N}(I_f)_i \tag{3.4}$$

where N is the total number of image.

3.6.2(c) Normalisation

Normalisation is performed to find out the distinct feature of each image. Normalisation of training and testing image is performed by subtract the mean, u from all image. Normalised training image matrix, A is calculated in equation (3.5). Normalised test image matrix, B is calculated in equation (3.6).

$$A = trainmat - u \tag{3.5}$$

$$B = testmat - u \tag{3.6}$$

3.6.2(d) Calculate Covariance

Covariance of A can be calculated by two way. First, covariance, L and size of L, s is calculated by using the equation (3.7) and equation (3.8), respectively [15]. s will be $r^2\ x\ c^2$. The size of eigenvalues and eigenvectors also will be $r^2\ x\ c^2$. The large size of the L will cause system slow down sharply or run out of memory because system needs a lot of calculation for the eigenvalues and eigenvectors. This method will not be used.

$$C = \frac{1}{numtrain}\sum_{i=1}^{numtrain} A_i A_i^T \tag{3.7}$$

$$s = [(rxc)x\ numtrain]\ [numtrain\ x(rxc)]$$

$$s = [(rxc)(rxc)] \tag{3.8}$$

Where *numtrain* is the total number of training image.

Second, reduced dimensionality will be used to reduce the calculations needed and effect of noise on eigenvectors. Covariance, *C* and size of *C*, *S* is calculated by using the equation (3.9) and equation (3.10), respectively [15]. S will be $numtrain^2$. The size of eigenvalues and eigenvectors also will be $numtrain^2$. *S* of the reduced dimensionality will be smaller. This method will be applying.

$$C = \frac{1}{numtrain} \sum_{i=1}^{numtrain} A_i^T A_i \tag{3.9}$$

$$S = [(numtrain\ x\ (rxc)]\ [(rxc)\ x\ numtrain]$$

$$S = [numtrain^2] \tag{3.10}$$

Where *numtrain* is the total number of training image.

3.6.2(e) Calculate Eigenvector and Eigenvalue

Calculation of eigenvector and eigenvalue of *C* is shown in equation (3.11) [13].

$$Cv_i = \ A^T A v_i \ = \gamma_i \ v_i \tag{3.11}$$

where v_i is the eigenvector of *C* and γ_i is the eigenvalue of *C*.

3.6.2(f) Choose the Best K Eigenvector

The eigenvalue, γ_i will sort in descending order followed by the eigenvector, $v_{i.}$ This is to prepare for the dimension reduction. Not all eigenvector is necessary used for the forming of eigenface. K significant eigenvector can be calculated in the equation (3.12) by compare the *Y* with the 95% of total variance that have set. The sum of the largest eigenvalue that Y is less than 95% is determined. Eigenvector which correspond to that eigenvalue is the M largest significant eigenvector [15]

$$Y = \sum_{i=1}^{numtrain} \frac{\gamma_i}{S} x\ 100\% \qquad (3.12)$$

Where S is sum of the eigenvalue

3.6.2(g) Form the Eigenface

Formed of the eigenface of image, E_K is shown in the equation (3.13)

$$E_K = \sum_{i=1}^{M} Av_i \qquad (3.13)$$

Where M is the largest significant eigenvector.

3.6.2(h) Project the Image into Face Space

Training weight, $wtrain_K$ can be formed to represent the feature of the test image is shown in equation (3.14).

$$wtrain_K = E_K^T A \qquad (3.14)$$

Where K=1,2,3…. M.

Training weight vector, Ω_i can be formed from $wtrain_K$ is shown in equation (3.15).

$$\Omega_i = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_M \end{pmatrix} \qquad (3.15)$$

where M is the largest significant eigenvector and i =1,2,… $numtrain$.

Test weight vector, $wtest_k$ can be formed to represent the feature of the test image is shown in equation (3.16).

$$wtest_K = E_K^T A \quad (3.16)$$

Where K=1,2,3…. M.

Test weight vector, Ω_j can be formed from $wtest_K$ is shown in equation (3.17).

$$\Omega_j = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_M \end{pmatrix} \quad (3.17)$$

Where M is the largest significant eigenvector and j =1,2,… $numtest$.

3.6.2(i) Compare between training image and testing image

The Euclidean distance between each test image and training image, $\mathcal{E}_k$ is calculated by using the weight vector that formed is shown in equation (3.18) and find the training image which has the shortest distance with the test image.

$$\mathcal{E}_k = \sum_{j=1}^{numtest} \sum_{i=1}^{numtrain} \sqrt{\Omega_j^2 - \Omega_i^2} \quad (3.18)$$

Find the training image which has the shortest $\mathcal{E}_k$ with the test image. The label of training image is compared to test image to determine whether it is matched. Face recognition is success if the label of training image and test image is matched. Accuracy is calculated by determine the number of matches within the number of image in each fold in equation (3.19). Mean of the accuracy of 10 folds will be calculated in equation (3.20) and this is the face recognition accuracy.

Accuracy=(sum(labeltest= labeltrain))/(num_test) x 100% (3.19)

$$MeanAccuracy = mean(Accuracy) \tag{3.20}$$

3.6.3 Modular PCA

Figure 3.5 shows the flowchart of feature extraction of Modular PCA.

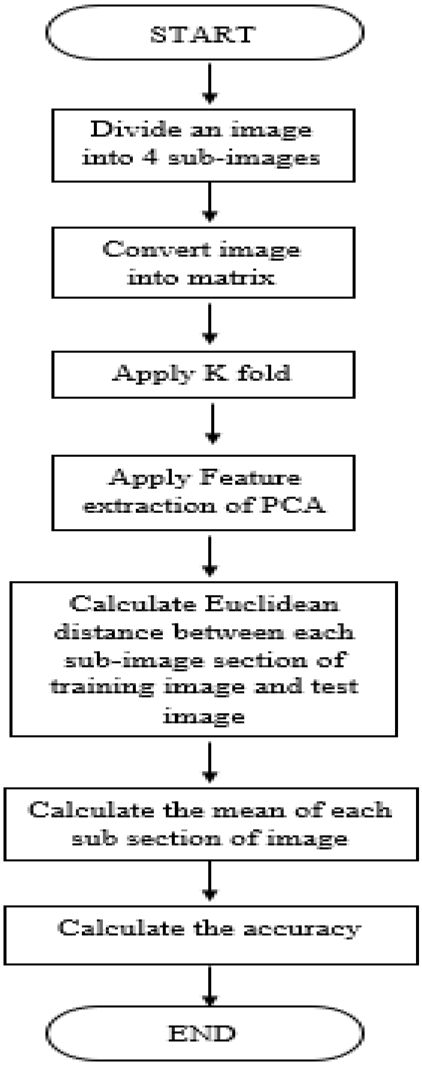

Figure 3.5: Flowchart of feature extraction of Modular PCA

Every face image will be divided into certain number of sub-image, q which is 4 in Modular PCA [4]. 4 sub-images are chosen in this study because it is more simple. There will be total z sub-image as 4 sub-image multiply the total number of original image,