**FACE RECOGNITION TECHNIQUE USING GABOR WAVELETS AND SINGULAR VALUE DECOMPOSITION**

By

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13950

FINAL PROJECT REPORT

submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfilment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

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## CERTIFICATION OF APPROVAL

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Approved by,

__________________________

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May 2014

# CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

LIM SONG LI

# ABSTRACT

Gabor Wavelets (GWs) (also known as Gabor filter) and Singular Value Decomposition (SVD) have been studied extensively in the area of face recognition. In this project, face recognition system is developed using combination of GWs and SVD. Both techniques are used to extract facial features from the human facial image and presented in the form of feature vector. For GWs, only 12 out of 40 GWs are selected to extract facial features from the facial images. This offers the advantage of reducing computational time of feature extraction. As for SVD, only the first five singular values are selected and its associated right singular vectors are used as the facial feature vectors. The use of SVD in addition to the GWs increases the reliability of the face recognition system. In the face verification and matching stage, the similarity level between facial images is determined by computing the distance between the resulting facial feature vectors obtained from GWs and SVD respectively. Overall, the Gabor-SVD based face recognition technique showed constructive and promising result in recognizing the valid user and rejecting invalid users on the JAFFE database.

# ACKNOWLEDGMENT

First of all, I would like to express my immense gratitude to Miss Norashikin Bt Yahya who is not only my supervisor but also a mentor who guided, inspired and assisted me throughout my Final Year Project. She has shared her valuable knowledge and experience during the whole period of Final Year Project. Without her guidance and advices, I would not be able to complete Final Year Project successfully.

Besides, I would like to thank my family, who has been supportive to me throughout the duration of Final Year Project. Their understanding, motivation, encouragement and financial support are much appreciated.

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| | |
|---|---|
| GWs | Gabor Wavelets |
| SVD | Singular Value Decomposition |
| JAFFE | Japanese Female Facial Expression |

# CHAPTER 1

# INTRODUCTION

## 1.1 Background of Study

Nowadays, with rapid expanding of human population, people started to realize the importance of security, access control and organizations. Some information and areas are highly restricted to authorize personnel. Hence, identity authentication methods must be developed to ensure that only authorized personnel have access to these classified information and areas.

Various verification methods either physical or biometric have been developed for automatic authentication, each with its own limitations. The physical recognition techniques include badges, smart cards, keys, entering PIN codes or passwords while biometric recognition techniques include voice, iris, fingerprints, retina and face recognition. In this project, face recognition will be used to recognize the identity of the individual.

A face recognition system is a computer-based application for automatic verification of a person from a digital camera or a video recording. It performs the face recognition by matching facial features of the test image with facial features of the training images. Designing face recognition system is a challenging field of object recognition as a human face is not a unique and rigid object and potentially affected by extrinsic and intrinsic factors [1]. Extrinsic factors like poses, illumination and scales of the face image as well as intrinsic factors such as facial hairs, make-up and glasses are also likely to affect the accuracy of the face recognition. Hence, these factors must be taken into consideration when designing face recognition system.

Currently, there are various face recognition systems available commercially. Even though with these attainments, face recognition is still an active and attractive field in computer vision as the current face recognition systems only work well under certain predefined conditions but perform poorly when testing under different conditions such as illumination, head pose, orientation, occlusion, etc. Therefore, the purpose of the ongoing research is to improve the performance of the face recognition system against different settings.

## 1.2 Problem Statement

There are some major drawbacks with the current identification methods. For instance, keys, badges, PIN code, passwords and smart card are susceptible to being taken away, forgotten or lost whereas fingerprint, retina and voice recognition encountered low user acceptance issue and are claimed to be intrusive. Biometric recognition are claimed to be intrusive as the users have to stand still in front of machine for scanning his/her retina, fingerprints or iris which make them feel like being suspected. Besides, it is inconvenient to users who need to access the restricted areas or information multiples times a day. Recently, a novel approach has been introduced for identity authentication. The approach is known as face recognition. Face recognition technique appeared to be non-intrusive as the surveillance cameras are able to capture the input face image of the users further away without having the users to stand still in front of machines. Moreover, face recognition techniques also produces higher user acceptance rate as compared to other biometric recognition techniques.

In this project, the face recognition technique is based on Gabor Wavelets (GWs) and Singular Value Decomposition (SVD). The conventional face recognition technique which uses 40 Gabor Wavelets (GWs) with 5 scales and 8 orientations is time-consuming and computationally expensive. Therefore, it is desirable to select only most prominent and discriminating scales and orientation of GWs to reduce computational time and complexity. Besides, singular values and singular vectors of Singular Value Decomposition (SVD) contain redundant facial information which occupies the memory space.

### 1.3 Objective and Scope of Study

This project relies on the application of GWs and SVD to extract features from the input face image. Gabor Wavelets and Gabor filters are used interchangeably in this project. The extracted features will be presented in form of feature vector. The similarity level is obtained by computing distance between feature vector of test image and training images using cosine of principal angles [2].

In this project, the scope of study is limited to the frontal view of the face images with fixed position and orientation and no occlusion. Besides, the different illumination conditions and scale of the face images are excluded from the scope of study. The impacts of the different facial expressions to the face recognition rate are included in the scope of study. Japanese Female Facial Expressions (JAFFE) images are used for test subjects. All the coding and algorithms of this project will be implemented and displayed in Matlab 2010a running by 64-bit and 4-GB RAM Operating system.

The objectives of this project are

- To determine the most prominent scales and orientations of GWs for facial feature extraction.
- To determine the principal singular vectors of SVD that carries the maximal energy of the facial features.
- To implement and evaluate the performance of Gabor-SVD based face recognition method.

# CHAPTER 2

# LITERATURE REVIEW AND THEORY

Numerous techniques for face recognition had been developed and can be categorized into geometric feature-based approach and template- based approach. In geometric feature based method, significant facial features such as eyes, nose, eyebrow and mouth are spotted and the geometric characteristics between features are combined to become feature vector. The feature vectors of the input image and training image in the database is compared for their similarity. For template-based technique, the whole face image is represented by the feature vector instead of only significant facial features. In most application, the template-based method outperforms the geometric feature method because template-based method collects more information by using entire face image [3].

Karhunen-Loeve transform or Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Linear Binary Pattern (LBP), Gabor Wavelets analysis, Singular Value Decomposition (SVD) etc. are popular face recognition techniques among the template-based approach. These face recognition techniques are described in the succeeding section.

## 2.1 Principal Component Analysis (PCA)

Principal component analysis which is also known as Karhunen-Loeve transformation is one of the popular techniques used in face recognition as well as dimensionality reduction. The application of the Karhunen-Loeve expansion in representing the human face was first proposed by Kirby and Sirovich in 1990. This technique is worked on image-based representation. In this technique, faces are represented in terms of an optimal coordinate system where the coordinate system is constructed based on the feature vectors called eigenvectors. The conversion of the 2 dimension face image matrices into 1 dimension image vectors results in high dimension of vector space. The high dimensionality of vector space causes difficulty in evaluating the covariance matric precisely [4]. 2-dimensional PCA (2DPCA) was later introduced. In 2DPCA, the conversion of image matrix to vector is not necessary. Instead, the original image matrices are used to build the image covariance matrix and the image covariance matrix of 2DPCA is actually smaller in size as compared to that of PCA [5]. However, the major drawback of PCA in face recognition is that no class information was employed thus it may lose some significant information for classification.

## 2.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis which is known as Fisher Discriminant Analysis is well-known technique used in face recognition as well as dimensionality reduction. This technique applies the same principle as the PCA except it preserves the class discriminatory information by maximizing the between-class variance and minimizing within-class variance. In this technique, the training face image is projected into a subspace known as fisher space. The comparison between facial images can be done by projecting the testing faces into the fisher space of the training faces [6]. This technique of face recognition is unaffected by large variation of illumination condition and facial expressions [7].

## 2.3 Local Binary Pattern (LBP)

Local binary Pattern (LBP) features are first proposed by Ojala et al [8] for the purpose of texture analysis and it is later introduced to represent the face images. The idea of using LBP features in representing face images come from the fact that the face images can be perceived as composition of micro pattern [9]. In this technique, the face images are first divided equally into small regions and LBP texture features are extracted from these small regions. These extracted features will be concatenated into a single feature histogram. The matching process between face images is done by using distance metric measurements to compare the histogram.

The most significant advantages of the LBP features include its robustness against illumination and simplicity in computation [10].

## 2.4 Singular Value Decomposition (SVD)

Suppose a matrix A with dimension of M x N ($A \in R^{MxN}$), perform SVD on the matric will factorize the matrix to the following form

$$A = U\,S\,V \tag{1}$$

where U and V are orthogonal matrices with dimension of M x M and N x N respectively whereas S is a diagonal matrix with dimension of M x N. Matrices U and V compose of left and right singular vectors in its columns and diagonal of matrix S consists of singular values of the matrix A in descending order . Columns of U and V are the orthonormal eigenvectors of matrix $AA^T$ and $A^TA$ respectively. The singular values of the matrix A are equivalent to the squared root of Eigen value of matrix $A^TA$ or $AA^T$. These singular values represent the variance of the linearly independent component along the dimension [11].

SVD-based face recognition method is an algebraic feature extraction approach in which its facial features are extracted and stored in the singular vectors of U and V and its singular value is invariant against translation and rotation [12]. The image reconstruction from lesser singular values and its associated singular vectors of SVD is able to diminish noises and varying illuminating condition in the face image which will improve the recognition rate [13]. Besides, image reconstruction using smaller set of singular values and singular vectors preserve the essential information of an image with smaller memory space [14]. Singular value is shown to have insufficient information for face recognition and orthogonal matrices U and V contain the most important features about the faces [15]. Due to this reason, right singular vectors of V are used instead of singular values to represent facial features for this project.

### 2.5 Gabor Wavelets (GWs)

Gabor Wavelets (GWs) which are also known as Gabor filters are among the popular techniques used in face recognition. GWs were introduced by Dennis Gabor, a Hungarian-born electrical engineer in 1946. GW is a complex exponential modulated by a Gaussian function in the spatial domain [16].

The 2-D Gabor function in the spatial domain is defined as:

$$\varphi_{u,v}(x,y) = \frac{{f_u}^2}{\pi\gamma n} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{n^2}y'^2\right)} e^{-j2\pi f_u x'} \tag{2}$$

The parameters of the $\varphi_{u,v}(x,y)$ are defined as follows:

$x' = x\ \cos\theta_v + y\ \sin\theta_v$ $\quad$ $y' = -x\ \sin\theta_v + y \cos\theta_v$

$f_u$=center frequency $= \frac{0.25}{\sqrt{2}^u}$, $u$ = Scale $\quad$ $\theta_v$ = Orientation

$n$ = Size of the Gaussian envelope $\quad$ γ = Ratio between center frequency

Biological relevance and computational properties of GWs are the key factors for its widespread use in automatic face recognition system. For biological property, 2-D Gabor Wavelets can be used to represent simple cells in the visual cortex of mammalian brains. For computational properties, Gabor wavelets exhibit appealing properties such as orientation selectivity and spatial locality [17]. Besides, face recognition using GWs approach is proven to be robust against illumination, scales, translation, deviation in head pose and face features such as facial hair and glasses [18]. However, there are some drawbacks on this technique as well. One of major drawbacks includes the non-orthogonal characteristic of the GWs. This will increase the size of the Gabor face representation as well as redundant information stored in the face representation [19].

Face recognition using GWs is categorized as template-based technique. Generally, features of every input face image are extracted by using a filter bank consists of multi-orientation and multi-scale of GWs. A filter bank with 5 scales and 8 orientations of GWs are commonly used in face recognition application [20]. Figure 1 and Figure 2 show real part and magnitude response of Gabor Wavelet with 5 different scales and 8 different orientations. Certain orientations of GWs are shown to be more discriminating and significant as compared to the rest of the GWs [21].

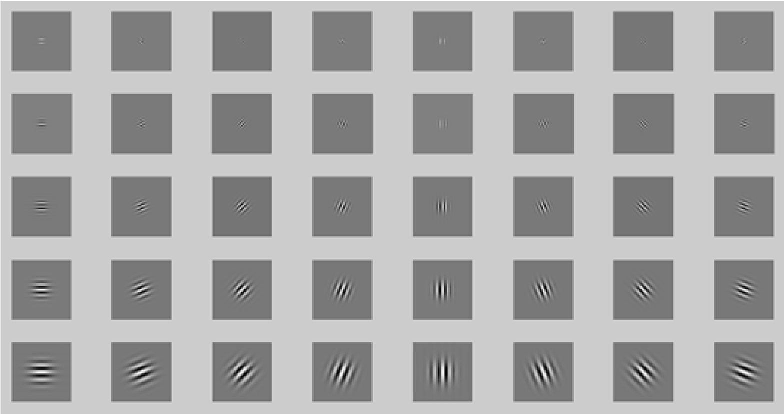


***Figure 1: Real Parts of Gabor Wavelets with 5 scales and 8 orientations***

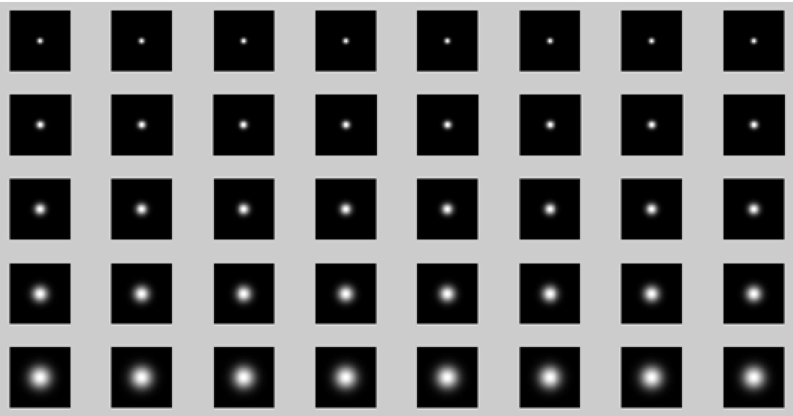


***Figure 2 : Magnitude responses of Gabor Wavelets with 5 scales and 8 orientations***

The steps of feature extraction from facial images by using GWs are briefly descripted. A grey-scale input face image with 128 x 128 pixels (shown in Figure 3) is represented by $I(x, y)$ and $\varphi_{u,v}(x, y)$ represents a Gabor filter.

***Figure 3: Face image with 128x128 pixels***

The filtering process of the grey-scale input face image by the Gabor filter is represented by the complex convolution between the input face image and the Gabor filter as follows:

$$G_{u,v}(x, y) = I(x, y) * \varphi_{u,v}(x, y) \tag{3}$$

Where equation (3) shows the result of the complex convolution which can be further decomposed into real part $E_{u,v}(x, y)$ and imaginary part $O_{u,v}(x, y)$ by using equation (4) and (5).

$$E_{u,v}(x, y) = Re\left[G_{u,v}(x, y)\right] \tag{4}$$

$$O_{u,v}(x, y) = IM[G_{u,v}(x, y)] \tag{5}$$

The magnitude and phase responses of the filtered result can be determined from the equation (6) and (7):

$$M_{u,v}(x, y) = \sqrt{E_{u,v}(x, y)^2 + O_{u,v}(x, y)^2} \tag{6}$$

$$\theta_{u,v}(x, y) = \tan^{-1} \frac{O_{u,v}(x,y)}{E_{u,v}(x,y)} \tag{7}$$

The phase response $\theta_{u,v}(x, y)$ is always being ignored as it varies significantly even only a few pixels a part [22]. Conversely, the magnitude response $M_{u,v}(x, y)$ is accepted option as it varies gradually in spatial location. The computation of magnitude responses for every Gabor filters in the filter bank are performed in order to derive the face representation of the input image. However, this will result in tremendous amount of information and require lengthy time in computing the output. For instance, a filter bank consists of Gabor filter of 6 scales and 8 orientations with the input face image of 128 x 128 pixels will perform 786432 times of calculation. The total output will be stored in the form of feature vector.

Various downsampling, subspace projection or feature selection techniques are exploited to reduce the feature vector to an acceptable dimensionality. Some of the effective techniques used in reducing the dimension of feature vectors are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and neural networks [23]. Figure 4 shows the magnitude responses of filtered face image of Figure 3 with 5 scales and 8 orientations of GWs.

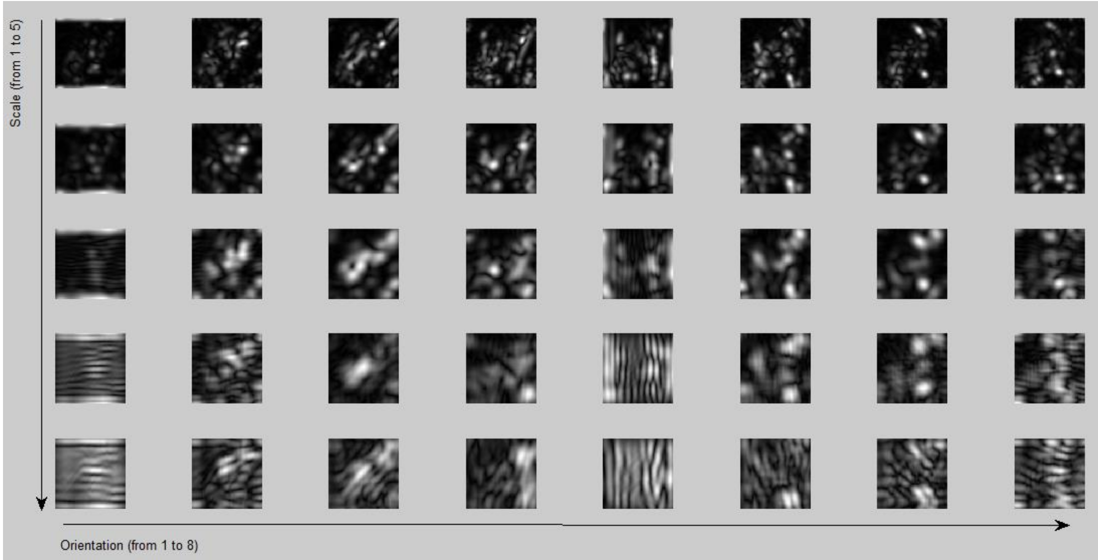



***Figure 4: Magnitude responses of filtered face image for 5 scales and 8 orientations of GWs***

Once the dimension of feature vector is reduced, face verification phase will be commenced. The degree of similarity between the feature vector of the input image and the database is calculated by using distance metric measurement such as chi-square metric, cosines of principal angles, G-statistics or log-likelihood statistics [24]. Among these techniques, chi-square metric is proven to be most stable and reliable technique in distance metric measurement [25]. The similarity threshold is usually selected in advance. Setting higher similarity threshold increase the security of the face recognition system but at the same time increase the chance of rejecting a legitimate identity [26].

# CHAPTER 3

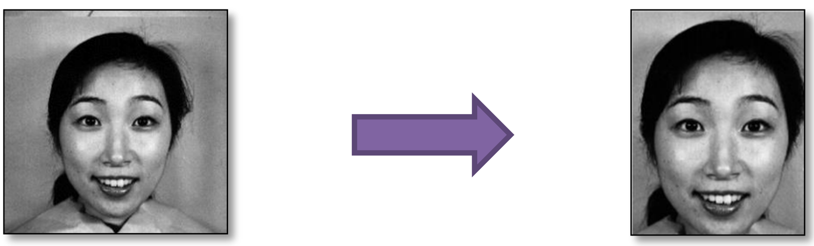
# METHODOLOGY/PROJECT WORK

## 3.1 Project Methodology

The project methodology consists of three main stages, which are image acquisition and face detection, feature extraction, and face verification and matching.


1. **Image Acquisition and Face Detection**

   In this stage, the frontal face image of the individual is obtained from the video sequences or digital camera. The exact location of the face is identified and cropped from the input image. The background of the image is removed. The resulting face image is converted to grayscale image by using rgb2gray in Matlab because the grayscale facial image contains sufficient information for feature extraction and recognition.



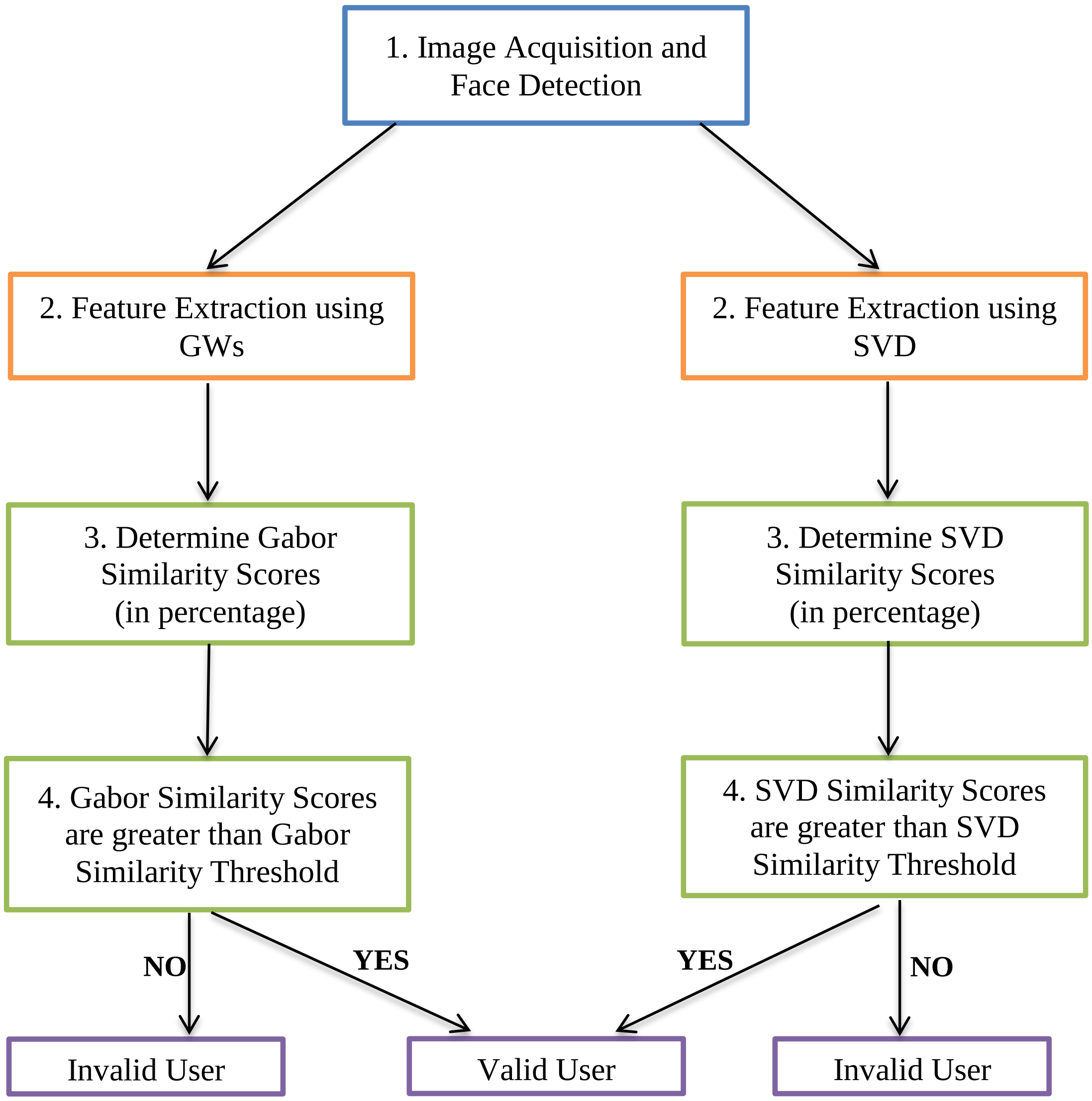
2. **Feature Extraction**

   In this stage, GWs and SVD are used to extract facial feature from the identified facial image. For GWs, only 12 GWs out of 40 filters are selected to extract facial feature from the face images. As for the SVD, only the first five singular values are selected and its associated principal right singular vectors are used to represent the facial feature. The extracted facial feature will be presented in form of feature vector. The resulting Gabor and SVD facial feature vectors will be then used in face verification stage.

3. **Face Recognition and Verification**

   In this stage, the distance between feature vectors of the test image and the training images are computed by using cosines of principal angles. The distance between feature vectors of the test image and training images is known as similarity score. These similarity scores are presented in the form of percentage. The similarity score obtained from the comparison must reach or exceed the preset Gabor and SVD similarity threshold in order to authenticate the identity.

The overall processes of face recognition using GWs and SVD




### 3.2 Tools and Software

- Matlab Software 2010a
- Face Database (JAFFE)
- Microsoft Excel

### 3.3 Key Milestone and Gantt Chart

**FYP 1**

| Description/week | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Selection of Project Topic | | | | | | | | | | | | | | |
| 2. Preliminary Research Work on Gabor Wavelets and its application | | | | | | | | | | | | | | |
| 3. Research and understand the Gabor Wavelet Matlab coding | | | | | | | | | | | | | | |
| 4. Submission of Extended Proposal | | | | | | | | | | | | | | |
| 5. Apply Gabor Wavelets on face image with different scales and orientations and interpret the outputs. | | | | | | | | | | | | | | |
| 6. Determine the similarity score between same face images with different expressions. | | | | | | | | | | | | | | |
| 7. Preparation for Proposal Defense | | | | | | | | | | | | | | |
| 8. Proposal Defense | | | | | | | | | | | | | | |
| 9. Select certain prominent scales and orientations of Gabor filters (out of 40 Gabor filters) | | | | | | | | | | | | | | |
| 10. Select suitable Gabor similarity threshold and test the performance of the selected Gabor filters | | | | | | | | | | | | | | |
| 11. Interim Report Preparation | | | | | | | | | | | | | | |
| 12. Submission of Interim Draft Report | | | | | | | | | | | | | | |
| 13. Submission of Interim Report | | | | | | | | | | | | | | |

Project milestone

Process

**FYP 2**

| Description/week | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Research on SVD based face recognition technique | | | | | | | | | | | | | | | |
| 2. Selection of principal singular vectors of SVD and determine SVD similarity threshold | | | | | | | | | | | | | | | |
| 3. Testing of SVD-based face recognition technique | | | | | | | | | | | | | | | |
| 4. Combining SVD and Gabor for Face Recognition | | | | | | | | | | | | | | | |
| 5. Test the performance of Gabor-SVD based Face Recognition | | | | | | | | | | | | | | | |
| 6. Submission of Progress Report | | | | | | | | | | | | | | | |
| 7. Enhance the system to improve correct acceptance rate | | | | | | | | | | | | | | | |
| 8. Test the performance of the system with personal database | | | | | | | | | | | | | | | |
| 9. Prepare Poster for Pre-SEDEX | | | | | | | | | | | | | | | |
| 10. Pre-SEDEX | | | | | | | | | | | | | | | |
| 11. Submission of Draft Final Report | | | | | | | | | | | | | | | |
| 12. Submission of Dissertation (Soft Bound) | | | | | | | | | | | | | | | |
| 13. Submission of Technical Paper | | | | | | | | | | | | | | | |
| 14. Viva | | | | | | | | | | | | | | | |

Project milestone

Process

# CHAPTER 4

# RESULT AND DISCUSSION

This chapter is divided into three main sections. Section 4.1 explains on the GW facial feature extraction and selection of the 12 most prominent scales and orientations of GWs. Besides, similarity threshold for GWs is determined and the performance of the 12 prominent GWs is tested. Section 4.2 elaborates on SVD facial feature extraction and the selection of principal singular vectors based on singular values of SVD. Moreover, the similarity threshold for SVD is determined as well. Section 4.3 shows the performance of the Gabor-SVD based face recognition on JAFFE database in term of correct acceptance rate and correct rejection rate as well as enhancement on the system to improve correct acceptance rate.

## 4.1 Feature Extraction Using GWs

### 4.1.1 Selection of the Most Prominent Scales and Orientations of GWS

Five images (A, B, C, D and E) with dimension of 256 X 256 pixels as shown Figure 5, 6, 7,8 and 9 are the facial images of the same person (Person A) with 5 different expressions. These facial images are selected from the **JAFFE database** for the experiment. These images are then cropped to remove background and only left with the facial image. The resulting images with dimension of 215 x 165 pixels are shown in the Figure 10, 11, 12, 13 and 14.

*Figure 5 : Image A*

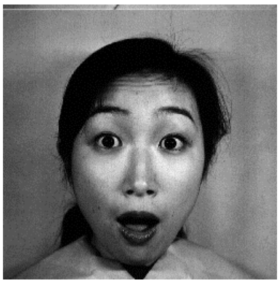


*Figure 6 : Image B*

*Figure 7 : Image C*

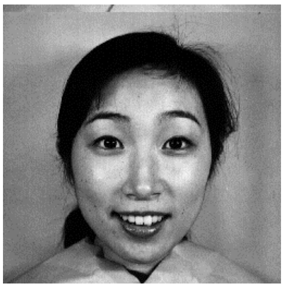


*Figure 8 : Image D*

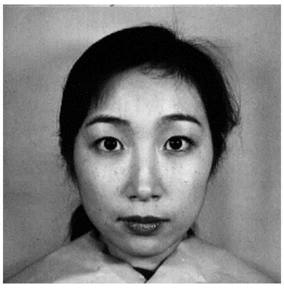


*Figure 9 : Image E*

*Figure 10 : Face image A*

*Figure 11 : Face image B*

*Figure 12 : Face image C*

*Figure 13 : Face image D*

*Figure 14 : Face image E*

These face images are used as the input images to be convolved with the Gabor filter banks with 5 scales and 8 orientations (total 40 Gabor filters). For each face image, there will be 40 outputs generated from the Gabor filters. So for 5 face images, there will be 200 outputs from the Gabor filters. Every output consists of unique feature vectors.

The cosines of principle angles method are used to determine the similarity score between the five face images and the results are presented in the form of percentage. For 5 facial images, a total of 10 comparisons are performed, which are between face images A-B, A-C, A-D, A-E, B-C, B-D, B-E, C-D, C-E and D-E. The similarity scores are measured between the outputs of Gabor filter with same scale and orientation. For instance, the output from Gabor filter of scale 3 and orientation 5 for facial image A is compared with the Gabor filter output of the same scale and orientation of another facial image. Therefore, even for two facial images, there will be 40 comparisons to be done. The average similarity score for 40 Gabor filters with 5 face images are computed and plotted in the Figure 15.

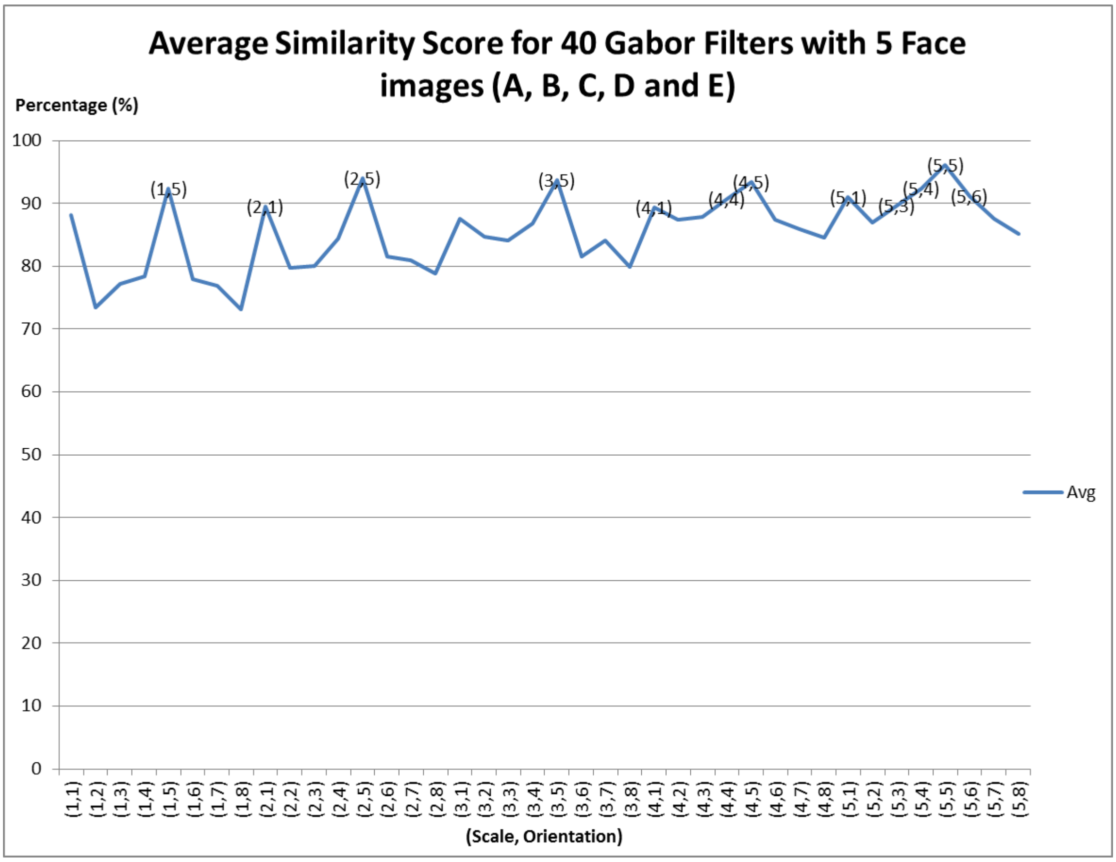



*Figure 15: Average similarity score for 40 Gabor filters with 5 face images*

### 4.1.2 Selecting Discriminating Gabor Filters

From the Figure 15, certain scales and orientations of the Gabor filters have higher average similarity score as compared with others. Since performing 40 Gabor filters to every face image are too time-consuming and computationally expensive, therefore it is desirable to select only certain discriminating and representative Gabor filters. In this case, the Gabor filters with average similarity score over 89% will be selected as the prominent Gabor filters for rest of the experiment. There are a total of 12 Gabor filters with average similarity score over 89% and these filters are shown and labelled with its respective scale and orientation as shown in the Figure 15.

Besides, the time taken to construct 12 Gabor filters with the same dimension as the face images is shorter (0.3138 seconds) as compared to the construction of whole Gabor filter bank comprised of 40 Gabor filters which requires 0.8543 seconds. Besides, time saving is more obvious in the convolution operation between input facial image and the Gabor filters. The time for the convolution between 40 Gabor filters and single facial image takes up about 12 seconds. Since the number of Gabor filters used had been reduced to only 12 filters, the time required for the convolution process had been reduced to around 4 seconds which is three times shorter than original filter bank. This time difference is more apparent when the number of test images is increased.

### 4.1.3 Determine Similarity Threshold

The average similarity score between five face images for the selected Gabor filters are compiled in the form of table as shown in Table 1. The average similarity scores of the 12 selected Gabor filters for any two face images are computed in the right end column of the Table 1. From the average similarity scores of the 12 Gabor filters, it can be seen that the lowest similarity score occurs between face image C and face image E which is 89.51. For this reason, it is practical to set the similarity score of 88% as threshold value.

***Table 1 : Average similarity score between five face images with 12 Gabor filters***

| | | Gabor Filters (scale, orientation) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1,5) | (2,1) | (2,5) | (3,5) | (4,1) | (4,4) | (4,5) | (5,1) | (5,3) | (5,4) | (5,5) | (5,6) | Average |
| Face images | A-B | 94.73 | 89.81 | 94.6 | 93.73 | 89.41 | 89.36 | 94.19 | 89.21 | 89.13 | 91.87 | 97.49 | 91.99 | 92.127 |
| | A-C | 92.15 | 86.64 | 93.45 | 93.13 | 89.27 | 86.08 | 93.16 | 87.38 | 87.7 | 89.04 | 95.06 | 88.69 | 90.146 |
| | A-D | 93.55 | 88.85 | 94.59 | 92.99 | 86.84 | 90.85 | 94.67 | 91.44 | 88.79 | 93.61 | 97.71 | 92.42 | 92.193 |
| | A-E | 93.5 | 91.96 | 93.44 | 94.8 | 87.19 | 89.77 | 94.98 | 89.05 | 88.09 | 93.41 | 96.94 | 91.18 | 92.026 |
| | B-C | 93.73 | 92.92 | 95.01 | 96.41 | 94.53 | 92.68 | 93.36 | 96.01 | 91.53 | 92.36 | 95.32 | 94.58 | 94.037 |
| | B-D | 91.6 | 90.99 | 94.05 | 92.67 | 87.11 | 92.69 | 92.87 | 92.63 | 91.46 | 93.93 | 96.7 | 93.71 | 92.534 |
| | B-E | 91.2 | 89.28 | 94.12 | 93.73 | 91.44 | 91.99 | 92.05 | 89.83 | 87.55 | 93.14 | 95.21 | 90.03 | 91.631 |
| | C-D | 90.33 | 87.34 | 92.86 | 94.03 | 87.71 | 88.64 | 91.38 | 92.41 | 90.05 | 90.34 | 94.58 | 89.05 | 90.727 |
| | C-E | 89.22 | 84.97 | 91.39 | 91.9 | 88.17 | 89.47 | 91.15 | 89.08 | 89.06 | 90.93 | 93.71 | 85.07 | 89.51 |
| | D-E | 93.41 | 92.33 | 95.87 | 94.33 | 92.36 | 94.88 | 96.47 | 93.45 | 92.5 | 95.57 | 98.45 | 94.82 | 94.537 |
| | Average | 92.342 | 89.509 | 93.938 | 93.772 | 89.403 | 90.641 | 93.428 | 91.049 | 89.586 | 92.42 | 96.117 | 91.154 | |

### 4.1.4 Performance Testing

Three images (Image P, Q, R) as shown in the Figure 16, 18 and 20 are selected as the test subjects to test the performance of the selected Gabor filters. The images consist of the two different females and one same female as Person A with another facial expression. The three images are preprocessed to remove the background and left with only the face images as shown in Figure 17, 19 and 21. The same procedures are applied to three images and the similarity scores for 12 selected Gabor filters are tabulated in the Table 2, 3 and 4 respectively.

For face images P, all the average similarity score exceed threshold value of 88% since this is the same person as Person A. For face image Q, the highest average similarity score for 5 comparisons of the 12 Gabor filters is 83.685% which is below the defined threshold value. For face image R, the highest average similarity score for 5 comparisons is 87.568% which is still below the selected threshold value (88%). Since the average similarity scores for different face images are quite high, a ratio value can be set to reduce the possibility of the false acceptance rate. For instance, only 4 out of 5 comparisons which exceed threshold value of 88% are accepted as the valid user. By setting suitable ratio value, it will increase the performance of this Gabor-SVD face recognition technique.

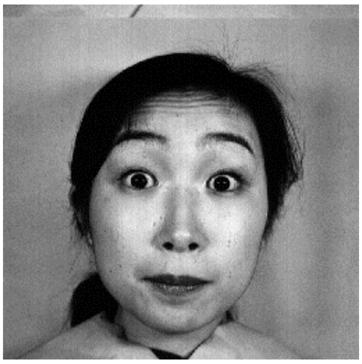


*Figure 16 : Image P*

*Figure 17 : Face Image P*

***Table 2: Average similarity score between face image P and five face images for 12 Gabor filters***

| | | Gabor Filters (scale, orientation) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1,5) | (2,1) | (2,5) | (3,5) | (4,1) | (4,4) | (4,5) | (5,1) | (5,3) | (5,4) | (5,5) | (5,6) | Average |
| Face images | A-P | 93.81 | 89.9 | 94.47 | 93.6 | 84.51 | 88.32 | 94 | 88.08 | 87.58 | 91.59 | 97.14 | 89.74 | 91.062 |
| | B-P | 93.38 | 95.02 | 95.76 | 95.49 | 94.77 | 93.09 | 93.31 | 96.26 | 93.6 | 93.26 | 97.56 | 96.26 | 94.813 |
| | C-P | 93.1 | 92.94 | 96.87 | 96.16 | 92.4 | 90.49 | 90.94 | 94.97 | 88.14 | 89.36 | 94.74 | 93.86 | 92.831 |
| | D-P | 92.91 | 88.92 | 95.34 | 94.8 | 87.9 | 90.99 | 97.31 | 89.79 | 86.97 | 93.49 | 98.02 | 92.61 | 92.421 |
| | E-P | 92.19 | 89.81 | 94.62 | 93.38 | 91.51 | 88.75 | 94.22 | 89.96 | 82.68 | 91.88 | 96.52 | 88.91 | 91.203 |

*Figure 18 : Image Q*

*Figure 19 : Face Image Q*

***Table 3 : Average similarity score between face image Q and five face images for 12 Gabor filters***

| | | Gabor Filters (scale, orientation) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1,5) | (2,1) | (2,5) | (3,5) | (4,1) | (4,4) | (4,5) | (5,1) | (5,3) | (5,4) | (5,5) | (5,6) | Average |
| Face images | A-Q | 75.3 | 86.93 | 76.3 | 80.27 | 88.63 | 85.34 | 85.78 | 87.54 | 81.85 | 79.2 | 90.84 | 86.24 | 83.685 |
| | B-Q | 71.08 | 83.25 | 72.22 | 75.95 | 86.48 | 83.86 | 74.54 | 87.5 | 81.12 | 71.74 | 88.46 | 84.3 | 80.042 |
| | C-Q | 72.49 | 87.03 | 72.33 | 73.75 | 86.2 | 83.61 | 71.49 | 85.16 | 81.37 | 73.53 | 88.03 | 84.05 | 79.92 |
| | D-Q | 77.04 | 84.89 | 76.47 | 78.41 | 86.06 | 90.11 | 82.94 | 89.59 | 83.08 | 71.02 | 92.27 | 86.53 | 83.201 |
| | E-Q | 79.29 | 86.29 | 77 | 81.96 | 90.33 | 89.98 | 84.74 | 91.3 | 83.29 | 75.27 | 93.53 | 86.6 | 84.965 |

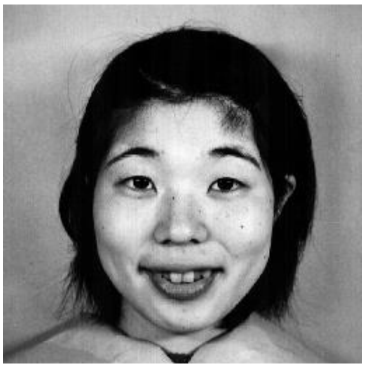


*Figure 20 : Image R*

*Figure 21 : Face Image R*

***Table 4: Average similarity score between face image R and five face images for 12 Gabor filters***

| | | Gabor Filters (scale, orientation) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1,5) | (2,1) | (2,5) | (3,5) | (4,1) | (4,4) | (4,5) | (5,1) | (5,3) | (5,4) | (5,5) | (5,6) | Average |
| Face images | A-R | 78.94 | 90.17 | 79.98 | 84.16 | 88.06 | 81.07 | 89.49 | 88.4 | 81.73 | 82.2 | 93.51 | 84.55 | 85.188 |
| | B-R | 74.73 | 86.78 | 77.92 | 83.22 | 86.29 | 77.01 | 86.56 | 84.85 | 80.66 | 78.93 | 91.6 | 85.09 | 82.803 |
| | C-R | 77.97 | 86.12 | 79.46 | 82.72 | 86.72 | 73.48 | 84.62 | 82.3 | 81.71 | 76.45 | 90.27 | 84.03 | 82.154 |
| | D-R | 82.51 | 89.21 | 83.39 | 84.12 | 86.96 | 81.46 | 90.91 | 89.05 | 83.86 | 80.6 | 94.23 | 88.58 | 86.24 |
| | E-R | 82.65 | 90.63 | 83.77 | 86.45 | 91.38 | 81.8 | 92.02 | 90.15 | 87.09 | 83.83 | 94.8 | 86.25 | 87.568 |

### 4.2 Feature Extraction Using SVD

#### 4.2.1 Determine the Principal Singular Vectors Based on the Singular Values

Singular Value Decomposition is performed on the face image to obtain matrices U and V in which its columns consist of left and right singular vectors respectively and matrix S with its diagonal contains singular values in decreasing order.

In literature, it has been stated that discriminating facial information are stored in first few singular values and its corresponding left and right singular vectors. This can be shown by applying SVD to facial image A, B, C, D and E of Figure 10, 11, 12, 13 and 14. The five sets of singular values obtained are then plotted in Figure 22. From the plotted graph, it can be seen clearly that for 5 sets of singular values, only the first few singular values of the facial images have outstanding magnitude and then the magnitude of the rest of the singular values decrease abruptly and start to approach 0. This implies that only first few singular values and its associated singular vectors carry the maximal energy. In other words, they contain the most discriminating facial features.

This can be further shown by the reconstruction of face image D using different number of first few singular values and its corresponding left and right singular vectors of SVD, as shown in the Figure 24, 25, 26 and 27. From the Figures, the face image reconstruction is very similar to the original face image by using just first 40 singular values and singular vectors which imply that the remaining singular values and singular vectors contains redundant facial information. In this project, only first five singular values with highest magnitude are selected and its corresponding right singular vectors are used to compute the similarity score between facial images. The similarity score between first five singular vectors of two facial images are computed by performing cosine of principle angles.

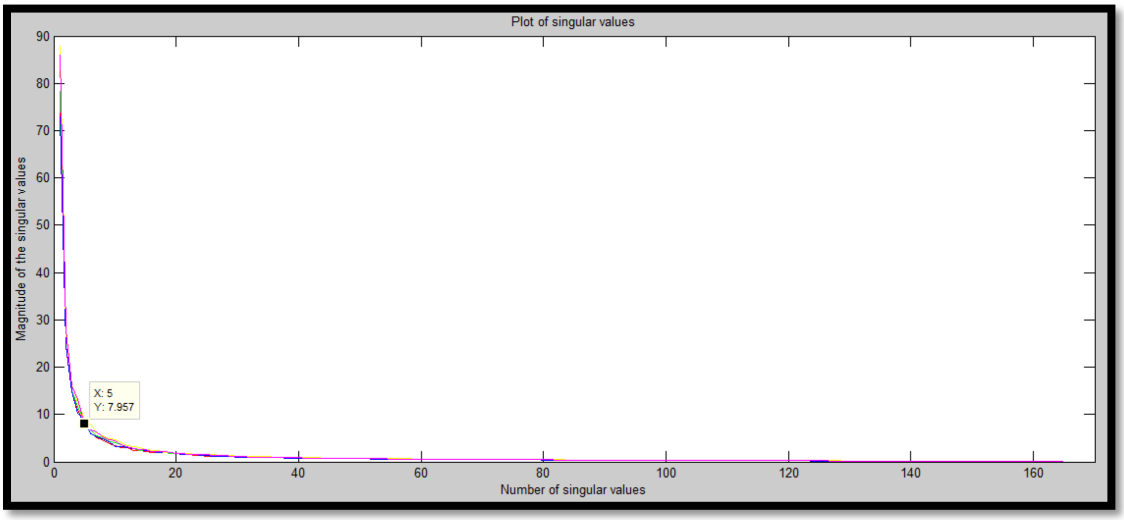



*Figure 22 : Plot of Singular values of Facial image A, B, C, D and E*

*Figure 23 : Original Facial Image D*

*Figure 24 : Image Reconstruction with first 5 singular values and singular vectors*

*Figure 25 : Image Reconstruction with first 10 singular values and singular vectors*

*Figure 26 : Image Reconstruction with first 20 singular values and singular vectors*

*Figure 27 : Image Reconstruction with first 40 singular values and singular vectors*

### 4.2.2 Determine Similarity Threshold for SVD-based Face Recognition

Five facial images of same person (Person F) with different facial expressions are selected from JAFFE database. The images are used to determine the similarity threshold for SVD-based Face Recognition. These images are first cropped to remove background and left with the only facial images. The resulting face images with dimension of 215 x 165 pixels are shown in the Figure 26, 27, 28, 29 and 30. The face images are SVD transformed and the similarity scores between 5 face images are computed by performing cosine of principal angles on the first 5 singular vectors. The similarity scores between facial images are tabulated in Table 5. From the table, the lowest similarity score takes place between facial image F1 and facial image F4 which is 85.42. Therefore, it is reasonable to set the similarity score of 85% as threshold value.

***Figure 28 : Face Image F1***

***Figure 29 : Face Image F2***

***Figure 30 : Face Image F3***

***Figure 31 : Face Image F4***

***Figure 32 : Face Image F5***

*Table 5 : Similarity Score (in Percentage) between Five Face Images of Person F*

| | | Similarity Score |
|---|---|---|
| Face images | F1-F2 | 96.14 |
| | F1-F3 | 96.56 |
| | F1-F4 | 85.42 |
| | F1-F5 | 88.75 |
| | F2-F3 | 98.81 |
| | F2-F4 | 91.39 |
| | F2-F5 | 89.63 |
| | F3-F4 | 93.24 |
| | F3-F5 | 92.44 |
| | F4-F5 | 91.02 |

## 4.3 Performance of Gabor-SVD Based Face Recognition System

With the selected 12 prominent Gabor Wavelets and first five principal singular vectors as feature extraction tools, the performance of Gabor-SVD based face recognition system is now ready for testing. The similarity thresholds for GWs and SVD are determined to be 88% and 85% respectively. The similarity scores of the test image have to reach or exceed the similarity threshold for both GWs and SVD in order to be accepted as legitimate user. Two facial images are used as training images to improve the robustness of the system. The performance of the system is evaluated in term of correct acceptance rate and correct rejection rate with JAFFE database as the test subjects. Correct acceptance rate is defined as the rate at which the system is able to successfully recognize and approve the valid user while correct rejection rate refers to the rate at which the system is able to successfully decline the invalid user. In JAFFE database, there are a total of ten different individuals with different facial expressions.

### 4.3.1 Correct Acceptance Rate

The first step in determining correct acceptance rate is to first select two facial images of one person as training images and then uses the facial images of the same person with different facial expressions as its test images. The similarity scores of the test images to the training images are computed. The similarity scores of the test images which exceed both Gabor and SVD similarity threshold are considered as successful recognition of valid user.

The example can be showed with one of the person in JAFFE database. Two facial images (T1 and T2) of the person are chosen to be training images (as shown in Figure 33). The remaining facial images of the same person (F1, F2, F3, F4, F5, F6 and F7) are chosen to be test images (as shown in Figure 34). Table 3 shows the similarity scores of the test images of Figure 34 and the overall result of the face recognition system. Note that all the similarity scores of every test images have achieved the similarity threshold of Gabor (88%) and SVD (85%) which means that the test images matched with the training images. Therefore, the system considers the entire test images as valid user as shown in the last column of Table 6. The same procedure is applied to the rest of the JAFFE database to obtain overall correct acceptance rate.

***Figure 33 : Training Images T1 and T2***

***Figure 34 : Test Images F1,F2,F3,F4,F5,F6 and F7***

*Table 6 : Similarity scores of the test images (Figure 34) with the training images (Figure 33)*

| TEST IMAGES | TRAINING IMAGES | | | | OVERALL RESULT |
|---|---|---|---|---|---|
| | T1 | | T2 | | |
| | SIMILARITY SCORES (%) | | | | |
| | Gabor | SVD | Gabor | SVD | |
| F1 | 92 | 93 | 93 | 91 | VALID |
| F2 | 92 | 92 | 92 | 90 | VALID |
| F3 | 90 | 89 | 98 | 88 | VALID |
| F4 | 95 | 96 | 96 | 95 | VALID |
| F5 | 88 | 91 | 89 | 90 | VALID |
| F6 | 93 | 95 | 91 | 94 | VALID |
| F7 | 90 | 92 | 91 | 87 | VALID |

### 4.3.2 Correct Rejection Rate

The first step in determining correct rejection rate is to first select two facial images of one person as training images and then uses the facial images of the different person as its test images. The similarity scores of the test images to the training images are computed. The similarity scores of the test images which are less than both Gabor and SVD similarity threshold are considered as successful rejection of invalid user.

The example can be showed with one of the person in JAFFE database. Two facial images (T1 and T2) of the person are chosen to be training images (as shown in Figure 33). The test images consist of seven facial images of totally different person (E1, E2, E3, E4, E5, E6 and E7) from the JAFFE database (as shown in Figure 35). Table 3 shows the similarity scores of the test images of Figure 35 and the overall result of the face recognition system. Note that almost all the similarity scores of every test images are below the similarity threshold for both Gabor and SVD which means that no single test images matched with the training images.

Therefore, the system considers the entire test images as invalid user as shown in the last column of Table 7.

Besides, for the test images E6, its SVD similarity scores have exceeded SVD similarity threshold of 85%, but its Gabor similarity scores are still less than Gabor similarity threshold of 88%, therefore the system considered the test images as invalid user. This example shows the advantage of combining these two techniques which improves the correct rejection rate of the system.

***Figure 35 : Test Images E1,E2,E3,E4,E5,E6 and E7***

***Table 7 : Similarity scores of the test images (Figure 35) with the training images (Figure 33)***

| TEST IMAGES | TRAINING IMAGES | | | | OVERALL RESULT |
|---|---|---|---|---|---|
| | T1 | | T2 | | |
| | SIMILARITY SCORES (%) | | | | |
| | Gabor | SVD | Gabor | SVD | |
| E1 | 75 | 66 | 75 | 65 | INVALID |
| E2 | 87 | 83 | 88 | 83 | INVALID |
| E3 | 85 | 68 | 86 | 64 | INVALID |
| E4 | 81 | 81 | 83 | 78 | INVALID |
| E5 | 78 | 58 | 79 | 58 | INVALID |
| E6 | 86 | 85 | 86 | 86 | INVALID |
| E7 | 83 | 70 | 85 | 70 | INVALID |

### 4.3.3 Additional Spare Training Image to Enhance Correct Acceptance Rate

There are cases where the valid user is rejected by the system due to one of the similarity scores either Gabor or SVD failed to achieve its respective similarity threshold. The example for this scenario can be showed with test image P1 (as shown in Figure 36) and training images Q1 and Q2 (as shown in Figure 37). Table 8 shows similarity scores for this test images. The SVD similarity scores of the test image P1 with the first training images Q1 which is 82% failed to achieve SVD similarity scores of 85%. Therefore, in this case, the system rejected the legitimate user. This will cause the system suffers from low correct acceptance rate.

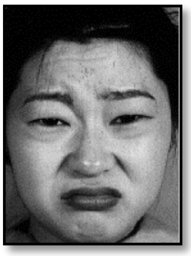


***Figure 36: Test Image P1***

***Figure 37 : Training Images Q1 and Q2***

***Table 8 : Similarity scores of the test images P1 with the training images Q1 and Q2***

<table>
<tr><td rowspan="3">TRAINING IMAGES</td><td colspan="2">TEST IMAGE P1</td></tr>
<tr><td colspan="2">SIMILARITY SCORES (%)</td></tr>
<tr><td>Gabor</td><td>SVD</td></tr>
<tr><td>Q1</td><td>88</td><td>82</td></tr>
<tr><td>Q2</td><td>88</td><td>88</td></tr>
<tr><td>OVERALL RESULT</td><td colspan="2">INVALID</td></tr>
</table>

To counter for this limitation, another facial image is added to training database to serve as spare training images. This additional spare training image will come into action only if one out of four similarity scores either Gabor or SVD failed to achieve similarity threshold. The spare training image will be used to compare with the test image to obtain similarity score for the failed categorize. In other words, if the Gabor similarity threshold is not reached, then the Gabor similarity score between the spare training images and the test images will be computed. Similarly, if the SVD similarity threshold is not reached, then the SVD similarity score between the spare training images and the test images will be computed. The system will only recognize and approve the user if the new similarity score reach similarity threshold as illustrated in Table 9.

***Table 9 : Possible outputs of the system with additional spare training image***

| TRAINING IMAGES | TEST IMAGE | |
|---|---|---|
| | SIMILARITY SCORES | |
| | Gabor | SVD |
| Training image 1 | Pass | Pass |
| Training image 2 | Fail | Pass |
| Spare training image | **Pass** | - |
| **OVERALL RESULT** | **VALID** | |
| Training image 1 | Pass | Pass |
| Training image 2 | Fail | Pass |
| Spare training image | **Fail** | - |
| **OVERALL RESULT** | **INVALID** | |
| Training image 1 | Pass | Pass |
| Training image 2 | Pass | Fail |
| Spare training image | - | **Pass** |
| **OVERALL RESULT** | **VALID** | |
| Training image 1 | Pass | Pass |
| Training image 2 | Pass | Fail |
| Spare training image | - | **Fail** |
| **OVERALL RESULT** | **INVALID** | |

For the previous example in which one of the similarity scores failed to reach SVD similarity threshold, one extra facial image is selected from the JAFFE database to act as spare training image as shown in Figure 38. Table 10 shows the SVD similarity score of the test images with the additional spare training image and the overall result of the system. The new SVD similarity score managed to reach the similarity threshold which allows the system recognized and approved the legitimate user. With this additional spare training image, the correct acceptance rate of the system is greatly improved.

***Figure 38 : Spare Training Image Q3***

***Table 10 : Similarity scores of the test images P1 with the training images Q1 and Q2***

| TRAINING IMAGES | TEST IMAGE P1 SIMILARITY SCORES (%) | |
|---|---|---|
| | Gabor | SVD |
| Q1 | 88 | 82 |
| Q2 | 88 | 88 |
| Q3 | - | 85 |
| OVERALL RESULT | VALID | |

# CHAPTER 5

# CONCLUSION AND RECOMMENDATION

## 5.1 Conclusion

Due to large number of Gabor filters, only selected 12 out of 40 Gabor filters which exhibit higher similarity scores are selected as the most prominent Gabor filters to extract facial features. By reducing the number of Gabor filters, it helps to decrease the computational time as well as computational complexity. With only 12 GWs used for feature extraction, the computational time is 3 times faster than the conventional GWs face recognition technique. The suitable Gabor similarity threshold has been carefully determined in order to improve correct acceptance rate and correct rejection rate. In this project, the Gabor similarity threshold is set to be 88%.

As for SVD, the first five singular vectors of SVD are selected as the principal vectors. The selection of these singular vectors is based on the singular values of the facial images. The SVD similarity threshold is determined and set to be 85%.

Overall, the Gabor-SVD based face recognition system is a reliable system with average correct acceptance rate of 75.2% and average correct rejection rate of 100% tested on JAFFE database. The use of SVD in addition to the Gabor Wavelets has indeed improved the reliability of the face recognition system. This face recognition system has proved its robustness by recognizing the individual with various facial expressions.

## 5.2 Recommendation and Future Work

The future works that can be further developed from this Gabor-SVD face recognition technique include testing with the face images with different scales, poses and orientations as well as with occlusions such as facial hairs, glasses and make-up. Since this project mainly focuses on JAFFE database which consists of only female faces, the other database such as ORL, FERET, YALE databases could also be used as testing databases.

Besides, the dimension of every prominent 12 GWs can be reduced by using suitable dimension reduction technique such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) to remove redundant facial features.

Furthermore, left singular vectors of SVD can also be used together with right singular vectors in computing SVD similarity score because both left and right singular vectors of SVD contain essential facial information. The incorporation of left singular vectors of SVD in determining SVD similarity score may further increase the reliability of the face recognition system.

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