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Comparison of Computer-Based and Optical Face Recognition Paradigms

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COMPARISON OF COMPUTER-BASED AND OPTICAL FACE RECOGNITION PARADIGMS

By

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A THESIS

Submitted in partial fulfillment of the requirements for the degree of

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This thesis has been approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE in Electrical Engineering.

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To my mother, father and wife.

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Abstract

The main objectives of this thesis are to validate an improved principal components analysis (IPCA) algorithm on images; designing and simulating a digital model for image compression, face recognition and image detection by using a principal components analysis (PCA) algorithm and the IPCA algorithm; designing and simulating an optical model for face recognition and object detection by using the joint transform correlator (JTC); establishing detection and recognition thresholds for each model; comparing between the performance of the PCA algorithm and the performance of the IPCA algorithm in compression, recognition and, detection; and comparing between the performance of the digital model and the performance of the optical model in recognition and detection. The MATLAB © software was used for simulating the models.

PCA is a technique used for identifying patterns in data and representing the data in order to highlight any similarities or differences. The identification of patterns in data of high dimensions (more than three dimensions) is too difficult because the graphical representation of data is impossible. Therefore, PCA is a powerful method for analyzing data. IPCA is another statistical tool for identifying patterns in data. It uses the information theory for improving PCA. The joint transform correlator (JTC) is an optical correlator used for synthesizing a frequency plane filter for coherent optical systems.

The IPCA algorithm, in general, behaves better than the PCA algorithm in the most of the applications. It is better than the PCA algorithm in image compression because it obtains higher compression, more accurate reconstruction, and faster processing speed with acceptable errors; in addition, it is better than the PCA algorithm in real-time image detection due to the fact that it achieves the smallest error rate as well as remarkable speed. On the other hand, the PCA algorithm performs better than the IPCA algorithm in face recognition because it offers an acceptable error rate, easy calculation, and a reasonable speed. Finally, in detection and recognition, the performance of the digital model is better than the performance of the optical model.

Chapter 1

Introduction

1.1 Background

1.1.1 Digital Processing

PRINCIPAL components analysis (PCA) [1] and improved principal components analysis (IPCA) [2] are statistical tools frequently used for analyzing data. Their main applications are pattern recognition such as face detection and recognition, and data compression such as image compression.

PCA is a technique used for identifying patterns in data and representing the data in such a way that their similarities and differences are highlighted. The identification of patterns in data of high dimensions (more than three dimensions) is too difficult because the graphical representation of data is impossible. Therefore, PCA is a powerful method for analyzing data. The PCA algorithm starts with the creation of a data set and ends with the projection of the data on the eigenspace. A covariance matrix is computed for the data; in addition, the eigenvectors and eigenvalues of the covariance matrix are obtained. Eigenvectors associated with the biggest eigenvalues of the covariance matrix follow the most significant patterns of the data. Those eigenvectors are called the principle components of the data set. Therefore, the eigenvalues of the covariance matrix work as measures of how much information is contained in each of the principal components. The principal components form a feature vector matrix. In order to select principal components that form the feature vector matrix, the variance contribution rate (VCR) and the total variance contribution rate (TVC) (they are proposed in the IEEE paper presented in Reference [2]) are computed. When the TVC is significantly high then q eigenvectors associated with the biggest q eigenvalues can be selected. The feature vector matrix is used for projecting the data on the eigenspace. Finally, by projecting the data on the eigenspace, the PCA algorithm is completed.

IPCA is another statistical tool for identifying patterns in data. It is similar to PCA except for the way that it selects eigenvectors that form the feature vector matrix. It affords a new accurate method to measure the information content of the principal components based on the information theory for improving PCA. For measuring the degree of information content of the eigenvectors, two new concepts are used; the first is the information rate (IR) and the second is the accumulated information rate (AIR) (they are proposed in the IEEE paper presented in Reference [2]). When the AIR is significantly high then q eigenvectors associated with the biggest q eigenvalues can be selected.

1.1.2 Optical Processing

Spatially coherent light is going to be used in the optical model. Coherent optical systems are linear in complex amplitude; therefore, filtering processes can be performed by direct manipulation of complex amplitude appearing in the back focal plane of a Fourier transforming lens. There are at least two methods for synthesizing the frequency plane filter for coherent optical systems. One of these methods is by using the joint transform correlator (JTC), Reference [3], Section 8.5.

The JTC is an optical correlator used for synthesizing the frequency plane filter for coherent optical systems. This correlator was invented by Weaver and Goodman [4]. The filter is divided into two stages: recording the filter, and getting the filter output. The transparencies of the desired impulse response h and the data g (here it is called the object) to be filtered are aligned simultaneously in the input plane. They are then Fourier transformed together. At that point, a spatial light modulator (SLM) captures the intensity distribution of the transformed field. The intensity is then Fourier transformed again for producing the cross-correlated field in the output plane. The output field is composed of four terms; two terms respectively represent the cross-correlation of the impulse response h and itself as well as the cross-correlation of the data g and itself; the third and fourth terms represent the cross-correlations of h and g. Lastly, the joint transform correlator has a great feature: its ability to change the filter impulse response quickly. Therefore, it is considered beneficial for real-time systems. On the other hand, its defect is that the input bandwidth of the data is reduced due to the filter impulse response being introduced simultaneously with the data to be filtered.

1.2 Problem Statement

The main objectives of this thesis are to validate the improved principal components analysis (IPCA) algorithm on images; designing and simulating a digital model for image compression, face recognition, and image detection by using the principal components analysis (PCA) algorithm and the IPCA algorithm; designing and simulating an optical model for face recognition and object detection by using the joint transform correlator (JTC); establishing detection and recognition thresholds for each model; comparing between the performance of the PCA algorithm and the performance of the IPCA algorithm in compression, recognition and detection; and comparing between the performance of the digital model and the performance of the optical model in recognition and detection.

1.3 Technical Approach

1.3.1 Digital Model

1.3.1.1 Introduction

This subsection provides a general overview of technical approaches behind the application of the PCA and IPCA algorithms in image compression, face recognition, and image detection.

Here, the database for each algorithm is composed of some images of faces (training faces). The principal components that form the feature vector matrix are here called eigenfaces.

1.3.1.2 Image Compression

When some of the eigenvectors that are calculated from the covariance matrix for all training faces are selected to form the feature vector matrix then the dimensions of the reconstructed data set will be reduced. This implies that the PCA and IPCA algorithms work as compression. The algorithms are said to be lossy because a decompressed image is not exactly the same as the original one, but is generally worse.

Compression performance for each algorithm as analyzed from three points of view are the speed of compression and reconstruction, the quality of a reconstructed image, and the size of compression. The number of the eigenfaces that is used to compress and reconstruct the training faces mainly controls the processing speed of compression and reconstruction. When a small number of the eigenfaces is used to project and reconstruct the training faces then the processing speed will increase and vice versa. For measuring the quality of a reconstructed image, the mean squared error (MSE) between the image and its reconstruction can be computed. The size of compression can be measured in two ways: these are through the information rate and the mean squared error (MSE) of compressed images. The information rate measures how much information is present after compression compared with information present before compression; in other words, it measures the number of pixels after compression compared to before compression.

1.3.1.3 Face Recognition

The PCA and IPCA algorithms are used to recognize an unknown face image based on the database that contains the training faces. For doing face recognition, an unknown face image is taken. The training faces and the unknown face image are projected on the eigenspace by using the PCA or IPCA feature vector matrix. The Euclidean distance between the projected unknown face image and each projected training face is computed. Then the unknown face image is recognized as a training face, which has the minimum distance from the unknown face image.

Unfortunately, when the unknown face image does not have a similar training face then getting the minimum distance does not *always* mean that the unknown face image is recognized as a training face that has the minimum distance from the unknown face image. Therefore, a certain threshold must be used to increase the accuracy of recognition. For setting up a recognition threshold, the mean and standard deviation (the average distance from the mean to a point) are established for each training face. Then recognition can be updated as, when the obtained minimum distance between the unknown face image and a training face is less than or equal to the mean plus the standard deviation for the training face and bigger than or equal to the mean minus the standard deviation for the training face. At that point, the unknown face image is recognized as that training face; otherwise, it is an unknown face image.

Recognition performance can be analyzed from two points of view: these are the speed of recognition and the error rate. The number of selected eigenfaces that are used to recognize the unknown face image mainly controls the recognition speed. When the number of the selected eigenfaces decreases, the processing speed increases and vice versa. The error rate computes the percentage of error in recognition.

1.3.1.4 Image Detection

The PCA and IPCA algorithms are used to detect whether or not an unknown image contains a face based on a determined threshold for detection. Hence, in image detection, only a detection threshold is needed.

To obtain the detection threshold, the mean and the standard deviation are established for some images that contain faces. In regards to detection, an unknown image is taken. It is projected on the eigenspace and reconstructed again by using the PCA or IPCA feature vector matrix. Then, detection can be performed as if the Euclidean distance between the unknown image and its reconstruction is less than or equal to the computed mean plus standard deviation and bigger than or equal to the computed mean minus standard deviation then the unknown image is detected as a face image; otherwise, it is not a face image.

Detection performance can be analyzed from two points of view: these are the speed of detection and the error rate. The number of selected eigenfaces that are used to detect the unknown image mainly controls the detection speed. When the number of selected eigenfaces decreases, the processing speed increases and vice versa. The error rate computes the percentage of error in detection.

1.3.2 Optical Model

1.3.2.1 Introduction

This subsection provides a general overview of technical approaches behind the application of the joint transform correlator (JTC) in face recognition and object detection.

1.3.2.2 Face Recognition

The joint transform correlator (JTC) is used to recognize an unknown face object based on a database of desired impulses. The database is composed of some images of faces (impulses). For face recognition, an unknown face object is picked. The cross-correlated field between the unknown face object and each impulse is obtained. Then, the unknown face object is recognized as an impulse, which has the biggest cross-correlation with the unknown face object among other impulses.

Unfortunately, when the unknown face object does not have a similar impulse response, getting the biggest cross-correlation does not *always* mean that the unknown face object is recognized as an impulse, which has the biggest cross-correlation with the unknown face object. Therefore, a certain threshold must be used to increase the accuracy of recognition. For setting up a recognition threshold, the mean and standard deviation (the average distance from the mean to a point) are established for each impulse. Then, recognition can be updated, when the biggest cross-correlation with an impulse is less than or equal to the mean plus the standard deviation for the impulse and bigger than or equal to the mean minus the standard deviation for the impulse then the unknown face object is recognized as that impulse response; otherwise, it is an unknown face object.

Recognition performance can be analyzed by calculating an error rate of recognition. The error rate computes the percentage of error in recognition.

1.3.2.3 Object Detection

The joint transform correlator (JTC) is used to detect whether or not an unknown object contains a face based on a determined threshold for detection. Hence, in object detection, only a detection threshold is needed.

To obtain the detection threshold, the mean and the standard deviation are established for some objects that contain faces. For doing detection, an unknown object is taken. The unknown object is cross-correlated with any impulse response. Then, detection can be performed as if the resulted cross-correlation is less than or equal to the computed mean plus standard deviation and bigger than or equal to the computed mean minus standard deviation then the unknown object is detected as a face object; otherwise, it is not a face object.

Detection performance can be analyzed by calculating an error rate of detection. The error rate computes the percentage of error in detection.

1.4 Summary of Key Results

The IPCA algorithm, in general, behaves better than the PCA algorithm in the most of the applications. It is better than the PCA algorithm in image compression because it obtains higher compression, more accurate reconstruction, and faster processing speed with acceptable errors; in addition, it is better than the PCA algorithm in real-time image detection due to the fact that it achieves the smallest error rate as well as remarkable speed. On the other hand, the PCA algorithm performs better than the IPCA algorithm in face recognition because it offers an acceptable error rate, easy calculation, and a reasonable speed. Finally, in detection and recognition, the performance of the digital model is better than the performance of the optical model.

1.5 Organization

The remainder of this thesis is organized as follows:

- Chapter 1: provides a general overview of this thesis.
- Chapter 2: covers theoretical backgrounds behind the PCA and IPCA algorithms, their applications, and their performance in the applications. A comparison between the PCA and IPCA algorithms is also provided in this chapter. Finally, it shows a theoretical background for designing an optical model for object detection and face recognition; and theories behind the joint transform correlator (JTC), its applications, and its performance in the applications.
- Chapter 3: presents the simulations of the PCA and IPCA algorithms by using the MATLAB © software and comparison between the simulations. It also presents the simulations of the PCA and IPCA applications by using the MATLAB © software. Lastly, this chapter provides the simulations of the joint transform correlator (JTC) and its applications by using the MATLAB © software.
- Chapter 4: covers the performance results of the PCA and IPCA algorithms in their applications. Also, this chapter provides the results of JTC performance in its applications.
- Chapter 5: presents a conclusion of this thesis.

Chapter 2

Theoretical Background

2.1 Preview

DIGITAL and optical image processing are areas used experimentally to establish solutions to given problems. In this chapter, theoretical backgrounds for a couple of digital and optical processing techniques are demonstrated.

2.2 Digital Processing

2.2.1 Introduction

Principal components analysis (PCA) and improved principal components analysis (IPCA) are statistical tools frequently used for analyzing data. Their main applications are pattern recognition such as face detection and recognition, and data compression such as image compression. It is found that IPCA acts better than PCA in the most of applications. The analysis of each one is covered in this section.

2.2.2 A Principal Components Analysis (PCA) Algorithm

2.2.2.1 Introduction

PCA is a technique used for identifying patterns in data and representing the data in such a way as to highlight their similarities and differences. The identification of patterns in data of high dimensions (more than three dimensions) is too difficult because the graphical representation of data is impossible. Therefore, PCA is a powerful method for analyzing data.

This subsection covers the steps that are needed for performing PCA on a set of data and reconstructing the data set along with examples; as well as the steps that are needed for performing PCA on images and reconstructing the images back. How and why the technique works are explained as well as what is happening at each step is demonstrated.

2.2.2.2 Analysis of the PCA Algorithm

The PCA algorithm is built up based on the following steps:

Step 1: getting some data.

Step 2: computing the mean vector $\boldsymbol{m}_D$ of the data set as in Equation 2.1. Where $\boldsymbol{D}_k$ is a column vector contains one data item such that $\boldsymbol{D}_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix}$; and n is the total number of the data items.

$$\boldsymbol{m}_D = \frac{1}{n} \sum_{k=1}^{n} \boldsymbol{D}_k \tag{2.1}$$

Step 3: subtracting the mean from each of the data dimensions as in Equation 2.2. This produces a data set whose mean is zero which means the data set is centered. This step is really an important step for decreasing the error rate of face recognition.

$$R = [\boldsymbol{D}_1 - \boldsymbol{m}_D, \ldots, \boldsymbol{D}_n - \boldsymbol{m}_D] \tag{2.2}$$

Step 4: calculating a covariance matrix as in Equation 2.3. The covariance matrix is real and symmetric. $\frac{1}{n-1}$ can be removed or left because it is just a normalization factor which affects all values by the same amount. The division on $n-1$ and not n because the data set is a sample of the population. It is found that gives an answer is very close to the answer that will result if the entire population is used. If the covariance matrix is calculated for the entire population then the division must be on n.

$$C = \frac{1}{n-1} \sum_{k=1}^{n} (\boldsymbol{D}_k - \boldsymbol{m}_D)(\boldsymbol{D}_k - \boldsymbol{m}_D)^T = \frac{1}{n-1} \times RR^T \tag{2.3}$$

Step 5: obtaining the eigenvectors and eigenvalues of the covariance matrix C as in Equation 2.4 and Equation 2.5 respectively. Where the columns of the matrix A are the eigenvectors of C; the diagonal of the matrix Λ contains the eigenvalues of C; and d is the number of the dimensions of the data set.

$$A = [\boldsymbol{v}_1, \boldsymbol{v}_2, \boldsymbol{v}_3, \ldots, \boldsymbol{v}_d] \tag{2.4}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_d \end{bmatrix}, \qquad \text{where } \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d \tag{2.5}$$

Since the covariance matrix C is a real and symmetric (Reference [5]; Pages 207 and 208; Theorems 5.9, 5.10, 5.11 and 5.12) $d \times d$ matrix then its eigenvectors form an orthonormal basis. Therefore, the matrix A is an orthonormal matrix.

Step 6: choosing principal components and forming a feature vector matrix. Eigenvectors associated with the biggest eigenvalues of the covariance matrix C follow the most significant patterns of the data. Those eigenvectors are called the principle components of the data set. Therefore, the eigenvalues of the covariance matrix C work as measures of how much information is contained in the principal components.

The feature vector matrix A_q represented in Equation 2.6 is an $d \times q\,(q < d)$ matrix that contains only q eigenvectors (principal components) from the matrix of eigenvectors A.

$$A_q = [\boldsymbol{v}_1, \boldsymbol{v}_2, \boldsymbol{v}_3, \ldots, \boldsymbol{v}_q] \tag{2.6}$$

In order to select the principal components that form the feature vector matrix A_q, the variance contribution rate (VCR) and the total variance contribution rate (TVC) (they are proposed in the IEEE paper presented in Reference [2]) are computed as in Equation 2.7 and Equation 2.8 respectively. When the TVC is significantly high then q eigenvectors associated with the biggest q eigenvalues can be selected.

$$VCR_k\,(\%) = \frac{\lambda_k}{\sum_{k=1}^{d} \lambda_k} \times 100, \qquad k = 1, \ldots, d \tag{2.7}$$

$$TVC\,(\%) = \frac{\sum_{k=1}^{q} \lambda_k}{\sum_{k=1}^{d} \lambda_k} \times 100, \qquad q = 1, \ldots, d \tag{2.8}$$

Step 7: performing the principal components transform (also called the Hotelling or Karhunen-Loéve transform).
Equation 2.9 is used for projecting the data on the eigenspace. The columns of the matrix Y represent the coordinates of the projected data in the eigenspace.

$$Y = A_q^T R \tag{2.9}$$

The mean of the matrix Y is $\boldsymbol{m}_Y = E\left[A_q^T R\right] = A_q^T \underbrace{E\,[R]}_{\mathbf{0}} = \mathbf{0}$. This has important meaning in face recognition. In fact, Y gives the original centered data solely in terms of the selected principal components instead of the original axes. It is possible to express data in terms of any two perpendicular axes as shown in Reference [6], Page 167, Theorem 5.7.

Finally, by projecting the centered data on the eigenspace, the PCA algorithm is completely done.

2.2.2.3 An Example of the PCA Algorithm

The example moves simultaneously with the PCA steps illustrated in Sub-subsection 2.2.2.2 until a data set is transformed as follows:

Step 1: the two-dimensional data set D shown in Equation 2.10 is obtained for performing the PCA algorithm. The plot of the data is shown in Figure 2.1.

$$D = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \\ 2 & 1 & 5 & 2 & 6 & 5 & 10 & 7 & 11 & 8 \end{bmatrix}. \tag{2.10}$$

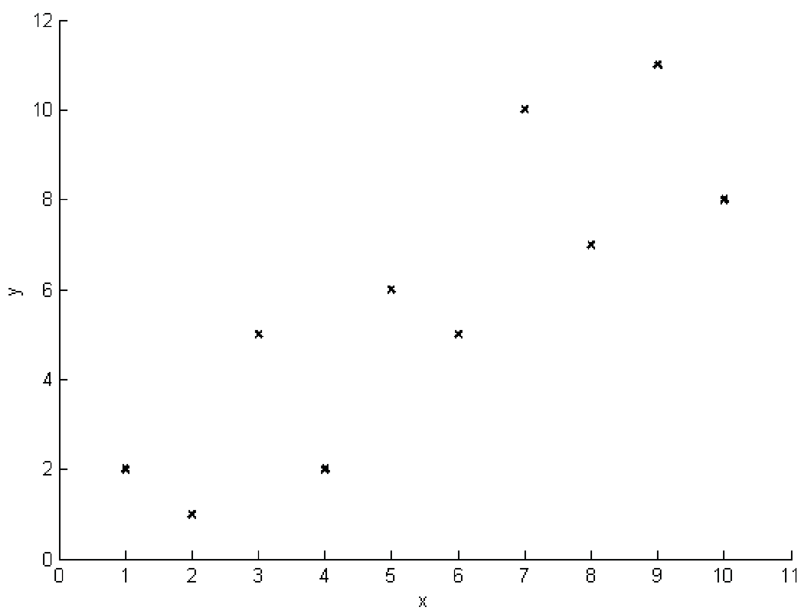

Figure 2.1: The plot of the data set D.

Step 2: the mean vector $\boldsymbol{m}_D$ of the data set is computed as in Equation 2.11.

$$\boldsymbol{m}_D = \frac{1}{10}\sum_{k=1}^{10} \boldsymbol{D}_k = \begin{bmatrix} 5.50 \\ 5.70 \end{bmatrix}. \tag{2.11}$$

Step 3: the mean is subtracted from each of the data dimensions then the centered data set R is obtained as in Equation 2.12. The plot of the centered data is shown in Figure 2.2.

$$R = [\boldsymbol{D}_1 - \boldsymbol{m}_D, \ldots, \boldsymbol{D}_{10} - \boldsymbol{m}_D]$$

$$= \begin{bmatrix} -4.50 & -3.50 & -2.50 & -1.50 & -0.50 & 0.50 & 1.50 & 2.50 & 3.50 & 4.50 \\ -3.70 & -4.70 & -0.70 & -3.70 & 0.30 & -0.70 & 4.30 & 1.30 & 5.30 & 2.30 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}. \tag{2.12}$$

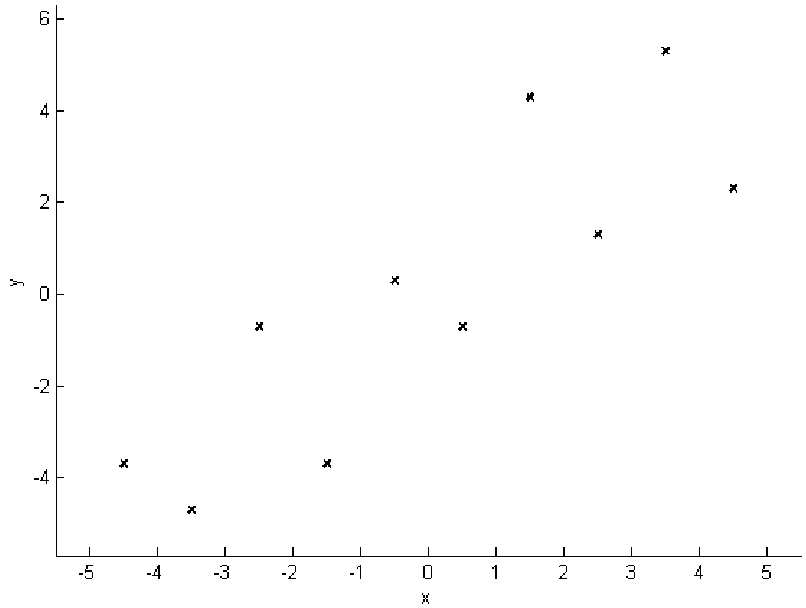

Figure 2.2: The plot of the centered data set R.

Step 4: the covariance matrix C is computed as in Equation 2.13. Since the non-diagonal elements of the covariance matrix are positive then both the x and y variables are expected to increase together.

$$\begin{aligned} C &= \frac{1}{10-1}\sum_{k=1}^{10}(\boldsymbol{D}_k - \boldsymbol{m}_D)(\boldsymbol{D}_k - \boldsymbol{m}_D)^T \\ &= \frac{1}{10-1} \times RR^T \\ &= \begin{bmatrix} 9.1667 & 8.7222 \\ 8.7222 & 11.5667 \end{bmatrix}. \end{aligned} \tag{2.13}$$

Step 5: the eigenvectors and eigenvalues of the covariance matrix C are computed respectively as in Equation 2.14 and Equation 2.15.

$$A = [\boldsymbol{v}_1, \boldsymbol{v}_2] = \begin{bmatrix} 0.6572 & -0.7538 \\ 0.7538 & 0.6572 \end{bmatrix}. \tag{2.14}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}, \qquad \text{where } \lambda_1 \geq \lambda_2 = \begin{bmatrix} 19.1711 & 0 \\ 0 & 1.5623 \end{bmatrix}. \tag{2.15}$$

The centered data as well as the orthonormal eigenvectors are plotted together in Figure 2.3. Figure 2.3 shows how the data have totally a noticed pattern; and as anticipated from the covariance matrix, the two variables are increasing together. The eigenvectors are plotted as diagonal dotted lines. As expected, they are perpendicular to each other; more importantly they highlight patterns in the data where the highly correlated eigenvector passes through the middle of the points. It divides the points to two sets, like drawing a line of the best fit; and it describes the most significant relationship between the data dimensions. The other eigenvector follows little patterns of the data.

Step 6: for choosing principal components and forming the feature vector matrix A_q, the variance contribution rate (VCR) and the total variance contribution rate (TVC) are calculated in Table 2.1. Based on Table 2.1, the feature vector matrix in Equation 2.16 only contains the eigenvector which is associated with the biggest eigenvalue (the highly correlated eigenvector).

Table 2.1: The calculations of the VCR and TVC.

k	λ_k	VCR_k (%)	TVC (%)
1	19.1711	92.4648	92.4649
2	1.5623	7.5352	100

$$A_q = \begin{bmatrix} 0.6576 \\ 0.7538 \end{bmatrix}. \tag{2.16}$$

Therefore, by computing the eigenvectors of the covariance matrix C and selecting the highest correlated ones then lines that describe the data are extracted. The rest

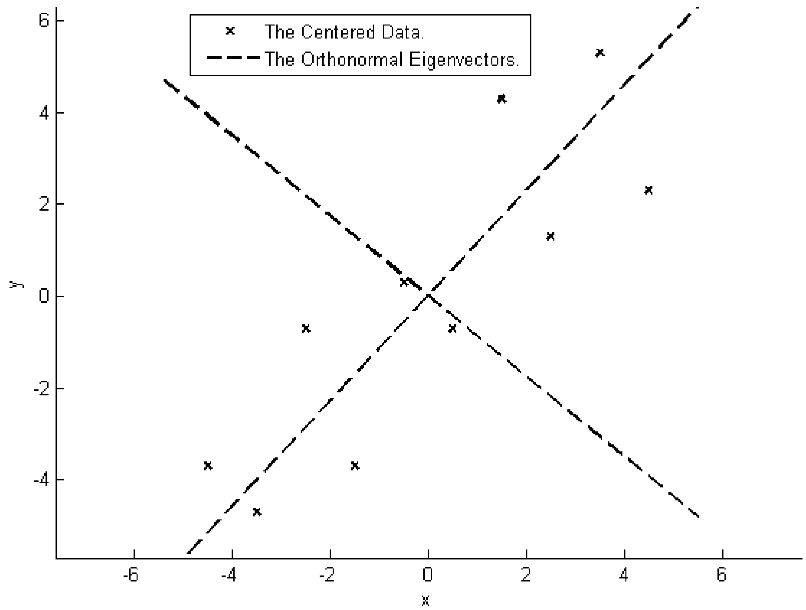

Figure 2.3: The plot of the centered data set R as well as the orthonormal eigenvectors.

of the steps involve transforming the data such that they are expressed in terms of the extracted lines.

Step 7: Equation 2.9 is used for performing the principal components transform; and the coordinates of the projected data in the eigenspace are shown in Equation 2.17.

$$Y^T = \begin{bmatrix} \text{Along } \boldsymbol{v}_1 \text{ axis} \\ -5.7461 \\ -5.8427 \\ -2.1705 \\ -3.7746 \\ -0.1025 \\ -0.1991 \\ 4.2269 \\ 2.6228 \\ 6.2950 \\ 4.6908 \end{bmatrix}. \tag{2.17}$$

In Equation 2.17, it can be seen that the dimensions of the projected data are reduced because the highest correlated eigenvector is only selected and the lowest one is neglected then some information is lost here. The projected centered data are plotted as in Figure 2.4. As shown in Figure 2.4, the projected centered data represent a series of data items along the highest correlated eigenvector axis $\boldsymbol{v}_1$ without any information about the data along the axis of the lowest correlated eigenvector $\boldsymbol{v}_2$.

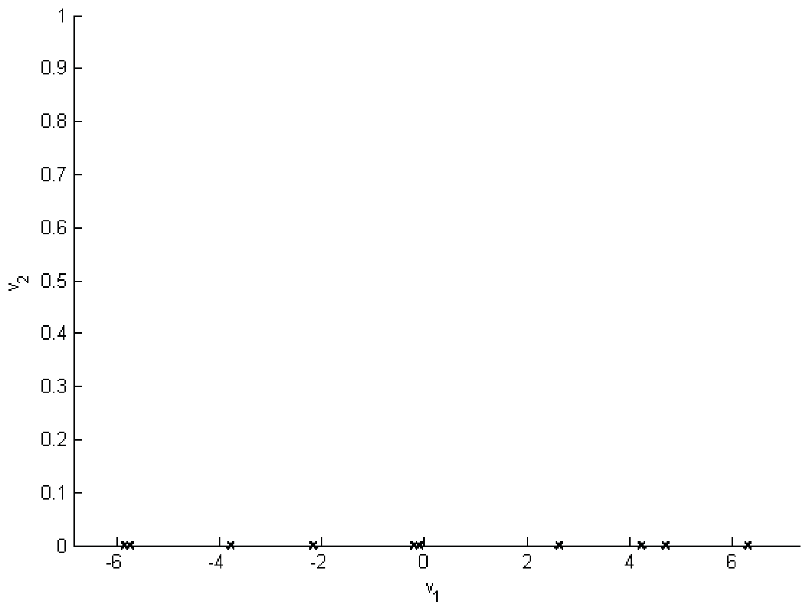

Figure 2.4: The projected centered data by using just the highest correlated eigenvector $\boldsymbol{v}_1$.

Therefore, in this step, the data are expressed in terms of the patterns between them where the patterns are the extracted lines that highly characterize the relationships between the data.

2.2.2.3.1 Taking All Eigenvectors as Principal Components for Doing PCA

We want to figure out what happens in the example presented in Sub-subsection 2.2.2.3 when all eigenvectors are selected as principal components?

The coordinates of the projected data in the eigenspace when all eigenvectors are taken to form the feature vector matrix A_q (i.e. $A = A_q$) are shown in Equation 2.18; and they are plotted in Figure 2.5. The projected data in Equation 2.17 is exactly equal to the first dimension of the projected data in Equation 2.18. The plot in Figure 2.5 and the plot of the original centered data in Figure 2.2 are typically the same except that in Figure 2.5 the eigenvectors are the axes instead of x and y axes.

$$Y^T = \begin{bmatrix} \text{Along } \boldsymbol{v}_1 \text{ axis} & \text{Along } \boldsymbol{v}_2 \text{ axis} \\ -5.7461 & 0.9604 \\ -5.8427 & -0.4505 \\ -2.1705 & 1.4244 \\ -3.7746 & -1.3008 \\ -0.1025 & 0.5740 \\ -0.1991 & -0.8369 \\ 4.2269 & 1.6951 \\ 2.6228 & -1.0301 \\ 6.2950 & 0.8448 \\ 4.6908 & -1.8805 \end{bmatrix}. \tag{2.18}$$

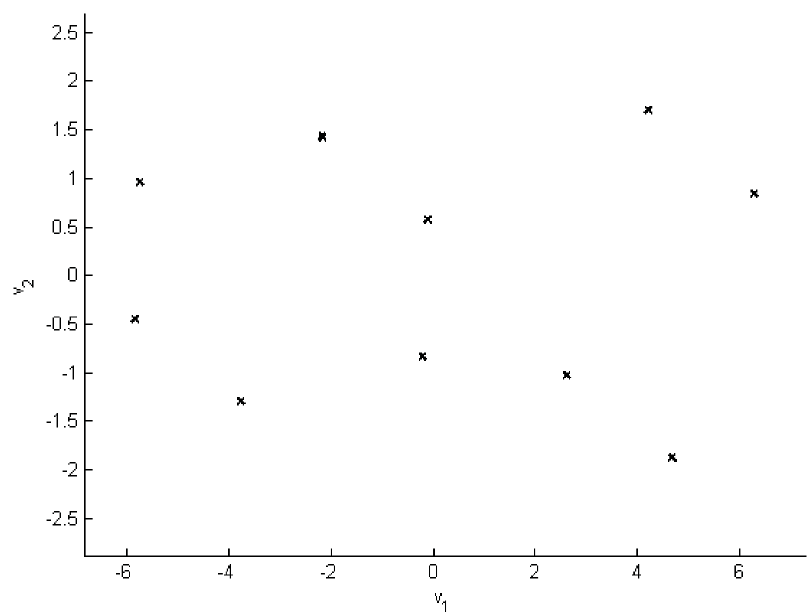

Figure 2.5: The projected centered data when all eigenvectors are used as principal components.

Therefore, there is no loss of information when all eigenvectors are selected as principal components for doing PCA.

2.2.2.4 Reconstruction of the Data Set D

For reconstructing the data set, Equation 2.9 is turned around to get the centered data set R as in Equation 2.19. Then the mean vector $\boldsymbol{m}_D$ is added again to obtain the reconstructed data set $\widehat{D}$ as in Equation 2.20.

$$R = \left(A_q^T\right)^{-1} \times Y \tag{2.19}$$

$$\widehat{D} = \left(A_q^T\right)^{-1} \times Y + [\boldsymbol{m}_D, \ldots, \boldsymbol{m}_D]_{d\times n} \tag{2.20}$$

Since A_q^T in Equation 2.20 is not a square matrix and it has orthonormal (implies orthogonality) column vectors then the left inverse (Reference [6], Page 21, Definition 1.11) can be used to obtain its inverse. Its inverse is found to be $\left(A_q^T\right)^{-1} = \left(A_q^T\right)^T = A_q$. Then Equation 2.20 can be simplified as in Equation 2.21.

$$\widehat{D} = A_q \times Y + [\boldsymbol{m}_D, \ldots, \boldsymbol{m}_D]_{d\times n} \tag{2.21}$$

2.2.2.5 Reconstruction of the Data Set D of the Example in Sub-subsection 2.2.2.3

Equation 2.21 is used to reconstruct the data set D of the example in Sub-subsection 2.2.2.3 as in Equation 2.22. The reconstructed data are plotted in Figure 2.6. As seen in Figure 2.6, some information is lost from the reconstructed data due to some of the eigenvectors are used as principal components in performing PCA transform.

$$\widehat{D} = \begin{bmatrix} \text{Along } \boldsymbol{x} \text{ axis} & \text{Along } \boldsymbol{y} \text{ axis} \\ 1.7239 & 1.3689 \\ 1.6605 & 1.2960 \\ 4.0736 & 4.0640 \\ 3.0195 & 2.8549 \\ 5.4327 & 5.6228 \\ 5.3692 & 5.5500 \\ 8.2777 & 8.8860 \\ 7.2236 & 7.6769 \\ 9.6368 & 10.4449 \\ 8.5826 & 9.2357 \end{bmatrix}. \tag{2.22}$$

2.2.2.5.1 Using All Eigenvectors for Reconstructing the Data Set D

When all eigenvectors are selected as principal components for performing PCA in the example in Sub-subsection 2.2.2.3 then the original data set D will be reconstructed perfectly (i.e. $\widehat{D} = D$) without loss of information.

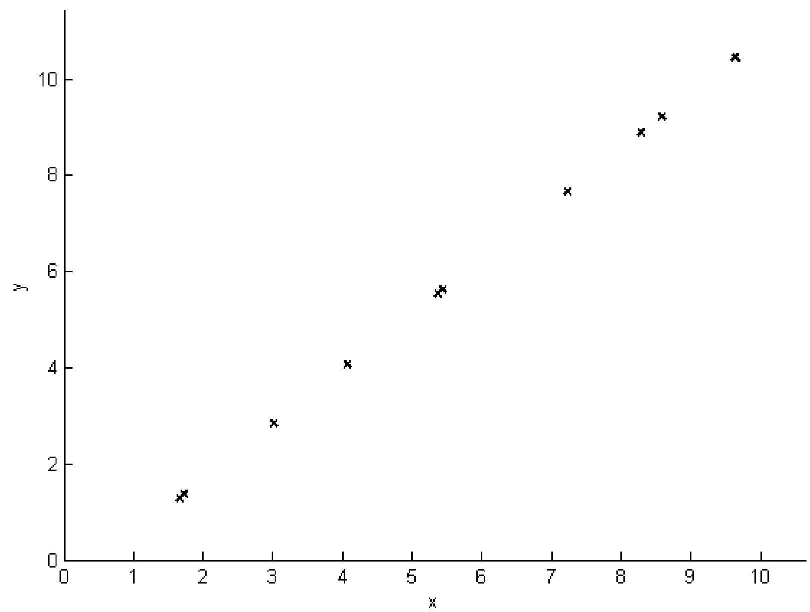

Figure 2.6: The reconstructed data by using just the highest correlated eigenvector $\boldsymbol{v}_1$.

2.2.2.6 Application of the PCA Algorithm to Images

The reason beyond performing the PCA algorithm on a simple database is to be able to provide plots of data for showing PCA behavior at each step. After demonstrating the PCA algorithm on a simple database, the idea can be generalized to see how the PCA algorithm works when the data set is composed of images. This idea is based on References [7] and [8]; and Reference [9], Section 12.5. The PCA algorithm can be applied to images as in the following steps:

Step 1: creating a database.
The database is composed of n, $N \times N$ images of faces (training faces) on black backgrounds such that I_k where $k = 1, \ldots, n$; and n is the total number of the training faces.

For decreasing the error rates of face detection and recognition, all face projections must be defined in the database; images must have the same size; images must have only faces and they are expanded to the boarders of the images; finally, images must have unified backgrounds in order to discriminate between the pixels occupying the backgrounds and the pixels occupying the faces.

Step 2: normalizing each training face I_k.
This normalization is for removing lighting effects on the training faces. It is very important to increase the accuracy of face recognition but it does not affect face

detection.

The normalization must be done just for the pixels occupying the faces to keep variations among the images just in the faces without the effects of the backgrounds. In order to block the pixels occupying the backgrounds for all training faces, a threshold must be picked to distinguish between the pixels occupying the faces and the pixels occupying the backgrounds. Note that, a number zero can not be taken to be the threshold although the training faces have black backgrounds because the MATLAB © software does not read a black color exactly zero then some error will occur.

According to the definition of an image histogram (Reference [10], Section 3.3), if a training face has a unified background then the biggest histogram of the intensity levels will be for the pixels occupying the backgrounds because pixels that have the same intensity levels are the pixels occupying the backgrounds of the training face. Therefore, the threshold can be selected based on the average histogram for all training faces.

Step 3: centering each training face I_k.
Since operations are performed on two-dimensional images then images must be centered before centering the whole database. This can be done by simply subtracting the mean of the pixels occupying the face for a training face from each pixel on the face as in Equation 2.23 where I_{C_k} is the k^{th} centered training face; and m_{f_k} is the mean of the pixels occupying the face for the k^{th} training face. By doing that the pixels on the face will have zero mean that means the face is centered.

$$I_{C_k} = I_k - m_{f_k}, \qquad \text{where } k = 1, \ldots, n \tag{2.23}$$

Step 4: representing each centered training face I_{C_k} as a column image vector $\mathbf{\Gamma}_k$.
Each $N \times N$ centered training face is represented as an N^2 column image vector by transposing the rows of pixels then stacking them one after another to form a column vector as in Equation 2.24.

$$\mathbf{\Gamma}_k = \begin{bmatrix} Row_1^T \\ Row_2^T \\ \vdots \\ Row_N^T \end{bmatrix} \tag{2.24}$$

Step 5: calculating the average training face vector $\mathbf{\Psi}$ as in Equation 2.25.

$$\mathbf{\Psi} = \frac{1}{n} \sum_{k=1}^{n} \mathbf{\Gamma}_k \tag{2.25}$$

Step 6: centering the set of the training faces.
The set of the training faces is centered by simply subtracting the mean training face vector $\mathbf{\Psi}$ from each centered training face vector $\mathbf{\Gamma}_k$ as in Equation 2.26 where $\mathbf{\Phi}_k$ is the k^{th} centered (with respect to the set of the training faces) training face. By doing

that the set of the training faces will have zero mean which means the database is centered.

$$\mathbf{\Phi}_k = \mathbf{\Gamma}_k - \mathbf{\Psi}, \qquad \text{where } k = 1, \ldots, n \tag{2.26}$$

Step 7: calculating a covariance matrix for all training faces as in Equation 2.27 where $R = [\mathbf{\Phi}_1, \mathbf{\Phi}_2, \ldots, \mathbf{\Phi}_n]$. The covariance matrix can be equal to RR^T due to $\frac{1}{n}$ can be removed or left because it is just a normalization factor which affects all values by the same amount.

$$C = \frac{1}{n}\sum_{k=1}^{n} \mathbf{\Phi}_k \mathbf{\Phi}_k^T = RR^T \tag{2.27}$$

Step 8: computing the eigenvectors and eigenvalues of the covariance matrix C. The covariance matrix C is $N^2 \times N^2$ matrix where N^2 is the total number of pixels along one of its dimensions. The covariance matrix is usually too big which makes the calculation of the eigenvalues and eigenvectors is very difficult if not impossible. Hence, it is not practical to calculate the eigenvalues and eigenvectors for the such matrix but we will calculate them in this work for examining the performance of the PCA and IPCA algorithms.

The dimensions of the covariance matrix can be reduced to the number of the training faces. Let's suppose the $n \times n$ matrix $R^T R$; the eigenvectors and eigenvalues of this matrix are found as in Equation 2.28 where $\boldsymbol{u}_k$ is the k^{th} eigenvector of the matrix $R^T R$; and μ_k is the k^{th} eigenvalue.

$$R^T R\boldsymbol{u}_k = \mu_k \boldsymbol{u}_k, \qquad \text{where } k = 1, \ldots, n \tag{2.28}$$

The relationship between the eigenvector $\boldsymbol{v}_k$ of the matrix RR^T and the eigenvector $\boldsymbol{u}_k$ of the matrix $R^T R$ can be obtained as in Equation 2.29.

$$R^T R\boldsymbol{u}_k = \mu_k \boldsymbol{u}_k$$

$$RR^T R\boldsymbol{u}_k = \mu_k R\boldsymbol{u}_k$$

$$CR\boldsymbol{u}_k = \mu_k R\boldsymbol{u}_k$$

$$C\boldsymbol{v}_k = \mu_k \boldsymbol{v}_k, \qquad \text{where } \boldsymbol{v}_k = R\boldsymbol{u}_k \tag{2.29}$$

Equation 2.29 implies a couple of important notes are RR^T can have up to N^2 eigenvalues and eigenvectors; $R^T R$ can have up to n eigenvalues and eigenvectors; and n eigenvectors of the matrix RR^T associated with the biggest eigenvalues are exactly identical to the eigenvectors of the matrix $R^T R$ and they are related as, $\boldsymbol{v}_k = R\boldsymbol{u}_k$.

The generated eigenvectors by using the reduced covariance matrix must be normalized. The normalization can be performed by dividing the vector $\boldsymbol{v}_k$ by its length such that $\frac{\boldsymbol{v}_k}{\|\boldsymbol{v}_k\|}$ then the length of the normalized eigenvector $\boldsymbol{v}_k$ will be equal to one;

i.e., $\|\boldsymbol{v}_k\| = 1$. From now on, the reduced covariance matrix is going to be used for calculating desired eigenvectors and eigenvalues.

Step 9: selecting principal components and forming a feature vector matrix.
Here, principal components are called eigenfaces. They constitute the calculated eigenvectors associated with the biggest eigenvalues.

The feature vector matrix A_q represented in Equation 2.30 is an $N^2 \times q$ matrix that contains only q eigenvectors (principal components) such that $q << N^2$. Since the number of calculated eigenvectors by using the reduced covariance matrix $R^T R$ is equal to the total number of the training faces then $q \leq n$.

$$A_q = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_q], \qquad \text{where } q \leq n \tag{2.30}$$

In order to select the eigenfaces that form the feature vector matrix A_q, the variance contribution rate (VCR) and the total variance contribution rate (TVC) (they are proposed in the IEEE paper presented in Reference [2]) are computed as in Equation 2.31 and Equation 2.32 respectively. When the TVC is significantly high then q eigenvectors associated with the biggest q eigenvalues can be selected.

$$VCR_k\,(\%) = \frac{\lambda_k}{\sum_{k=1}^{n} \lambda_k} \times 100, \qquad k = 1, \ldots, n \tag{2.31}$$

$$TVC\,(\%) = \frac{\sum_{k=1}^{q} \lambda_k}{\sum_{k=1}^{n} \lambda_k} \times 100, \qquad q = 1, \ldots, n \tag{2.32}$$

Step 10: performing the principal components transform (also called the Hotelling or Karhunen-Loéve transform).
Equation 2.33 is used for projecting the training faces on the eigenspace. The columns of the matrix Y represent the coordinates of the projected training faces in the eigenspace; and $\boldsymbol{\Omega}^n$ contains the coordinates of the n^{th} projected training face.

$$Y = A_q^T R = \left[\boldsymbol{\Omega}^1 \ldots \boldsymbol{\Omega}^n\right], \qquad \text{where } \boldsymbol{\Omega}^n = \begin{bmatrix} w_1^n \\ \vdots \\ w_q^n \end{bmatrix} \tag{2.33}$$

Finally, by projecting the training faces on the eigenspace, the PCA algorithm is completely done.

2.2.2.7 Reconstruction of the Original Images

For reconstructing the training faces, Equation 2.33 is turned around to get the centered training faces matrix R as in Equation 2.34. The average training face vector $\boldsymbol{\Psi}$ is added again to obtain the reconstructed centered training faces vectors as in Equation 2.35 where $\widehat{\boldsymbol{\Gamma}}_n$ is the n^{th} reconstructed centered training face vector.

Also, the means of the pixels occupying the faces are added to get the reconstructed training faces vectors as in Equation 2.36 where $\widehat{\boldsymbol{I}}_n$ is the n^{th} reconstructed training face vector. Finally, $\widehat{\boldsymbol{I}}_n$ can be represented in the same manner as in Step 4, Sub-subsection 2.2.2.6; to obtain the reconstructed training face $\widehat{I}_n$.

$$R = A_q Y \tag{2.34}$$

$$\left[\widehat{\boldsymbol{\Gamma}}_1 \ldots \widehat{\boldsymbol{\Gamma}}_n\right] = A_q Y + [\boldsymbol{\Psi} \ldots \boldsymbol{\Psi}]_{N^2 \times n} \tag{2.35}$$

$$\left[\widehat{\boldsymbol{I}}_1 \ldots \widehat{\boldsymbol{I}}_n\right] = A_q Y + [\boldsymbol{\Psi} \ldots \boldsymbol{\Psi}]_{N^2 \times n} + [m_{f_1} \ldots m_{f_n}] \tag{2.36}$$

2.2.3 An Improved Principal Components Analysis (IPCA) Algorithm

2.2.3.1 Introduction

IPCA is another statistical tool for identifying patterns in data. It is typically like PCA except in the way of selecting eigenvectors that form the feature vector matrix A_q. It affords a new accurate method to measure the information content of principal components based on the information theory for improving PCA. IPCA acts better than PCA in the most of applications.

2.2.3.2 Analysis of the IPCA Algorithm

In order to estimate the degree of information content of eigenvectors, the concepts of Shannon information theory are fully used then two new concepts called the possibility information function (PIF) and the possibility information entropy (PIE) are obtained.

Eigenvalues can be transformed as in Equation 2.37 where d is the number of the dimensions of the data set. In Equation 2.37, it can be seen that $0 \leq \rho_k \leq 1$, where $k = 1, \ldots, d$. Therefore, ρ_k has the numerical properties of probability. Being similar with the definition of entropy, the PIF and PIE can be defined respectively as in Equation 2.38 and Equation 2.39. In Equation 2.39, $H(T)$ reflects the unevenness of ρ_k. According to the PIF and PIE, it can be obtained that firstly $I(\lambda_k)$ denotes the information content included by λ_k where the bigger λ_k is associated with the bigger $I(\lambda_k)$; Secondly, when all ρ_k are equal (i.e. uniformly distributed) then the PIE reaches its maximum.

$$\rho_k = 1 - \frac{\lambda_k}{\sum_{k=1}^{d} \lambda_k}, \qquad k = 1, \ldots, d \tag{2.37}$$

$$I(\lambda_k) = -\log_2 \rho_k, \qquad k = 1, \ldots, d \tag{2.38}$$

$$H(T) = H(\rho_1, \ldots, \rho_d) = -\sum_{k=1}^{d} \rho_k \log_2 \rho_k \tag{2.39}$$

For measuring the degree of information content of eigenvectors, two new concepts are used. The first one is the information rate (IR) shown in Equation 2.40; and the second one is the accumulated information rate (AIR) shown in Equation 2.41. When the AIR is significantly high then q eigenvectors associated with the biggest q eigenvalues can be selected.

$$IR_k\,(\%) = \frac{I\left(\lambda_k\right)}{\sum_{k=1}^{d} I\left(\lambda_k\right)} \times 100, \qquad k = 1, \ldots, d \tag{2.40}$$

$$AIR\,(\%) = \frac{\sum_{k=1}^{q} I\left(\lambda_k\right)}{\sum_{k=1}^{d} I\left(\lambda_k\right)} \times 100, \qquad q = 1, \ldots, d \tag{2.41}$$

2.2.3.3 Applying IPCA on the Example in Sub-subsection 2.2.2.3

The IR and AIR are computed for the eigenvectors of the covariance matrix C in the example in Sub-subsection 2.2.2.3; and the results are shown in Table 2.2. Based on Table 2.2, the feature vector matrix A_q in Equation 2.42 only contains the eigenvector which is associated with the biggest eigenvalue (the highly correlated eigenvector).

Table 2.2: The calculations of the IR and AIR.

k	λ_k	ρ_k	$I\left(\lambda_k\right)$	$IR_k\,(\%)$	$AIR\,(\%)$
1	19.1711	0.0754	3.7293	97.0616	97.0616
2	1.5623	0.9247	0.1129	2.9384	100

$$A_q = \begin{bmatrix} 0.6576 \\ 0.7538 \end{bmatrix}. \tag{2.42}$$

2.2.4 Comparison of the PCA and IPCA Algorithms

Comparison between the PCA and IPCA algorithms is based on the values of the TVC and AIR that determine the selected eigenvectors for the feature vector matrix A_q in Sub-subsection 2.2.2.3, Step 6; and in Sub-subsection 2.2.3.3.

The computed TVC and AIR are respectively equal to 92.4649% and 97.0616%. The AIR is big enough but the TVC is slightly small. Then the AIR is providing us with more confidence to pick the eigenvector which is associated with the biggest eigenvalue but the TVC is not. Therefore, the AIR tells us more about information contained in the eigenvectors of the covariance matrix C.

2.2.5 Applications of the PCA and IPCA Algorithms

2.2.5.1 Introduction

PCA and IPCA are applied in many fields. They have acceptable performance in many of them. In this subsection, the applications of the PCA and IPCA algorithms in image compression, face recognition and image detection are covered.

2.2.5.2 Image Compression

When some of the eigenvectors that are calculated from the covariance matrix C for all training faces are selected to form the feature vector matrix A_q then the dimensions of the reconstructed data set will be reduced. This implies that the PCA and IPCA algorithms work as compression. The algorithms are said to be lossy because a decompressed image is not exactly the same as the original one, but is generally worse.

2.2.5.3 Face Recognition

The PCA and IPCA algorithms are used to recognize an unknown face image based on the database which contains the training faces. For doing face recognition, an unknown face image is taken. It must have the same properties of the training faces. Hence, it must have the same size as the training faces; it has the same background; it has a projection as one of the training faces; finally, it has only face and it is expanded to the boarders of the image.

A couple of the operations explained in Sub-subsection 2.2.2.6 are applied to the unknown face image. The pixels occupying the face of the unknown face image are normalized and centered as in Step 2 and Step 3 respectively. The centered unknown face image is represented as a column image vector as in Step 4. The centered unknown image vector is centered in the set of the training faces by simply subtracting the mean training face vector $\mathbf{\Psi}$ from it as in Step 6. Then the unknown face image is projected on the eigenspace by using the PCA or IPCA feature vector matrix as in Step 10. The coordinates of the projected unknown face image in the eigenspace are shown in Equation 2.43.

$$\mathbf{\Omega}^{Unknown} = \begin{bmatrix} w_1^{Unknown} \\ \vdots \\ w_q^{Unknown} \end{bmatrix} \tag{2.43}$$

The Euclidean distance between the coordinates of the projected unknown face image and the coordinates of each training face is computed as in Equation 2.44. d_k is the distance between the coordinates of the projected unknown face image $\mathbf{\Omega}^{Unknown}$ and the coordinates of the k^{th} projected training face $\mathbf{\Omega}^k$; and n is the total number of the training faces. Note that, the distances between the unknown face image and the training faces are measured along the new axes derived from the PCA algorithm but not along the original axes. It turns out that these axes work much better for recognizing faces because PCA has given us the original training faces in terms of the differences and similarities between them.

$$d_k = \left\| \boldsymbol{\Omega}^{Unknown} - \boldsymbol{\Omega}^k \right\|, \qquad \text{where } k = 1, \ldots, n \tag{2.44}$$

Then recognition can be performed by using Condition 2.1 where md_k is the minimum distance between the coordinates of the projected unknown face image $\boldsymbol{\Omega}^{Unknown}$ and the coordinates of the k^{th} projected training face $\boldsymbol{\Omega}^k$.

Condition 2.1. *If,*

$$md_k = min\left([d_1, \ldots, d_n]\right), \qquad \textit{where } k \textit{ can be any number between 1 to } n$$

Then the unknown face image is recognized as the k^{th} training face; otherwise, it is an unknown face image.

At this point, it can be answered why the normalization of the training faces as well as the centering of the database and faces increase the accuracy of face recognition. That because when the database and faces are centered, the set of the projected vectors in the eigenspace will have zero mean; that means the vectors begin from the same origin; then the distance between a training face and its corresponding unknown face image will be very small compared with other training faces. Regarding the normalization of the training faces, when a training face and its corresponding unknown face image are normalized (i.e. they have the same length), the distance between them will decrease as shown in Figure 2.7. On the other hand, if they are unnormalized (i.e. they do not have the same length), the distance between them will increase as shown in Figure 2.8.

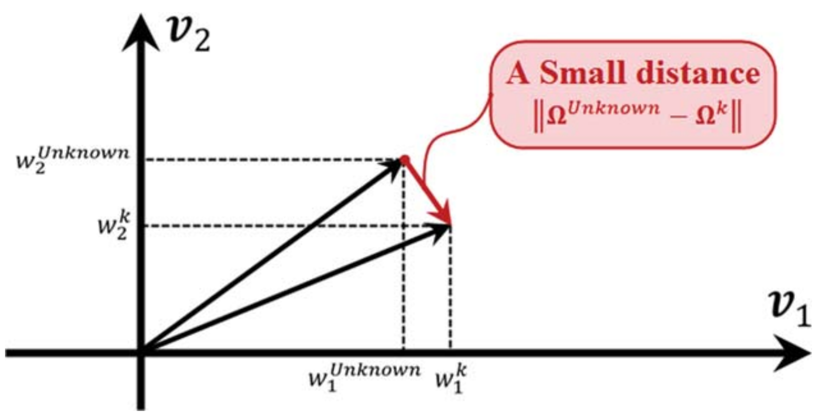

Figure 2.7: A normalized training face and its normalized corresponding unknown face image.

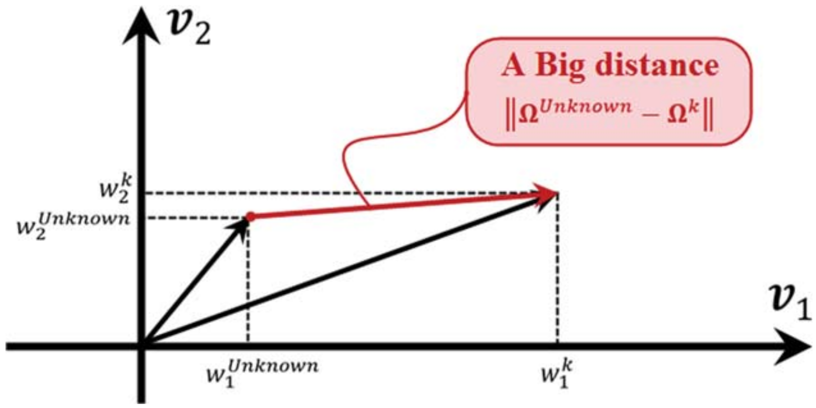

Figure 2.8: An unnormalized training face and its unnormalized corresponding unknown face image.

2.2.5.3.1 Setting up a Recognition Threshold

Unfortunately, when the unknown face image does not have a similar training face then getting the minimum distance md_k does not *always* mean that the unknown face image is recognized as the k^{th} training face. Therefore, a certain threshold must be used to increase the accuracy of recognition.

For setting up a recognition threshold, some different images are taken for each training face. These images are called tested images. They are known here just for picking the threshold. The distances between each training face and its *corresponding* tested images are obtained; and they are stacked in the row vectors $\boldsymbol{T}_1, \ldots, \boldsymbol{T}_k, \ldots, \boldsymbol{T}_n$, where $\boldsymbol{T}_k$ contains the smallest expected distances because the k^{th} training face and its *corresponding* tested images have the same person and the same face projection.

Thereafter, the mean m_k and standard deviation STD_k (the average distance from the mean to a point) are computed for each row vector $\boldsymbol{T}_k$ of the smallest distances. By calculating the means and the standard deviations, a certain threshold is established for each training face.

Then the recognition threshold can be applied to recognize the unknown face image by using Condition 2.2.

Condition 2.2. *If,*

$$m_k - STD_k \leq md_k \leq m_k + STD_k, \qquad \textit{where } k = 1, \ldots, n$$

Then the unknown face image is recognized as the k^{th} training face; otherwise, it is an unknown face image.

2.2.5.4 Image Detection

The PCA and IPCA algorithms are used to detect if an unknown image contains a face or not based on a determined threshold for detection. Hence, in image detection, only a detection threshold is needed.

To obtain the detection threshold, tested images are generated from the database of the training faces in the same manner as in Sub-sub-subsection 2.2.5.3.1. From Sub-subsection 2.2.2.6, the preprocessing operations illustrated in Step 2, Step 3, Step 4, Step 6 and Step 10 are respectively applied to the tested images. Then the projected centered (with respect to the set of the training faces) tested images are reconstructed again without adding the average training face neither the means of the pixels occupying the faces. Each reconstructed tested image is normalized and multiplied by the biggest intensity from its centered tested image; this is done in order to make each centered tested image and its reconstruction have approximately the same dynamic range.

The Euclidean distance between each centered tested image and its reconstruction is computed as in Equation 2.45 where a_k is the distance between the k^{th} centered tested image $\mathbf{\Phi}_k^{Tested\,Im}$ and its reconstruction $\widehat{\mathbf{\Phi}}_k^{Tested\,Im}$; as well as t is the total number of the tested images. Thereafter, the computed distances are placed in the row vector $\boldsymbol{S}$. The mean $m_{\boldsymbol{S}}$ and the standard deviation $STD_{\boldsymbol{S}}$ (the average distance from the mean to a point) are calculated for the vector $\boldsymbol{S}$. By calculating the mean and the standard deviation, the detection threshold is established.

$$a_k = \left\| \mathbf{\Phi}_k^{Tested\,Im} - \widehat{\mathbf{\Phi}}_k^{Tested\,Im} \right\|, \qquad \text{where } k = 1, \ldots, t \tag{2.45}$$

For applying the detection threshold, the unknown image $I^{Unknown}$ is picked for detection. The Euclidean distance $a^{Unknown}$ between the centered unknown image $\mathbf{\Phi}^{Unknown}$ and its reconstruction $\widehat{\mathbf{\Phi}}^{Unknown}$ is computed. Then the unknown image $I^{Unknown}$ can be detected by means of Condition 2.3.

Condition 2.3. *If,*

$$m_{\boldsymbol{S}} - STD_{\boldsymbol{S}} \leq a^{Unknown} \leq m_{\boldsymbol{S}} + STD_{\boldsymbol{S}}$$

Then the unknown image $I^{Unknown}$ is detected as a face image; otherwise, it is not a face image.

2.2.6 Performance Analysis of the PCA and IPCA Algorithms

2.2.6.1 Introduction

In studying performance, attention is paid to study how each application behaves when the eigenfaces that are generated by using the PCA algorithm are used; the eigenfaces that are generated by using the IPCA algorithm are used; and when different eigenfaces are selected to form the feature vector matrix.

2.2.6.2 Analysis of Compression Performance

2.2.6.2.1 Introduction

Compression performance can be analyzed from three points of view are the speed of compression and reconstruction, the quality of a reconstructed image, and the size of compression. Each one is explained in details in this sub-subsection.

2.2.6.2.2 Speed of Compression and Reconstruction

The number of the eigenfaces that is used to compress and reconstruct the training faces mainly controls the processing speed of compression and reconstruction. When a small number of the eigenfaces is used to project and reconstruct the training faces then the processing speed will increase and vice versa.

2.2.6.2.3 Quality of a Reconstructed Image

For measuring the quality of a reconstructed image, the mean squared error (MSE) is computed as in Equation 2.46 to measure an error between the image I_k and its reconstruction $\widehat{I}_k$; where N is the number of rows and columns of the image I_k.

$$e_{MSE} = \frac{1}{N^2} \sum_{r=1}^{N} \sum_{c=1}^{N} \left[\widehat{I}_k(r,c) - I_k(r,c) \right]^2 \tag{2.46}$$

2.2.6.2.4 Size of Compression

2.2.6.2.4.1 Introduction

The size of compression can be measured in two ways are an information rate and the mean squared error (MSE) of compressed images.

2.2.6.2.4.2 Information Rate

An information rate measures how much information is after compression compared with information before compression; in other words, it measures the number of pixels after compression compared with before. This can be accomplished as in

Equation 2.47.

Before Compression : After Compression

$$\frac{\left(\underbrace{n}_{\substack{\text{The total}\\ \text{number of}\\ \text{the training}\\ \text{faces}}} \times \underbrace{N^2}_{\substack{\text{An image}\\ \text{size}}}\right)}{n \times N^2}\times 100 : \frac{\left(\underbrace{N^2 \times q}_{\substack{\text{The feature}\\ \text{vector matrix}\\ A_q}} + \underbrace{q \times n}_{\substack{\text{The coordinates}\\ \text{matrix } Y \text{ of}\\ \text{the projected}\\ \text{training faces}}} + \underbrace{N^2}_{\substack{\text{The average}\\ \text{training}\\ \text{face vector}\\ \boldsymbol{\Psi}}}\right)}{n \times N^2}\times 100 \tag{2.47}$$

In Equation 2.47 the rows and columns for the pixels occupying the faces as well as the means of the pixels on the faces are not considered in the overall size after compression because the operation of face centering is not really important in image compression; and it does not have any effect if it is done or not; but it has been done here because it is important for other applications. The normalization is done in Equation 2.47 to make the overall information before compression is equal to 100% all the time in order to make comparison easier.

2.2.6.2.4.3 Mean Squared Error (MSE) of Compressed Images

The mean squared error (MSE) between the exact and approximate reconstruction of the training face vector $\boldsymbol{I}_k$ is calculated as follows,

Equation 2.48 shows the exact reconstruction of the training face vector $\boldsymbol{I}_k$.

$$\boldsymbol{I}_k = \sum_{i=1}^{n} w_i^k \boldsymbol{v}_i + \boldsymbol{\Psi} \tag{2.48}$$

And, Equation 2.49 shows the approximate reconstruction of the training face vector $\boldsymbol{I}_k$.

$$\widehat{\boldsymbol{I}}_k = \sum_{i=1}^{q} w_i^k \boldsymbol{v}_i + \boldsymbol{\Psi} \tag{2.49}$$

The error between $\boldsymbol{I}_k$ and $\widehat{\boldsymbol{I}}_k$ can be computed as in Equation 2.50.

$$\begin{aligned}
\boldsymbol{e} &= \boldsymbol{I}_k - \widehat{\boldsymbol{I}}_k \\
&= \sum_{i=1}^{n} w_i^k \boldsymbol{v}_i + \boldsymbol{\Psi} - \sum_{i=1}^{q} w_i^k \boldsymbol{v}_i - \boldsymbol{\Psi} \\
&= \sum_{i=1}^{n} w_i^k \boldsymbol{v}_i - \sum_{i=1}^{q} w_i^k \boldsymbol{v}_i \\
&= \sum_{i=q+1}^{n} w_i^k \boldsymbol{v}_i
\end{aligned} \tag{2.50}$$

For computing the MSE of the linear estimate $\widehat{\boldsymbol{I}}_k$, Equation 2.51 can be used.

$$\begin{aligned}
E\left[\boldsymbol{e}^{\boldsymbol{T}}\boldsymbol{e}\right] &= E\left[\left(\sum_{i=q+1}^{n} w_i^k \boldsymbol{v}_i\right)^T \left(\sum_{m=q+1}^{n} w_m^k \boldsymbol{v}_m\right)\right] \\
&= E\left[\sum_{i=q+1}^{n} w_i^k \boldsymbol{v}_i^T \sum_{m=q+1}^{n} w_m^k \boldsymbol{v}_m\right] \\
&= E\left[\sum_{i=q+1}^{n} \sum_{m=q+1}^{n} w_i^k w_m^k \boldsymbol{v}_i^T \boldsymbol{v}_m\right] \\
&= \sum_{i=q+1}^{n} \sum_{m=q+1}^{n} E\left[w_i^k w_m^k\right] \boldsymbol{v}_i^T \boldsymbol{v}_m
\end{aligned} \tag{2.51}$$

To find $E\left[w_i^k w_m^k\right]$, a covariance matrix for the coordinates matrix Y of the projected training faces must be computed as in Equation 2.52

$$\begin{aligned} C_Y &= YY^T \\ &= \left[A^T R\right]\left[A^T R\right]^T \\ &= \left[A^T R\right]\left[R^T A\right] \\ &= A^T \underbrace{RR^T}_{C} A \\ &= A^T C A \end{aligned} \tag{2.52}$$

From Reference [3], Page 169, Theorem A.1.30; since C is a real and symmetric matrix as well as A is an orthonormal matrix then C_Y can be written as in Equation 2.53 where I is the identity matrix.

$$\begin{aligned} C_Y &= A^T C A \\ &= \underbrace{A^T A}_{I} \Lambda \underbrace{A^T A}_{I} \\ &= I \Lambda I \\ &= \Lambda \\ &= \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & 0 & \lambda_n \end{bmatrix} \end{aligned} \tag{2.53}$$

Hence, from Equation 2.53, it can be concluded that,

$$E\left[w_i^k w_m^k\right] = \begin{cases} \lambda_i & \text{when } i = m \\ 0 & \text{when } i \neq m \end{cases}$$

And,

$$\boldsymbol{v}_i^T \boldsymbol{v}_m = \begin{cases} 1 & \text{when } i = m \\ 0 & \text{when } i \neq m \end{cases} \quad \text{Because } \boldsymbol{v}_i \text{ and } \boldsymbol{v}_m \text{ form an orthonormal basis.}$$

Therefore, when $i = m$, the MSE between the exact and approximate reconstruction of the training face vector $\boldsymbol{I}_k$ is obtained as in Equation 2.54.

$$\begin{aligned} E\left[\boldsymbol{e^T e}\right] &= \sum_{i=q+1}^{n} \sum_{m=q+1}^{n} E\left[w_i^k w_m^k\right] \boldsymbol{v}_i^T \boldsymbol{v}_m \\ &= \sum_{i=q+1}^{n} E\left[\left(w_i^k\right)^2\right] \cdot 1 \\ &= \sum_{i=q+1}^{n} \lambda_i \end{aligned} \tag{2.54}$$

2.2.6.3 Analysis of Recognition Performance

2.2.6.3.1 Introduction

Recognition performance can be analyzed from two points of view are the speed of recognition and an error rate. Each one is explained in details in this sub-subsection.

2.2.6.3.2 Speed of Recognition

The number of the selected eigenfaces that is used to recognize the unknown face image mainly controls the recognition speed. When the number of the selected eigenfaces decreases, the processing speed increases and vice versa.

2.2.6.3.3 Error Rate

The error rate computes the percentage of error in recognition. It can be computed as in Equation 2.55 where L is the total number of the tested images; SR is the total number of successes in the recognition of the tested images; FR is the total number of failures in the recognition of the tested images; and ER is the error rate.

$$ER\,(\%) = \frac{FR}{L} \times 100 \tag{2.55}$$

2.2.6.4 Analysis of Detection Performance

2.2.6.4.1 Introduction

Detection performance can be analyzed from two points of view are the speed of detection and an error rate. Each one is explained in details in this sub-subsection.

2.2.6.4.2 Speed of Detection

The number of the selected eigenfaces that is used to detect the unknown image mainly controls the detection speed. When the number of the selected eigenfaces decreases, the processing speed increases and vice versa.

2.2.6.4.3 Error Rate

The error rate computes the percentage of error in detection. It can be computed as in Equation 2.56 where L is the total number of the tested images; SD is the total number of successes in the detection of the tested images; FD is the total number of failures in the detection of the tested images; and ER is the error rate.

$$ER\,(\%) = \frac{FD}{L} \times 100 \qquad (2.56)$$

2.3 Analog Optical Information Processing

2.3.1 Introduction

Analog optical information processing is an important area which recalls the linearity concepts of imaging systems in order to synthesize an optical model that can perform one or multiple functions. The focus of this section is about providing a theoretical background for designing an optical model for object detection and face recognition. Concentration will be limited to coherent optical models for some reasons will be mentioned in the next subsection. This section is based on Reference [3], Chapter 8.

2.3.2 Coherent and Incoherent Optical Image Processing Systems

This subsection shows the difference between the usage of spatially incoherent light and the usage of spatially coherent light in optical information processing. Spatially incoherent light has some big advantages but on the other hand it has severe disadvantages. The advantages of spatially incoherent light are:

1. It is free from coherent artifacts such as dust specks on optical components and the speckle phenomenon.

2. Data can be introduced to a system by using incoherent light sources such as light-emitting diode (LED) arrays or cathode-ray tube (CRT) displays; but in coherent systems, complicated and costly spatial light modulators (SLMs) are used to introduce data.

3. In general, incoherent systems are easier than coherent systems in physical implementation.

On the other hand, spatially incoherent light has disadvantages that make us prefer to use spatially coherent light in our model. The disadvantages of spatially incoherent light are:

1. An incoherent optical system does not have a frequency plane but a coherent optical system has a plane at a distance f from a lens is called a frequency plane or a focal plane. The absence of this plane makes the manipulation of an input spectrum is very difficult rather than just the direct manipulation of a spectrum on a back focal plane.

2. Incoherent optical systems are linear in intensity. The manipulation of intensity in optical processing systems is very complex if it is not impossible because intensity is a positive and real physical quantity. For instance, there is no a normal optical method to subtract two intensity patterns; but coherent optical systems are linear in complex amplitude; consequently, if one wants to subtract two complex amplitude patterns then the patterns can be added together with a π radian phase shift between them.

3. The spectrum of an incoherent image that is generated from an incoherent optical system always has the biggest spectral component at the origin. This makes a produced incoherent image has low contrast. Therefore, incoherent optical systems need a huge use of electronics in order to enhance an output incoherent image and makes it comparable to an output coherent image.

Due to these serious disadvantages, spatially coherent light is going to be used in our model.

2.3.3 Coherent Optical Information Processing Systems

We now present the coherent optical information processing model used for object detection and face recognition. From the last subsection, it is known that coherent optical systems are linear in complex amplitude; therefore, filtering processes can be performed by direct manipulation of complex amplitude appearing in the back focal plane of a Fourier transforming lens. There are a large number of system architectures that can do frequency domain filtering but a pretty conceptually straightforward system shown in Figure 2.9 is implemented. This model for coherent optical information processing is called $4f$ model because a distance that separates the input plane P_1 form the output plane P_3 is composed of four separate distances of length f. The length of this model from the point source S until the output plane is $5f$.

The collimating lens L_1 is used to collimate light from the point source S. The input transparency is placed in the input plane P_1 against the collimating lens L_1.

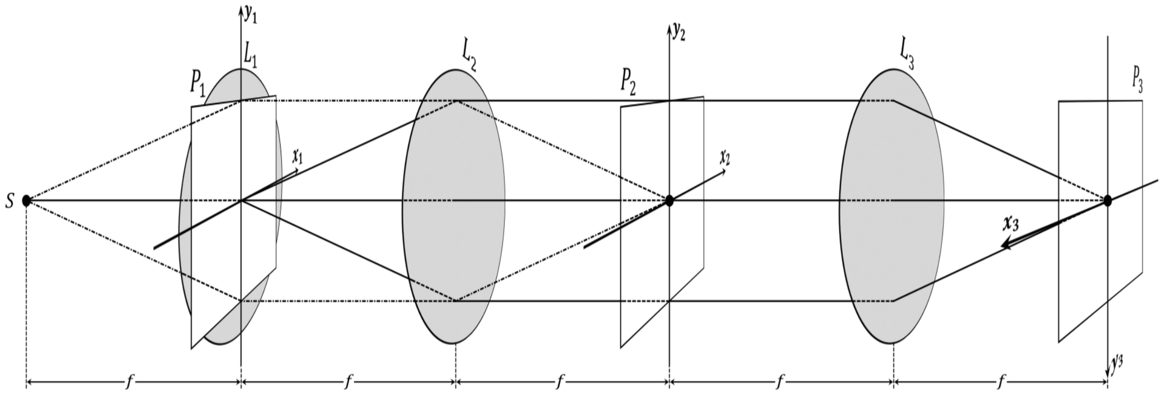

Figure 2.9: The architecture for coherent optical information processing.

The input plane is placed against the collimating lens in order to decrease the total length of the coherent model. The amplitude transmittance of the input transparency is $g(x_1, y_1)$. The input transparency is illuminated by a uniform normally incident plane (or spherical) wave of amplitude A. Then the complex amplitude distribution of the field just behind the input transparency (i.e. the field transmitted by the input transparency) is $U_1(x_1, y_1) = Ag(x_1, y_1)$. The Fourier transforming lens L_2 is Fourier transforming the illuminated input transparency in its back focal plane P_2. A transparency is inserted in the back focal plane to modulate the amplitude transmittance over that plane. Then the complex amplitude distribution $U_2(x_2, y_2)$ of the Fourier transformed field can be found as in Equation 2.57.

$$\begin{aligned}
U_2(x_2, y_2) &= \frac{1}{j\lambda f}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} U_1(x_1, y_1)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+y_1y_2)}\,dx_1dy_1 \\
&= \frac{A}{j\lambda f}\underbrace{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x_1, y_1)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+y_1y_2)}\,dx_1dy_1}_{f_X=\frac{x_2}{\lambda f}\ \&\ f_Y=\frac{y_2}{\lambda f}} \\
&= \frac{A}{j\lambda f}G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \\
&= k_1G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \qquad (2.57)
\end{aligned}$$

Where k_1 is a complex constant; λ is the light wavelength in meter (m); and $G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right)$ is the Fourier spectrum of the Fourier transformed field.

A desired filter can be synthesized and placed in the plane P_2 in order to manipulate $G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right)$. Let the transfer function of a synthesized filter be represented by H then the complex amplitude distribution in the back focal plane of the filter should be as in Equation 2.58 where k_2 is a complex constant.

$$U_f\left(x_2, y_2\right) = k_2 H\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \tag{2.58}$$

The spectrum of the field just behind the transparency of the plane P_2 is $G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) H\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right)$. The Fourier transforming lens L_3 Fourier transforms the altered spectrum in its back focal plane P_3. There is no an optical component does inverse Fourier transform; therefore, another Fourier transforming lens is used to produce the final complex amplitude distribution on the output plane P_3. The usage of the two consecutive Fourier transforming lenses makes the coordinates of the output plane P_3 inverted (Reference [11], Page 25, "Application of the Fourier Transform"). The coordinates inversion problem can be overcome by inverting the coordinates of the output plane P_3.

This coherent model has a disadvantage that vignetting can happen through performing the first Fourier transform. In order to overcome this problem, the input plane $P1$ can be placed against the Fourier transforming lens L_2.

There are at least two methods for synthesizing the frequency plane filter for coherent optical systems. One of these methods is by using the joint transform correlator (JTC). This method is discussed in the next subsection.

2.3.4 The Joint Transform Correlator (JTC)

This correlator is used to synthesize the frequency plane filter in order to manipulate the spectrum on the back focal plane of the Fourier transforming lens L_2. This method was invented by Weaver and Goodman [4] and called as the joint transform correlator. The filter architecture is shown in Figure 2.10.

The filter is divided to two stages: recording the filter and getting the filter output. In the recording process, the lens L_1 collimates light from the point source S. Two input transparencies are placed in the input plane P_1. The first transparency is for the desired impulse response h and centered at the coordinate $\left(0, \frac{Y}{2}\right)$. The other transparency is for the data g to be filtered and centered at the coordinate $\left(0, -\frac{Y}{2}\right)$. Hence, their centers are separated by the distance Y. The input transparencies are illuminated by a uniform normally incident plane (or spherical) wave of amplitude A. Then the complex amplitude distribution of the field just behind the input transparencies (i.e. the field transmitted by the input transparencies) is obtained as in Equation 2.59.

$$U_1\left(x_1, y_1\right) = A\left[h\left(x_1, y_1 - \frac{Y}{2}\right) + g\left(x_1, y_1 + \frac{Y}{2}\right)\right] \tag{2.59}$$

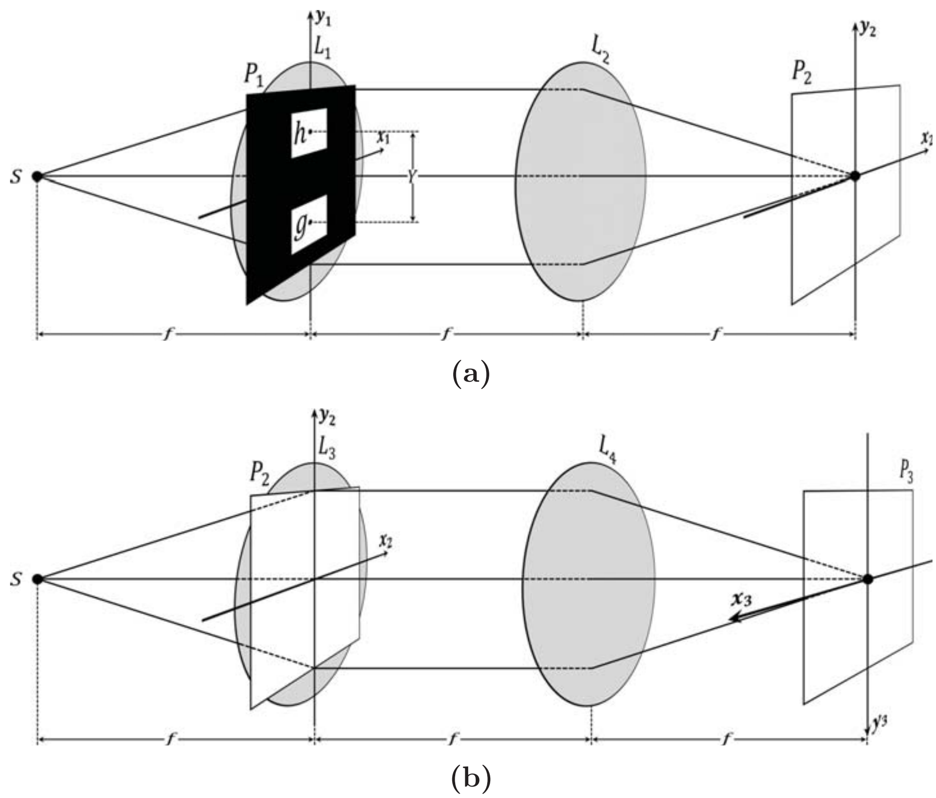

Figure 2.10: The joint transform correlator: **(a)** Recording the filter; and **(b)** getting the filter output.

The Fourier transforming lens L_2 is Fourier transforming the field transmitted by the input transparencies in its back focal plane P_2. The complex amplitude distribution $U_2(x_2, y_2)$ of the Fourier transformed field is obtained as in Equation 2.60. The derivation of $U_2(x_2, y_2)$ is shown in Appendix E.

$$U_2(x_2, y_2) = \frac{A}{j\lambda f} \exp^{-j\frac{\pi Y}{\lambda f}y_2} H\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) + \frac{A}{j\lambda f} \exp^{j\frac{\pi Y}{\lambda f}y_2} G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \tag{2.60}$$

From linear algebra, if Z_1 and Z_2 are complex numbers; as well as Z_1^* and Z_2^* are their conjugates respectively then $|Z_1 + Z_2|^2 = |Z_1|^2 + |Z_2|^2 + (Z_1 Z_2^* + Z_2 Z_1^*)$. Using this operation on complex numbers and another operation is that the conjugate of the exponential function $\exp^{jx}$ is equal to $\exp^{-jx}$ (conversely, the conjugate of the exponential function $\exp^{-jx}$ is equal to $\exp^{jx}$) then the incident intensity on the back focal plane of the lens L_2 is computed as in Equation 2.61.

$$I(x_2, y_2) = \frac{A^2}{\lambda^2 f^2} \left[\left| H\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right)\right|^2 + \left| G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right)\right|^2 + \right.$$

$$+ H\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) G^*\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \exp^{-j\frac{2\pi Y}{\lambda f} y_2} +$$

$$\left. + H^*\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) G\left(\frac{x_2}{\lambda f}, \frac{y_2}{\lambda f}\right) \exp^{j\frac{2\pi Y}{\lambda f} y_2} \right] \tag{2.61}$$

Note that, the recorded transparency in the plane P_2 is supposed to have an amplitude transmittance that is proportional to the intensity $I(x_2, y_2)$. To obtain the output of the filter, the recorded transparency is illuminated by a uniform normally incident plane (or spherical) wave of amplitude B. The complex amplitude distribution of the field just behind the recorded transparency (i.e. the field transmitted by the recorded transparency) is $U_r(x_2, y_2) = BI(x_2, y_2)$. The lens L_4 is Fourier transforming the transmitted field in its back focal plane P_3. The complex amplitude distribution of the Fourier transformed field in the output plane P_3 is computed in Equation 2.62.

$$U_3(x_3, y_3) = \mathfrak{F}\{U_r(x_2, y_2)\}$$

$$= B\,\mathfrak{F}\{I(x_2, y_2)\} \tag{2.62}$$

From linear algebra, if Z_1 is a complex number and Z_1^* is its conjugate then $|Z_1|^2 = Z_1 Z_1^*$. Using this operation on complex numbers; and using another properties and theorems of Fourier transform are the convolution theorem (Reference [12], Page 37, Property 12), the complex conjugation property (Reference [12], Page 28, Property 3), and the property that the Fourier transform of the shifted impulse response $\delta(t - t_o)$ is equal to $\exp^{-j2\pi f t_o}$ where t_o is the amount of the shift; then the field in the back focal plane P_3 is found as in Equation 2.63.

$$U_3(x_3, y_3) = B\frac{A^2}{\lambda^2 f^2} \left[h(x_3, y_3) \otimes h^*(-x_3, -y_3) + g(x_3, y_3) \otimes g^*(-x_3, -y_3) + \right.$$

$$+ h(x_3, y_3) \otimes g^*(-x_3, -y_3) \otimes \delta(x_3, y_3 - Y) +$$

$$\left. + h^*(-x_3, -y_3) \otimes g(x_3, y_3) \otimes \delta(x_3, y_3 + Y) \right] \tag{2.63}$$

The complex distribution is composed of four terms. The first two terms respectively represent the cross-correlation of the impulse response h and itself as well as the cross-correlation of the data g and itself. The third and fourth terms represent the cross-correlations of h and g. The third and fourth terms are typically the same except that the third cross-correlation is centered at $(0, Y)$ and the fourth term is centered at $(0, -Y)$. There is not too much thing to do with the first and second terms but the third and fourth terms are of interest. The cross-correlations of h and g can be written as in Equation 2.64 and Equation 2.65.

$$h(x_3, y_3) \otimes g^*(-x_3, -y_3) \otimes \delta(x_3, y_3 - Y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(\xi, \eta)\, g^*(\xi - x_3, \eta - (y_3 - Y))\, d\xi d\eta$$
$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(\xi, \eta)\, g^*(\xi - x_3, \eta - y_3 + Y)\, d\xi d\eta \qquad (2.64)$$

Note that,

$$h(x_3, y_3) \otimes g^*(-x_3, -y_3) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(\xi, \eta)\, g^*(\xi - x_3, \eta - y_3)\, d\xi d\eta$$

Similarly,

$$h^*(-x_3, -y_3) \otimes g(x_3, y_3) \otimes \delta(x_3, y_3 + Y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(\xi, \eta)\, h^*(\xi - x_3, \eta - y_3 - Y)\, d\xi d\eta \qquad (2.65)$$

From digital signal processing (DSP), the main difference between cross-correlation and convolution is that in cross-correlation the functions $g^*(-x_3, -y_3)$ and $h^*(-x_3, -y_3)$ are not rotated by 180^o before doing the cross-correlation process but in convolution they must be rotated by 180^o before doing a convolution process. To get the convolution of the impulse response h and the data g, the input transparency of h or g (just one of them) in the recording stage must be rotated by 180^o along the spatial coordinate x_1 as well as along the spatial coordinate y_1. If the input transparency of the impulse response h is rotated then it will be $h\left(-x_1, -y_1 + \frac{Y}{2}\right)$ instead of $h\left(x_1, y_1 - \frac{Y}{2}\right)$; similarly, if the input transparency of the data g is rotated then it will be $g\left(-x_1, -y_1 - \frac{Y}{2}\right)$ instead of $g\left(x_1, y_1 + \frac{Y}{2}\right)$.

From digital signal processing (DSP), the bandwidth of a resulting function from the convolution, correlation or cross-correlation of two functions is equal to the sum of their bandwidths [13]. For example, if the bandwidths of the functions $m(t)$ and $f(t)$ are three and one respectively; then the bandwidth of their convolution is equal to four. Therefore, the bandwidths of the patterns of the cross-correlated field in the output plane P_3 along the spatial coordinates x_3 and y_3 are illustrated in Figure 2.11.

Obviously from Figure 2.11, in order to prevent overlapping between the patterns of the cross-correlated field that are centered at $(0, 0)$, $(0, Y)$ and $(0, -Y)$ (i.e. they are fully separated); the distance between the centers of the input transparencies must satisfy Relation 2.1 where W_g and W_h are the widths of g and h respectively in the

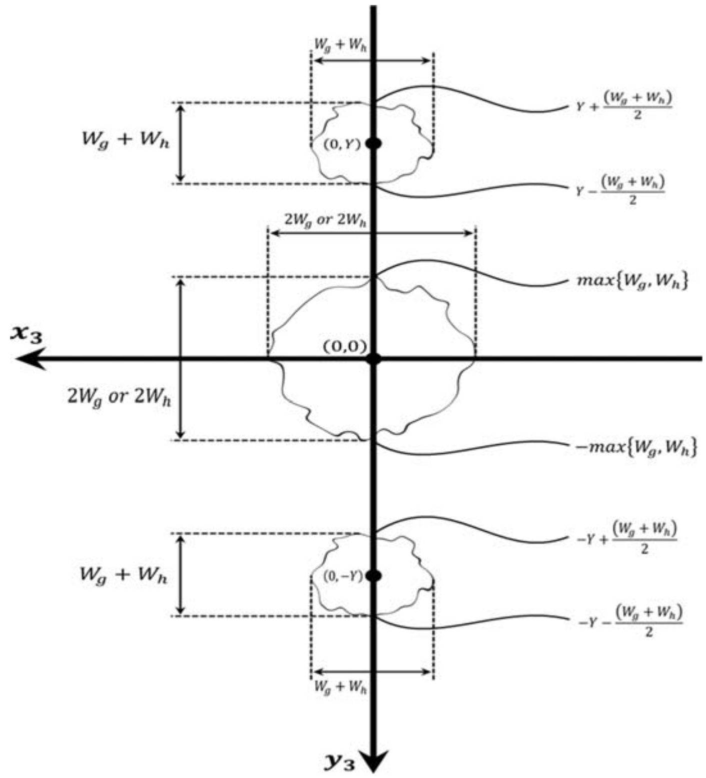

Figure 2.11: The bandwidths of the patterns of the cross-correlated field in the output plane P_3 along the spatial coordinates x_3 and y_3.

direction of the y-coordinate. It is really important to be noticed that in Figure 2.11, the highest cross-correlation exists in the center of each cross-correlated pattern and decreases by moving away from the center.

Relation 2.1.

$$Y > max\,\{W_h, W_g\} + \frac{W_g}{2} + \frac{W_h}{2}$$

The constant c is added to the distance Y for realizing Relation 2.1. In order to confine the patterns of the cross-correlations of the impulse response h and the data g in the output plane P_3, the distance d_1 which is from the horizontal axis x_1 to the top edge of the input plane P_1 shown in Figure 2.12 must be bigger than or equal to the distance D obtained in Equation 2.66 which is from the horizontal axis x_3 in the output plane P_3 to the top edge of the pattern centered at $(0, Y)$ or the bottom edge of the pattern centered at $(0, -Y)$ shown in Figure 2.13; as well as the distance d_2 which is from the horizontal axis x_1 to the bottom edge of the input plane P_1 shown in Figure 2.12 must be bigger than or equal to the distance D. For making d_1 is equal to D, the amount $D - r_1$ has to be added to the distance r_1; where the distance r_1 obtained in Equation 2.67 is from the horizontal axis x_1 to the top edge of h as shown in Figure 2.12. Similarly, to make d_2 is equal to D, the amount $D - r_2$ has to be added to the distance r_2; where the distance r_2 obtained in Equation 2.68 is from the horizontal axis x_1 to the bottom edge of g as shown in Figure 2.12. The distances $D - r_1$ and $D - r_2$ are respectively obtained as in Equation 2.69 and Equation 2.70. Finally, the distance d_1 will be equal to the distance D as in Equation 2.71; similarly, the distance d_2 will also be equal to D as in Equation 2.72.

$$D = Y + c + \frac{W_g}{2} + \frac{W_h}{2} = max\left\{W_h, W_g\right\} + W_h + W_g + c \tag{2.66}$$

$$r_1 = \frac{Y+c}{2} + \frac{W_h}{2} = \left[\frac{max\{W_h,W_g\}}{2} + \frac{W_h}{4} + \frac{W_g}{4} + \frac{c}{2}\right] + \frac{W_h}{2} = \frac{max\{W_h,W_g\}}{2} + \frac{3}{4}W_h + \frac{1}{4}W_g + \frac{c}{2} \tag{2.67}$$

$$r_2 = \frac{Y+c}{2} + \frac{W_g}{2} = \left[\frac{max\{W_h,W_g\}}{2} + \frac{W_h}{4} + \frac{W_g}{4} + \frac{c}{2}\right] + \frac{W_g}{2} = \frac{max\{W_h,W_g\}}{2} + \frac{1}{4}W_h + \frac{3}{4}W_g + \frac{c}{2} \tag{2.68}$$

$$D - r_1 = \frac{1}{2}max\left\{W_h, W_g\right\} + \frac{1}{4}W_h + \frac{3}{4}W_g + \frac{c}{2} \tag{2.69}$$

$$D - r_2 = \frac{1}{2}max\left\{W_h, W_g\right\} + \frac{3}{4}W_h + \frac{1}{4}W_g + \frac{c}{2} \tag{2.70}$$

$$d_1 = r_1 + (D - r_1) = D \tag{2.71}$$

$$d_2 = r_2 + (D - r_2) = D \tag{2.72}$$

Lastly, the joint transform correlator has a great feature is that its ability to change the filter impulse response quickly; therefore, it is considered beneficial for real-time systems. On the other hand, it has a defect is that the input bandwidth of the data is reduced due to the filter impulse response is introduced simultaneously with the data to be filtered.

2.3.4.1 Sampling Issues

2.3.4.1.1 Introduction

Sampling is considered the first important step for simulating optical models. In order to generate the cross-correlated field in the back focal plane P_3; then the input plane P_1, the back focal plane of the lens L_2 and the back focal plane of the lens L_4 must be sampled properly. Sampling for each one of these is completely discussed in this sub-subsection.

2.3.4.1.2 Sampling of the Input Plane P_1

The input plane P_1 is located in a rectangular array has N samples along the spatial space coordinate x_1 and M samples along the spatial space coordinate y_1. L_{x_1} is the physical side length in meter (m) of the array in the x_1 direction; similarly, L_{y_1} is

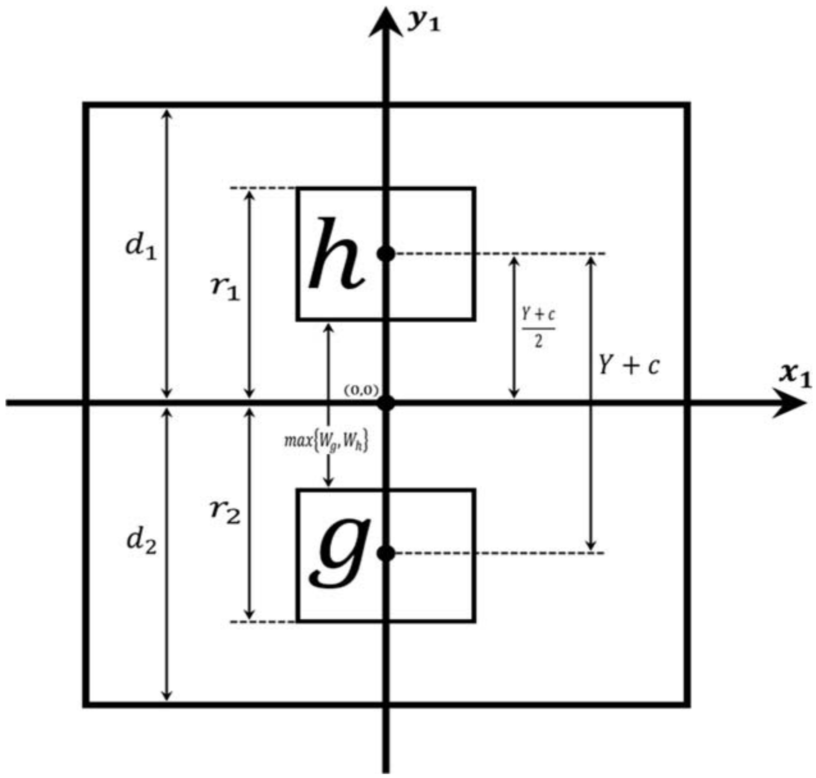

Figure 2.12: The alignment of the input transparencies in the input plane P_1.

the physical side length in meter of the array in the y_1 direction. Then the sample spacing Δx_1 along the x_1-coordinate in meter is equal to $\frac{L_{x_1}}{N}$; and the sample spacing Δy_1 along the y_1-coordinate in meter is equal to $\frac{L_{y_1}}{M}$.

2.3.4.1.3 Sampling of the Back Focal Plane P_2

From Fourier transform, the spatial frequency coordinate f_{X_2} of the back focal plane P_2 in cycles per meter $\left(\frac{cyc}{m}\right)$ is obtained as in Equation 2.73.

$$f_{X_2} = \frac{x_2}{\lambda f} \tag{2.73}$$

By turning around Equation 2.73, the spatial space coordinate x_2 can be expressed as in Equation 2.74.

$$x_2 = \lambda f f_{X_2} \tag{2.74}$$

Note that, x_2 is in meter (m) because the units of the variables in Equation 2.74 can be concluded as $m \times m \times \frac{cyc}{m} = m$. Then the spatial space sampling interval Δx_2 in

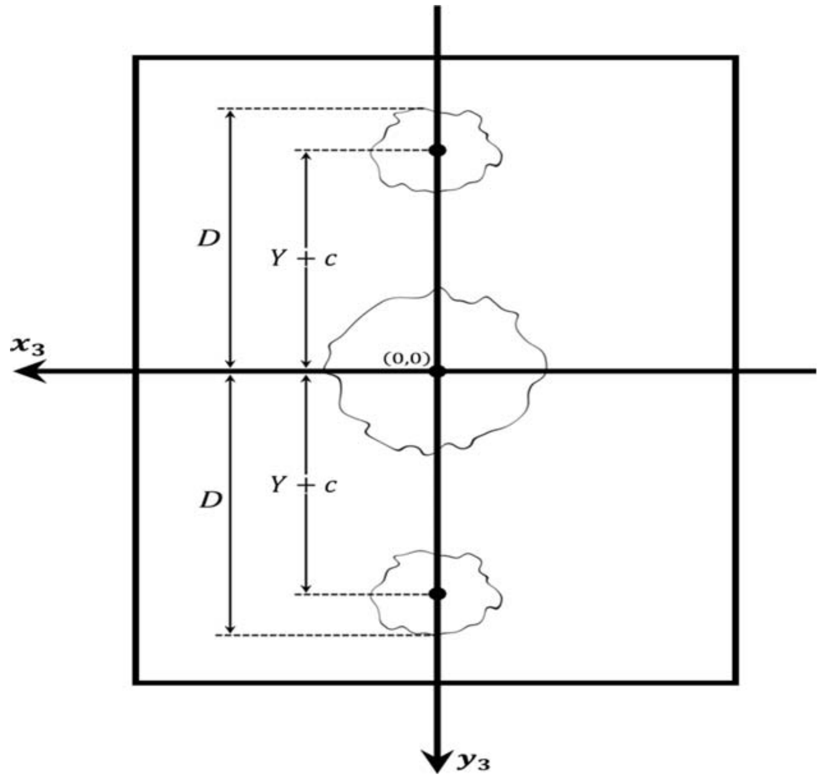

Figure 2.13: The alignment of the patterns of the cross-correlated field in the output plane P_3.

meter (m) along the spatial space coordinate x_2 is computed as in Equation 2.75.

$$\Delta x_2 = \lambda f \Delta f_{X_2} \tag{2.75}$$

From discrete Fourier transform (DFT), the relationship between the spatial space sampling interval Δx_1 in the input plane and the spatial frequency sampling interval Δf_{X_2} is shown in Equation 2.76.

$$\Delta f_{X_2} = \frac{1}{N \Delta x_1} \tag{2.76}$$

For more information about how the relation in Equation 2.76 is obtained; Reference [14], Subsection 4.4.2 can be consulted. By substitution from Equation 2.76 in Equation 2.75 then the spatial space sampling interval Δx_2 in meter (m) along the spatial space coordinate x_2 is obtained as in Equation 2.77.

$$\Delta x_2 = \frac{\lambda f}{N \Delta x_1} \tag{2.77}$$

Similarly, the spatial space sampling interval Δy_2 in meter (m) along the spatial space coordinate y_2 can be computed as in Equation 2.78.

$$\Delta y_2 = \frac{\lambda f}{M \Delta y_1} \tag{2.78}$$

2.3.4.1.4 Sampling of the Back Focal Plane P_3

From Fourier transform, the spatial frequency coordinate f_{X_3} of the back focal plane P_3 in cycles per meter $\left(\frac{cyc}{m}\right)$ is obtained as in Equation 2.79.

$$f_{X_3} = \frac{x_3}{\lambda f} \tag{2.79}$$

By turning around Equation 2.79, the spatial space coordinate x_3 can be expressed as in Equation 2.80.

$$x_3 = \lambda f f_{X_3} \tag{2.80}$$

Then the spatial space sampling interval Δx_3 in meter (m) along the spatial space coordinate x_3 is computed as in Equation 2.81.

$$\Delta x_3 = \lambda f \Delta f_{X_3} \tag{2.81}$$

From discrete Fourier transform (DFT), the relationship between the spatial space sampling interval Δx_2 in the back focal plane P_2 and the spatial frequency sampling interval Δf_{X_3} is shown in Equation 2.82.

$$\Delta f_{X_3} = \frac{1}{N \Delta x_2} \tag{2.82}$$

By substitution from Equation 2.82 in Equation 2.81 then the spatial space sampling interval Δx_3 in meter (m) along the spatial space coordinate x_3 is obtained as in Equation 2.83.

$$\Delta x_3 = \frac{\lambda f}{N \Delta x_2} = \Delta x_1 \tag{2.83}$$

Similarly, the spatial space sampling interval Δy_3 in meter (m) along the spatial space coordinate y_3 can be computed as in Equation 2.84.

$$\Delta y_3 = \frac{\lambda f}{M \Delta y_2} = \Delta y_1 \tag{2.84}$$

The spatial space sampling intervals in the input plane P_1 and the back focal plane P_3 are equal because the focal lengths of the lenses L_2 and L_4 are equal; but if the focal lengths are not identical then the sampling intervals will not be equal anymore.

2.3.4.2 Applications of the JTC

2.3.4.2.1 Introduction

The joint transform correlator (JTC) is one of the techniques frequently used in the field of optical pattern identification and classification. It plays an important role in object detection, face recognition, fingerprint recognition, and many other areas. In this sub-subsection, the usage of the JTC for object detection and face recognition is fully covered.

2.3.4.2.2 Face Recognition

The joint transform correlator (JTC) is used to recognize an unknown face object based on a database of desired impulses. The database is composed of n, $N \times N$ images of faces (impulses) on black backgrounds such that I_k where $k = 1, \ldots, n$; and n is the total number of the impulses. For decreasing the error rates of face recognition and object detection, all face projections must be defined in the database; impulses must have the same size; impulses must have only faces and they are expanded to the boarders of the images; finally, impulses must have unified backgrounds to discriminate between the pixels occupying the backgrounds and the pixels on the faces. For doing face recognition, an unknown face object have to be picked. It must have the same properties of the impulses. Hence, it must have the same size as the impulses; it has a black background; it has a projection as one of the impulses; and it has only face that is expanded to the boarders of the image. The pixels occupying the faces of the impulses and the unknown face object are normalized in the same manner as the normalization of the pixels occupying the faces of the training faces in Step 2 in Sub-subsection 2.2.2.6.

The cross-correlated field between the unknown face object and each impulse is obtained. An adaptive filtering mask is used to produce the cross-correlated patterns that are centered at $(0, Y)$. The maximum values of the cross-correlated patterns are computed; such that c_1 is the maximum value of the cross-correlated pattern between the unknown face object and the first impulse; similarly, c_n is the maximum value of the cross-correlated pattern between the unknown face object and the n^{th} impulse.

Then recognition can be performed by using Condition 2.4 where bc_k is the biggest cross-correlation among the maximum values of the cross-correlated patterns between the unknown face object and impulses.

Condition 2.4. *If,*

$$bc_k = max\left([c_1, \ldots, c_n]\right), \qquad \text{where } k \text{ can be any number between 1 to } n$$

Then the unknown face object is recognized as the k^{th} *impulse response; otherwise, it is an unknown face object.*

2.3.4.2.2.1 Setting up a Recognition Threshold

Unfortunately, when the unknown face object does not have a similar impulse response then getting the biggest cross-correlation bc_k among the maximum values of the cross-correlated patterns does not *always* mean that the unknown face object is recognized as the k^{th} impulse response. Therefore, a certain threshold must be used to increase the accuracy of recognition.

For setting up a recognition threshold, some different objects are taken for each impulse; consequently, the objects are known here just for picking the threshold. The cross-correlated patterns that are centered at $(0, Y)$ resulting from the cross-correlations between each impulse and its *corresponding* objects are produced. After that, the maximum values of the cross-correlated patterns between the impulses and their *corresponding* objects are obtained; and they are stacked in the row vectors $\boldsymbol{T}_1, \ldots, \boldsymbol{T}_k, \ldots, \boldsymbol{T}_n$, where $\boldsymbol{T}_k$ contains the biggest expected cross-correlations because the k^{th} impulse response and its *corresponding* objects have the same person and the same face position.

Thereafter, the mean m_k and the standard deviation STD_k (the average distance from the mean to a point) are computed for each row vector $\boldsymbol{T}_k$ of the biggest cross-correlations. By calculating the means and the standard deviations, a certain threshold is established for each impulse response.

Then the recognition threshold can be applied to recognize the unknown face object by using Condition 2.5.

Condition 2.5. *If,*

$$m_k - STD_k \leq bc_k \leq m_k + STD_k, \qquad \textit{where } k = 1, \ldots, n$$

Then the unknown face object is recognized as the k^{th} *impulse response; otherwise, it is an unknown face object.*

2.3.4.2.3 Object Detection

The joint transform correlator (JTC) is used to detect if an unknown object contains a face or not based on a determined threshold for detection. Therefore, in object detection, only a detection threshold is needed.

To obtain the detection threshold, objects are generated from the database of the impulses in the same manner as in Sub-sub-sub-subsection 2.3.4.2.2.1. The cross-correlated patterns that are centered at $(0, Y)$ resulting from the cross-correlations between each impulse and all objects are produced. The maximum values of the cross-correlated patterns between the impulses and all objects are computed and placed in the row vector $\boldsymbol{S}$. After that, the mean $m_{\boldsymbol{S}}$ and the standard deviation $STD_{\boldsymbol{S}}$ (the average distance from the mean to a point) are computed for the vector $\boldsymbol{S}$. By calculating the mean and the standard deviation, the detection threshold is established.

For applying the detection threshold, the unknown object $I^{Unknown}$ is picked for detection. The maximum value $c^{Unknown}$ of the cross-correlated pattern between the unknown object and any impulse response is computed. Then the unknown object $I^{Unknown}$ can be detected by means of Condition 2.6.

Condition 2.6. *If,*

$$m_{\boldsymbol{S}} - STD_{\boldsymbol{S}} \leq c^{Unknown} \leq m_{\boldsymbol{S}} + STD_{\boldsymbol{S}}$$

Then the unknown object $I^{Unknown}$ is detected as a face object; otherwise, it is not a face object.

2.3.4.3 Analysis of JTC Performance

2.3.4.3.1 Introduction

Joint transform correlator (JTC) performance is analyzed through analyzing the performance of its applications. In order to study the performance of face recognition and object detection, their error rates are computed and analyzed. Hence, in this sub-subsection, attention is paid for calculating the error rates of face recognition and object detection.

2.3.4.3.2 Analysis of Recognition Performance

The error rate computes the percentage of error in recognition. For computing the error rate of face recognition, let L is the total number of objects; SR is the total number of successes in the recognition of the objects; and FR is the total number of failures in the recognition of the objects. Then the error rate can be computed as in Equation 2.85.

$$ER\,(\%) = \frac{FR}{L} \times 100 \tag{2.85}$$

2.3.4.3.2.1 Improvement of Recognition Performance

The error rate of face recognition is usually big then it has to be improved. One of the techniques for decreasing the error rate is optimizing the database of the impulses. The optimization of the database means trying to find the best combination of impulses that ensures the smallest error rate.

Some different objects are taken for each impulse response; consequently, the objects are known here just for optimizing the database of the impulses. Then this technique can be simulated by trying different combinations out of the generated objects until finding a combination that produces the lowest error rate of face recognition then the combination can be used to form the database of the impulses.

2.3.4.3.3 Analysis of Detection Performance

The error rate computes the percentage of error in detection. For computing the error rate of object detection, let L is the total number of objects; SD is the total number of successes in the detection of the objects; and FD is the total number of failures in the detection of the objects. Then the error rate can be computed as in Equation 2.86.

$$ER\,(\%) = \frac{FD}{L} \times 100 \tag{2.86}$$

2.3.4.3.3.1 Improvement of Detection Performance

The error rate of object detection is usually big then it has to be improved. The error rate is improved by optimizing the database of the impulses in the same manner as the optimization of the error rate of face recognition in Sub-sub-sub-subsection 2.3.4.3.2.1.

Chapter 3

Modelling

3.1 Digital Modelling

3.1.1 Introduction

In this section, PCA and IPCA algorithms are simulated by using the MATLAB © software when the data set is composed of images; as well as comparison between two algorithms is illustrated. The simulation begins from generating the database of the training faces until projecting the training faces on the eigenspace. The applications of the PCA and IPCA algorithms are simulated too. The complete MATLAB © code that had been written to simulate this work is shown in Appendix A.

3.1.2 Application of the PCA Algorithm to Images

The steps for analyzing the PCA algorithm to images presented in Sub-subsection 2.2.2.6 are simulated as follows:

Step 1: the database is created to be composed of nine, 50×50 images of faces (training faces) on black backgrounds such that I_k where $k = 1, \ldots, 9$. The training faces are taken for three people where each person has three training faces with different projections as shown in Figure 3.1.

Step 2: the average histogram for all training faces is obtained as in Figure 3.2. From Figure 3.2, it turns out all intensity levels below the threshold represent the backgrounds of images because these levels have the biggest histogram; and all intensity levels above the threshold represent the faces; therefore, the threshold is equal to eight. The threshold is applied on the training faces; Figure 3.3 shows how good the applied threshold is on the training faces. As seen from Figure 3.3, the applied

Figure 3.1: The database of the training faces.

threshold is doing pretty well; and it can be used for normalizing the training faces as in Figure 3.4.

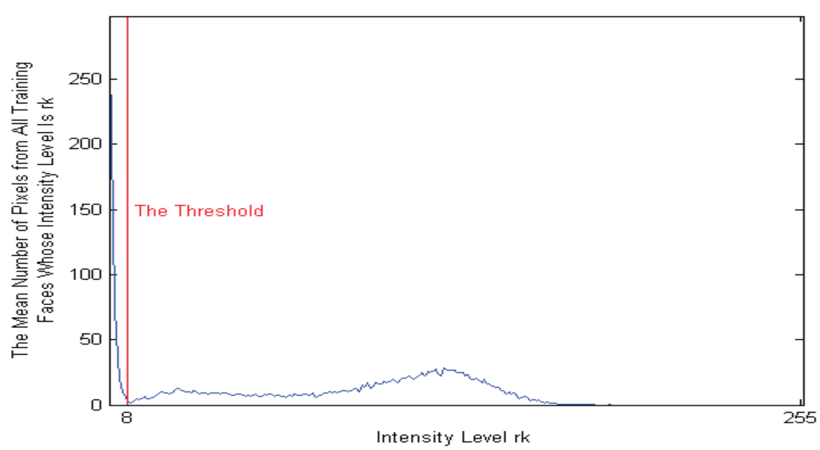

Figure 3.2: The average histogram for all training faces.

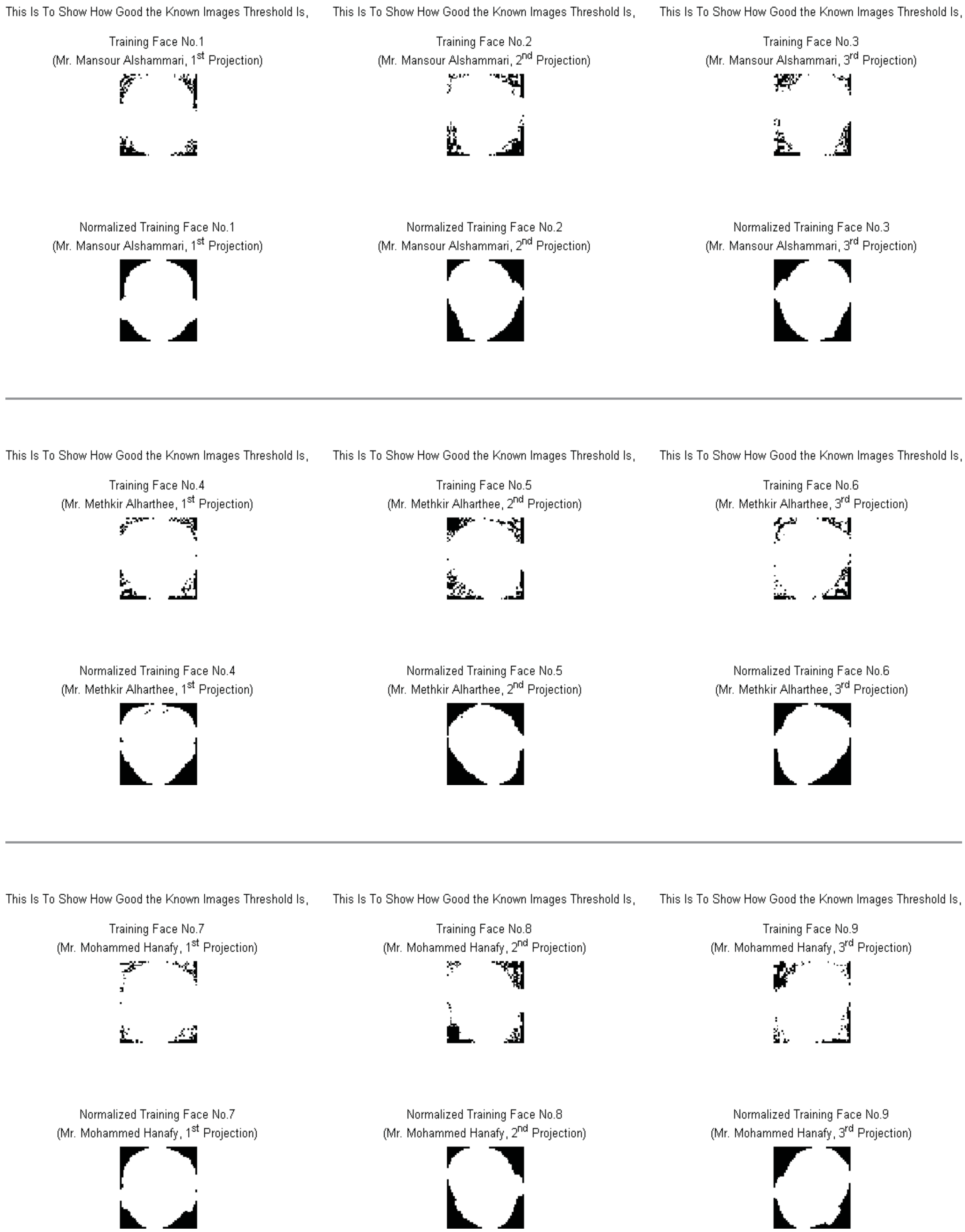

Figure 3.3: The application of the threshold on the training faces.

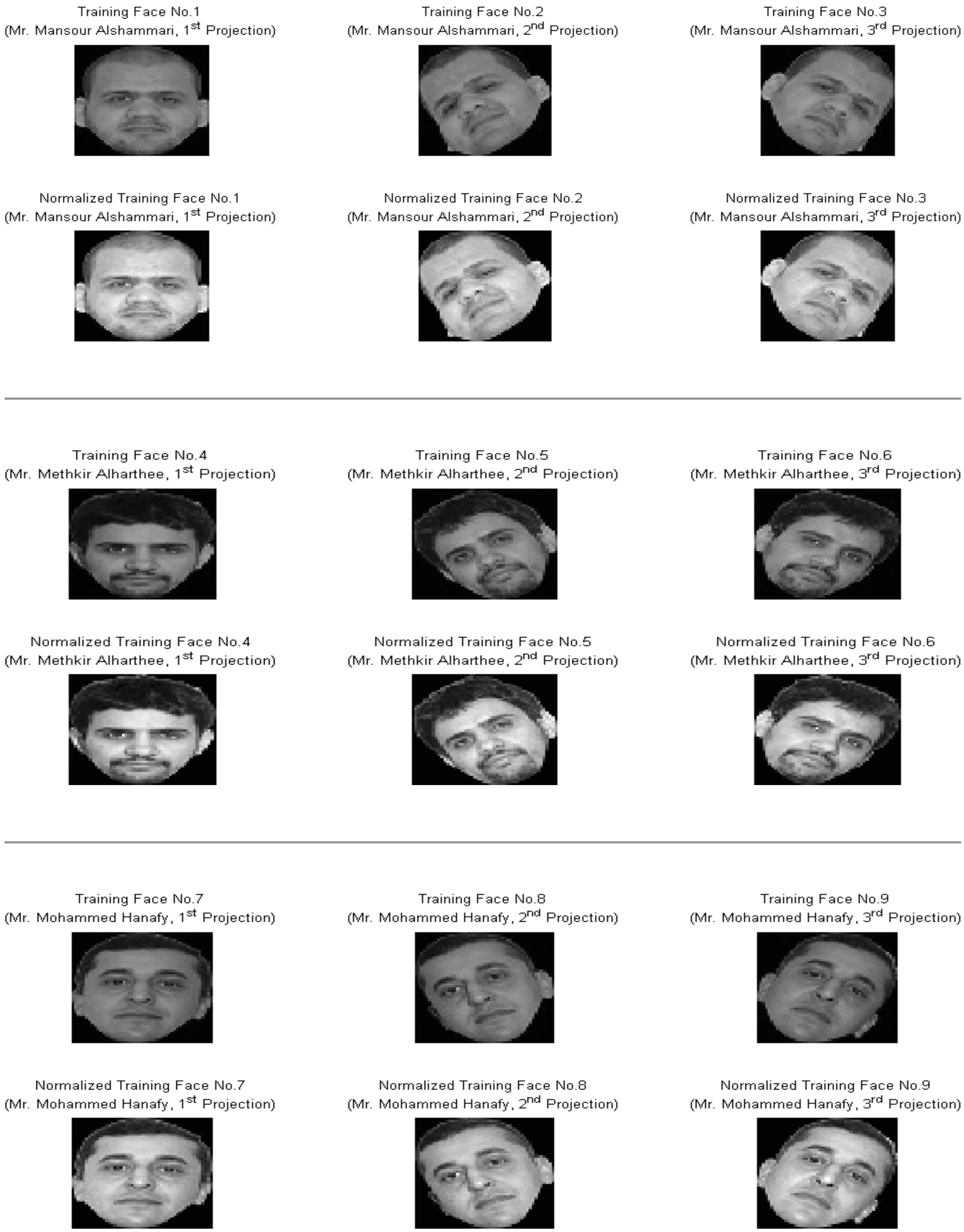

Figure 3.4: The normalization of all training faces by means of the selected threshold.

Step 3: all training faces are centered as shown in Figure 3.5.

Figure 3.5: The centered training faces.

Step 4: all centered training faces are represented as 50^2 column vectors.

Step 5: The average training face vector $\mathbf{\Psi}$ is computed and the average training face is shown in Figure 3.6.

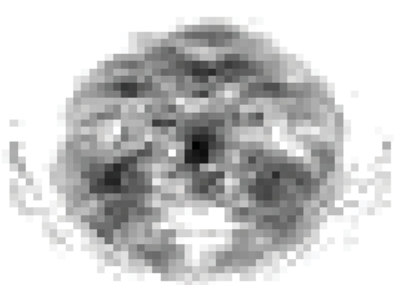

Figure 3.6: The average training face. Note that, this is a negative image.

Step 6: the set of the training faces is centered; and the centered (with respect to the set of the training faces) training faces are presented in Figure 3.7.

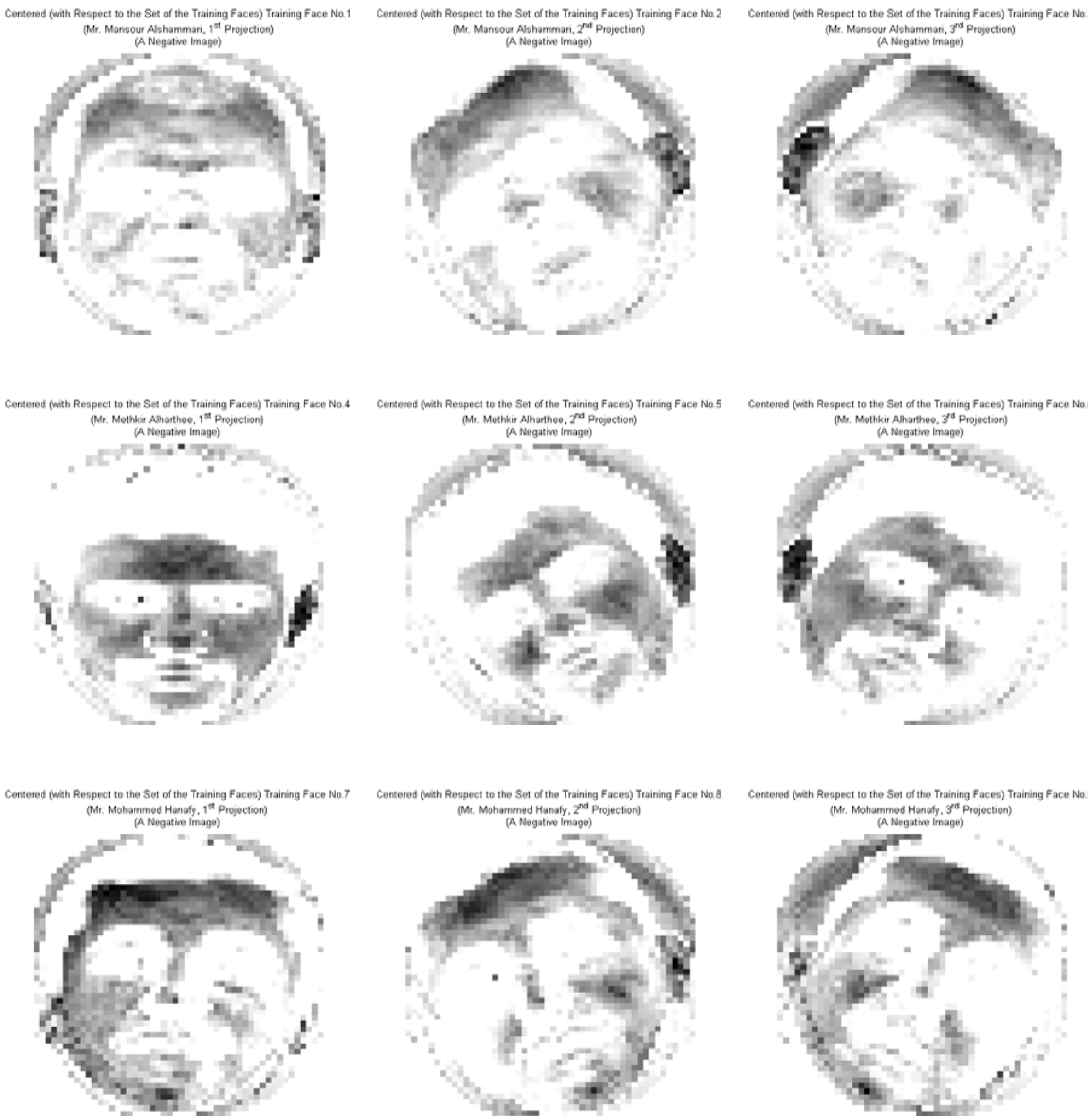

Figure 3.7: The centered (with respect to the set of the training faces) training faces. Note that, these are negative images.

Step 7: a 2500×2500 covariance matrix for all training faces is calculated.

Step 8: the eigenvectors and eigenvalues of the covariance matrix C are computed.

Step 9: for choosing principal components and forming the feature vector matrix A_q, the variance contribution rate (VCR) and the total variance contribution rate (TVC) are computed in Table 3.1. When the TVC is over 95.5% then q eigenvectors associated with the biggest q eigenvalues are selected. Hence, Based on Table 3.1, the biggest eight eigenvectors associated with the biggest eigenvalues are selected to form the feature vector matrix. The selected eigenfaces (the highly correlated eigenvectors) are shown in Figure 3.8.

Table 3.1: The calculations of the VCR and TVC.

$\boldsymbol{k}$	$\boldsymbol{\lambda_k}$	$\boldsymbol{VCR_k}$ (%)	$\boldsymbol{TVC}$ (%)
1	9732585.1016	29.0361	29.0361
2	6578765.9806	19.6270	48.6631
3	4576184.9630	13.6525	62.3157
4	4054857.8169	12.0972	74.4129
5	3000248.2414	8.9509	83.3638
6	2204809.6081	6.5778	89.9416
7	1816000.6101	5.4178	95.3595
8	1555452.9118	4.6405	100
9	0	0	100

Step 10: the principal components transform is performed and the training faces are projected on the eigenspace.

3.1.3 Application of the IPCA Algorithm to Images

The IPCA algorithm shown in Sub-subsection 2.2.3.2 is used for calculating the IR and AIR for the computed eigenvectors of the covariance matrix C in Subsection 3.1.2 where d here is equal to the total number of the training faces n; and the results are shown in Table 3.2. When the AIR is over 95.5% then q eigenvectors associated with the biggest q eigenvalues are selected. Hence, Based on Table 3.2, the biggest seven eigenvectors associated with the biggest eigenvalues are selected to form the feature vector matrix A_q. The selected eigenfaces (the highly correlated eigenvectors) are the first seven selected eigenfaces by using the PCA algorithm shown in Figure 3.8.

Figure 3.8: The eigenfaces. Note that, these are negative images.

3.1.4 Comparison of the PCA and IPCA Algorithms

Comparison between the PCA and IPCA algorithms is based on the values of the TVC and AIR that determine the selected eigenfaces for the feature vector matrix A_q in Subsection 3.1.2, Step 9 and in Subsection 3.1.3.

When $k = 7$ in Table 3.2, the AIR is equal to 95.6891% which is bigger than 95.5% but the TVC is slightly small; consequently, if the eigenvectors are selected

Table 3.2: The calculations of the IR and AIR.

k	λ_k	ρ_k	$I(\lambda_k)$	IR_k (%)	AIR (%)
1	9732585.1016	0.7096	0.4948	31.1180	31.1180
2	6578765.9806	0.8037	0.3152	19.8224	50.9404
3	4576184.9630	0.8635	0.2118	13.3174	64.2578
4	4054857.8169	0.8790	0.1860	11.6978	75.9555
5	3000248.2414	0.9105	0.1353	8.5073	84.4628
6	2204809.6081	0.9342	0.0982	6.1729	90.6357
7	1816000.6101	0.9458	0.0804	5.0534	95.6891
8	1555452.9118	0.9536	0.0686	4.3109	100
9	0	1	0	0	100

based on the TVC then the first eight eigenvectors must be taken in order to make sure that the TVC is big enough. Therefore, the AIR tells us more about the information contained in the eigenfaces. Figure 3.9 shows a comparison between the biggest calculated eigenvalues by using the PCA and IPCA algorithms as well as the calculated eigenvalues from the covariance matrix C for all training faces.

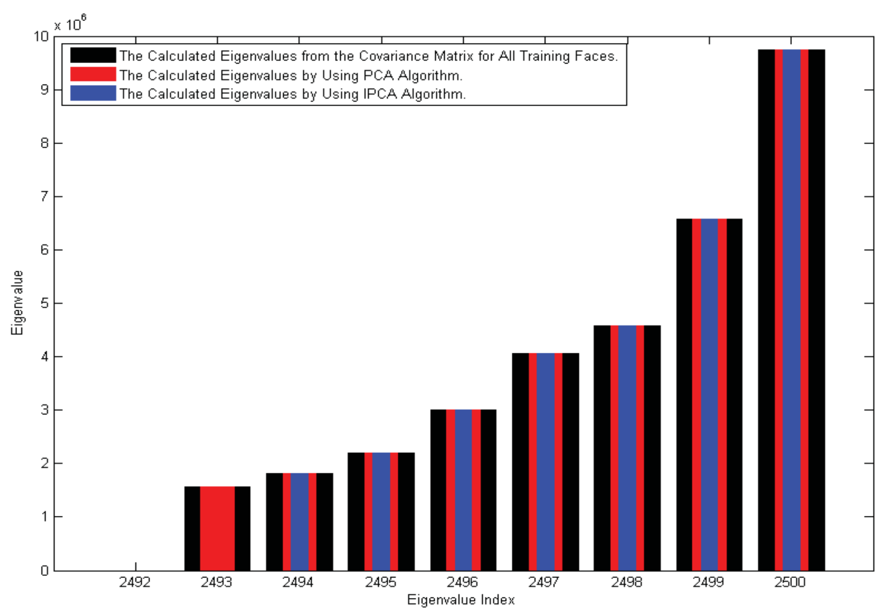

Figure 3.9: A comparison between the biggest calculated eigenvalues by using the PCA and IPCA algorithms as well as the calculated eigenvalues from the covariance matrix for all training faces.

3.1.5 Image Compression

In image compression modelling, the training faces in Figure 3.1 are projected on the eigenspace and recostructed again by using the PCA and IPCA algorithms; as well as by using different selected eigenfaces to form the feature vector matrix A_q.

3.1.6 Face Recognition

The database of the training faces created in Step 1 in Subsection 3.1.2 is used for recognition. Some tested images are taken out of the database for setting up a recognition threshold. Thirty-six tested images are taken for the first projection of each person; twelve tested images are taken for the second projection of each person; and twelve tested images are taken for third projection of each person; therefore, the total number of the tested images is equal to 180. Some samples of the tested images are shown in Figure 3.10; the full database of the tested images is shown in Appendix B.

By using the PCA algorithm, a recognition threshold is specified for each training face by means of the method explained in Sub-sub-subsection 2.2.5.3.1. The tested images are processed as unknown images of faces as illustrated in Sub-subsection 2.2.5.3. Then Condition 2.2 is used for recognizing the tested images. The recognition results of the tested images in Figure 3.10 by using the PCA algorithm are presented in Table 3.3. The recognition of all 180 tested images by using the PCA algorithm is shown in Appendix C. Finally, the tested images can be recognized in the same way when the IPCA algorithm is used; or different eigenfaces are selected to form the feature vector matrix.

Table 3.3: The recognition of the tested images in Figure 3.10.

Tested Image No.	Input Face	Recognized Output Face	Status
4	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
15	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
38	Mr. Mansour Alshammari	Unknown Image	Failure
62	Mr. Methkir Alharthee	Unknown Image	Failure
72	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
120	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
124	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
160	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
179	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success

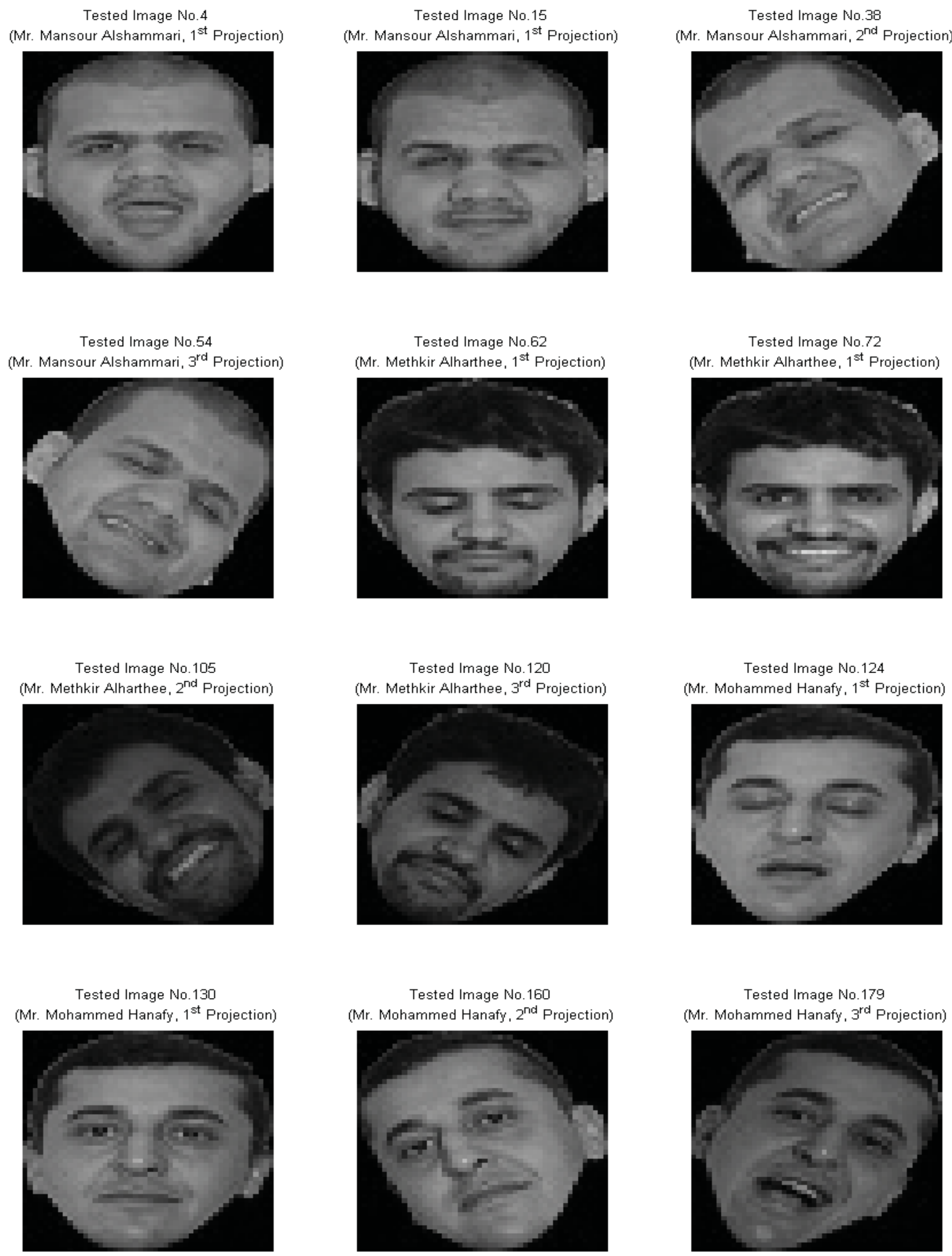

Figure 3.10: Some samples of the tested images.

3.1.7 Image Detection

The generated database of the tested images in Subsection 3.1.6 is used for detection. By using the PCA algorithm, a detection threshold is specified by means of the method explained in Sub-subsection 2.2.5.4. Then Condition 2.3 is used for detecting the tested images. The detection results of the tested images in Figure 3.10 by using the PCA algorithm are presented in Table 3.4. The detection of all 180 tested images by using the PCA algorithm is shown in Appendix D. Finally, the tested images can be detected in the same way when the IPCA algorithm is used; or different eigenfaces are selected to form the feature vector matrix.

Table 3.4: The detection of the tested images in Figure 3.10.

Tested Image No.	Input Image	Detected Output Image	Status
4	a face	a face	Success
15	a face	a face	Success
38	a face	not a face	Failure
62	a face	a face	Success
72	a face	a face	Success
120	a face	not a face	Failure
124	a face	a face	Success
160	a face	a face	Success
179	a face	a face	Success

3.2 Optical Modelling

3.2.1 Introduction

In this section, the joint transform correlator (JTC) is fully simulated by using the MATLAB © software. The simulation begins from scratch until generating the desired pattern of the cross-correlated field in the back focal plane P_3 by using an adaptive filtering mask designed for that. The JTC applications are simulated too. The complete MATLAB © code that had been written to simulate this work is shown in Appendix F.

In the simulation, lenses are assumed to be ideally focused (i.e. the model is an aberration-free system) as in Figure 3.11; where f in the figure is the focal length.

3.2.2 Simulation of the JTC

We are at level that we can start in simulating the joint transform correlator (JTC). The desired impulse response h and the data g (here it is called the object) are 100×100 images of faces for two people. They are respectively shown in Figure 3.12 and Figure 3.13. The impulse response and the object are normalized in order to remove lighting effects on them then increasing the accuracy of cross-correlation. To

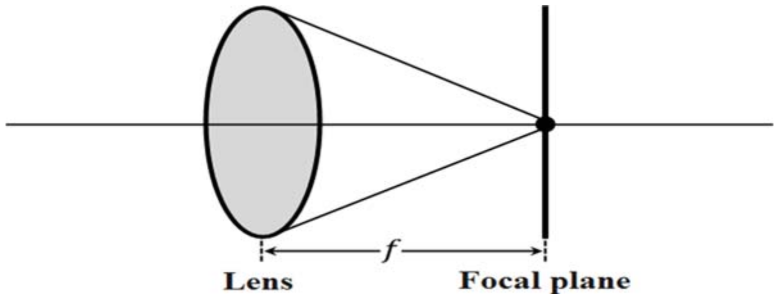

Figure 3.11: A focused lens.

keep variations among them just in the faces without the effects of the backgrounds, the normalization is performed on the pixels occupying the faces in the same manner as the normalization of the pixels on the faces of the training faces in Step 2 in Sub-subsection 2.2.2.6.

Figure 3.12: The desired impulse response h.

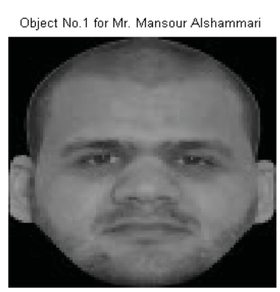

Figure 3.13: The object g.

The transparencies of the impulse response h and the object g are located in a square array in the input plane P_1. The width W_g of g in the direction of the y-coordinate is 100 pixels; the width W_h of h in the direction of the y-coordinate is 100 pixels; then the distance Y that separates the centers of h and g is equal to 200 pixels. The constant c is selected to be 10 pixels then Relation 2.1 is satisfied. The distance D obtained in Equation 2.66 is 130 pixels; the distance r_1 obtained in Equation 2.67 is 155 pixels; the distance r_2 obtained in Equation 2.68 is 155 pixels; $D - r_1$ and $D - r_2$ are respectively equal to 155 pixels and 155 pixels; then the distances d_1 and d_2 obtained respectively in Equation 2.71 and Equation 2.72 are respectively equal to 310 pixels and 310 pixels. Since the distance d_1 is equal to the distance D as well as the distance d_2 is also equal to the distance D then the input transparencies of h and g are aligned properly in the input plane P_1.

The number of samples N along the spatial space coordinate x_1 in the input plane P_1 is 630; and the number of samples M along the spatial space coordinate y_1 is 630. The physical side length L_{x_1} of the array in the x_1 direction is $10\,(m)$; and the physical side length L_{y_1} of the array in the y_1 direction is $10\,(m)$. Then the sample spacing Δx_1 along the x_1-coordinate is equal to $\frac{10}{630} = 0.0159\,(m)$; and the sample spacing Δy_1 along the y_1-coordinate is equal to $\frac{10}{630} = 0.0159\,(m)$. The transmitted field $U_1\,(x_1, y_1)$ from the input plane P_1 is shown in Figure 3.14.

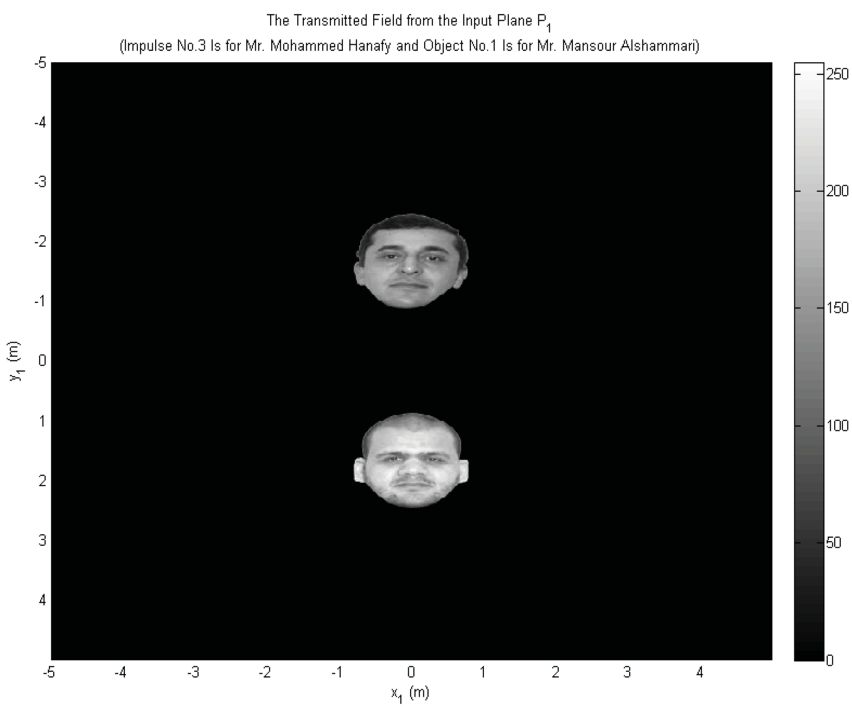

Figure 3.14: The transmitted field $U_1\,(x_1, y_1)$ from the input plane P_1.

The light wavelength λ is $550 \times 10^{-9}\,(m)$; and the focal length f is $0.055\,(m)$. Then the spatial space sampling interval Δx_2 along the spatial space coordinate x_2 is equal to $\frac{\lambda f}{N \Delta x_1} = \frac{550 \times 10^{-9} \times 0.055}{630 \times 0.0159} = 3.0250 \times 10^{-9}\,(m)$; similarly, the spatial space sampling interval Δy_2 along the spatial space coordinate y_2 is equal to $\frac{\lambda f}{M \Delta y_1} = \frac{550 \times 10^{-9} \times 0.055}{630 \times 0.0159} = 3.0250 \times 10^{-9}\,(m)$. The incident intensity $I\,(x_2, y_2)$ on the back focal plane P_2 is shown in Figure 3.15.

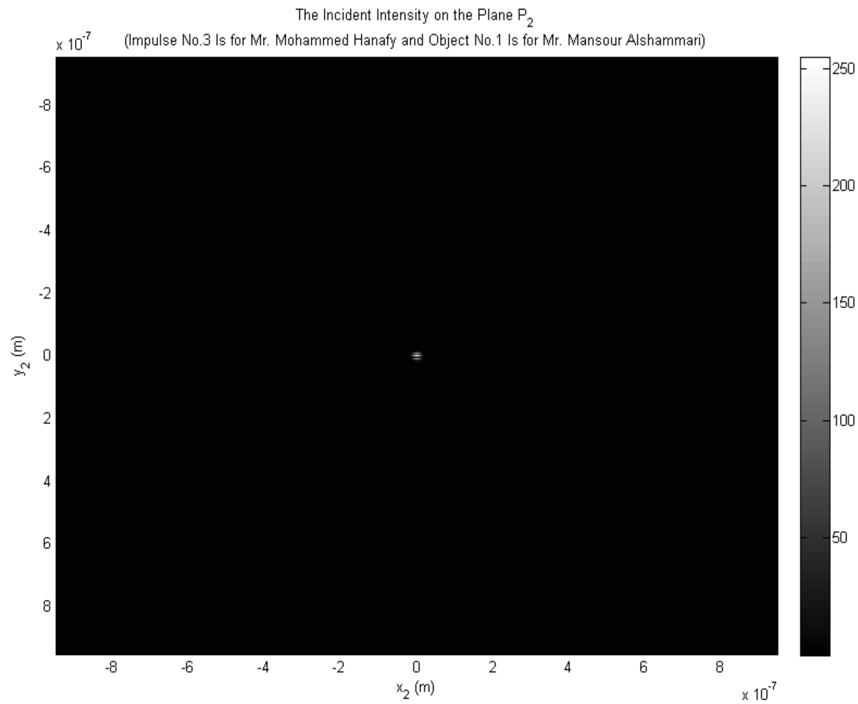

Figure 3.15: The incident intensity $I\,(x_2, y_2)$ on the back focal plane P_2.

Since the focal lengths of the lenses L_2 and L_4 are equal, the spatial space sampling intervals Δx_3 and Δy_3 in the back focal plane P_3 are respectively equal to the spatial space sampling intervals Δx_1 and Δy_1 in the input plane P_1. The cross-correlated field $U_3\,(x_3, y_3)$ in the back focal plane P_3 is obtained as in Figure 3.16 by calculating the inverse Fourier transform for the incident intensity $I\,(x_2, y_2)$ on the back focal plane P_2.

Figure 3.17 shows the designed adaptive mask for obtaining the desired pattern of the cross-correlations of the impulse response h and the object g in the back focal plane P_3. The mask produces the cross-correlated pattern that is centered at $(0, Y)$. It is multiplied by the cross-correlated field in the plane P_3 in order to obtain the filtered filed as in Figure 3.18.

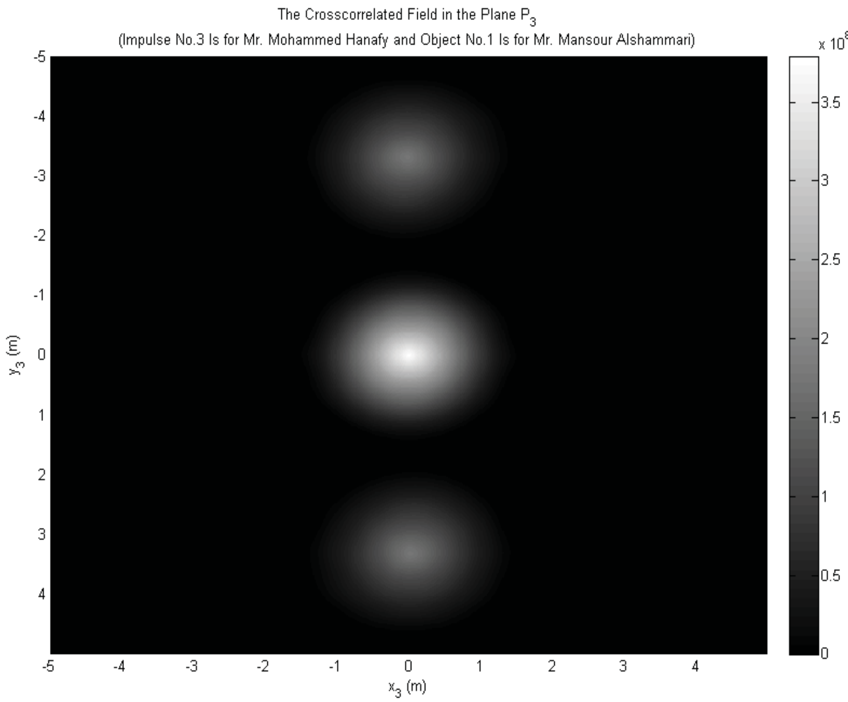

Figure 3.16: The cross-correlated field $U_3(x_3, y_3)$ in the back focal plane P_3.

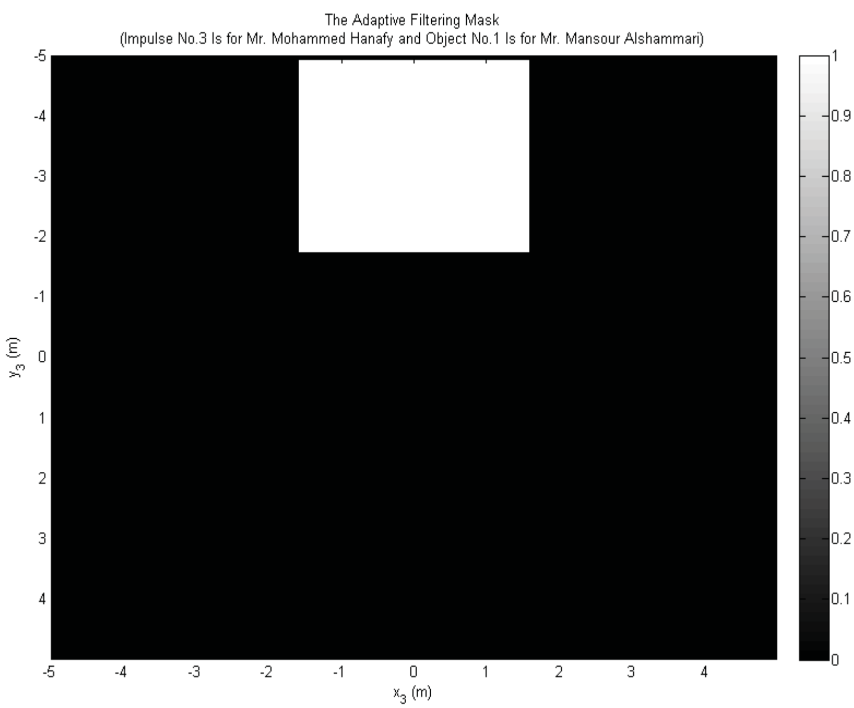

Figure 3.17: The adaptive filtering mask.

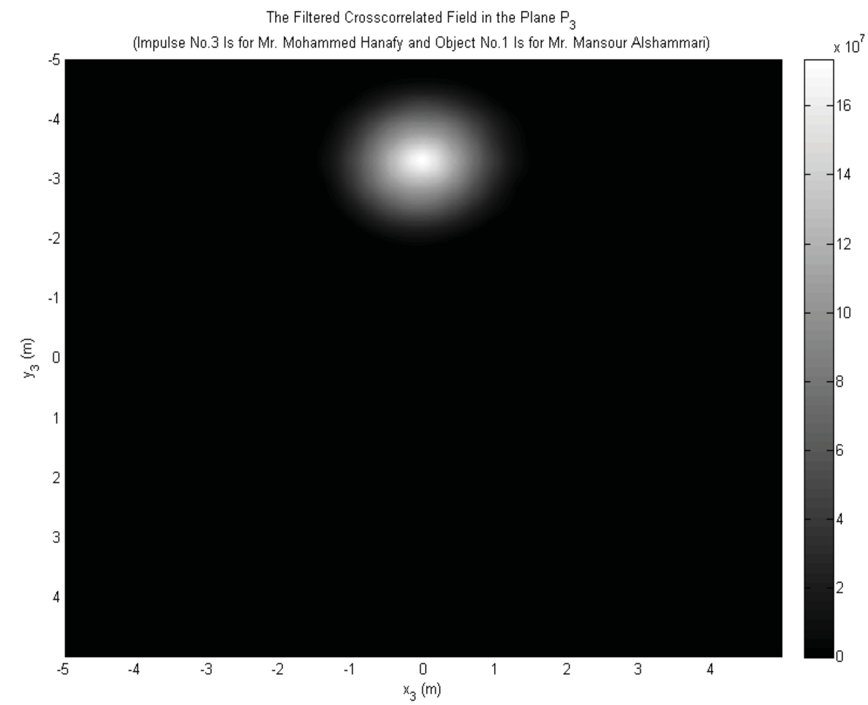

Figure 3.18: The filtered cross-correlated field in the back focal plane P_3.

3.2.3 Face Recognition

The database of the impulses for face recognition is picked to contain three, 100×100 impulses (images of faces) on black backgrounds. The impulses are taken for vertical faces to people's shoulders where oblique faces are ignored as shown in Figure 3.19. Taking just vertical faces will simplify the optimization of the database of the impulses. Some objects are taken out of the database for setting up a recognition threshold. Thirty-six objects are taken for each impulse then the total number of the objects is equal to 108. Some samples of the objects are shown in Figure 3.20; the full database of the objects is shown in Appendix A.

A recognition threshold is specified for each impulse by means of the method explained in Sub-sub-sub-subsection 2.3.4.2.2.1. The objects are processed as unknown images of faces as illustrated in Sub-sub-subsection 2.3.4.2.2. Then Condition 2.5 is used for recognizing the objects. The recognition results of the objects in Figure 3.20 are presented in Table 3.5. The recognition of all 108 objects is shown in Appendix G.

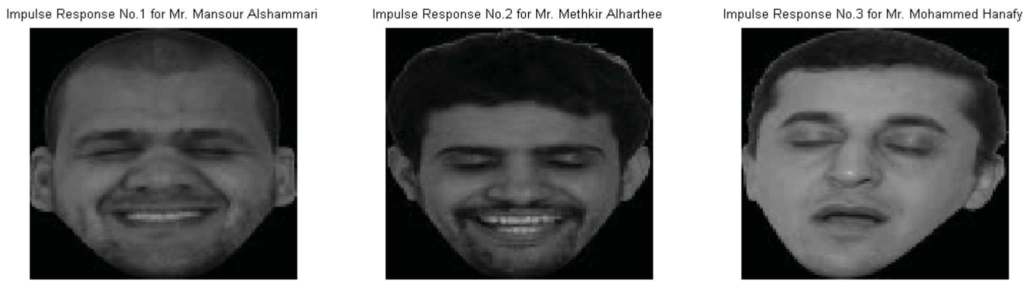

Figure 3.19: The database of the impulses.

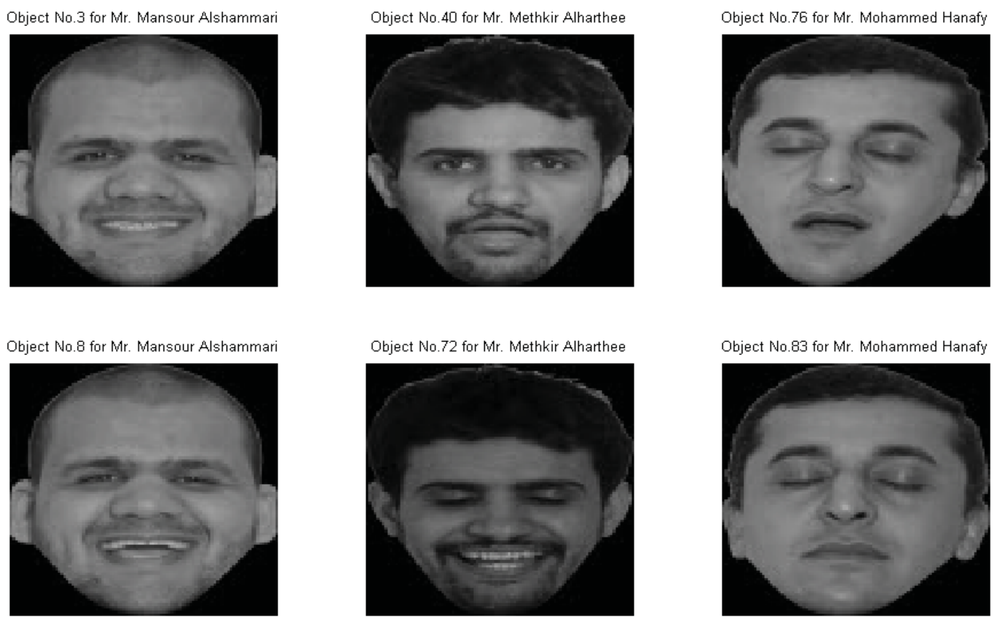

Figure 3.20: Some samples of the objects.

Table 3.5: The recognition of the objects in Figure 3.20.

Object No.	Input Face	Recognized Output Face	Status
3	Mr. Mansour Alshammari	Unknown Object	Failure
8	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
40	Mr. Methkir Alharthee	Unknown Object	Failure
72	Mr. Methkir Alharthee	Unknown Object	Failure
76	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
83	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success

3.2.4 Object Detection

The database of the generated objects in Subsection 3.2.3 is used for detection. A detection threshold is specified by means of the method explained in Sub-sub-subsection 2.3.4.2.3. Then Condition 2.6 is used for detecting the objects. The detection results of the objects in Figure 3.20 are presented in Table 3.6. The detection of all 108 objects is shown in Appendix H.

Table 3.6: The detection of the objects in Figure 3.20.

Object No.	Input Object	Detected Output Object	Status
3	a face	not a face	Failure
8	a face	not a face	Failure
40	a face	a face	Success
72	a face	not a face	Failure
76	a face	a face	Success
83	a face	not a face	Failure

Chapter 4

Results of Performance Analysis

4.1 Performance Results of the PCA and IPCA Algorithms

4.1.1 Introduction

After modelling the applications of the PCA and IPCA algorithms, the performance results for each application are obtained in this subsection. The results show the behavior of each application when the eigenfaces that are generated by using the PCA algorithm are used; the eigenfaces that are generated by using the IPCA algorithm are used; and when different eigenfaces are selected to form the feature vector matrix.

4.1.2 Results of Compression Performance

4.1.2.1 Speed of Compression and Reconstruction

When a small number of the eigenfaces is used to project and reconstruct the training faces then the processing speed will increase and vice versa. Therefore, the IPCA algorithm is the fastest one; then the PCA algorithm comes second; finally, the smallest processing speed occurs when all calculated eigenvectors from the covariance matrix for all training faces are used as eigenfaces.

4.1.2.2 Quality of a Reconstructed Image

When a small number of the eigenfaces is used to project and reconstruct the training faces then the training faces will have bad quality. Therefore, the highest error in reconstruction occurs when the IPCA algorithm is used; then the PCA algorithm comes second; finally, the usage of all eigenvectors as eigenfaces produces the samllest reconstruction error.

For measuring the quality of the reconstructed training faces, Equation 2.46 is used for computing the mean squared errors (MSEs) between the training faces and their reconstructions. Figure 4.1 shows the plot of the MSEs of reconstructing training face number five for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used. The plots of the MSEs of reconstructing other training faces are shown in Appendix I. Figure 4.2 shows the reconstruction of training face number five by using the highest correlated eigenface ($q = 1$), the PCA eigenfaces ($q = 8$), the IPCA eigenfaces ($q = 7$), and all eigenvectors as eigenfaces ($q = 2500$); along with mean squared errors resulted from reconstructing the training face by using those eigenfaces.

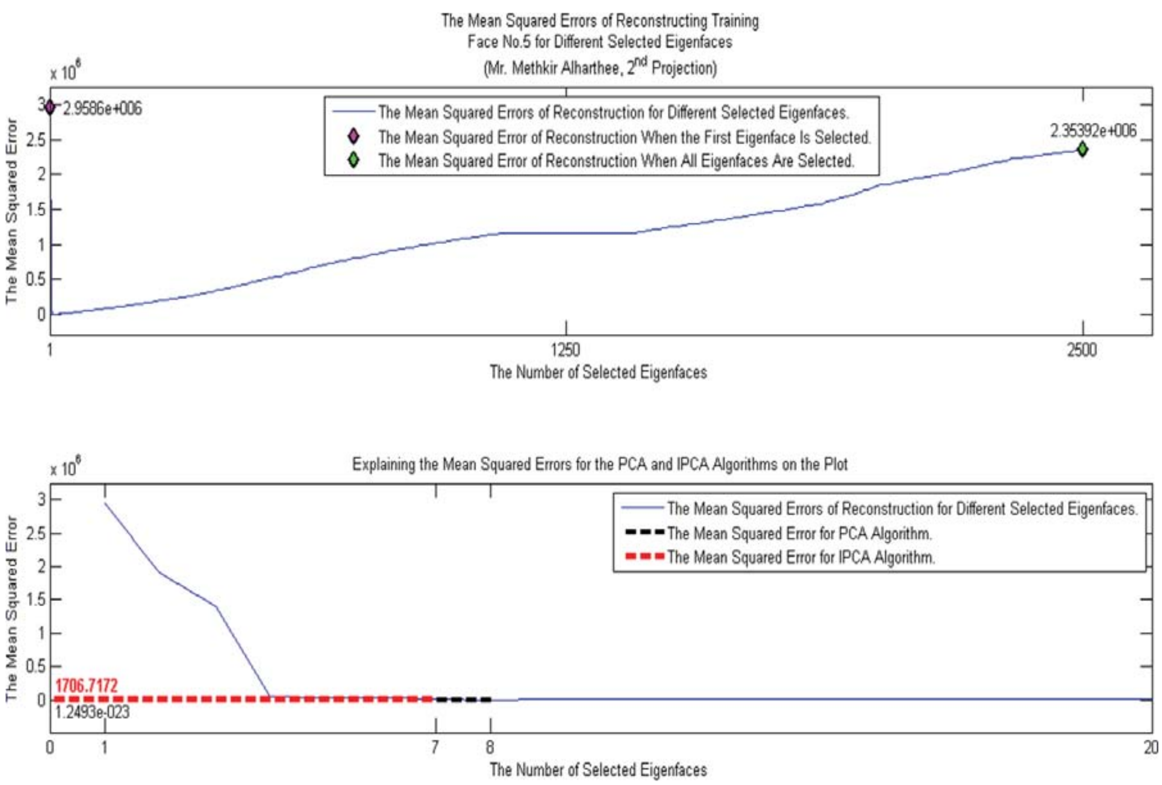

Figure 4.1: The plot of the mean squared errors (MSEs) of reconstructing training face number five for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

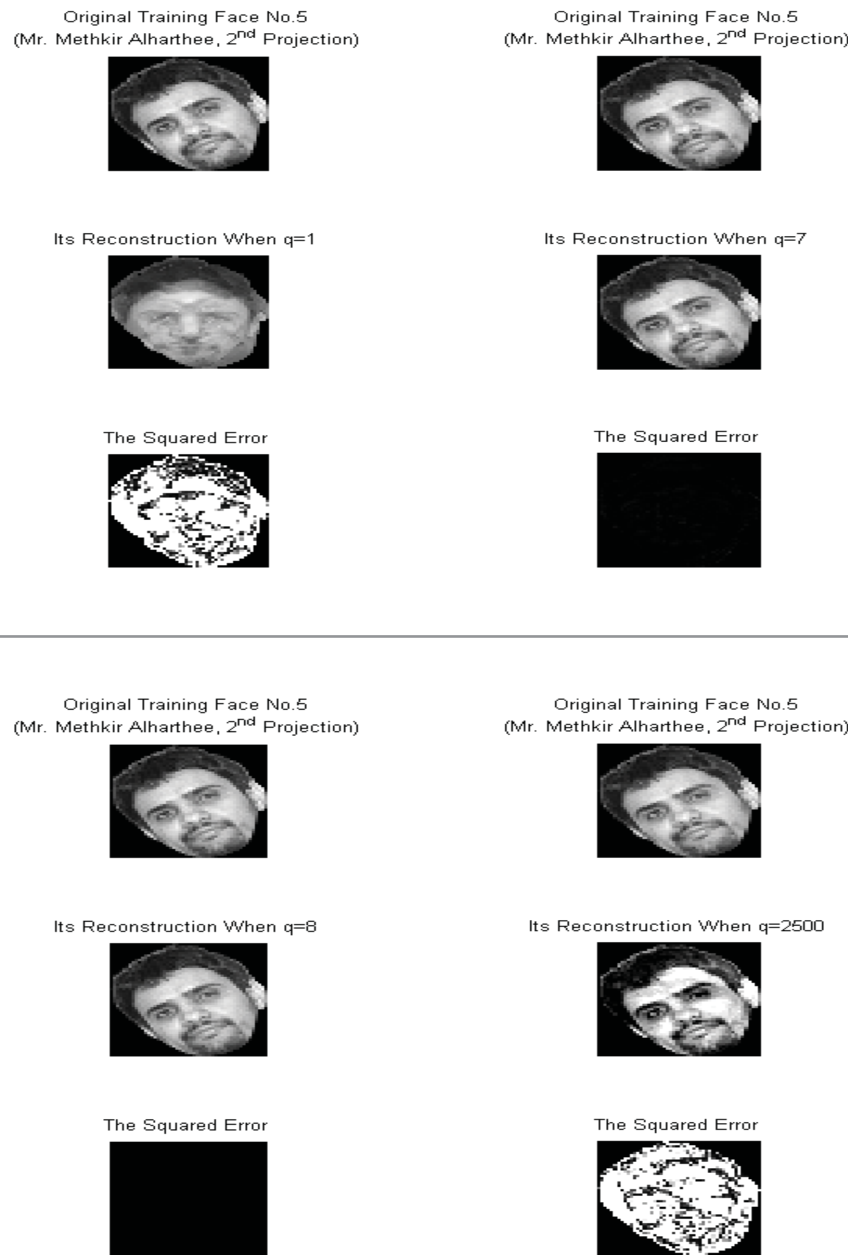

Figure 4.2: The reconstruction of training face number five by using the highest correlated eigenface ($q = 1$), the PCA eigenfaces ($q = 8$), the IPCA eigenfaces ($q = 7$), and all eigenvectors as eigenfaces ($q = 2500$); along with mean squared errors resulted from reconstructing the training face by using those eigenfaces.

From Figure 4.1 and Figure 4.2, it can be noticed that when all eigenvectors are used as eigenfaces then the reconstructed training faces have the worst resolution; that because the covariance matrix is too big then the calculation of 2500 eigenvectors by using the MATLAB © software leads to some round-off errors in the eigenvectors associated with the smallest eigenvalues. Hence, it is not recommended to select the lowest correlated eigenvectors for reconstructing training faces due to they add some noise to the reconstructed training faces. In addition, due to round-off error, the MATLAB © software makes the smallest eigenvalues negative while they must be positive because they are calculated from a positive definite covariance matrix. Those negative eigenvectors must be set to zero.

4.1.2.3 Size of Compression

4.1.2.3.1 Information Rate

Obviously, from Equation 2.47, an information rate depends on the number of the selected eigenfaces q. Note that, when all eigenvectors are picked to form the feature vector matrix then there will not be any compression; and the overall size when there is no any compression method is used will be the optimum one. Consequently, when the number of the selected eigenfaces decreases then an information rate will decrease (i.e. compression will increase) and vice versa. Therefore, the IPCA algorithm offers the highest compression with the highest loss of information; after that, when the PCA algorithm is used, there will not be information lost (i.e. there is no compression); lastly, the usage of all eigenvectors as eigenfaces add some information (i.e. there is no compression).

For measuring how much information is after compression compared with information before compression, Equation 2.47 is used. Figure 4.3 shows the rates of information for different selected eigenfaces compared with resulted information rates when the PCA and IPCA algorithms are used.

4.1.2.3.2 Mean Squared Error (MSE) of Compressed Images

Lost information increases when a small number of eigenfaces is picked and vice versa. Therefore, the IPCA algorithm offers the highest compression with the highest error; then the PCA algorithm comes second; lastly, the usage of all eigenvectors as eigenfaces produce the lowest compression with the lowest error.

Equation 2.54 is used for computing the mean squared error (MSE) of compression. Figure 4.4 shows the mean squared errors (MSEs) of compression for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

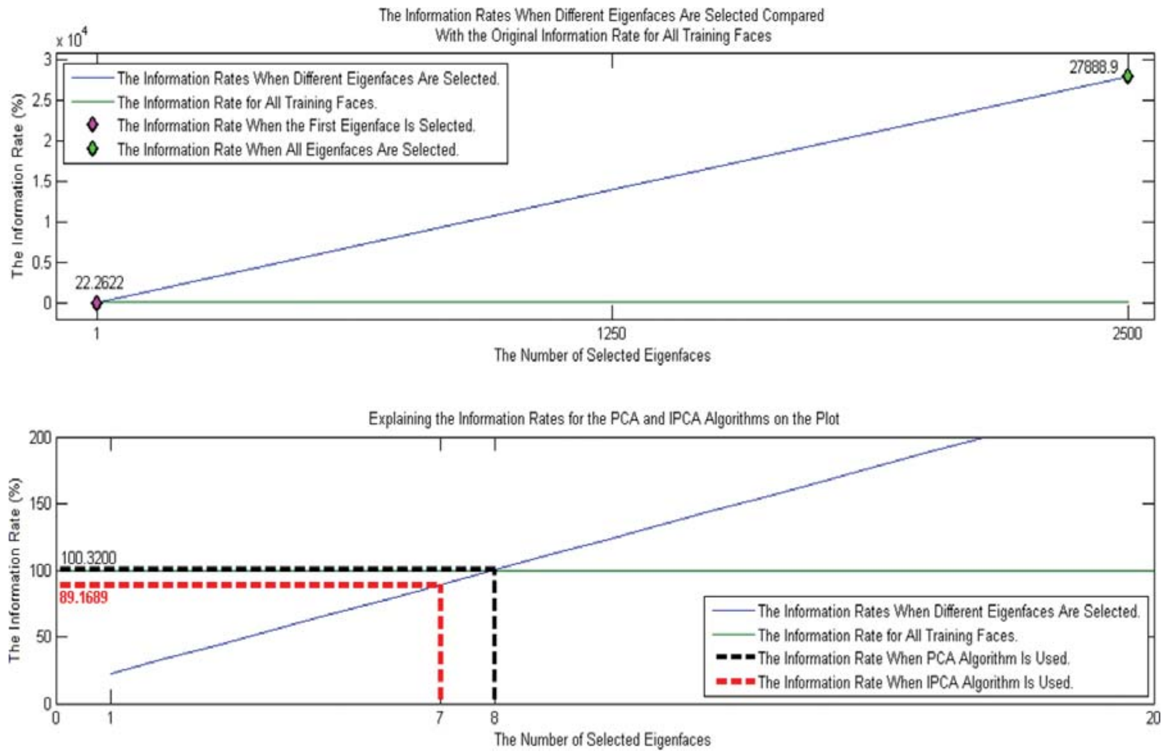

Figure 4.3: The rates of information for different selected eigenfaces compared with resulted information rates when the PCA and IPCA algorithms are used.

4.1.3 Results of Recognition Performance

4.1.3.1 Speed of Recognition

When the number of the selected eigenfaces decreases, the processing speed increases and vice versa. Therefore, the usage of all calculated eigenvectors as eigenfaces leads to the biggest processing time; then the usage of the calculated eigenfaces by using the PCA algorithm comes second; finally, the usage of the calculated eigenfaces by using the IPCA algorithm leads to the smallest processing time.

4.1.3.2 Error Rate

When the number of the selected eigenfaces increases, the error rate decreases; that because the unknown face image will be projected precisely next to its corresponding training face. On the other hand, when the selected eigenfaces decreases, the error rate increases. Therefore, the usage of all calculated eigenvectors as eigenfaces leads to the smallest error rate; then the usage of the calculated eigenfaces by using the PCA algorithm comes second; finally, the usage of the calculated eigenfaces by using

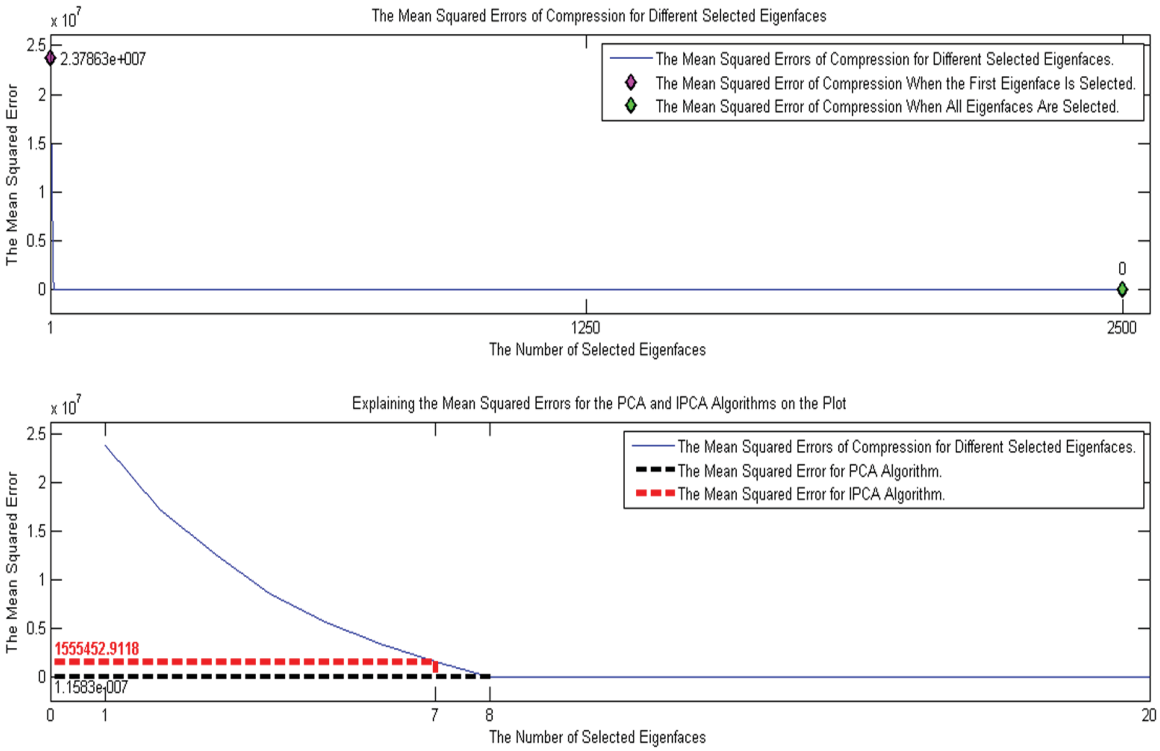

Figure 4.4: The mean squared errors (MSEs) of compression for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

the IPCA algorithm leads to the biggest error rate.

In the recognition of all 180 tested images in Subsection 3.1.6, $L = 180$; $SR = 133$; and $FR = 47$. Then by using Equation 2.55, the error rate $ER(\%)$ is equal to $\frac{47}{180} \times 100 = 26.1111\%$. Figure 4.5 shows the error rates of recognition for different selected eigenfaces compared with resulted error rates when the PCA and IPCA algorithms are used.

4.1.4 Results of Detection Performance

4.1.4.1 Speed of Detection

When the number of the selected eigenfaces decreases, the processing speed increases and vice versa. Therefore, the IPCA algorithm is the fastest one; then the PCA algorithm comes second; finally, the smallest processing speed occurs when all calculated eigenvectors from the covariance matrix for all training faces are used as eigenfaces.

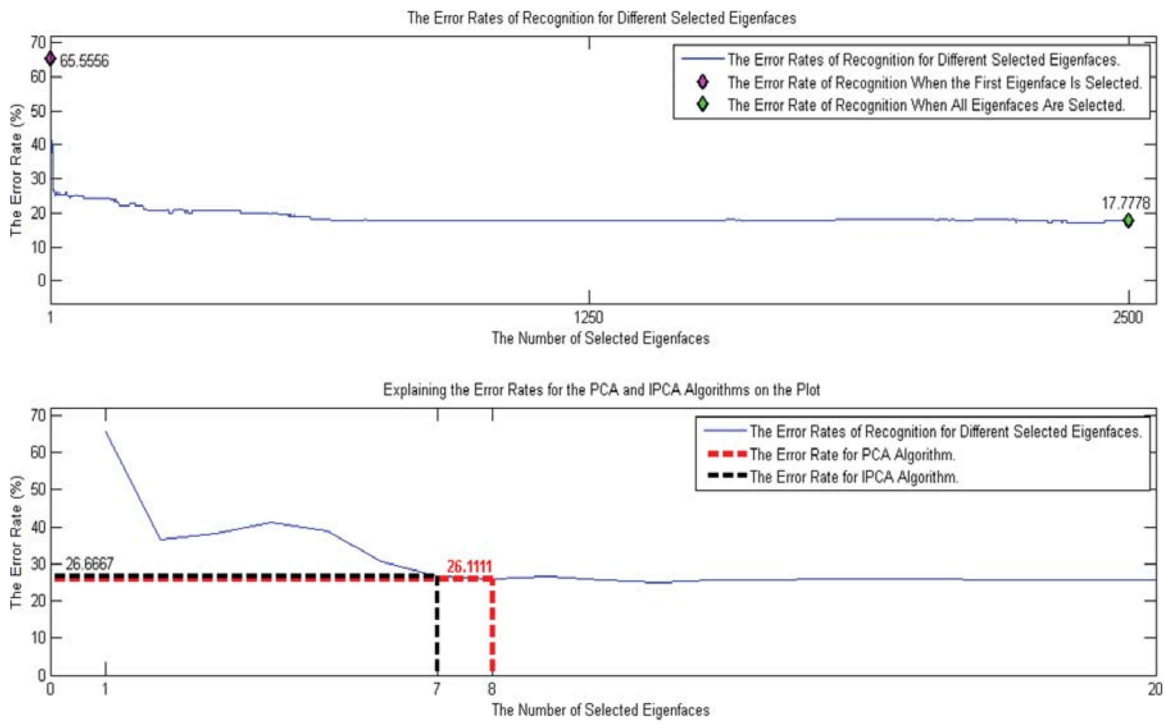

Figure 4.5: The error rates of recognition for different selected eigenfaces compared with resulted error rates when the PCA and IPCA algorithms are used.

4.1.4.2 Error Rate

When the eigenfaces that contain the most significant patterns from the correlated training faces (highly correlated eigenvectors) are only selected then the accuracy of face detection increases. That because in face detection, distance calculation is between the centered unknown image and its reconstruction; consequently, if the unknown image is not a face then the distance will be big; therefore, the unknown image will not be detected as a face image. As a result of that, the usage of the calculated eigenfaces by using the IPCA algorithm produces the smallest error rate; then the usage of the calculated eigenfaces by using the PCA algorithm comes second; finally, the usage of all calculated eigenvectors as eigenfaces obtains the biggest error rate.

In the detection of all 180 tested images in Subsection 3.1.7, $L = 180$; $SD = 147$; and $FD = 33$. Then by using Equation 2.56, the error rate $ER(\%)$ is equal to $\frac{33}{180} \times 100 = 18.3333\%$. Figure 4.6 shows the error rates of detection for different selected eigenfaces compared with resulted error rates when the PCA and IPCA algorithms are used.

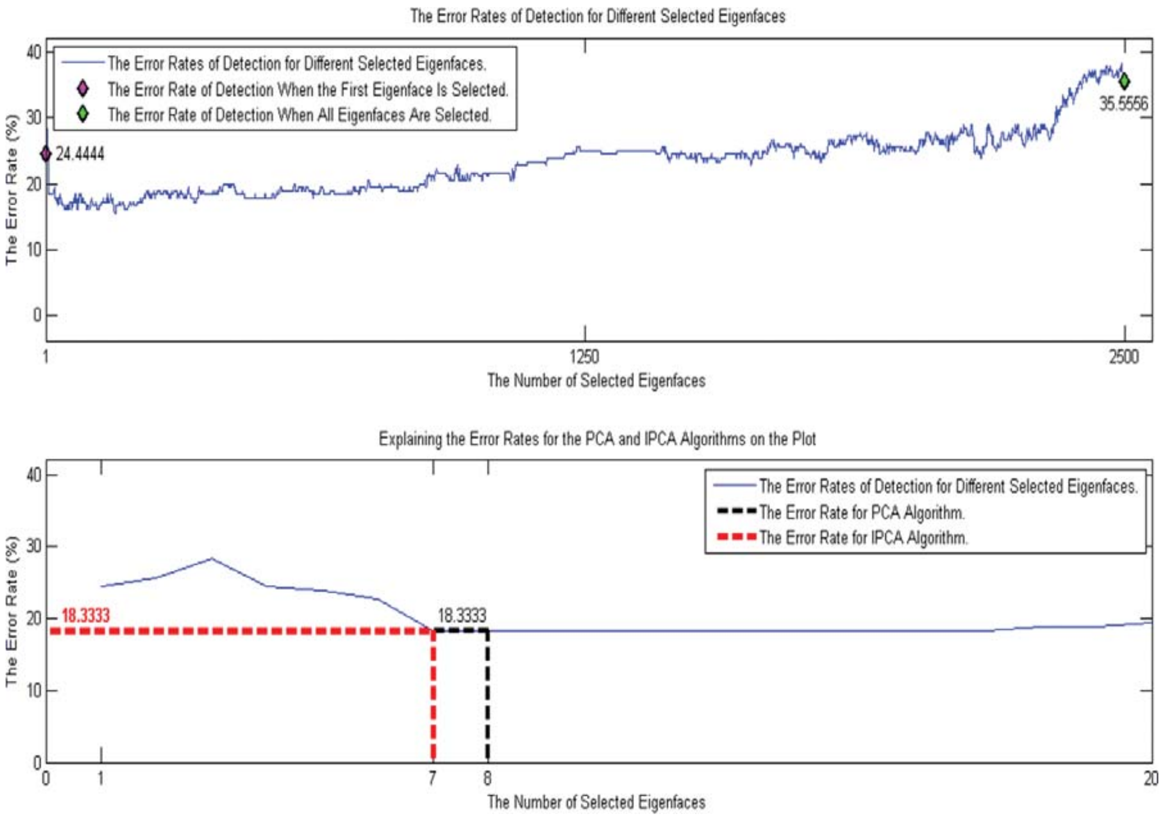

Figure 4.6: The error rates of detection for different selected eigenfaces compared with resulted error rates when the PCA and IPCA algorithms are used.

4.2 Results of JTC Performance

4.2.1 Results of Recognition Performance

In the recognition of all 108 objects in Subsection 3.2.3, $L = 108$; $SR = 20$; and $FR = 88$. Then by using Equation 2.85, the error rate $ER\,(\%)$ is equal to $\frac{88}{108} \times 100 = 81.4815\%$.

4.2.1.1 Improvement of Recognition Performance

For finding the optimal combination out of the 108 objects in Subsection 3.2.3, 46656 $(36 \times 36 \times 36)$ iterations are performed until the database of the optimal impulses for face recognition is obtained as in Figure 4.7. The complete MATLAB © code that had been written to optimize the database of the impulses for face recognition is shown in Appendix J. When the database of the optimal impulses is used for recognizing all 108 objects then the total number of successes SR becomes 71;

and the total number of failures FR becomes 37. Therefore, the error rate $ER\,(\%)$ is equal to $\frac{37}{108} \times 100 = 34.2593\%$ which is much less than the resulted error rate when the database of the impulses is not optimized.

Figure 4.7: The database of the optimal impulses for face recognition.

4.2.2 Results of Detection Performance

In the detection of all 108 objects in Subsection 3.2.4, $L = 108$; $SD = 58$; and $FD = 50$. Then by using Equation 2.86, the error rate $ER\,(\%)$ is equal to $\frac{50}{108} \times 100 = 46.2963\%$.

4.2.2.1 Improvement of Detection Performance

For finding the optimal combination out of the 108 objects in Subsection 3.2.4, 46656 $(36 \times 36 \times 36)$ iterations are performed until the database of the optimal impulses for object detection is obtained as in Figure 4.8. The complete MATLAB © code that had been written to optimize the database of the impulses for object detection is shown in Appendix J. When the database of the optimal impulses is used for detecting all 108 objects then the total number of successes SD becomes 79; and the total number of failures FD becomes 29. Therefore, the error rate $ER\,(\%)$ is equal to $\frac{29}{108} \times 100 = 26.8519\%$ which is much less than the resulted error rate when the database of the impulses is not optimized.

Figure 4.8: The database of the optimal impulses for object detection.

Chapter 5

Conclusion

5.1 Discussion of Results

5.1.1 Introduction

In fact, the results of the joint transform correlator (JTC) applications are obviously shown in Section 4.2; but the results of the PCA and IPCA applications are not summarized yet. Hence, in this section, these results are fully discussed and summarized.

5.1.2 Comparison of the PCA and IPCA Algorithms

5.1.2.1 Introduction

In this sub-subsection, it is determined which algorithm behaves better in each application. It concludes that the IPCA algorithm, in general, behaves better than the PCA algorithm in the most of the applications.

It is very important to be noticed that the calculation of all eigenvectors from the covariance matrix for all training faces is too difficult because the covariance matrix is too big as explained in Step 8 in Sub-subsection 2.2.2.6. Therefore, it is impractical to use all eigenvectors as eigenfaces; but they are computed for comparison purposes with the PCA and IPCA algorithms.

5.1.2.2 Results of Image Compression

The results of image compression are summarized in Table 5.1. From Table 5.1, the IPCA algorithm behaves better than any other algorithm or technique. It offers wonderful compression, reconstruction and processing speed with acceptable errors.

Table 5.1: The results of image compression.

		The Mean Squared Error (MSE) of Reconstructing Training Face No. 5	An information rate (%) Before Compression : After Compression	The MSE of Compression	Processing Speed
The Number of Selected Eigenfaces q	$q = 1$	2.96×10^6	100 : 22.26	2.38×10^7	The fastest
	$q = 7$ (IPCA Algorithm)	1706.72	100 : 89.17	1.56×10^6	Second
	$q = 8$ (PCA Algorithm)	1.25×10^{-23}	100 : 100.32	1.16×10^{-7}	Third
	$q = 2500$ (All Eigenvectors)	2.35×10^6	100 : 27888.9	0	The slowest

5.1.2.3 Results of Face Recognition

The results of face recognition are summarized in Table 5.2. From Table 5.2, the PCA algorithm behaves better than any other algorithm or technique. It offers an acceptable error rate, easy calculation and the speed is not bad.

Table 5.2: The results of face recognition.

		An Error Rate (%)	Processing Speed
The Number of Selected Eigenfaces q	$q = 1$	65.56	The fastest
	$q = 7$ (IPCA Algorithm)	26.67	Second
	$q = 8$ (PCA Algorithm)	26.11	Third
	$q = 2500$ (All Eigenvectors)	17.78	The slowest

5.1.2.4 Results of Face Detection

The results of face detection are summarized in Table 5.3. From Table 5.3, the IPCA algorithm behaves better than any other algorithm or technique. It offers the smallest error rate as well as remarkable speed.

Table 5.3: The results of face detection.

		An Error Rate (%)	Processing Speed
The Number of Selected Eigenfaces q	$q = 1$	24.44	The fastest
	$q = 7$ (IPCA Algorithm)	18.33	Second
	$q = 8$ (PCA Algorithm)	18.33	Third
	$q = 2500$ (All Eigenvectors)	35.56	The slowest

5.2 Methods to Improve the Digital and the Optical Models

5.2.1 Introduction

In fact, the discussed models are not in their final stage where they can be optimized. Some ideas are presented in this section for each model that are going to help in enhancing their performance.

5.2.2 Improvement of the Digital and the Optical Models

The performance of face recognition and image detection of the digital model can be improved by increasing the size of the training faces and the detected or recognized unknown image. Also, increasing the size of the impulses and the detected or recognized unknown object of the optical model improves its performance in detection and recognition.

The performance of digital and optical recognition can be improved by obtaining a good way for blocking the pixels occupying the background of a face especially if the background is not black. If it is not black such as white, the error rate of recognition will increase because the intensities on the face will be close to 255 (i.e. they will be close to the intensities on the background) then discrimination between the intensities occupying the background and the intensities occupying the face becomes too hard.

For decreasing the error rates of face recognition and image detection of the digital model, the database of the training faces can be optimized in the same manner as the optimization of the database of the impulses for the optical model that is presented in Sub-sub-sub-subsection 2.3.4.3.2.1 and Sub-sub-sub-subsection 2.3.4.3.3.1.

The models performance can be improved by using another technique for enhancing the optimization speed of the databases. This technique measures information contained in the 180 tested images (or in the 108 objects) then picking the tested images (or the objects) that contain the highest information than the others to form the database of the training faces (or the database of the impulses).

Finally, the models performance can be improved by trying different detection and recognition thresholds such as thresholds generated by receiver operating characteristics (ROC).

5.3 The Digital Model Versus the Optical Model

In this section, we are going to compare between the digital model and the optical model in detection and recognition based on a couple of criteria. The comparison is summarized in Table 5.4.

Table 5.4: The comparison between the digital and the optical models.

A Comparison Criterion	The Digital Model	The Optical Model
The Database	It is not necessarily to be optimized	It must be optimized
Implementation	Easier	Harder
Speed	Slower	Faster because it uses the speed of light
Detection and Recognition Performance	Better	Good

5.4 Future Work

For developing this work in future, the proposed ideas for improving the digital and the optical models presented in Section 5.2 are going to be achieved. Also, there is another idea that is considered to be performed in future is testing the models performance under various types of noises.

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Appendix A

A Code for the Digital Model

THIS code is for testing face reconstruction, detection and recognition processes as well as the process of image compression by using principal components analysis (PCA) and improved principal components analysis (IPCA) algorithms. In addition to that this code is for setting up recognition and detection thresholds.

```

% This Code Is for Testing Face Reconstruction, Detection and
% Recognition Processes as Well as the Process of Image Compression
% by Using Principal Components Analysis (PCA) and Improved
% Principal Components Analysis (IPCA) Algorithms. In Addition to
% That This Code Is for Setting up Recognition and Detection
% Thresholds.


clc
clear all
close all
format long


% Faces images are NxN images.
N=size(imread('Mr. Mansour Alshammari.jpg'),1); % This N is the
                                                 % number of pixels.


% Training faces.
Total_No_of_Known_Im=9; % The total number of the training faces.

All_Known_Im_V=zeros(N*N,Total_No_of_Known_Im); % An N^2xP, 2D
                                                 % matrix where P is
                                                 % the total number
```

```
                                                % of the training
                                                % faces. Each
                                                % training face is
                                                % vectorized and
                                                % placed in one of
                                                % the columns of
                                                % the 2D matrix.
                                                % The size of each
                                                % training face
                                                % vector is N^2.

Known_Images_Folder=...............
    [cd '/The Known Images of Black Backgrounds']; % The folder of
                                                   % the black
                                                   % background
                                                   % training
                                                   % faces.
% Known_Images_Folder=..........
%     [cd '/The Known Images of White Backgrounds']; % The folder
                                                     % of the white
                                                     % background
                                                     % training
                                                     % faces.

if isdir(Known_Images_Folder)==0
    Error_Message=sprintf(...................
        'Error: The following folder does not exist\n%s', .......
        Known_Images_Folder);
    warndlg(Error_Message);
end

Known_Images=dir(fullfile(Known_Images_Folder,'*.jpg'));
for k=1:length(Known_Images)
    Known_Image=Known_Images(k).name;
    Known_Image_Location=fullfile(Known_Images_Folder,Known_Image);
    All_Known_Im_V(:,k)=...............
        reshape(double(rgb2gray(imread(Known_Image_Location))).....
        ,N*N,1);

%     figure('units','centimeters','position',[16 7 7.5 8.5])
%     subplot(1,1,1)
%     imshow(uint8(reshape(All_Known_Im_V(:,k),N,N)))
%     if k==1
%         title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) .........
%              ', 1^{st} Projection)']})
%     elseif k==2
%         title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ........
%              ', 2^{nd} Projection)']})
```

```
%      elseif k==3
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ........
%              ', 3^{rd} Projection)']})
%      elseif k==4
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 1^{st} Projection)']})
%      elseif k==5
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 2^{nd} Projection)']})
%      elseif k==6
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) .....
%              ', 3^{rd} Projection)']})
%      elseif k==7
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 1^{st} Projection)']})
%      elseif k==8
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) .....
%              ', 2^{nd} Projection)']})
%      elseif k==9
%          title({['Training Face No.' num2str(k)];.............
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 3^{rd} Projection)']})
%      end
%      disp(['Please, press any keyboard button to explore '......
%          'the remaining training faces >>>>>>>'])
%      pause
%      close all
%      clc
end
All_Known_Im_V;

% Imhist for setting up a threshold to work on just the pixels of a
% face and throwing the background pixels. Imhist calculates the
% number of pixels in an image that have the same intensity levels.
% So, if a training face has a unified background then the biggest
% histogram of the intensity levels will be for the backgroubd
% pixels because the total number of pixels that have the same
% intensity levels are the background pixels of the training face.
% Note that, the histogram of a digital image is defined as the
% discrete function, h(rk)=nk, where rk is the kth intensity level
% and nk is the number of pixels in the image whose intensity level
% is rk.
hist_Known_Im=zeros(Total_No_of_Known_Im,256);
for A=1:Total_No_of_Known_Im
```

```
    % Note that, a training face has to be scaled between 0 to 255
    % before using imhist. For doing that, uint8 can be used for
    % converting the training face class form double to uint8.
    hist_Known_Im(A,:)=.............
        imhist(uint8(reshape(All_Known_Im_V(:,A),N,N)));

%     Known_Image=Known_Images(A).name;
%     plot(hist_Known_Im(A,:))
%     if A==1
%         title({['The Histogram of Training Face No.' .......
%             num2str(A)];.......
%             ['(' Known_Image(1:length(Known_Image)-6) .........
%             ', 1^{st} Projection)']})
%     elseif A==2
%         title({['The Histogram of Training Face No.' ......
%             num2str(A)];......
%             ['(' Known_Image(1:length(Known_Image)-6) ........
%             ', 2^{nd} Projection)']})
%     elseif A==3
%         title({['The Histogram of Training Face No.' ......
%             num2str(A)];......
%             ['(' Known_Image(1:length(Known_Image)-6) ........
%             ', 3^{rd} Projection)']})
%     elseif A==4
%         title({['The Histogram of Training Face No.' .....
%             num2str(A)];......
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 1^{st} Projection)']})
%     elseif A==5
%         title({['The Histogram of Training Face No.' .......
%             num2str(A)];......
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 2^{nd} Projection)']})
%     elseif A==6
%         title({['The Histogram of Training Face No.' ......
%             num2str(A)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 3^{rd} Projection)']})
%     elseif A==7
%         title({['The Histogram of Training Face No.' .....
%             num2str(A)];.....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 1^{st} Projection)']})
%     elseif A==8
%         title({['The Histogram of Training Face No.' .....
%             num2str(A)];.....
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 2^{nd} Projection)']})
%     elseif A==9
%         title({['The Histogram of Training Face No.' ....
```

```
%              num2str(A)];......
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 3^{rd} Projection)']})
%      end
%      xlabel('Intensity Level rk')
%      ylabel({'The Number of Pixels in the Training Face'.........
%          ' Whose Intensity Level Is rk Where h(rk)=nk'})
%      axis tight
%      disp(['Please, press any keyboard button to explore '......
%          'the remaining histograms >>>>>>>'])
%      pause
%      clc
end
hist_Known_Im;

Mean_hist_Known_Im=sum(hist_Known_Im,1)/......
    Total_No_of_Known_Im; % The average histogram
                          % for all training faces.
Threshold_Known_Im=8; % The picked threshold is based on the
                      % average histogram for all training faces
                      % when the training faces have black
                      % backgrounds. Note that, all intesity levels
                      % below the threshold represent the images
                      % backgrounds because these levels have the
                      % biggest histogram.
% Threshold_Known_Im=180; % The Picked threshold is based on the
                          % average histogram for all training
                          % faces when the training faces have
                          % white backgrounds. Note that, all
                          % intesity levels above the threshold
                          % represent the images backgrounds
                          % because these levels have the biggest
                          % histogram.
% plot(Mean_hist_Known_Im)
% line([Threshold_Known_Im Threshold_Known_Im],......
%     [0 max(Mean_hist_Known_Im)],'Color','r')
% text(Threshold_Known_Im+0.5,max(Mean_hist_Known_Im)/2,.....
%     '{\color{red} The Threshold}')
% title('The Mean Histogram of All Training Faces')
% xlabel('Intensity Level rk')
% set(gca,'XTick',[0 Threshold_Known_Im 255])
% ylabel({'The Mean Number of Pixels from All Training' ..........
%     'Faces Whose Intensity Level Is rk'})
% axis tight
% pause

% Normalizing all training faces for removing the lightening
% effects on them and to increase the resolution of face detection
% and recognition. Note that, the normalization will be done just
% for face pixels for keeping the variations among the images just
```

```
% in the faces without the backgrounds effects.
Threshold_Known_Image=.......
    zeros(N,N,Total_No_of_Known_Im); % The training faces after
                                     % applying the threshold.
Normalized_Known_Im_V=......
    zeros(N*N,Total_No_of_Known_Im); % An N^2xP, 2D matrix where
                                     % each column represents a
                                     % normalized training face
                                     % vector.
for M=1:Total_No_of_Known_Im
    t=reshape(All_Known_Im_V(:,M),N,N);
    T=t>Threshold_Known_Im; % The pixels bigger than the threshold
                            % are of interest because they
                            % represent the pixels of a face.
%     T=t<Threshold_Known_Im; % The pixels smaller than the
%                             % threshold are of interest because
%                             % they represent the pixels of
%                             % a face.
    for R=1:N
        for C=1:N
            if T(R,C)==1
                Threshold_Known_Image(R,C,M)=.......
                    floor(255*(double(t(R,C))/........
                    max(max(double(t))))); % The normalization of a
                                           % training face. This is
                                           % done to increase the
                                           % dynamic range of the
                                           % training face for
                                           % visualization by
                                           % scaling the
                                           % intensities of the
                                           % training face from 0
                                           % to 255.
            end;
        end;
    end;
    Normalized_Known_Im_V(:,M)=.........
        reshape(Threshold_Known_Image(:,:,M),N*N,1);

%     Known_Image=Known_Images(M).name;
%     figure
%     subplot(2,1,1)
%     imshow(t)
%     if M==1
%         title({['This Is To Show How Good the Known '.......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 1^{st} Projection)']})
%     elseif M==2
```

```
%         title({['This Is To Show How Good the Known '......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 2^{nd} Projection)']})
%     elseif M==3
%         title({['This Is To Show How Good the Known '......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 3^{rd} Projection)']})
%     elseif M==4
%         title({['This Is To Show How Good the Known '......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) ....
%             ', 1^{st} Projection)']})
%     elseif M==5
%         title({['This Is To Show How Good the Known '.....
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 2^{nd} Projection)']})
%     elseif M==6
%         title({['This Is To Show How Good the Known '.....
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 3^{rd} Projection)']})
%     elseif M==7
%         title({['This Is To Show How Good the Known '......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 1^{st} Projection)']})
%     elseif M==8
%         title({['This Is To Show How Good the Known '.....
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) ....
%             ', 2^{nd} Projection)']})
%     elseif M==9
%         title({['This Is To Show How Good the Known '......
%             'Images Threshold Is,'];.....
%             blanks(1);['Training Face No.' num2str(M)];
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 3^{rd} Projection)']})
%     end
%     subplot(2,1,2)
%     imshow(reshape(Normalized_Known_Im_V(:,M),N,N))
```

```
%      if M==1
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) .......
%              ', 1^{st} Projection)']})
%      elseif M==2
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 2^{nd} Projection)']})
%      elseif M==3
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 3^{rd} Projection)']})
%      elseif M==4
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 1^{st} Projection)']})
%      elseif M==5
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 2^{nd} Projection)']})
%      elseif M==6
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) .....
%              ', 3^{rd} Projection)']})
%      elseif M==7
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) ......
%              ', 1^{st} Projection)']})
%      elseif M==8
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) .......
%              ', 2^{nd} Projection)']})
%      elseif M==9
%          title({['Normalized Training Face No.' num2str(M)];....
%              ['(' Known_Image(1:length(Known_Image)-6) .......
%              ', 3^{rd} Projection)']})
%      end
%      disp(['Please, press any keyboard button to see how '.....
%          'good the applied'])
%      disp('threshold on the normalized training faces is >>>>>>>')
%      pause
%      close all
%      clc
%
%      figure
%      subplot(2,1,1)
%      imshow(uint8(t))
%      if M==1
%          title({['Training Face No.' num2str(M)];...........
%              ['(' Known_Image(1:length(Known_Image)-6) ......
```

```
%               ', 1^{st} Projection)']})
%       elseif M==2
%           title({['Training Face No.' num2str(M)];.......
%               ['(' Known_Image(1:length(Known_Image)-6) .....
%               ', 2^{nd} Projection)']})
%       elseif M==3
%           title({['Training Face No.' num2str(M)];.......
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 3^{rd} Projection)']})
%       elseif M==4
%           title({['Training Face No.' num2str(M)];...........
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 1^{st} Projection)']})
%       elseif M==5
%           title({['Training Face No.' num2str(M)];........
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 2^{nd} Projection)']})
%       elseif M==6
%           title({['Training Face No.' num2str(M)];......
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 3^{rd} Projection)']})
%       elseif M==7
%           title({['Training Face No.' num2str(M)];......
%               ['(' Known_Image(1:length(Known_Image)-6) .......
%               ', 1^{st} Projection)']})
%       elseif M==8
%           title({['Training Face No.' num2str(M)];......
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 2^{nd} Projection)']})
%       elseif M==9
%           title({['Training Face No.' num2str(M)];......
%               ['(' Known_Image(1:length(Known_Image)-6) .......
%               ', 3^{rd} Projection)']})
%       end
%       subplot(2,1,2)
%       imshow(uint8(reshape(Normalized_Known_Im_V(:,M),N,N)))
%       if M==1
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 1^{st} Projection)']})
%       elseif M==2
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 2^{nd} Projection)']})
%       elseif M==3
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) .......
%               ', 3^{rd} Projection)']})
%       elseif M==4
%           title({['Normalized Training Face No.' num2str(M)];....
```

```
%               ['(' Known_Image(1:length(Known_Image)-6) .....
%               ', 1^{st} Projection)']})
%       elseif M==5
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 2^{nd} Projection)']})
%       elseif M==6
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) .......
%               ', 3^{rd} Projection)']})
%       elseif M==7
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) ......
%               ', 1^{st} Projection)']})
%       elseif M==8
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) .....
%               ', 2^{nd} Projection)']})
%       elseif M==9
%           title({['Normalized Training Face No.' num2str(M)];....
%               ['(' Known_Image(1:length(Known_Image)-6) .......
%               ', 3^{rd} Projection)']})
%       end
%       disp(['Please, press any keyboard button to explore '......
%           'the remaining normalized training faces >>>>>>>'])
%       pause
%       close all
%       clc
end;
Normalized_Known_Im_V;

% Centering each face by simply subtracting the mean of the face
% pixels from each pixel in the face. By doing that the new face
% pixels will have zero mean that means the face is centered.
Rows_Columns=zeros(1,1,..........
    Total_No_of_Known_Im); % The rows and columns for the pixels
                           % of the faces. Note that, the training
                           % faces are not similar so the rows and
                           % columns of the faces pixels will not
                           % be equal. Therefore, MATLAB will add
                           % zero rows and columns to make the
                           % matrices of the rows and columns of
                           % the faces pixels are equal.
Means=zeros(1,Total_No_of_Known_Im); % The means of the
                                     % faces pixels.
Centered_Known_Im=zeros(N*N,................
    Total_No_of_Known_Im); % An N^2xP, 2D matrix where each
                           % column represents a training
                           % face vector with a centered
                           % face.
```

```
Centered_Known_Image=zeros(N,N,........
    Total_No_of_Known_Im); % The training faces after
                           % centering the faces.
for j=1:Total_No_of_Known_Im
    x=reshape(Normalized_Known_Im_V(:,j),N,N);
    [rr cc]=find(x>0); % The pixels bigger than zero are of
                       % interest because they represent the
                       % pixels of a face.
    Rows_Columns(1,1:size(rr,1),j)=rr.';
    Rows_Columns(2,1:size(rr,1),j)=cc.';
    Sum=0;
    No=0;
    for RR=1:size(rr,1)
        Sum=Sum+x(rr(RR),cc(RR));
        No=No+1;
    end
    Means(1,j)=Sum/No;

    for RR1=1:size(rr,1)
        Centered_Known_Image(rr(RR1),cc(RR1),j)=........
            x(rr(RR1),cc(RR1))-Means(1,j);
    end
    Centered_Known_Im(:,j)=.........
        reshape(Centered_Known_Image(:,:,j),N*N,1);

%     figure('units','centimeters','position',[16 7 7 8.5])
%     subplot(1,1,1)
%     Known_Image=Known_Images(j).name;
%     imshow(uint8(reshape(Centered_Known_Im(:,j),N,N)))
%     if j==1
%         title({['Centered Training Face No.' num2str(j)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 1^{st} Projection)']})
%     elseif j==2
%         title({['Centered Training Face No.' num2str(j)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 2^{nd} Projection)']})
%     elseif j==3
%         title({['Centered Training Face No.' num2str(j)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 3^{rd} Projection)']})
%     elseif j==4
%         title({['Centered Training Face No.' num2str(j)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 1^{st} Projection)']})
%     elseif j==5
%         title({['Centered Training Face No.' num2str(j)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .....
%             ', 2^{nd} Projection)']})
%     elseif j==6
```

```
%           title({['Centered Training Face No.' num2str(j)];....
%                ['(' Known_Image(1:length(Known_Image)-6) .....
%                ', 3^{rd} Projection)']})
%       elseif j==7
%           title({['Centered Training Face No.' num2str(j)];....
%                ['(' Known_Image(1:length(Known_Image)-6) .....
%                ', 1^{st} Projection)']})
%       elseif j==8
%           title({['Centered Training Face No.' num2str(j)];....
%                ['(' Known_Image(1:length(Known_Image)-6) ......
%                ', 2^{nd} Projection)']})
%       elseif j==9
%           title({['Centered Training Face No.' num2str(j)];....
%                ['(' Known_Image(1:length(Known_Image)-6) ......
%                ', 3^{rd} Projection)']})
%       end
%       disp(['Please, press any keyboard button to explore '......
%           'the remaining centered training faces >>>>>>>'])
%       pause
%       close all
%       clc
end
Centered_Known_Im;


% Tested images are supposed to be unknown but here multiple
% images for each training face are taken for testing the face
% reconstruction, recognition and detection processes as well
% as selecting a decision threshold for face detection and
% recognition.
Total_No_of_Tested_Im=180; % Total number of the
                           % tested images.

Im_P=[36 12 12 36 12 12 36 12 12]; % Each element in this vector
                                   % represents the total number of
                                   % the taken images for each
                                   % training face.

L1=Im_P(1);
L2=L1+Im_P(2);
L3=L2+Im_P(3); % L3=60 is the total number of the tested
               % images for Mr. Mansour Alshammari.
L4=L3+Im_P(4);
L5=L4+Im_P(5);
L6=L5+Im_P(6); % L6=120 is the total number of the tested images
               % for Mr. Methkir Alharthee.
L7=L6+Im_P(7);
L8=L7+Im_P(8);
L9=L8+Im_P(9); % L9=180 is the total number of the tested images
               % for Mr. Mohammed Hanafy.
```

```
All_Tested_Im_V=zeros(N*N,...........
    Total_No_of_Tested_Im); % An N^2xP1, 2D matrix where P1 is the
                            % total number of the tested images.
                            % Each tested image is vectorized and
                            % placed in one of the columns of the
                            % 2D matrix. The size of each tested
                            % image vector is N^2.

Tested_Images_Folder=............
    [cd '/The Tested Images of Black Backgrounds']; % The folder of
                                                    % the black
                                                    % background
                                                    % tested
                                                    % images.
% Tested_Images_Folder=..............
%     [cd '/The Tested Images of White Backgrounds']; % The folder
                                                    % of the white
                                                    % background
                                                    % tested
                                                    % images.

if isdir(Tested_Images_Folder)==0
    Error_Message1=sprintf(.........
        'Error: The following folder does not exist\n%s'.......
        ,Tested_Images_Folder);
    warndlg(Error_Message1);
end

Tested_Images=dir(fullfile(Tested_Images_Folder,'*.jpg'));
for k1=1:length(Tested_Images)
    Tested_Image_Number=[num2str(k1) '.jpg'];
    Tested_Image_Location=............
        fullfile(Tested_Images_Folder,Tested_Image_Number);
    All_Tested_Im_V(:,k1)=reshape...............
        (double(rgb2gray(imread(Tested_Image_Location))),N*N,1);

%     figure('units','centimeters','position',[16 7 7.5 8.5])
%     subplot(1,1,1)
%     imshow(uint8(reshape(All_Tested_Im_V(:,k1),N,N)))
%     if k1<=L1
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%     elseif k1>L1 && k1<=L2
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif k1>L2 && k1<=L3
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif k1>L3 && k1<=L4
```

```
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%     elseif k1>L4 && k1<=L5
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%     elseif k1>L5 && k1<=L6
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%     elseif k1>L6 && k1<=L7
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%     elseif k1>L7 && k1<=L8
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%     elseif k1>L8 && k1<=L9
%         title({['Tested Image No.' num2str(k1)];...........
%             '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%     end
%     disp(['Please, press any keyboard button to explore '......
%         'the remaining tested images >>>>>>>'])
%     pause
%     close all
%     clc
end
All_Tested_Im_V;

% Imhist for setting up a threshold to work on just the pixels of a
% face and throwing the background pixels. Imhist calculates the
% number of pixels in an image that have the same intensity levels.
% So, if a tested image has a unified background then the biggest
% histogram of the intensity levels will be for the background
% pixels because the total number of pixels that have the same
% intensity levels are the background pixels of the tested image.
% Note that, the histogram of a digital image is defined as the
% discrete function, h(rk)=nk, where rk is the kth intensity level
% and nk is the number of pixels in the image whose intensity level
% is rk.
hist_Tested_Im=zeros(Total_No_of_Tested_Im,256);
for A1=1:Total_No_of_Tested_Im
    % Note that, a tested image has to be scaled between 0 to 255
    % before using imhist. For doing that, uint8 can be used for
    % converting the tested image class form double to uint8.
    hist_Tested_Im(A1,:)=.......
        imhist(uint8(reshape(All_Tested_Im_V(:,A1),N,N)));

%     plot(hist_Tested_Im(A1,:))
%     if A1<=L1
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
```

```
%     elseif A1>L1 && A1<=L2
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif A1>L2 && A1<=L3
%         title({['The Histogram of Training Face No.' .......
%             num2str(A1)];.......
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif A1>L3 && A1<=L4
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%     elseif A1>L4 && A1<=L5
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%     elseif A1>L5 && A1<=L6
%         title({['The Histogram of Training Face No.' .....
%             num2str(A1)];.......
%             '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%     elseif A1>L6 && A1<=L7
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%     elseif A1>L7 && A1<=L8
%         title({['The Histogram of Training Face No.' ......
%             num2str(A1)];.......
%             '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%     elseif A1>L8 && A1<=L9
%         title({['The Histogram of Training Face No.' .....
%             num2str(A1)];.......
%             '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%     end
%     xlabel('Intensity Level rk')
%     ylabel({'The Number of Pixels in the Tested Image' ........
%         ' Whose Intensity Level Is rk Where h(rk)=nk'})
%     axis tight
%     disp(['Please, press any keyboard button to explore '......
%         'the remaining histograms >>>>>>>'])
%     pause
%     clc
end
hist_Tested_Im;

Mean_hist_Tested_Im=...........
    sum(hist_Tested_Im,1)/Total_No_of_Tested_Im; % The average
                                                 % histogram for
                                                 % all tested
                                                 % images.
Threshold_Tested_Im=8; % The picked threshold is based on the
```

```
                       % average histogram for all tested images
                       % when the tested images have black
                       % backgrounds. Note that, all intesity
                       % levels below the threshold represent the
                       % images backgrounds because these levels
                       % have the biggest histogram.
% Threshold_Tested_Im=180; % The picked threshold is based on the
                           % average histogram for all tested
                           % images when the tested images have
                           % white backgrounds. Note that, all
                           % intesity levels above the threshold
                           % represent the images backgrounds
                           % because these levels have the biggest
                           % histogram.
% plot(Mean_hist_Tested_Im)
% line([Threshold_Tested_Im Threshold_Tested_Im],..............
%     [0 max(Mean_hist_Tested_Im)],'Color','r')
% text(Threshold_Tested_Im+0.5,max(Mean_hist_Tested_Im)/2,........
%     '{\color{red} The Threshold}')
% title('The Mean Histogram of All Tested Images')
% xlabel('Intensity Level rk')
% set(gca,'XTick',[0 Threshold_Tested_Im 255])
% ylabel({'The Mean Number of Pixels from All Tested'......
%     'Images Whose Intensity Level Is rk'})
% axis tight
% pause

% Normalizing all the tested images for removing the lightening
% effects on them and to increase the resolution of face detection
% and recognition. Note that, the normalization will be done just
% for face pixels for keeping the variations among the images just
% in the faces without the backgrounds effects.
Threshold_Tested_Image=.........
    zeros(N,N,Total_No_of_Tested_Im); % The tested images after
                                      % applying the threshold.
Normalized_Tested_Im_V=zeros(N*N,...........
    Total_No_of_Tested_Im); % An N^2xP1, 2D matrix where each
                            % column represents a normalized
                            % tested image vector.
for M1=1:Total_No_of_Tested_Im
    t1=reshape(All_Tested_Im_V(:,M1),N,N);
    T1=t1>Threshold_Tested_Im; % The pixels bigger than the
                               % threshold are of interest because
                               % they represent the pixels of
                               % a face.
%     T1=t1<Threshold_Tested_Im; % The pixels smaller than the
%                                % threshold are of interest
%                                % because they represent the
%                                % pixels of a face.
    for R1=1:N
```

```
            for C1=1:N
                if T1(R1,C1)==1
                    Threshold_Tested_Image(R1,C1,M1)=..........
                        floor(255*(double(t1(R1,C1))/.......
                        max(max(double(t1))))); % The normalization of
                                                % a tested image. This
                                                % is done to increase
                                                % the dynamic range of
                                                % the tested image for
                                                % visualization by
                                                % scaling the
                                                % intensities of the
                                                % tested image from 0
                                                % to 255.
                end;
            end;
        end;
        Normalized_Tested_Im_V(:,M1)=..............
            reshape(Threshold_Tested_Image(:,:,M1),N*N,1);

%     figure
%     subplot(2,1,1)
%     imshow(t1)
%     if M1<=L1
%         title({['This Is To Show How Good the Tested '....
%             'Images Threshold Is,'];.....
%             blanks(1);['Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%     elseif M1>L1 && M1<=L2
%         title({['This Is To Show How Good the Tested '....
%             'Images Threshold Is,'];.....
%             blanks(1);['Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif M1>L2 && M1<=L3
%         title({['This Is To Show How Good the Tested '....
%             'Images Threshold Is,'];.....
%             blanks(1);['Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif M1>L3 && M1<=L4
%         title({['This Is To Show How Good the Tested '.....
%             'Images Threshold Is,'];.....
%             blanks(1);['Tested Image No.' num2str(M1)];....
%             '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%     elseif M1>L4 && M1<=L5
%         title({['This Is To Show How Good the Tested '.....
%             'Images Threshold Is,'];.....
%             blanks(1);['Tested Image No.' num2str(M1)];.....
%             '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%     elseif M1>L5 && M1<=L6
%         title({['This Is To Show How Good the Tested '.....
```

```
%               'Images Threshold Is,'];.....
%               blanks(1);['Tested Image No.' num2str(M1)];.....
%               '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%       elseif M1>L6 && M1<=L7
%           title({['This Is To Show How Good the Tested '....
%               'Images Threshold Is,'];.....
%               blanks(1);['Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%       elseif M1>L7 && M1<=L8
%           title({['This Is To Show How Good the Tested '.....
%               'Images Threshold Is,'];.....
%               blanks(1);['Tested Image No.' num2str(M1)];.....
%               '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%       elseif M1>L8 && M1<=L9
%           title({['This Is To Show How Good the Tested '....
%               'Images Threshold Is,'];.....
%               blanks(1);['Tested Image No.' num2str(M1)];......
%               '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%       end
%       subplot(2,1,2)
%       imshow(reshape(Normalized_Tested_Im_V(:,M1),N,N))
%       if M1<=L1
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%       elseif M1>L1 && M1<=L2
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%       elseif M1>L2 && M1<=L3
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%       elseif M1>L3 && M1<=L4
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%       elseif M1>L4 && M1<=L5
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%       elseif M1>L5 && M1<=L6
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%       elseif M1>L6 && M1<=L7
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%       elseif M1>L7 && M1<=L8
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%       elseif M1>L8 && M1<=L9
%           title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%       end
%       disp(['Please, press any keyboard button to '......
```

```
%         'see how good the applied'])
%     disp('threshold on the normalized tested images is >>>>>>>')
%     pause
%     close all
%     clc
%
%     figure
%     subplot(2,1,1)
%     imshow(uint8(t1))
%     if M1<=L1
%         title({['Tested Image No.' num2str(M1)];.........
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%     elseif M1>L1 && M1<=L2
%         title({['Tested Image No.' num2str(M1)];.......
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif M1>L2 && M1<=L3
%         title({['Tested Image No.' num2str(M1)];......
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif M1>L3 && M1<=L4
%         title({['Tested Image No.' num2str(M1)];.......
%             '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%     elseif M1>L4 && M1<=L5
%         title({['Tested Image No.' num2str(M1)];......
%             '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%     elseif M1>L5 && M1<=L6
%         title({['Tested Image No.' num2str(M1)];.....
%             '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%     elseif M1>L6 && M1<=L7
%         title({['Tested Image No.' num2str(M1)];.......
%             '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%     elseif M1>L7 && M1<=L8
%         title({['Tested Image No.' num2str(M1)];.....
%             '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%     elseif M1>L8 && M1<=L9
%         title({['Tested Image No.' num2str(M1)];.......
%             '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%     end
%     subplot(2,1,2)
%     imshow(uint8(reshape(Normalized_Tested_Im_V(:,M1),N,N)))
%     if M1<=L1
%         title({['Normalized Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%     elseif M1>L1 && M1<=L2
%         title({['Normalized Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif M1>L2 && M1<=L3
%         title({['Normalized Tested Image No.' num2str(M1)];....
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif M1>L3 && M1<=L4
%         title({['Normalized Tested Image No.' num2str(M1)];....
```

```
%               '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%      elseif M1>L4 && M1<=L5
%          title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%      elseif M1>L5 && M1<=L6
%          title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%      elseif M1>L6 && M1<=L7
%          title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%      elseif M1>L7 && M1<=L8
%          title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%      elseif M1>L8 && M1<=L9
%          title({['Normalized Tested Image No.' num2str(M1)];....
%               '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%      end
%      disp(['Please, press any keyboard button to explore '....
%          'the remaining normalized tested images >>>>>>>'])
%      pause
%      close all
%      clc
end
Normalized_Tested_Im_V;

% Centering each face by simply subtracting the mean of the face
% pixels from each pixel in the face. By doing that the new face
% pixels will have zero mean that means the face is centered.
Rows_Columns1=zeros(1,1,.......
    Total_No_of_Tested_Im); % The rows and columns for the
                            % pixels of the faces. Note that,
                            % the tested images are not similar
                            % so the rows and columns of the
                            % faces pixels will not be equal.
                            % Therefore, MATLAB will add zero
                            % rows and columns to make the
                            % matrices of the rows and columns
                            % of the faces pixels are equal.
Means1=zeros(1,Total_No_of_Tested_Im);
Centered_Tested_Im=.........
    zeros(N*N,Total_No_of_Tested_Im); % An N^2xP1, 2D matrix where
                                      % each column represents a
                                      % tested image vector with a
                                      % centered face.
Centered_Tested_Image=..........
    zeros(N,N,Total_No_of_Tested_Im); % The tested images after
                                      % centering the faces.
for j1=1:Total_No_of_Tested_Im
    x1=reshape(Normalized_Tested_Im_V(:,j1),N,N);
    [rr1 cc1]=find(x1>0); % The pixels bigger than zero are of
```

```
                              % interest because they represent the
                              % pixels of the faces.
    Rows_Columns1(1,1:size(rr1,1),j1)=rr1.';
    Rows_Columns1(2,1:size(rr1,1),j1)=cc1.';
    Sum1=0;
    No1=0;
    for RR2=1:size(rr1,1)
        Sum1=Sum1+x1(rr1(RR2),cc1(RR2));
        No1=No1+1;
    end

    Means1(1,j1)=Sum1/No1;
    for RR3=1:size(rr1,1)
        Centered_Tested_Image(rr1(RR3),cc1(RR3),j1)=.......
            x1(rr1(RR3),cc1(RR3))-Means1(1,j1);
    end
    Centered_Tested_Im(:,j1)=..........
        reshape(Centered_Tested_Image(:,:,j1),N*N,1);

%     figure('units','centimeters','position',[16 7 7 8.5])
%     subplot(1,1,1)
%     imshow(uint8(reshape(Centered_Tested_Im(:,j1),N,N)))
%     if j1<=L1
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Mansour Alshammari, 1^{st} Projection)'})
%     elseif j1>L1 && j1<=L2
%         title({['Centered Tested Image No.' num2str(j1)];.....
%             '(Mr. Mansour Alshammari, 2^{nd} Projection)'})
%     elseif j1>L2 && j1<=L3
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Mansour Alshammari, 3^{rd} Projection)'})
%     elseif j1>L3 && j1<=L4
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Methkir Alharthee, 1^{st} Projection)'})
%     elseif j1>L4 && j1<=L5
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Methkir Alharthee, 2^{nd} Projection)'})
%     elseif j1>L5 && j1<=L6
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Methkir Alharthee, 3^{rd} Projection)'})
%     elseif j1>L6 && j1<=L7
%         title({['Centered Tested Image No.' num2str(j1)];.....
%             '(Mr. Mohammed Hanafy, 1^{st} Projection)'})
%     elseif j1>L7 && j1<=L8
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Mohammed Hanafy, 2^{nd} Projection)'})
%     elseif j1>L8 && j1<=L9
%         title({['Centered Tested Image No.' num2str(j1)];....
%             '(Mr. Mohammed Hanafy, 3^{rd} Projection)'})
%     end
```

```
%     disp(['Please, press any keyboard button to explore '......
%         'the remaining centered tested images >>>>>>>'])
%     pause
%     close all
%     clc
end
Centered_Tested_Im;


% Centering the set of the training faces by simply subtracting the
% mean training face from each training face in the set. By doing
% that the new set of the training faces will have zero mean which
% means the set is centered.
Av_Image=sum(Centered_Known_Im,2)./......
    Total_No_of_Known_Im; % The average training face.
% figure('units','centimeters','position',[12 4 12.5 13])
% subplot(1,1,1)
% Reshaped_Av_Image=reshape(Av_Image,N,N);
% Negative_Av_Image=255*ones(N,N)-255*(Reshaped_Av_Image/.....
%     max(max(Reshaped_Av_Image))); % Obtaining a negative image
%                                    % for the mean training face
%                                    % in order to enhance its
%                                    % appearance.
% imshow(uint8(Negative_Av_Image))
% title('The Average Training Face')
% pause
% close all

Known_Im_Subt_Mean=......
    zeros(N*N,Total_No_of_Known_Im); % An N^2xP, 2D matrix where
                                     % each column represents a
                                     % centered (with respect to
                                     % the set of the training
                                     % faces) training face vector.
for J=1:Total_No_of_Known_Im
    Known_Im_Subt_Mean(:,J)=Centered_Known_Im(:,J)-Av_Image;
    Reshaped_Known_Im_Subt_Mean=........
        reshape(Known_Im_Subt_Mean(:,J),N,N);
    Negative_Known_Im_Subt_Mean=255*ones(N,N)-.......
        255*(Reshaped_Known_Im_Subt_Mean/max(max(.......
        Reshaped_Known_Im_Subt_Mean))); % Obtaining a negative
                                        % image for the centered
                                        % training face in order
                                        % to enhance its
                                        % appearance.

    Known_Image=Known_Images(J).name;
%     figure('units','centimeters','position',[12 4 12.5 14])
%     subplot(1,1,1)
%     imshow(uint8(Negative_Known_Im_Subt_Mean))
```

```
%     if J==1
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .......
%             ', 1^{st} Projection)'];'(A Negative Image)'})
%     elseif J==2
%         title({['Centered (with Respect to the Set of the '....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ........
%             ', 2^{nd} Projection)'];'(A Negative Image)'})
%     elseif J==3
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .......
%             ', 3^{rd} Projection)'];'(A Negative Image)'})
%     elseif J==4
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .........
%             ', 1^{st} Projection)'];'(A Negative Image)'})
%     elseif J==5
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 2^{nd} Projection)'];'(A Negative Image)'})
%     elseif J==6
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .......
%             ', 3^{rd} Projection)'];'(A Negative Image)'})
%     elseif J==7
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) ......
%             ', 1^{st} Projection)'];'(A Negative Image)'})
%     elseif J==8
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .......
%             ', 2^{nd} Projection)'];'(A Negative Image)'})
%     elseif J==9
%         title({['Centered (with Respect to the Set of the '.....
%             'Training Faces) Training Face No.' num2str(J)];....
%             ['(' Known_Image(1:length(Known_Image)-6) .......
%             ', 3^{rd} Projection)'];'(A Negative Image)'})
%     end
%     disp(['Please, press any keyboard button to explore '......
%         'the remaining centered training faces >>>>>>>'])
%     pause
%     close all
```

```
%     clc
end
Known_Im_Subt_Mean;


Tested_Im_Subt_Mean=.......
    zeros(N*N,Total_No_of_Tested_Im); % An N^2xP1, 2D matrix where
                                      % each column represents a
                                      % tested image vector after
                                      % subtracting the average
                                      % training face.
for J1=1:Total_No_of_Tested_Im
    Tested_Im_Subt_Mean(:,J1)=Centered_Tested_Im(:,J1)-Av_Image;
    Reshaped_Tested_Im_Subt_Mean=........
        reshape(Tested_Im_Subt_Mean(:,J1),N,N);
    Negative_Tested_Im_Subt_Mean=255*ones(N,N)-255*.......
        (Reshaped_Tested_Im_Subt_Mean/max(max(.......
        Reshaped_Tested_Im_Subt_Mean))); % Obtaining a negative
                                         % image for the tested
                                         % image in order to
                                         % enhance its appearance.

%     figure('units','centimeters','position',[12 4 12.5 14])
%     subplot(1,1,1)
%     imshow(uint8(Negative_Tested_Im_Subt_Mean))
%     if J1<=L1
%         title({['Tested Image No.' num2str(J1) .........
%             ' (Mr. Mansour Alshammari, '.....
%             '1^{st} Projection)'];........
%             'After Subtracting the Average Training Face';.....
%             '(A Negative Image)'})
%     elseif J1>L1 && J1<=L2
%         title({['Tested Image No.' num2str(J1) .......
%             ' (Mr. Mansour Alshammari, '.....
%             '2^{nd} Projection)'];.........
%             'After Subtracting the Average Training Face';.....
%             '(A Negative Image)'})
%     elseif J1>L2 && J1<=L3
%         title({['Tested Image No.' num2str(J1) .....
%             ' (Mr. Mansour Alshammari, '.....
%             '3^{rd} Projection)'];.......
%             'After Subtracting the Average Training Face';.....
%             '(A Negative Image)'})
%     elseif J1>L3 && J1<=L4
%         title({['Tested Image No.' num2str(J1) .....
%             ' (Mr. Methkir Alharthee, '.......
%             '1^{st} Projection)'];.....
%             'After Subtracting the Average Training Face';....
%             '(A Negative Image)'})
%     elseif J1>L4 && J1<=L5
```

```
%           title({['Tested Image No.' num2str(J1) .....
%               ' (Mr. Methkir Alharthee, '.......
%               '2^{nd} Projection)'];.....
%               'After Subtracting the Average Training Face';.....
%               '(A Negative Image)'})
%       elseif J1>L5 && J1<=L6
%           title({['Tested Image No.' num2str(J1) .....
%               ' (Mr. Methkir Alharthee, '.......
%               '3^{rd} Projection)'];....
%               'After Subtracting the Average Training Face';....
%               '(A Negative Image)'})
%       elseif J1>L6 && J1<=L7
%           title({['Tested Image No.' num2str(J1) .....
%               ' (Mr. Mohammed Hanafy, '.......
%               '1^{st} Projection)'];.....
%               'After Subtracting the Average Training Face';....
%               '(A Negative Image)'})
%       elseif J1>L7 && J1<=L8
%           title({['Tested Image No.' num2str(J1) .....
%               ' (Mr. Mohammed Hanafy, '.......
%               '2^{nd} Projection)'];.....
%               'After Subtracting the Average Training Face';.....
%               '(A Negative Image)'})
%       elseif J1>L8 && J1<=L9
%           title({['Tested Image No.' num2str(J1) .....
%               ' (Mr. Mohammed Hanafy, '.......
%               '3^{rd} Projection)'];.....
%               'After Subtracting the Average Training Face';....
%               '(A Negative Image)'})
%       end
%       disp(['Please, press any keyboard button to explore '.....
%           'the remaining tested images'])
%       disp(['after subtracting the average training face '.....
%           'from them >>>>>>>'])
%       pause
%       close all
%       clc
end
Tested_Im_Subt_Mean;


% The calculation of a covariance matrix for all training faces.
Cov_Matrix=Known_Im_Subt_Mean*......
    transpose(Known_Im_Subt_Mean); % The covariance matrix
                                   % for all training faces.

% Another way for calculating the covariance matrix for all
% training faces.
% m=zeros(N*N,N*N);
% for i=1:Total_No_of_Known_Im
```

```
%      C=Known_Im_Subt_Mean(:,i)*transpose(Known_Im_Subt_Mean(:,i));
%      m=m+C;
% end
% Cov_Matrix=(1/Total_No_of_Known_Im)*m; % The covariance matrix
                                          % for all training faces.


% The calculation of eigenvalues and eigenvectors for the
% covariance matrix.
[Eigenvectors Eigenvalues]=.......
    eig(Cov_Matrix); % Note that, The calculated covariance
                     % matrix is usually too big which makes
                     % the calculation of eigenvalues and
                     % eigenvectors is very difficult if not
                     % impossible. So, it is not practical to
                     % calculate the eigenvalues and eigenvectors
                     % for the such matrix. The dimensions of the
                     % covariance matrix can be reduced to the
                     % number of the training faces as will be
                     % proved shortly.
Eigenvalues=(diag(Eigenvalues)).';

% Eigenvectors must be positive because the covariance matrix is
% positive definite. Due to round-off error, MATLAB makes the
% smallest eigenvectors negative. Then those negative eigenvectors
% must be set to zero.
for jjj=1:length(Eigenvalues)
    if Eigenvalues(1,jjj)<0
        Eigenvalues(1,jjj)=0;
    end
end


% The calculation of a more practical covariance matrix.
New_Cov_Matrix=transpose(Known_Im_Subt_Mean)*Known_Im_Subt_Mean;


[Eigvect Eigval]=eig(New_Cov_Matrix); % The calculation of
                                      % eigenvalues and
                                      % eigenvectors for the
                                      % reduced covariance matrix.

Eigval_Reduced_Cov=(diag(Eigval)).';
Eigvect_Reduced_Cov=Known_Im_Subt_Mean*.........
    Eigvect; % The columns of this matrix represent unnormalized
             % eigenvectors that are calculated based on the more
             % practical covariance matrix.

% Ordering the calculated eigenvalues from the reduced covariance
% matrix along with their eigenvectors in descending order as well
```

```
% as normalizing the eigenvectors.
Eigenvalues_Reduced_Cov=sort(Eigval_Reduced_Cov,'descend');
Eigenvectors_Reduced_Cov=zeros(size(Eigvect_Reduced_Cov,1),.....
    size(Eigvect_Reduced_Cov,2));
for ii=1:length(Eigenvalues_Reduced_Cov)
    for pp=1:length(Eigval_Reduced_Cov)
        if Eigenvalues_Reduced_Cov(1,ii)==Eigval_Reduced_Cov(1,pp)
            Eigenvectors_Reduced_Cov(:,ii)=........
                Eigvect_Reduced_Cov(:,pp)/.....
                norm(Eigvect_Reduced_Cov(:,pp));
            break
        end
    end
end


% PCA and IPCA algoritms for calculating a feature vector matrix.
% A feature vector matrix is a matrix that is composed of a couple
% of eigenvectors that follow the most significant patterns of the
% correlated faces. These eigenvectors are called eigenfaces. In
% fact, the eigenvalues associated with those eigenfaces are
% corresponding to the biggest calculated eigenvalues. Note that,
% the PCA is approximately similar to the IPCA. The main difference
% between them is that the way of selecting eigenvectors which form
% the feature vector matrix.

fid=fopen('PCA vs. IPCA.txt','w'); % A text file for typing the
                                   % required results to select the
                                   % desired eigenvectors for the
                                   % feature vector matrix.
fprintf(fid,['\n  ***** The Results of PCA and IPCA Used to'.....
    ' Select the Desired Eigenvectors *****\r\n']);
fprintf(fid,['    ***** for the Feature Vector'......
    ' Matrix. These Results Are Obtained from *****\r\n']);
fprintf(fid,['\t ***** the PCA and IPCA Code for Testing '......
    'and Setting up Thresholds *****\r\n\n']);
fprintf(fid,'\t\t\t\t      Transformed\r\n');
fprintf(fid,['No.    Eigenvalues    Eigenvalues   PIF'......
    '        IR(%%)\t    AIR(%%)      VCR(%%)    TVC(%%)\r\n']);
fprintf(fid,['====   ============   ===========   ======='......
    '    =======   ========    =======   ========\r\n']);

% The calculation of the transformed eigenvalues.
ro=zeros(1,length(Eigenvalues_Reduced_Cov));
for v=1:length(Eigenvalues_Reduced_Cov)
    ro(1,v)=1-(Eigenvalues_Reduced_Cov(1,v)/......
        sum(Eigenvalues_Reduced_Cov));
end

% The calculation of the possibility information function (PIF).
```

```
PIF=zeros(1,length(Eigenvalues_Reduced_Cov));
for nn=1:length(Eigenvalues_Reduced_Cov)
    PIF(1,nn)=-log2(ro(1,nn));
end

% The calculation of the possibility information entropy (PIE).
PIE=0;
for n1=1:length(Eigenvalues_Reduced_Cov)
    PIE=PIE-ro(1,n1)*log2(ro(1,n1));
end
PIE;

% The calculation of the information rate (IR) and accumulated
% information rate (AIR).
IR=zeros(1,length(Eigenvalues_Reduced_Cov));
AIR=zeros(1,length(Eigenvalues_Reduced_Cov));
PIF1=0;
for u=1:length(Eigenvalues_Reduced_Cov);
    IR(1,u)=PIF(1,u)/sum(PIF);
    PIF1=PIF(1,u)+PIF1;
    AIR(1,u)=PIF1/sum(PIF);
end

% The calculation of the variance contribution rate (VCR) and total
% variance contribution rate (TVC).
VCR=zeros(1,length(Eigenvalues_Reduced_Cov));
TVC=zeros(1,length(Eigenvalues_Reduced_Cov));
TVC1=0;
for Q=1:length(Eigenvalues_Reduced_Cov);
    VCR(1,Q)=Eigenvalues_Reduced_Cov(1,Q)/......
        sum(Eigenvalues_Reduced_Cov);
    TVC1=Eigenvalues_Reduced_Cov(1,Q)+TVC1;
    TVC(1,Q)=TVC1/sum(Eigenvalues_Reduced_Cov);
    fprintf(fid,['%-4.0f   %-12.4f   %-6.4f\t    %-7.4f   '....
        '%-7.4f   %-8.4f   %-7.4f   %-8.4f \r\n\n'],Q,.....
        Eigenvalues_Reduced_Cov(1,Q),ro(1,Q),PIF(1,Q),....
        IR(1,Q)*100,AIR(1,Q)*100,VCR(1,Q)*100,TVC(1,Q)*100);
end

fprintf(fid,['=============================================='.....
    '=======================================\r\n']);
fprintf(fid,['** Notice that, in IPCA we can take the first '.....
    'seven eigenvectors associated with the\r\n']);
fprintf(fid,['   biggest eigenvalues to form the feature '.....
    'vector matrix but in PCA we must take the\r\n']);
fprintf(fid,['   first eight eigenvectors. That because when '....
    'm=7, the AIR=95.6891%% which is good\r\n']);
fprintf(fid,['   enough but the TVC is slightly small. So, '.....
    'if we want to pick the eigenvectors\r\n']);
fprintf(fid,['   based on the TVC then we have to take the '.....
```

```
    'first eight eigenvectors in order to\r\n']);
fprintf(fid,['   make sure that the TVC is big enough. '......
    'Therefore, the AIR tells us more about the\r\n']);
fprintf(fid,['   information contained in the eigenfaces. '.....
    '\r\n\n\n']);
fclose(fid);

disp(['Please see the documented results of PCA and IPCA in '....
    'the open text file. Then select the'])
disp(['number of the eigenvectors for each algorithm required '....
    'to form the feature vector matrix.'])
disp(['After that, press any keyboard button to resume the '.....
    'code >>>>>>>>>>>>'])
Text='PCA vs. IPCA.txt';
open(Text) % Opening the text file which contains
           % the PCA and IPCA results.
pause
clc
open('PCA_IPCA_Testing_and_Setting_up_Thresholds.m')

% Customizing and fixing the number of eigenfaces for PCA and IPCA.
Prompt={['1 to m, enter the value of m for PCA, where m is '.....
    'the lower bound of eigenfaces. It can take up to ' ......
    num2str(length(Eigenvalues_Reduced_Cov)) ':'],.....
    ['1 to m, enter the value of m for IPCA, where m is the '.....
    'lower bound of eigenfaces. It can take up to ' .......
    num2str(length(Eigenvalues_Reduced_Cov)) ':']};
Dlg_Title='The Lower Bound of Eigenfaces for PCA and IPCA';
Num_Lines=1;
Def={'8','7'};
L=inputdlg(Prompt,Dlg_Title,Num_Lines,Def,'on');
V=str2num(char(L));
for xx=1:2
    if xx==1
        if V(xx)<1 || V(xx)>length(Eigenvalues_Reduced_Cov) || ....
                mod(V(xx),1)~=0 || V(xx)<=V(2)
            if V(xx)<1
                W=errordlg(['m for PCA Is Invalid Because It '.....
                    'Is Less Than One'],'An Error Dialog');
                return
            elseif V(xx)>length(Eigenvalues_Reduced_Cov)
                W=errordlg(['m for PCA Is Invalid Because It '....
                    'Is Bigger Than the Upper Bound of '......
                    'Eigenfaces'],'An Error Dialog');
                return
            elseif mod(V(xx),1)~=0
                W=errordlg(['m for PCA Is Invalid Because It '....
                    'Is Not an Integer'],'An Error Dialog');
                return
            elseif V(xx)<=V(2)
```

```
                W=errordlg(['m for PCA Is Invalid Because It '....
                    'Must Be Bigger Than IPCA']);
                return
            end
        end
    else
        if V(xx)<1 || mod(V(xx),1)~=0
            if V(xx)<1
                W=errordlg(['m for IPCA Is Invalid Because It '....
                    'Is Less Than One'],'An Error Dialog');
                return
            elseif mod(V(xx),1)~=0
                W=errordlg(['m for IPCA Is Invalid Because It '....
                    'Is Not an Integer'],'An Error Dialog');
                return
            end
        end
    end
end

Best_Eigenvalues_PCA=Eigenvalues_Reduced_Cov(1,1:V(1));
Best_Eigenvectors_PCA=........
    Eigenvectors_Reduced_Cov(:,1:V(1)); % The columns of this
                                        % matrix represent the
                                        % eigenfaces that are
                                        % calculated based on
                                        % PCA algorithm.
Best_Eigenvalues_IPCA=Eigenvalues_Reduced_Cov(1,1:V(2));
Best_Eigenvectors_IPCA=..........
    Eigenvectors_Reduced_Cov(:,1:V(2)); % The columns of this
                                        % matrix represent the
                                        % eigenfaces that are
                                        % calculated based on
                                        % IPCA algorithm.


% Plotting the eigenvalues for each explained algorithm compared
% with the calculated eigenvalues from the covariance matrix for
% all training faces.
Threshold=0.1; % This threshold is for picking
               % up the biggest eigenvalues.
[WW LL]=find(Eigenvalues>Threshold);
Flipped_Eigenvalues_Reduced_Cov=fliplr(Eigenvalues_Reduced_Cov);
if length(LL)<length(Flipped_Eigenvalues_Reduced_Cov)
    LL1=LL;
    LL=[LL(1)-ones(1,length(Flipped_Eigenvalues_Reduced_Cov)-....
        length(LL)) LL];
end
figure('units','centimeters','position',[6 1.2 25 16.9])
subplot(1,1,1)
```

```
bar(LL,[zeros(length(LL)-length(LL1)) Eigenvalues(LL1)],.......
    0.8,'FaceColor','k','EdgeColor','k')
hold on
bar(LL,[zeros(1,length(LL)-length(Best_Eigenvalues_PCA)) ........
    fliplr(Best_Eigenvalues_PCA)],0.8/2,'FaceColor',......
    'r','EdgeColor','r')
hold on
bar(LL,[zeros(1,length(LL)-length(Best_Eigenvalues_IPCA)) .......
    fliplr(Best_Eigenvalues_IPCA)],0.8/4,........
    'FaceColor','b','EdgeColor','b')
hold off
title({['The Calculated Eigenvalues for Each Proposed '.....
    'Algorithm Compared '];['with the Calculated Eigenvalues '....
    'form the Covariance Matrix for All Training Faces']})
xlabel('Eigenvalue Index')
ylabel('Eigenvalue')
legend(['The Calculated Eigenvalues from the Covariance '.....
    'Matrix for All Training Faces.'],['The Calculated '.....
    'Eigenvalues by Using PCA Algorithm.'],['The Calculated '.....
    'Eigenvalues by Using IPCA Algorithm.'],'Location','NorthWest')
disp('Please, press any keyboard button to resume the code >>>>')
pause
clc
close all


% Displaying the calculated eigenfaces from the covariance matrix
% for all training faces.
for I=1:length(LL1)
    Eigenvalues1=fliplr(LL1);
    Eigenvectors1=......
        flipdim(Eigenvectors(:,LL1),2); % This flipping just
                                        % to make the highest
                                        % correlated eigenface
                                        % is associated with the
                                        % first eigenvalue and
                                        % so on. This is done to
                                        % be compatable with the
                                        % generated document
                                        % "PCA vs. IPCA".
    X=floor(255*(double(Eigenvectors1(:,I))/.......
        max(max(Eigenvectors1(:,I))))); % Normalized eigenface.
                                        % This is done to increase
                                        % the dynamic range of the
                                        % eigenface for
                                        % visualization by scaling
                                        % the intensities of the
                                        % eigenface from 0 to 255.
    Eigenface=reshape(X,N,N);
    Negative_Eigenface=255*ones(N,N)-255*.....
```

```
        (Eigenface/max(max(Eigenface))); % Obtaining a negative
                                         % image for the eigenface
                                         % in order to enhance its
                                         % appearance.

    figure('units','centimeters','position',[15.5 5.5 9 11.5])
    subplot(1,1,1)
    imshow(uint8(Negative_Eigenface))
    title({['Eigenface No.' num2str(I) ...............
        ' Associated with Eigenvalue No.'........
        num2str(Eigenvalues1(I)) '.'];......
        ['It Is Calculated from the '.......
        'Covariance Matrix'];'for All Training Faces.';......
        '(A Negative Image)'})

    disp(['Please, press any keyboard button to explore '......
        'the remaining calculated eigenfaces'])
    disp(['from the covariance matrix for all training '......
        'faces >>>>>>>'])
    pause
    clc
    close all
end

% Displaying the calculated eigenfaces by using PCA algorithm.
for I=1:length(Best_Eigenvalues_PCA)
    X=floor(255*(double(Best_Eigenvectors_PCA(:,I))/max(max(.....
        Best_Eigenvectors_PCA(:,I))))); % Normalized eigenface.
                                        % This is done to increase
                                        % the dynamic range of the
                                        % eigenface for
                                        % visualization by scaling
                                        % the intensities of the
                                        % eigenface from 0 to 255.
    Eigenface=reshape(X,N,N);
    Negative_Eigenface=255*ones(N,N)-255*.....
        (Eigenface/max(max(Eigenface))); % Obtaining a negative
                                         % image for the eigenface
                                         % in order to enhance its
                                         % appearance.

    figure('units','centimeters','position',[15.5 5.5 8 10.5])
    subplot(1,1,1)
    imshow(uint8(Negative_Eigenface))
    title({['Calculated Eigenface No.' num2str(I) .......
        ' Associated'];['with Eigenvalue No.' num2str(I) .....
        ' by Using'];'PCA Algorithm';'(A Negative Image)'})

    disp(['Please, press any keyboard button to explore the '.....
        'remaining calculated'])
```

```
    disp('eigenfaces by using PCA algorithm >>>>>>>')
    pause
    clc
    close all
end

% Displaying the calculated eigenfaces by using IPCA algorithm.
for I=1:length(Best_Eigenvalues_IPCA)
    X=floor(255*(double(Best_Eigenvectors_IPCA(:,I))/max(max(.....
        Best_Eigenvectors_IPCA(:,I))))); % Normalized eigenface.
                                          % This is done to increase
                                          % the dynamic range of the
                                          % eigenface for
                                          % visualization by scaling
                                          % the intensities of the
                                          % eigenface from 0 to 255.
    Eigenface=reshape(X,N,N);
    Negative_Eigenface=255*ones(N,N)-255*.....
        (Eigenface/max(max(Eigenface))); % Obtaining a negative
                                          % image for the eigenface
                                          % in order to enhance its
                                          % appearance.

    figure('units','centimeters','position',[15.5 5.5 8 10.5])
    subplot(1,1,1)
    imshow(uint8(Negative_Eigenface))
    title({['Calculated Eigenface No.' num2str(I) .......
        ' Associated'];['with Eigenvalue No.' num2str(I) .......
        ' by Using'];'IPCA Algorithm';'(A Negative Image)'})

    disp(['Please, press any keyboard button to explore the '.....
        'remaining calculated'])
    disp('eigenfaces by using IPCA algorithm >>>>>>>')
    pause
    clc
    close all
end


save('Eigenvectors','Eigenvectors')
save('Best_Eigenvectors_PCA','Best_Eigenvectors_PCA')
save('Best_Eigenvectors_IPCA','Best_Eigenvectors_IPCA')
break


%%
%%%%% The Compression and Reconstruction of the Training Faces %%%%


clc
```

```
close all


%%%%% When a small number of eigenfaces is used to compress and
%%%%% reconstruct the training faces then the processing speed
%%%%% will increase so the IPCA algorithm is the fastest one then
%%%%% PCA algorithm finally the smallest processing speed occurs
%%%%% when all calculated eigenvectors from the covariance matrix
%%%%% for all training faces are used as eigenfaces. When a small
%%%%% number of the eigenfaces is used to project and reconstruct
%%%%% the training faces then the training faces will have bad
%%%%% quality. Therefore, the highest error in reconstruction
%%%%% occurs when the IPCA algorithm is used; then the PCA
%%%%% algorithm comes second; finally, the usage of all
%%%%% eigenvectors as eigenfaces produces the samllest
%%%%% reconstruction error.

% Best_Eigenvectors=Eigenvectors; % Just try it to see how affects
                                  % on the reconstructed training
                                  % faces.
% Best_Eigenvectors=Best_Eigenvectors_PCA; % Just try it to see how
                                           % affects on the
                                           % reconstructed training
                                           % faces.
Best_Eigenvectors=Best_Eigenvectors_IPCA; % Just try it to see how
                                          % affects on the
                                          % reconstructed training
                                          % faces.


% Projecting each training face on the eigenspace. It is just
% expressing each training face in terms of the eigenfaces. This is
% called principal components transform (also called the Hotelling
% or Karhunen-Loéve transform)
All_Known_Transformed_Im=..............
    zeros(size(Best_Eigenvectors,2),........
    Total_No_of_Known_Im); % A 2D matrix where each column
                           % represents the  coordinates of a
                           % projected training face in the
                           % eigenspace.
for r=1:Total_No_of_Known_Im
    All_Known_Transformed_Im(:,r)=Best_Eigenvectors.'*.......
        Known_Im_Subt_Mean(:,r);
end
All_Known_Transformed_Im;


% The reconstruction of the projected training faces.
All_Known_Reconstructed_Im_V=...........
    zeros(N*N,Total_No_of_Known_Im); % An N^2xP, 2D matrix where
```

```
                                                % each column represents a
                                                % reconstructed training face
                                                % vector.
All_Known_Reconstructed_Im=zeros(N,N,Total_No_of_Known_Im);
for a=1:Total_No_of_Known_Im
    Pre=reshape(Best_Eigenvectors*............
        All_Known_Transformed_Im(:,a),N,N)+............
        reshape(Av_Image,N,N); % Adding the average training face.

    RC1=Rows_Columns(:,:,a);
    F=RC1(1,:);
    F1=RC1(2,:);
    D=F(F>0);
    D1=F1(F1>0);
    RC=[D;D1]; % The rows and columns for the pixels of a face
               % after removing the added zero rows and columns.
               % The added zero rows and columns are added by
               % MATLAB for making the matrices of the rows and
               % columns of the faces pixels are equal.
    for QQ=1:size(RC,2)
        All_Known_Reconstructed_Im(RC(1,QQ),RC(2,QQ),a)=.......
            Pre(RC(1,QQ),RC(2,QQ))+Means(1,a); % Adding the mean
                                               % of the pixels of
                                               % a face.
    end

    Y=All_Known_Reconstructed_Im(:,:,a); % Removing any pixel less
                                         % than zero in a training
                                         % face because the image
                                         % can not be negative.
    [UU NN]=find(Y<0);
    for CC=1:size(UU,1)
        Y(UU(CC),NN(CC))=0;
    end

    All_Known_Reconstructed_Im_V(:,a)=reshape(Y,N*N,1);

    Known_Image=Known_Images(a).name;
    figure('units','centimeters','position',[16 7 7.5 8.5])
    subplot(1,1,1)
    imshow(uint8(reshape(All_Known_Reconstructed_Im_V(:,a),N,N)))
    if a==1
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) .........
            ', 1^{st} Projection)']})
    elseif a==2
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ........
            ', 2^{nd} Projection)']})
    elseif a==3
```

```
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ........
            ', 3^{rd} Projection)']})
    elseif a==4
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ......
            ', 1^{st} Projection)']})
    elseif a==5
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ......
            ', 2^{nd} Projection)']})
    elseif a==6
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 3^{rd} Projection)']})
    elseif a==7
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ......
            ', 1^{st} Projection)']})
    elseif a==8
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 2^{nd} Projection)']})
    elseif a==9
        title({['Reconstructed Training Face No.' num2str(a)];....
            ['(' Known_Image(1:length(Known_Image)-6) ......
            ', 3^{rd} Projection)']})
    end
    disp(['Please, press any keyboard button to explore '......
        'the remaining'])
    disp('reconstructed training faces >>>>>>>')
    pause
    close all
    clc
end
All_Known_Reconstructed_Im_V;


%%
%%%%%%%% The Calculation of Compression and Reconstruction %%%%%%%%
%%%%%%%%                    Performance                   %%%%%%%%

clc
close all


After_Compression_Normalization=zeros(1,...................
    length(Eigenvalues)); % Measuring an information rate after
                          % compression. The elements of this
                          % vector represent the information
```

```
                                % rates after compression with respect
                                % to the information rates before
                                % compression.
MSE_Compression=.......
    zeros(1,length(Eigenvalues)); % Measuring compression
                                  % performance or how much
                                  % compressed information is.
                                  % The elements of this vector
                                  % represent the mean squared
                                  % errors in compression when
                                  % different eigenfaces are
                                  % selected.
MSE_Reconstruction=zeros(length(Eigenvalues),..........
    Total_No_of_Known_Im); % Measuring reconstruction performance
                           % or the quality of a reconstructed
                           % training face. The elements of each
                           % column of this matrix represent the
                           % mean squared errors between a
                           % projected training face and its
                           % reconstruction when different
                           % eigenfaces are selected.
Eigenvalues1=fliplr(Eigenvalues);
Eigenvectors1=flipdim(Eigenvectors,2); % This flipping just to make
                                       % the highest correlated
                                       % eigenface is associated
                                       % with the first eigenvalue
                                       % and so on. This is done to
                                       % be compatable with the
                                       % generated document
                                       % "PCA vs. IPCA".
for kk=1:length(Eigenvalues)
    ['Iteration No.: ' num2str(kk) ' Out of ' ..........
        num2str(length(Eigenvalues))]
    Selected_Eigenvectors=Eigenvectors1(:,1:kk);

    % Projecting each training face on the eigenspace. It is just
    % expressing each training face in terms of the eigenfaces.
    % This is called principal components transform (also called
    % the Hotelling or Karhunen-Loéve transform)
    All_Known_Transformed_Im=..............
        zeros(size(Selected_Eigenvectors,2),........
        Total_No_of_Known_Im); % A 2D matrix where each column
                               % represents the coordinates of a
                               % projected training face in the
                               % eigenspace.
    for r=1:Total_No_of_Known_Im
        All_Known_Transformed_Im(:,r)=Selected_Eigenvectors.'*.....
            Known_Im_Subt_Mean(:,r);
    end
    All_Known_Transformed_Im;
```

```

    % The calculation of an information ratio before and after
    % compression.
    Before_Compression=Total_No_of_Known_Im*.....
        N*N; % The overall information when there is
             % no any compression technique is used.
    After_Compression=N*N*kk+kk*Total_No_of_Known_Im+.............
        N*N; % The overall information when a compression technique
             % is used. The overall information here is controlled
             % by the selected number of eigenvectors. When the
             % selected number is small then the information will
             % be samll and vice versa. It is very important to
             % notice that when all eigenvectors are used then
             % there will not be any compression and the overall
             % information when there is no any compression
             % technique is used will be the optimum one. Also, it
             % is really important to notice that the rows and
             % columns for the pixels of each face as well as the
             % means of the faces pixels are not added to the
             % overall information after compression that because
             % the face centering operation is not really important
             % for the image compression process and will not have
             % any effect if it is done or not but it has been done
             % here because it is important for other processes.
    Before_Compression_Normalization=(Before_Compression/.......
        Before_Compression)*100; % Note that, the normalization is
                                 % done to make the overall
                                 % information before compression
                                 % is equal to 100 all the time
                                 % in order to make comparison
                                 % easier.
    After_Compression_Normalization(1,kk)=(After_Compression/.....
        Before_Compression)*100; % Note that, the normalization is
                                 % done to make the overall
                                 % information before compression
                                 % is equal to 100 all the time
                                 % in order to make comparison
                                 % easier.
%     The_Information_Ratio=[...............
%         num2str(Before_Compression_Normalization) ............
%         '% (Before Compression) : ' ...............
%         num2str(After_Compression_Normalization(1,kk))....
%         '% (After Compression)'] % This is just to make the
%                                  % information ratio is readable
%                                  % on the command window.

    % The reconstruction of the projected training faces.
    All_Known_Reconstructed_Im=zeros(N,N,Total_No_of_Known_Im);
    for a=1:Total_No_of_Known_Im
        Pre=reshape(Selected_Eigenvectors*...........
```

```
            All_Known_Transformed_Im(:,a),N,N)+.........
            reshape(Av_Image,N,N); % Adding the average
                                   % training face.

        RC1=Rows_Columns(:,:,a);
        F=RC1(1,:);
        F1=RC1(2,:);
        D=F(F>0);
        D1=F1(F1>0);
        RC=[D;D1]; % The rows and columns for the pixels of a
                   % face after removing the added zero rows and
                   % columns. The added zero rows and columns are
                   % added by MATLAB for making the matrices of
                   % the rows and columns of the faces pixels
                   % are equal.
        for QQ=1:size(RC,2)
            All_Known_Reconstructed_Im(RC(1,QQ),RC(2,QQ),a)=......
                Pre(RC(1,QQ),RC(2,QQ))+.........
                Means(1,a); % Adding the mean of the
                            % pixels of a face.
        end

        Y=All_Known_Reconstructed_Im(:,:,a); % Removing any pixel
                                             % less than zero in
                                             % a training face
                                             % because the image
                                             % can not be negative.
        [UU NN]=find(Y<0);
        for CC=1:size(UU,1)
            Y(UU(CC),NN(CC))=0;
        end

        MSE_Compression(1,kk)=sum(Eigenvalues1(1,kk+1:end));
        MSE_Reconstruction(kk,a)=.........
            sum(sum(..........
            (reshape(Normalized_Known_Im_V(:,a),N,N)-Y).^2))/N*N;

%         % Displaying the effect of the selected eigenvectors on
%         % the reconstructed training faces.
%         Known_Image=Known_Images(a).name;
%         figure('units','centimeters','position',[16 7 7.5 8.5])
%         subplot(3,1,1)
%         imshow(uint8(reshape(Normalized_Known_Im_V(:,a),N,N)))
%         if a==1
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) .....
%                 ', 1^{st} Projection)']})
%         elseif a==2
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) ....
```

```
%                 ', 2^{nd} Projection)']})
%         elseif a==3
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) .....
%                 ', 3^{rd} Projection)']})
%         elseif a==4
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) ......
%                 ', 1^{st} Projection)']})
%         elseif a==5
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) ......
%                 ', 2^{nd} Projection)']})
%         elseif a==6
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) .....
%                 ', 3^{rd} Projection)']})
%         elseif a==7
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) ......
%                 ', 1^{st} Projection)']})
%         elseif a==8
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) .....
%                 ', 2^{nd} Projection)']})
%         elseif a==9
%             title({['Original Training Face No.' num2str(a)];....
%                 ['(' Known_Image(1:length(Known_Image)-6) ......
%                 ', 3^{rd} Projection)']})
%         end
%         subplot(3,1,2)
%         imshow(uint8(Y))
%         if a==1
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==2
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==3
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==4
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==5
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==6
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==7
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==8
%             title(['Its Reconstruction When q=' num2str(kk)])
%         elseif a==9
%             title(['Its Reconstruction When q=' num2str(kk)])
```

```
%          end
%          subplot(3,1,3)
%          imshow(uint8(..........
%              (reshape(Normalized_Known_Im_V(:,a),N,N)-Y).^2))
%          if a==1
%              title('The Squared Error')
%          elseif a==2
%              title('The Squared Error')
%          elseif a==3
%              title('The Squared Error')
%          elseif a==4
%              title('The Squared Error')
%          elseif a==5
%              title('The Squared Error')
%          elseif a==6
%              title('The Squared Error')
%          elseif a==7
%              title('The Squared Error')
%          elseif a==8
%              title('The Squared Error')
%          elseif a==9
%              title('The Squared Error')
%          end
%
%          kk
%          pause
%          close all
    end
end


% Plotting the information rates when different eigenfaces are
% selected compared with the original information rate for all
% training faces and explaining the information rates for the PCA
% and IPCA algorithms on the plot.
clc
figure('units','centimeters','position',[0.15 1.2 35.8 16.9])
subplot(2,1,1)
Leg1=plot(1:length(Eigenvalues),After_Compression_Normalization);
Leg2=line([0 length(Eigenvalues)],[100 100],'Color',[0 102/255 0]);
hold on
Leg3=plot(1,After_Compression_Normalization(1),'kd',.....
    'LineWidth',1.5,'MarkerEdgeColor','k','MarkerFaceColor',.....
    'm','MarkerSize',8);
text(-50,After_Compression_Normalization(1)+3650,.....
    {'\fontsize{10} \color{black}' .......
    After_Compression_Normalization(1)})
hold on
Leg4=plot(length(Eigenvalues),.........
    After_Compression_Normalization(length(Eigenvalues)),'kd',.....
```

```
    'LineWidth',1.5,'MarkerEdgeColor','k','MarkerFaceColor',.....
    'g','MarkerSize',8);
text(length(Eigenvalues)-140,............
    After_Compression_Normalization(length(Eigenvalues))+2350,....
    {'\fontsize{10} \color{black}' .........
    After_Compression_Normalization(length(Eigenvalues))})
hold off
axis([-100 length(Eigenvalues)+(length(Eigenvalues)/40) -2000 .....
    max(After_Compression_Normalization)+........
    (max(After_Compression_Normalization)/10)])
set(gca,'XTick',[1 length(Eigenvalues)/2 length(Eigenvalues)])
title({['The Information Rates When Different Eigenfaces '......
    'Are Selected Compared '];.......
    'With the Original Information Rate for All Training Faces'})
xlabel('The Number of Selected Eigenfaces')
ylabel('The Information Rate (%)')
legend([Leg1 Leg2 Leg3 Leg4],['The Information Rates When '.......
    'Different Eigenfaces Are Selected.'],['The Information '.....
    'Rate for All Training Faces.'],['The Information Rate '.....
    'When the First Eigenface Is Selected.'],['The '.......
    'Information Rate When All Eigenfaces Are Selected.'],.....
    'Location','NorthWest');
subplot(2,1,2)
Leg1=plot(1:length(Eigenvalues),After_Compression_Normalization);
axis([0 20 0 200])
Leg2=line([0 length(Eigenvalues)],[100 100],'Color',[0 102/255 0]);
Leg3=line([length(Best_Eigenvalues_PCA) ......
    length(Best_Eigenvalues_PCA)],[0 .......
    After_Compression_Normalization(length(.......
    Best_Eigenvalues_PCA))],'LineStyle','--','Color','k',....
    'LineWidth',3);
line([0 length(Best_Eigenvalues_PCA)],.....
    [After_Compression_Normalization(.......
    length(Best_Eigenvalues_PCA)) ......
    After_Compression_Normalization(......
    length(Best_Eigenvalues_PCA))],......
    'LineStyle','--','Color','k','LineWidth',3)
text(0.1,After_Compression_Normalization(.........
    length(Best_Eigenvalues_PCA))+16,......
    {'\fontsize{10} \color{black}' ........
    num2str(After_Compression_Normalization(.......
    length(Best_Eigenvalues_PCA)),'%6.4f')})
Leg4=line([length(Best_Eigenvalues_IPCA) ........
    length(Best_Eigenvalues_IPCA)],[0 ........
    After_Compression_Normalization(.......
    length(Best_Eigenvalues_IPCA))],'LineStyle','--','Color',....
    'r','LineWidth',4);
line([0 length(Best_Eigenvalues_IPCA)],......
    [After_Compression_Normalization(.....
    length(Best_Eigenvalues_IPCA)) .....
```

```
    After_Compression_Normalization(......
    length(Best_Eigenvalues_IPCA))],'LineStyle','--','Color',....
    'r','LineWidth',4)
text(0.08,After_Compression_Normalization(.....
    length(Best_Eigenvalues_IPCA))-1.7,....
    {'\fontsize{10} \color{red} \bf' .......
    num2str(After_Compression_Normalization(.....
    length(Best_Eigenvalues_IPCA)),'%6.4f')})
vv=[length(Best_Eigenvalues_IPCA) length(Best_Eigenvalues_PCA)];
if vv(1)==1 || vv(2)==1
    set(gca,'XTick',[0 sort(vv) 20])
else set(gca,'XTick',[0 1 sort(vv) 20])
end
title(['Explaining the Information Rates for the PCA and '.....
    'IPCA Algorithms on the Plot'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Information Rate (%)')
legend([Leg1 Leg2 Leg3 Leg4],['The Information Rates When '.....
    'Different Eigenfaces Are Selected.'],['The Information '....
    'Rate for All Training Faces.'],['The Information Rate '......
    'When PCA Algorithm Is Used.'],['The Information '.....
    'Rate When IPCA Algorithm Is Used.'],'Location','SouthEast');
disp('Please, press any keyboard button to resume the code >>>>')
pause
clc
close all


% Plotting the mean squared errors of compression for different
% selected eigenfaces compared with the mean squared errors for
% the PCA and IPCA algorithms.
figure('units','centimeters','position',[0.15 1.2 35.8 16.9])
subplot(2,1,1)
Leg1=plot(1:length(Eigenvalues),MSE_Compression);
hold on
Leg2=plot(1,MSE_Compression(1),'kd','LineWidth',1.5,......
    'MarkerEdgeColor','k','MarkerFaceColor','m','MarkerSize',8);
text(25,MSE_Compression(1)+(10^7/11),.......
    {'\fontsize{10} \color{black}' MSE_Compression(1)})
hold on
Leg3=plot(length(Eigenvalues),......
    MSE_Compression(length(Eigenvalues)),'kd','LineWidth',1.5,....
    'MarkerEdgeColor','k','MarkerFaceColor','g','MarkerSize',8);
text(length(Eigenvalues)-8,........
    MSE_Compression(length(Eigenvalues))+10^7/3.2,.......
    {'\fontsize{10} \color{black}' ........
    MSE_Compression(length(Eigenvalues))})
hold off
axis([0 length(Eigenvalues)+(length(Eigenvalues)/40) ......
    -max(MSE_Compression)/10 .....
```

```
    max(MSE_Compression)+(max(MSE_Compression)/10)])
set(gca,'XTick',[1 length(Eigenvalues)/2 length(Eigenvalues)])
title(['The Mean Squared Errors of Compression for Different '....
    'Selected Eigenfaces'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Mean Squared Error')
legend([Leg1 Leg2 Leg3],['The Mean Squared Errors of '.....
    'Compression for Different Selected Eigenfaces.'],....
    ['The Mean Squared Error of Compression When the First '.....
    'Eigenface Is Selected.'],['The Mean Squared Error of '.....
    'Compression When All Eigenfaces Are Selected.'],......
    'Location','NorthEast');
subplot(2,1,2)
Leg1=plot(1:length(Eigenvalues),MSE_Compression);
axis([0 20 -10^7/4 max(MSE_Compression)+(10^7/4)])
Leg2=line([length(Best_Eigenvalues_PCA) ........
    length(Best_Eigenvalues_PCA)],.......
    [0 MSE_Compression(length(Best_Eigenvalues_PCA))],.....
    'LineStyle','--','Color','k','LineWidth',3);
line([0 length(Best_Eigenvalues_PCA)],......
    [MSE_Compression(length(Best_Eigenvalues_PCA)) ......
    MSE_Compression(length(Best_Eigenvalues_PCA))],.......
    'LineStyle','--','Color','k','LineWidth',3)
text(0.08,MSE_Compression(length(Best_Eigenvalues_PCA))+.....
    (-0.008*10^7),{'\fontsize{10} \color{black}' .....
    num2str(MSE_Compression(length(Best_Eigenvalues_PCA)))})
Leg3=line([length(Best_Eigenvalues_IPCA) .......
    length(Best_Eigenvalues_IPCA)],[0 .....
    MSE_Compression(length(Best_Eigenvalues_IPCA))],....
    'LineStyle','--','Color','r','LineWidth',4);
line([0 length(Best_Eigenvalues_IPCA)],.....
    [MSE_Compression(length(Best_Eigenvalues_IPCA)) .....
    MSE_Compression(length(Best_Eigenvalues_IPCA))],....
    'LineStyle','--','Color','r','LineWidth',4)
text(0.08,MSE_Compression(length(Best_Eigenvalues_IPCA))+.....
    0.24*10^7,{'\fontsize{10} \color{red} \bf' .......
    num2str(MSE_Compression(length(Best_Eigenvalues_IPCA)))})
if vv(1)==1 || vv(2)==1
    set(gca,'XTick',[0 sort(vv) 20])
else set(gca,'XTick',[0 1 sort(vv) 20])
end
title(['Explaining the Mean Squared Errors for the PCA and '....
    'IPCA Algorithms on the Plot'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Mean Squared Error')
legend([Leg1 Leg2 Leg3],['The Mean Squared Errors of '.....
    'Compression for Different Selected Eigenfaces.'],.....
    'The Mean Squared Error for PCA Algorithm.',.....
    'The Mean Squared Error for IPCA Algorithm.',.....
    'Location','NorthEast');
```

```
disp('Please, press any keyboard button to resume the code >>>>')
pause
clc
close all


% Plotting the mean squared errors between each training face and
% its reconstruction for different selected eigenfaces compared
% with the mean squared errors between each training face and its
% reconstruction for the PCA and IPCA Algorithms.
figure('units','centimeters','position',[0.15 1.2 35.8 16.9])
for jj=1:Total_No_of_Known_Im
    subplot(2,1,1)
    Leg1=plot(1:length(Eigenvalues),(MSE_Reconstruction(:,jj)).');
    hold on
    Leg2=plot(1,MSE_Reconstruction(1,jj),'kd','LineWidth',1.5,....
        'MarkerEdgeColor','k','MarkerFaceColor','m',.....
        'MarkerSize',8);
    text(35,MSE_Reconstruction(1,jj)+........
        max(MSE_Reconstruction(:,jj))/22,.........
        {'\fontsize{10} \color{black}' MSE_Reconstruction(1,jj)})
    hold on
    Leg3=plot(length(Eigenvalues),.......
        MSE_Reconstruction(length(Eigenvalues),jj),'kd',.....
        'LineWidth',1.5,'MarkerEdgeColor','k',.....
        'MarkerFaceColor','g','MarkerSize',8);
    text(length(Eigenvalues)-75,......
        MSE_Reconstruction(length(Eigenvalues),jj)+.....
        max(MSE_Reconstruction(:,jj))/7,.......
        {'\fontsize{10} \color{black}' .....
        MSE_Reconstruction(length(Eigenvalues),jj)})
    hold off
    axis([0 length(Eigenvalues)+(length(Eigenvalues)/15) .....
        -max(MSE_Reconstruction(:,jj))/10 ......
        max(MSE_Reconstruction(:,jj))+........
        (max(MSE_Reconstruction(:,jj))/10)])
    set(gca,'XTick',[1 length(Eigenvalues)/2 length(Eigenvalues)])
    Known_Image=Known_Images(jj).name;
    if jj==1
        title({['The Mean Squared Errors of Reconstructing '....
            'Training'];['Face No.' num2str(jj) .....
            ' for Different Selected Eigenfaces'];.....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 1^{st} Projection)']})
    elseif jj==2
        title({['The Mean Squared Errors of Reconstructing '....
            'Training']; ['Face No.' num2str(jj) .....
            ' for Different Selected Eigenfaces'];.....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 2^{nd} Projection)']})
```

```
    elseif jj==3
        title({['The Mean Squared Errors of Reconstructing '.....
            'Training']; ['Face No.' num2str(jj) .....
            ' for Different Selected Eigenfaces'];.....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 3^{rd} Projection)']})
    elseif jj==4
        title({['The Mean Squared Errors of Reconstructing '.....
            'Training']; ['Face No.' num2str(jj) .....
            ' for Different Selected Eigenfaces'];.....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 1^{st} Projection)']})
    elseif jj==5
        title({['The Mean Squared Errors of Reconstructing '.....
            'Training']; ['Face No.' num2str(jj) ......
            ' for Different Selected Eigenfaces'];....
            ['(' Known_Image(1:length(Known_Image)-6) ....
            ', 2^{nd} Projection)']})
    elseif jj==6
        title({['The Mean Squared Errors of Reconstructing '.....
            'Training']; ['Face No.' num2str(jj) ....
            ' for Different Selected Eigenfaces'];....
            ['(' Known_Image(1:length(Known_Image)-6) ....
            ', 3^{rd} Projection)']})
    elseif jj==7
        title({['The Mean Squared Errors of Reconstructing '....
            'Training']; ['Face No.' num2str(jj) .....
            ' for Different Selected Eigenfaces'];....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 1^{st} Projection)']})
    elseif jj==8
        title({['The Mean Squared Errors of Reconstructing '....
            'Training']; ['Face No.' num2str(jj) ....
            ' for Different Selected Eigenfaces'];.....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 2^{nd} Projection)']})
    elseif jj==9
        title({['The Mean Squared Errors of Reconstructing '....
            'Training']; ['Face No.' num2str(jj) ....
            ' for Different Selected Eigenfaces'];....
            ['(' Known_Image(1:length(Known_Image)-6) .....
            ', 3^{rd} Projection)']})
    end
    xlabel('The Number of Selected Eigenfaces')
    ylabel('The Mean Squared Error')
    Leg=legend([Leg1 Leg2 Leg3],['The Mean Squared Errors of '....
        'Reconstruction for Different Selected Eigenfaces.'],....
        ['The Mean Squared Error of Reconstruction When the '.....
        'First Eigenface Is Selected.'],['The Mean Squared '.....
        'Error of Reconstruction When All Eigenfaces '.....
```

```
            'Are Selected.'],'Location','North');
        subplot(2,1,2)
        MSE_Recons=(MSE_Reconstruction(:,jj)).';
        Leg1=plot(1:length(Eigenvalues),MSE_Recons);
        axis([0 20 -max(MSE_Recons)/6 ......
            max(MSE_Recons)+(max(MSE_Recons)/10)])
        Leg2=line([length(Best_Eigenvalues_PCA) .....
            length(Best_Eigenvalues_PCA)],[0 .....
            MSE_Recons(length(Best_Eigenvalues_PCA))],....
            'LineStyle','--','Color','k','LineWidth',3);
        line([0 length(Best_Eigenvalues_PCA)],.....
            [MSE_Recons(length(Best_Eigenvalues_PCA)) .....
            MSE_Recons(length(Best_Eigenvalues_PCA))],......
            'LineStyle','--','Color','k','LineWidth',3)
        text(0.1,MSE_Recons(length(Best_Eigenvalues_PCA)).....
            -(max(MSE_Recons)/88),{'\fontsize{10} \color{black}' .....
            num2str(MSE_Recons(length(Best_Eigenvalues_PCA)))})
        Leg3=line([length(Best_Eigenvalues_IPCA) .....
            length(Best_Eigenvalues_IPCA)],.....
            [0 MSE_Recons(length(Best_Eigenvalues_IPCA))],.....
            'LineStyle','--','Color','r','LineWidth',4);
        line([0 length(Best_Eigenvalues_IPCA)],....
            [MSE_Recons(length(Best_Eigenvalues_IPCA)) .....
            MSE_Recons(length(Best_Eigenvalues_IPCA))],.....
            'LineStyle','--','Color','r','LineWidth',4)
        text(0.1,MSE_Recons(length(Best_Eigenvalues_IPCA)).....
            +(max(MSE_Recons)/8),{'\fontsize{10} \color{red} \bf' ....
            num2str(MSE_Recons(length(Best_Eigenvalues_IPCA)))})
        if vv(1)==1 || vv(2)==1
            set(gca,'XTick',[0 sort(vv) 20])
        else set(gca,'XTick',[0 1 sort(vv) 20])
        end
        title(['Explaining the Mean Squared Errors for the '.....
            'PCA and IPCA Algorithms on the Plot'])
        xlabel('The Number of Selected Eigenfaces')
        ylabel('The Mean Squared Error')
        Leg=legend([Leg1 Leg2 Leg3],['The Mean Squared Errors of '.....
            'Reconstruction for Different Selected Eigenfaces.'],....
            'The Mean Squared Error for PCA Algorithm.',....
            'The Mean Squared Error for IPCA Algorithm.',....
            'Location','NorthEast');

        disp(['Please, press any keyboard button to explore '....
            'the remaining mean'])
        disp(['squared errors for other reconstructed training '....
            'faces >>>>>>>'])
        pause
        clc
    end
    close all
```

```
%%
%%%%%%%%%%%%%%%%%%%% A Face Recognition Process %%%%%%%%%%%%%%%%%%


clc
close all


%%%%% When the coordinates number of the projected training faces
%%%%% in the eigenspace increases, the error rate will decrease and
%%%%% vice versa as well as when the number decreases, the
%%%%% processing speed will increase and vice versa. So, the usage
%%%%% of all calculated eigenvectors as eigenfaces will lead to the
%%%%% smallest error rate and biggest processing time then the
%%%%% usage of the calculated eigenfaces by using PCA algorithm
%%%%% finally the usage of the calculated eigenfaces by using IPCA
%%%%% algorithm will lead to the biggest error rate and smallest
%%%%% processing time. It is very important to notice that the
%%%%% calculation of all eigenvectors from the covariance matrix
%%%%% for all training faces is too difficult because the
%%%%% covariance matrix is too big as explained before  so it is
%%%%% impractical to use all eigenvectors as eigenfaces.

% Best_Eigenvectors=Eigenvectors; % Just try it to see how affects
                                  % on the results of face
                                  % recognition.
Best_Eigenvectors=Best_Eigenvectors_PCA; % Just try it to see how
                                         % affects on the results
                                         % of face recognition.
% Best_Eigenvectors=Best_Eigenvectors_IPCA; % Just try it to see
                                            % how affects on the
                                            % results of face
                                            % recognition.


% Projecting each training face on the eigenspace. It is just
% expressing each training face in terms of the eigenfaces. This is
% called principal components transform (also called the Hotelling
% or Karhunen—Loéve transform)
All_Known_Transformed_Im=........
    zeros(size(Best_Eigenvectors,2),......
    Total_No_of_Known_Im); % A 2D matrix where each
                           % column represents the
                           % coordinates of a
                           % projected training
                           % face in the eigenspace.
for r=1:Total_No_of_Known_Im
    All_Known_Transformed_Im(:,r)=Best_Eigenvectors.'*......
```

```
        Known_Im_Subt_Mean(:,r);
end
All_Known_Transformed_Im;


% Projecting each tested image on the eigenspace. It is just
% expressing each tested image in terms of the eigenfaces. This is
% called principal components transform (also called the Hotelling
% or Karhunen-Loéve transform)
All_Tested_Transformed_Im=.....
    zeros(size(Best_Eigenvectors,2),....
    Total_No_of_Tested_Im); % A 2D matrix where each
                            % column represents the
                            % coordinates of a
                            % projected tested image
                            % in the eigenspace.
for r1=1:Total_No_of_Tested_Im
    All_Tested_Transformed_Im(:,r1)=Best_Eigenvectors.'*......
        Tested_Im_Subt_Mean(:,r1);
end
All_Tested_Transformed_Im;


fid=fopen('Face Recognition Results for Testing.txt',.....
    'w'); % A text file for typing
          % the results of face
          % recognition.
fprintf(fid,['\n\t ***** The Results of Face Recognition '.......
    'Obtained from the PCA and IPCA *****\r\n']);
fprintf(fid,['\t\t\t\t***** Code for Testing and Setting up '.....
    'Thresholds *****\r\n\n']);
fprintf(fid,['Image No.       The Image Is Originally for   '......
    'The Image Is Recognized as   The Status\r\n']);
fprintf(fid,['=============   ===========================   '.....
    '==========================   ==========\r\n']);

Distances_Vector=........
    zeros(Total_No_of_Tested_Im,.....
    Total_No_of_Known_Im); % A 2D matrix where each row
                           % represents the distances
                           % between the weights of each
                           % training face and the
                           % weights of one of the
                           % tested images.

% The distances between the weights of a training face and the
% weights of each corresponding tested image. Note that, here the
% training face and tested images have the same face and projection
% so these distances must be the smallest. The distances are
% extracted form the Distances_Vector matrix.
```

```
Distances_Vector_P1=zeros(1,Im_P(1));
Distances_Vector_P2=zeros(1,Im_P(2));
Distances_Vector_P3=zeros(1,Im_P(3));
Distances_Vector_P4=zeros(1,Im_P(4));
Distances_Vector_P5=zeros(1,Im_P(5));
Distances_Vector_P6=zeros(1,Im_P(6));
Distances_Vector_P7=zeros(1,Im_P(7));
Distances_Vector_P8=zeros(1,Im_P(8));
Distances_Vector_P9=zeros(1,Im_P(9));

for p=1:Total_No_of_Tested_Im
    for q=1:Total_No_of_Known_Im
        Distances_Vector(p,q)=.....
            norm(All_Tested_Transformed_Im(:,p)-.....
            All_Known_Transformed_Im(:,q));
    end

    if p<=L1
        Distances_Vector_P1(1,p)=Distances_Vector(p,1);
    elseif p>L1 && p<=L2
        Distances_Vector_P2(1,p-L1)=Distances_Vector(p,2);
    elseif p>L2 && p<=L3
        Distances_Vector_P3(1,p-L2)=Distances_Vector(p,3);
    elseif p>L3 && p<=L4
        Distances_Vector_P4(1,p-L3)=Distances_Vector(p,4);
    elseif p>L4 && p<=L5
        Distances_Vector_P5(1,p-L4)=Distances_Vector(p,5);
    elseif p>L5 && p<=L6
        Distances_Vector_P6(1,p-L5)=Distances_Vector(p,6);
    elseif p>L6 && p<=L7
        Distances_Vector_P7(1,p-L6)=Distances_Vector(p,7);
    elseif p>L7 && p<=L8
        Distances_Vector_P8(1,p-L7)=Distances_Vector(p,8);
    elseif p>L8 && p<=L9
        Distances_Vector_P9(1,p-L8)=Distances_Vector(p,9);
    end
end
d1=Distances_Vector_P1;
d2=Distances_Vector_P2;
d3=Distances_Vector_P3;
d4=Distances_Vector_P4;
d5=Distances_Vector_P5;
d6=Distances_Vector_P6;
d7=Distances_Vector_P7;
d8=Distances_Vector_P8;
d9=Distances_Vector_P9;

% The calculation of the mean and standard deviation for each
% vector of the minimum distances and stacking them in a vector for
% the means and another for the standard deviations. This is done
```

```
% for setting up a threshold for face recognition because when a
% distance between a training face and a tested image is the
% smallest with respect to the other training faces, that does not
% mean the tested image is recognized as the training face due to
% the tested image can be different than the training face and has
% the smallest distance in the same time. So, a certain threshold
% must be used to increase the accuracy of recognition.
P_Mean=[mean(d1);mean(d2);mean(d3);mean(d4);mean(d5);mean(d6);.....
    mean(d7);mean(d8);mean(d9)];
P_STD=[std(d1);std(d2);std(d3);std(d4);std(d5);std(d6);std(d7);....
    std(d8);std(d9)];
% save(['Means for Face Recognition When All Eigenvectors '....
%     'Are Used as Eigenfaces'],'P_Mean')
% save(['STDs for Face Recognition When All Eigenvectors '.....
%     'Are Used as Eigenfaces'],'P_STD')
save(['Means for Face Recognition When the Eigenfaces '.....
    'Computed by Using PCA Algorithm Are Used'],'P_Mean')
save(['STDs for Face Recognition When the Eigenfaces '.....
    'Computed by Using PCA Algorithm Are Used'],'P_STD')
% save(['Means for Face Recognition When the Eigenfaces '....
%     'Computed by Using IPCA Algorithm Are Used'],'P_Mean')
% save(['STDs for Face Recognition When the Eigenfaces '.....
%     'Computed by Using IPCA Algorithm Are Used'],'P_STD')

Failures_Vector=zeros(1,......
    Total_No_of_Tested_Im); % A vector for counting the number of
                            % failures in the face recognition
                            % process.

Latex_Matrix=cell(Total_No_of_Tested_Im,4); % This matrix is used
                                            % for creating a table
                                            % in Latex.
for w=1:Total_No_of_Tested_Im
    % The face recognition process.
    for h=1:Total_No_of_Known_Im
        if min(Distances_Vector(w,:))==.......
                Distances_Vector(w,h) && ......
                min(Distances_Vector(w,:))>=......
                (P_Mean(h,1)-P_STD(h,1)) &&.....
                min(Distances_Vector(w,:))<=......
                (P_Mean(h,1)+P_STD(h,1))
            s=transpose(struct2cell(Known_Images));
            c=sortrows(s,1);
            z=c(:,1);
            Recognized_As=char(z(h,1));
            Recognized_Image_Location=.......
                fullfile(Known_Images_Folder,Recognized_As);
            Recognized_image=im2double(rgb2gray(.......
                imread(Recognized_Image_Location)));
            break;
```

```
        else
            Recognized_As='Unknown Image';
            Recognized_image=imread('Unknown_Face.jpg');
        end
    end

    % Defining the face.
    if w<=L3
        n='Mr. Mansour Alshammari';
    elseif L3<w && w<=L6
        n='Mr. Methkir Alharthee';
    else n='Mr. Mohammed Hanafy';
    end

    y1=strcmp(Recognized_As(1:length(Recognized_As)-6),....
        'Mr. Mansour Alshammari');
    y2=strcmp(Recognized_As(1:length(Recognized_As)-6),.....
        'Mr. Methkir Alharthee');
    y3=strcmp(Recognized_As(1:length(Recognized_As)-6),....
        'Mr. Mohammed Hanafy');
    f='Success';
    if w<=L3 && y1==0;
        f='Failure';
        Failures_Vector(1,w)=1;
    elseif w>L3 && w<=L6 && y2==0;
        f='Failure';
        Failures_Vector(1,w)=1;
    elseif w>L6 && w<=L9 && y3==0;
        f='Failure';
        Failures_Vector(1,w)=1;
    end

%     Tested_Im_Number=[num2str(w) '.jpg'];
%     Tested_Im_Location=.....
%         fullfile(Tested_Images_Folder,Tested_Im_Number);
%     Tested_Im=im2double(rgb2gray(imread(Tested_Im_Location)));
%     subplot(2,1,1)
%     imshow(Tested_Im)
%     title({['Image No.' num2str(w) ' Is Originally for'];n})
%     subplot(2,1,2)
%     imshow(Recognized_image)
%     if y1==1 || y2==1 || y3==1
%         title({'The Image Is Recognized As';..............
%             Recognized_As(1:length(Recognized_As)-6)})
%     else title({'The Image Is Recognized As' .....
%             ['an' blanks(1) Recognized_As]})
%     end

    if y1==1 || y2==1 || y3==1
        fprintf(fid,['%0.3d\t\t\t    %-22s\t      %-22s\t   '.....
```

```
            '%s \r\n\n'],w,n,........
            Recognized_As(1:length(Recognized_As)-6),f);
        Latex_Matrix(w,1:4)={num2str(w) n ......
            Recognized_As(1:length(Recognized_As)-6) f};
    else fprintf(fid,.........
            '%0.3d\t\t\t    %-22s\t      %-22s\t   %s \r\n\n',....
            w,n,Recognized_As,f);
        Latex_Matrix(w,1:4)={num2str(w) n Recognized_As f};
    end

%     disp(['Please, press Any keyboard button to see another '....
%         'face and its recognition....'])
%     pause
%     clc
end
Total_Number_of_Failures=sum(Failures_Vector); % The total number
                                               % of failures in
                                               % the face
                                               % recognition
                                               % process.

fprintf(fid,['================================================'.....
    '======================================\r\n']);
fprintf(fid,['** The Total Number of Successes: %0.3d out of '.....
    '%0.3d (%3.4f%%) \r\n\n'],Total_No_of_Tested_Im-.....
    Total_Number_of_Failures,Total_No_of_Tested_Im,....
    ((Total_No_of_Tested_Im-Total_Number_of_Failures)/.....
    Total_No_of_Tested_Im)*100);
fprintf(fid,['** The Total Number of Failures: %0.3d out of '.....
    '%0.3d (%3.4f%%) \r\n\n'],....
    Total_Number_of_Failures,Total_No_of_Tested_Im,.......
    (Total_Number_of_Failures/Total_No_of_Tested_Im)*100);
fclose(fid);

close all
clc

disp(['Please, see the documented results of face recognition '....
    'in the open'])
disp(['text file then press any keyboard button to resume the '....
    'code >>>>'])
Text='Face Recognition Results for Testing.txt';
open(Text) % Opening the text file which contains
           % the results of face recognition.
pause
clc
open('PCA_IPCA_Testing_and_Setting_up_Thresholds.m')


%%
```

```
%%%%%%%%% The Computation of Face Recognition Performance %%%%%%%%%


clc
close all


Error_Rate_Recognition=.......
    zeros(1,length(Eigenvalues)); % Measuring recognition
                                  % performance. The elements
                                  % of this vector represent
                                  % the error rates in recognition
                                  % when different eigenfaces are
                                  % selected.
Eigenvalues1=fliplr(Eigenvalues);
Eigenvectors1=flipdim(Eigenvectors,2); % This flipping just to make
                                       % the highest correlated
                                       % eigenface is associated
                                       % with the first eigenvalue
                                       % and so on. This is done
                                       % to be compatable with the
                                       % generated document
                                       % "PCA vs. IPCA".
for kk=1:length(Eigenvalues)
    ['Iteration No.: ' num2str(kk) ' Out of ' .......
        num2str(length(Eigenvalues))]
    Selected_Eigenvectors=Eigenvectors1(:,1:kk);


    % Projecting each training face on the eigenspace. It is just
    % expressing each training face in terms of the eigenfaces.
    % This is called principal components transform (also called
    % the Hotelling or Karhunen-Loéve transform)
    All_Known_Transformed_Im=........
        zeros(size(Selected_Eigenvectors,2),......
        Total_No_of_Known_Im); % A 2D matrix where each column
                               % represents the coordinates of
                               % a projected training face in
                               % the eigenspace.
    for r=1:Total_No_of_Known_Im
        All_Known_Transformed_Im(:,r)=Selected_Eigenvectors.'*....
            Known_Im_Subt_Mean(:,r);
    end
    All_Known_Transformed_Im;


    % Projecting each tested image on the eigenspace. It is just
    % expressing each tested image in terms of the eigenfaces. This
    % is called principal components transform (also called the
    % Hotelling or Karhunen-Loéve transform)
```

```
    All_Tested_Transformed_Im=.......
        zeros(size(Selected_Eigenvectors,2),.....
        Total_No_of_Tested_Im); % A 2D matrix where each column
                                % represents the coordinates of
                                % a projected tested image in
                                % the eigenspace.
    for r1=1:Total_No_of_Tested_Im
        All_Tested_Transformed_Im(:,r1)=............
            Selected_Eigenvectors.'*Tested_Im_Subt_Mean(:,r1);
    end
    All_Tested_Transformed_Im;


    fid=fopen(['.\Face Recognition Performance\Recognition '.....
        'Results for Different Eigenfaces\Results for Testing '....
        'When q=' num2str(kk) '.txt'],'w'); % A text file for
                                            % typing the results
                                            % of face recognition.
    fprintf(fid,['\n\t ***** The Results of Face Recognition '....
        'When q=' num2str(kk) ' Obtained from the *****\r\n']);
    fprintf(fid,['\t   ***** PCA and IPCA Code for Testing '....
        'and Setting up Thresholds *****\r\n\n']);
    fprintf(fid,['Image No.       The Image Is Originally '......
        'for   The Image Is Recognized as   The Status\r\n']);
    fprintf(fid,['=============   ==========================='.....
        '    ==========================   ==========\r\n']);

    Distances_Vector=........
        zeros(Total_No_of_Tested_Im,......
        Total_No_of_Known_Im); % A 2D matrix where
                               % each row represents
                               % the distances between
                               % the weights of each
                               % training face and the
                               % weights of one of the
                               % tested images.

    % The distances between the weights of a training face and the
    % weights of each corresponding tested image. Note that, here
    % the training face and tested images have the same face and
    % projection so these distances must be the smallest. The
    % distances are extracted form the Distances_Vector matrix.
    Distances_Vector_P1=zeros(1,Im_P(1));
    Distances_Vector_P2=zeros(1,Im_P(2));
    Distances_Vector_P3=zeros(1,Im_P(3));
    Distances_Vector_P4=zeros(1,Im_P(4));
    Distances_Vector_P5=zeros(1,Im_P(5));
    Distances_Vector_P6=zeros(1,Im_P(6));
    Distances_Vector_P7=zeros(1,Im_P(7));
    Distances_Vector_P8=zeros(1,Im_P(8));
```

```
    Distances_Vector_P9=zeros(1,Im_P(9));

    for p=1:Total_No_of_Tested_Im
        for q=1:Total_No_of_Known_Im
            Distances_Vector(p,q)=.......
                norm(All_Tested_Transformed_Im(:,p)-.....
                All_Known_Transformed_Im(:,q));
        end

        if p<=L1
            Distances_Vector_P1(1,p)=Distances_Vector(p,1);
        elseif p>L1 && p<=L2
            Distances_Vector_P2(1,p-L1)=Distances_Vector(p,2);
        elseif p>L2 && p<=L3
            Distances_Vector_P3(1,p-L2)=Distances_Vector(p,3);
        elseif p>L3 && p<=L4
            Distances_Vector_P4(1,p-L3)=Distances_Vector(p,4);
        elseif p>L4 && p<=L5
            Distances_Vector_P5(1,p-L4)=Distances_Vector(p,5);
        elseif p>L5 && p<=L6
            Distances_Vector_P6(1,p-L5)=Distances_Vector(p,6);
        elseif p>L6 && p<=L7
            Distances_Vector_P7(1,p-L6)=Distances_Vector(p,7);
        elseif p>L7 && p<=L8
            Distances_Vector_P8(1,p-L7)=Distances_Vector(p,8);
        elseif p>L8 && p<=L9
            Distances_Vector_P9(1,p-L8)=Distances_Vector(p,9);
        end
    end
    d1=Distances_Vector_P1;
    d2=Distances_Vector_P2;
    d3=Distances_Vector_P3;
    d4=Distances_Vector_P4;
    d5=Distances_Vector_P5;
    d6=Distances_Vector_P6;
    d7=Distances_Vector_P7;
    d8=Distances_Vector_P8;
    d9=Distances_Vector_P9;

    % The calculation of the mean and standard deviation for each
    % vector of the minimum distances and stacking them in a vector
    % for the means and another for the standard deviations. This
    % is done for setting up a threshold for face recognition
    % because when a distance between a training face and a tested
    % image is the smallest with respect to the other training
    % faces, that does not mean the tested image is recognized as
    % the training face due to the tested image can be different
    % than the training face and has the smallest distance in the
    % same time. So, a certain threshold must be used to increase
    % the accuracy of recognition.
```

```
    P_Mean=[mean(d1);mean(d2);mean(d3);mean(d4);mean(d5);....
        mean(d6);mean(d7);mean(d8);mean(d9)];
    P_STD=[std(d1);std(d2);std(d3);std(d4);std(d5);std(d6);....
        std(d7);std(d8);std(d9)];
    save([cd '\Face Recognition Performance\Means and STDs '.....
        'for Different Eigenfaces\Means for Face Recognition '.....
        'When q=' num2str(kk)],'P_Mean')
    save([cd '\Face Recognition Performance\Means and STDs '.....
        'for Different Eigenfaces\STDs for Face Recognition '.....
        'When q=' num2str(kk)],'P_STD')

    Failures_Vector=zeros(1,......
        Total_No_of_Tested_Im); % A vector for counting the
                                % number of failures in the
                                % face recognition process.
    for w=1:Total_No_of_Tested_Im
        % The face recognition process.
        for h=1:Total_No_of_Known_Im
            if min(Distances_Vector(w,:))==.....
                    Distances_Vector(w,h) && .....
                    min(Distances_Vector(w,:))>=.....
                    (P_Mean(h,1)-P_STD(h,1)) &&.....
                    min(Distances_Vector(w,:))<=....
                    (P_Mean(h,1)+P_STD(h,1))
                s=transpose(struct2cell(Known_Images));
                c=sortrows(s,1);
                z=c(:,1);
                Recognized_As=char(z(h,1));
                Recognized_Image_Location=....
                    fullfile(Known_Images_Folder,Recognized_As);
                Recognized_image=im2double(rgb2gray(......
                    imread(Recognized_Image_Location)));
                break;
            else
                Recognized_As='Unknown Image';
                Recognized_image=imread('Unknown_Face.jpg');
            end
        end

        % Defining the face.
        if w<=L3
            n='Mr. Mansour Alshammari';
        elseif L3<w && w<=L6
            n='Mr. Methkir Alharthee';
        else n='Mr. Mohammed Hanafy';
        end

        y1=strcmp(Recognized_As(1:length(Recognized_As)-6),....
            'Mr. Mansour Alshammari');
        y2=strcmp(Recognized_As(1:length(Recognized_As)-6),.....
```

```
            'Mr. Methkir Alharthee');
        y3=strcmp(Recognized_As(1:length(Recognized_As)-6),....
            'Mr. Mohammed Hanafy');
        f='Success';
        if w<=L3 && y1==0;
            f='Failure';
            Failures_Vector(1,w)=1;
        elseif w>L3 && w<=L6 && y2==0;
            f='Failure';
            Failures_Vector(1,w)=1;
        elseif w>L6 && w<=L9 && y3==0;
            f='Failure';
            Failures_Vector(1,w)=1;
        end

%         clc
%         Tested_Im_Number=[num2str(w) '.jpg'];
%         Tested_Im_Location=.....
%             fullfile(Tested_Images_Folder,Tested_Im_Number);
%         Tested_Im=.....
%             im2double(rgb2gray(imread(Tested_Im_Location)));
%         subplot(2,1,1)
%         imshow(Tested_Im)
%         title({['Image No.' num2str(w) ' Is Originally for'];n})
%         subplot(2,1,2)
%         imshow(Recognized_image)
%         if y1==1 || y2==1 || y3==1
%             title({'The Image Is Recognized As';.......
%                 Recognized_As(1:length(Recognized_As)-6);.....
%                 ['When q=' num2str(kk)]})
%         else title({'The Image Is Recognized As';......
%                 ['an' blanks(1) Recognized_As];.....
%                 ['When q=' num2str(kk)]})
%         end

        if y1==1 || y2==1 || y3==1
            fprintf(fid,['%0.3d\t\t\t    %-22s\t      '.....
                '%-22s\t   %s \r\n\n'],......
                w,n,Recognized_As(1:length(Recognized_As)-6),f);
        else fprintf(fid,['%0.3d\t\t\t    %-22s\t      '.....
                '%-22s\t   %s \r\n\n'],.....
                w,n,Recognized_As,f);
        end

%         disp(['Please, press Any keyboard button to see '.....
%             'another face and its recognition when q=' .....
%             num2str(kk) ' .......'])
%         pause
%         clc
    end
```

```
    Total_Number_of_Failures=......
        sum(Failures_Vector); % The total number of failures in
                              % the face recognition process.

    Error_Rate_Recognition(1,kk)=(Total_Number_of_Failures/......
        Total_No_of_Tested_Im)*100;

    fprintf(fid,['============================================'.....
        '==========================================\r\n']);
    fprintf(fid,['** The Total Number of Successes: %0.3d out '....
        'of %0.3d (%3.4f%%) \r\n\n'],.......
        Total_No_of_Tested_Im-Total_Number_of_Failures,.....
        Total_No_of_Tested_Im,......
        ((Total_No_of_Tested_Im-Total_Number_of_Failures)/.....
        Total_No_of_Tested_Im)*100);
    fprintf(fid,['** The Total Number of Failures: %0.3d out '.....
        'of %0.3d (%3.4f%%) \r\n\n'],Total_Number_of_Failures,....
        Total_No_of_Tested_Im,(Total_Number_of_Failures/.....
        Total_No_of_Tested_Im)*100);
    fclose(fid);

%     close all
%     clc
%
%     disp(['Please, see the documented results of face '.......
%         'recognition when q=' num2str(kk) ' in the open'])
%     disp(['text file then press any keyboard button to '.....
%         'resume the code >>>>'])
%     Text=['.\Face Recognition Performance\Testing Face '.....
%         'Recognition Results for Different Eigenfaces\Face ' ....
%         'Recognition Results for Testing When q=' .....
%         num2str(kk) '.txt'];
%     open(Text) % Opening the text file which contains
%                % the results of face recognition.
%     pause
%     clc
%     open('PCA_IPCA_Testing_and_Setting_up_Thresholds.m')
end


% Plotting the error rates of face recognition for different
% selected eigenfaces compared with the error rates for PCA and
% IPCA algorithms.
clc
figure('units','centimeters','position',[0.15 1.2 35.8 16.9])
subplot(2,1,1)
Leg1=plot(1:length(Eigenvalues),Error_Rate_Recognition);
hold on
Leg2=plot(1,Error_Rate_Recognition(1),'kd','LineWidth',1.5,.....
    'MarkerEdgeColor','k','MarkerFaceColor','m','MarkerSize',8);
```

```
text(25,Error_Rate_Recognition(1)+2,{........
    '\fontsize{10} \color{black}' Error_Rate_Recognition(1)})
hold on
Leg3=plot(length(Eigenvalues),........
    Error_Rate_Recognition(length(Eigenvalues)),'kd',.....
    'LineWidth',1.5,'MarkerEdgeColor','k','MarkerFaceColor',.....
    'g','MarkerSize',8);
text(length(Eigenvalues)-60,........
    Error_Rate_Recognition(length(Eigenvalues))+8,.....
    {'\fontsize{10} \color{black}' .......
    Error_Rate_Recognition(length(Eigenvalues))})
hold off
axis([0 length(Eigenvalues)+(length(Eigenvalues)/40) ......
    -max(Error_Rate_Recognition)/10 .......
    max(Error_Rate_Recognition)+(max(Error_Rate_Recognition)/10)])
set(gca,'XTick',[1 length(Eigenvalues)/2 length(Eigenvalues)])
title(['The Error Rates of Recognition for Different '......
    'Selected Eigenfaces'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Error Rate (%)')
legend([Leg1 Leg2 Leg3],['The Error Rates of Recognition for '....
    'Different Selected Eigenfaces.'],..................
    ['The Error Rate of Recognition When the First Eigenface '....
    'Is Selected.'],['The Error Rate of Recognition When All '....
    'Eigenfaces Are Selected.'],'Location','NorthEast');
subplot(2,1,2)
Leg1=plot(1:length(Eigenvalues),Error_Rate_Recognition);
axis([0 20 0 ............
    max(Error_Rate_Recognition)+(max(Error_Rate_Recognition)/10)])
Leg2=line([length(Best_Eigenvalues_PCA) .....
    length(Best_Eigenvalues_PCA)],...
    [0 Error_Rate_Recognition(length(Best_Eigenvalues_PCA))],....
    'LineStyle','--','Color','r','LineWidth',4);
line([0 length(Best_Eigenvalues_PCA)],.....
    [Error_Rate_Recognition(length(Best_Eigenvalues_PCA)) .....
    Error_Rate_Recognition(length(Best_Eigenvalues_PCA))],....
    'LineStyle','--','Color','r','LineWidth',4)
text(length(Best_Eigenvalues_PCA)-0.8,.....
    Error_Rate_Recognition(length(Best_Eigenvalues_PCA))+5.7,.....
    {'\fontsize{10} \color{red} \bf' ......
    num2str(Error_Rate_Recognition(length(Best_Eigenvalues_PCA)))})
Leg3=line([length(Best_Eigenvalues_IPCA) ......
    length(Best_Eigenvalues_IPCA)],......
    [0 Error_Rate_Recognition(length(Best_Eigenvalues_IPCA))],.....
    'LineStyle','--','Color','k','LineWidth',3);
line([0 length(Best_Eigenvalues_IPCA)],.....
    [Error_Rate_Recognition(length(Best_Eigenvalues_IPCA)) .....
    Error_Rate_Recognition(length(Best_Eigenvalues_IPCA))],....
    'LineStyle','--','Color','k','LineWidth',3)
text(0.3,........
```

```
    Error_Rate_Recognition(length(Best_Eigenvalues_IPCA))+6,.....
    {'\fontsize{10} \color{black}' .....
    num2str(.......
    Error_Rate_Recognition(length(Best_Eigenvalues_IPCA)))})
vv=[length(Best_Eigenvalues_IPCA) length(Best_Eigenvalues_PCA)];
if vv(1)==1 || vv(2)==1
    set(gca,'XTick',[0 sort(vv) 20])
else set(gca,'XTick',[0 1 sort(vv) 20])
end
title(['Explaining the Error Rates for the PCA and IPCA '.......
    'Algorithms on the Plot'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Error Rate (%)')
legend([Leg1 Leg2 Leg3],['The Error Rates of Recognition for '....
    'Different Selected Eigenfaces.'],.....
    'The Error Rate for PCA Algorithm.',......
    'The Error Rate for IPCA Algorithm.','Location','NorthEast');


%%
%%%%%%%%%%%%%%%%%%%%% A Face Detection Process %%%%%%%%%%%%%%%%%%


clc
close all


%%%%% When we only select the eigenfaces which contain the most
%%%%% significant patterns from the correlated training faces then
%%%%% the accuracy of face detection and processing speed will
%%%%% increase. That because in face detection, distance
%%%%% calculation will be between a pre-processed unknown image and
%%%%% its reconstruction so if a reconstructed image is not a face
%%%%% then it will have a big distance hence it will not be
%%%%% detected as a face image. As a result of that, the usage of
%%%%% the calculated eigenfaces by using IPCA algorithm will
%%%%% produce the smallest error rate and processing time then the
%%%%% usage of the calculated eigenfaces by using PCA algorithm
%%%%% comes second finally the usage of all calculated eigenvectors
%%%%% as eigenfaces will produce the biggest error rate and
%%%%% processing time. It is very important to notice that the
%%%%% calculation of all eigenvectors from the covariance matrix
%%%%% for all training faces is too difficult because the
%%%%% covariance matrix is too big as explained before so it is
%%%%% impractical to use all eigenvectors as eigenfaces.

% Best_Eigenvectors=Eigenvectors; % Just try it to see how
                                  % affects on the results
                                  % of face detection.
% Best_Eigenvectors=Best_Eigenvectors_PCA; % Just try it to see how
```

```
                                                   % affects on the results
                                                   % of face detection.
Best_Eigenvectors=Best_Eigenvectors_IPCA; % Just try it to see how
                                          % affects on the results
                                          % of face detection.


% Projecting each training face on the eigenspace. It is just
% expressing each training face in terms of the eigenfaces. This is
% called principal components transform (also called the Hotelling
% or Karhunen-Loéve transform)
All_Known_Transformed_Im=.......
    zeros(size(Best_Eigenvectors,2),......
    Total_No_of_Known_Im); % A 2D matrix where each column
                           % represents the coordinates of
                           % a projected training face in
                           % the eigenspace.
for r=1:Total_No_of_Known_Im
    All_Known_Transformed_Im(:,r)=Best_Eigenvectors.'*.......
        Known_Im_Subt_Mean(:,r);
end
All_Known_Transformed_Im;


% Projecting each tested image on the eigenspace. It is just
% expressing each tested image in terms of the eigenfaces. This is
% called principal components transform (also called the Hotelling
% or Karhunen-Loéve transform)
All_Tested_Transformed_Im=.......
    zeros(size(Best_Eigenvectors,2),.....
    Total_No_of_Tested_Im); % A 2D matrix where each column
                            % represents the coordinates of
                            % a projected tested image in
                            % the eigenspace.
for r1=1:Total_No_of_Tested_Im
    All_Tested_Transformed_Im(:,r1)=Best_Eigenvectors.'*......
        Tested_Im_Subt_Mean(:,r1);
end
All_Tested_Transformed_Im;


fid=fopen('Face Detection Results for Testing.txt',.......
    'w'); % A text file for typing the
          % results of face detection.
fprintf(fid,['\n\t ***** The Results of Face Detection '.......
    'Obtained from the PCA and IPCA *****\r\n']);
fprintf(fid,['\t\t\t\t***** Code for Testing and Setting '.......
    'up Thresholds *****\r\n\n']);
fprintf(fid,['Image No.\t      The Image Originally Is\t  '......
    'The Detected Image Is\t    The Status\r\n']);
```

```
fprintf(fid,['=============\t  ========================\t  '.....
    '======================\t    ==========\r\n']);

% Note that, the tested images must be unknown whether they are
% face images or not but they are known here to be face images just
% for testing the face detection process and for setting up a
% detection threshold.
Distances_Vector1=zeros(1,......
    Total_No_of_Tested_Im); % A vector contains the distances
                            % between each pre-processed tested
                            % image and its reconstruction.
for i=1:Total_No_of_Tested_Im
    g=Best_Eigenvectors*All_Tested_Transformed_Im(:,i);
    Reconstructed_Tested_Im=max(Tested_Im_Subt_Mean(:,i))*.......
        (double(g)/max(max(g))); % This is for making each
                                 % pre-processed tested image
                                 % and its reconstruction have
                                 % approximately the same
                                 % dynamic range.

    Distances_Vector1(1,i)=norm(Tested_Im_Subt_Mean(:,i)-.....
        Reconstructed_Tested_Im); % Note that, a calculated
                                  % distance must be between
                                  % a pre-processed tested
                                  % image and its reconstruction
                                  % but it is not between an
                                  % original tested image and
                                  % its reconstruction.
end

% The calculation of the mean and standard deviation for the
% calculated distances between each pre-processed tested image and
% its reconstruction. This is done for setting up a threshold for
% face detection.
Mean=mean(Distances_Vector1);
Std=std(Distances_Vector1);
% save(['Computed Mean for Face Detection When All '....
%     'Eigenvectors Are Used as Eigenfaces'],'Mean')
% save(['Computed STD for Face Detection When All '.....
%     'Eigenvectors Are Used as Eigenfaces'],'Std')
% save(['Computed Mean for Face Detection When the Eigenfaces '....
%     'Computed by Using PCA Algorithm Are Used'],'Mean')
% save(['Computed STD for Face Detection When the Eigenfaces '.....
%     'Computed by Using PCA Algorithm Are Used'],'Std')
save(['Computed Mean for Face Detection When the Eigenfaces '....
    'Computed by Using IPCA Algorithm Are Used'],'Mean')
save(['Computed STD for Face Detection When the Eigenfaces '.....
    'Computed by Using IPCA Algorithm Are Used'],'Std')

Failures_Vector1=zeros(1,.....
```

```
    Total_No_of_Tested_Im); % A vector for counting the
                            % number of failures in the
                            % face detection process.

Latex_Matrix=cell(Total_No_of_Tested_Im,4); % This matrix is used
                                            % for creating a table
                                            % in Latex.
for w1=1:Total_No_of_Tested_Im
    % The face detection process.
    if  Distances_Vector1(1,w1)>=(Mean-Std) && ......
            Distances_Vector1(1,w1)<=(Mean+Std)
        Detected_As='a face';
        Detected_Image=imread('A_Face.jpg');
    else
        Detected_As='not a face';
        Detected_Image=imread('Not_a_Face.jpg');
    end

    b='a face'; % Defining an original tested image.

    f1='Success';
    e=strcmp(Detected_As,'a face');
    if w1<=L9 && e==0
        f1='Failure';
        Failures_Vector1(1,w1)=1;
    end

%     Tested_Im_Number1=[num2str(w1) '.jpg'];
%     Tested_Im_Location1=fullfile(Tested_Images_Folder,.....
%         Tested_Im_Number1);
%     Tested_Im1=im2double(rgb2gray(imread(Tested_Im_Location1)));
%     subplot(2,1,1)
%     imshow(Tested_Im1)
%     title(['Image No.' num2str(w1) ' Originally Is'])
%     subplot(2,1,2)
%     imshow(Detected_Image)
%     title('It Is Detected As')

    if e==1
        fprintf(fid,['%0.3d\t\t\t\t  %s\t\t\t\t\t  %s\t\t\t\t'....
            '    %s \r\n\n'],w1,b,Detected_As,f1);
        Latex_Matrix(w1,1:4)={num2str(w1) b Detected_As f1};
    else fprintf(fid,['%0.3d\t\t\t\t  %s\t\t\t\t\t  %s\t\t\t'.....
            '    %s \r\n\n'],w1,b,Detected_As,f1);
        Latex_Matrix(w1,1:4)={num2str(w1) b Detected_As f1};
    end

%     disp(['Please, press any keyboard button to see another '....
%         'image and its detection....'])
%     pause
```

```
%      clc
end
Total_Number_of_Failures1=......
    sum(Failures_Vector1); % The total number of failures
                           % in the face detection process.

fprintf(fid,['================================================'....
    '===================================\r\n']);
fprintf(fid,['** The Total Number of Successes: %0.3d out of '....
    '%0.3d (%3.4f%%) \r\n\n'],Total_No_of_Tested_Im-.....
    Total_Number_of_Failures1,Total_No_of_Tested_Im,.....
    ((Total_No_of_Tested_Im-Total_Number_of_Failures1)/.....
    Total_No_of_Tested_Im)*100);
fprintf(fid,['** The Total Number of Failures: %0.3d out '......
    'of %0.3d (%3.4f%%) \r\n\n'],Total_Number_of_Failures1,......
    Total_No_of_Tested_Im,........
    (Total_Number_of_Failures1/Total_No_of_Tested_Im)*100);
fclose(fid);

close all
clc

disp(['Please, see the documented results of face detection '.....
    'in the open'])
disp(['text file then press any keyboard button to resume '.....
    'the code >>>>'])
Text='Face Detection Results for Testing.txt';
open(Text) % Opening the text file which contains
           % the results of face detection.
pause
clc
open('PCA_IPCA_Testing_and_Setting_up_Thresholds.m')


%%
%%%%%%%%%% The Computation of Face Detection Performance %%%%%%%%%


clc
close all


Error_Rate_Detection=.......
    zeros(1,length(Eigenvalues)); % Measuring detection
                                  % performance. The elements
                                  % of this vector represent
                                  % the error rates in detection
                                  % when different eigenfaces are
                                  % selected.
Eigenvalues1=fliplr(Eigenvalues);
```

```
Eigenvectors1=flipdim(Eigenvectors,2); % This flipping just to make
                                       % the highest correlated
                                       % eigenface is associated
                                       % with the first eigenvalue
                                       % and so on. This is done to
                                       % be compatable with the
                                       % generated document
                                       % "PCA vs. IPCA".
for kk=1:length(Eigenvalues)
    ['Iteration No.: ' num2str(kk) ' Out of ' .....
        num2str(length(Eigenvalues))]
    Selected_Eigenvectors=Eigenvectors1(:,1:kk);


    % Projecting each training face on the eigenspace. It is just
    % expressing each training face in terms of the eigenfaces.
    % This is called principal components transform (also called
    % the Hotelling or Karhunen-Loéve transform)
    All_Known_Transformed_Im=.......
        zeros(size(Selected_Eigenvectors,2),........
        Total_No_of_Known_Im); % A 2D matrix where each column
                               % represents the coordinates of a
                               % projected training face in the
                               % eigenspace.
    for r=1:Total_No_of_Known_Im
        All_Known_Transformed_Im(:,r)=Selected_Eigenvectors.'*....
            Known_Im_Subt_Mean(:,r);
    end
    All_Known_Transformed_Im;


    % Projecting each tested image on the eigenspace. It is just
    % expressing each tested image in terms of the eigenfaces. This
    % is called principal components transform (also called the
    % Hotelling or Karhunen-Loéve transform)
    All_Tested_Transformed_Im=..........
        zeros(size(Selected_Eigenvectors,2),.....
        Total_No_of_Tested_Im); % A 2D matrix where each column
                                % represents the coordinates of a
                                % projected tested image in the
                                % eigenspace.
    for r1=1:Total_No_of_Tested_Im
        All_Tested_Transformed_Im(:,r1)=.....
            Selected_Eigenvectors.'*Tested_Im_Subt_Mean(:,r1);
    end
    All_Tested_Transformed_Im;


    fid=fopen(['.\Face Detection Performance\Detection '.....
        'Results for Different Eigenfaces\Results for Testing '....
```

```
        'When q=' num2str(kk) '.txt'],'w'); % A text file for
                                            % typing the results of
                                            % face Detection.
    fprintf(fid,['\n  ***** The Results of Face Detection '.....
        'When q=' num2str(kk) ......
        ' Obtained from the PCA and *****\r\n']);
    fprintf(fid,['\t\t   ***** IPCA Code for Testing and '......
        'Setting up Thresholds *****\r\n\n']);
    fprintf(fid,['Image No.\t      The Image Originally '.....
        'Is\t  The Detected Image Is\t    The Status\r\n']);
    fprintf(fid,['=============\t  =======================\t  '....
        '=======================\t    ==========\r\n']);

    % Note that, the tested images must be unknown whether they are
    % face images or not but they are known here to be face images
    % just for testing the face detection process and for setting
    % up a detection threshold.
    Distances_Vector1=zeros(1,.......
        Total_No_of_Tested_Im); % A vector contains the distances
                                % between each pre-processed tested
                                % image and its reconstruction.
    for i=1:Total_No_of_Tested_Im
        g=Selected_Eigenvectors*All_Tested_Transformed_Im(:,i);
        Reconstructed_Tested_Im=max(Tested_Im_Subt_Mean(:,i))*....
            (double(g)/max(max(g))); % This is for making each
                                     % pre-processed tested image
                                     % and its reconstruction have
                                     % approximately the same
                                     % dynamic range.

        Distances_Vector1(1,i)=norm(Tested_Im_Subt_Mean(:,i)-.....
            Reconstructed_Tested_Im); % Note that, a calculated
                                      % distance must be between a
                                      % pre-processed tested image
                                      % and its reconstruction but
                                      % it is not between an
                                      % original tested image and
                                      % its reconstruction.
    end

    % The calculation of the mean and standard deviation for the
    % calculated distances between each pre-processed tested image
    % and its reconstruction. This is done for setting up a
    % threshold for face detection.
    Mean=mean(Distances_Vector1);
    Std=std(Distances_Vector1);
    save([cd '\Face Detection Performance\Means and STDs for '....
        'Different Eigenfaces\Mean for Face Detection When q=' ....
        num2str(kk)],'Mean')
    save([cd '\Face Detection Performance\Means and STDs for '....
```

```
        'Different Eigenfaces\STD for Face Detection When q=' .....
        num2str(kk)],'Std')

    Failures_Vector1=zeros(1,.....
        Total_No_of_Tested_Im); % A vector for counting the
                                % number of failures in the
                                % face detection process.
    for w1=1:Total_No_of_Tested_Im
        % The face detection process.
        if  Distances_Vector1(1,w1)>=(Mean-Std) && .....
                Distances_Vector1(1,w1)<=(Mean+Std)
            Detected_As='a face';
            Detected_Image=imread('A_Face.jpg');
        else
            Detected_As='not a face';
            Detected_Image=imread('Not_a_Face.jpg');
        end

        b='a face'; % Defining an original tested image.

        f1='Success';
        e=strcmp(Detected_As,'a face');
        if w1<=L9 && e==0
            f1='Failure';
            Failures_Vector1(1,w1)=1;
        end

%         clc
%         Tested_Im_Number1=[num2str(w1) '.jpg'];
%         Tested_Im_Location1=fullfile(Tested_Images_Folder,....
%             Tested_Im_Number1);
%         Tested_Im1=im2double(......
%             rgb2gray(imread(Tested_Im_Location1)));
%         subplot(2,1,1)
%         imshow(Tested_Im1)
%         title(['Image No.' num2str(w1) ' Originally Is'])
%         subplot(2,1,2)
%         imshow(Detected_Image)
%         title({'It Is Detected As';['(When q=' num2str(kk) ')']})

        if e==1
            fprintf(fid,['%0.3d\t\t\t\t  %s\t\t\t\t\t  '......
                '%s\t\t\t\t    %s \r\n\n'],w1,b,Detected_As,f1);
        else fprintf(fid,['%0.3d\t\t\t\t  %s\t\t\t\t\t  '.....
                '%s\t\t\t    %s \r\n\n'],w1,b,Detected_As,f1);
        end

%         disp(['Please, press any keyboard button to see '......
%             'another image and its detection when q=' .....
%             num2str(kk) ' .......'])
```

```
%          pause
%          clc
    end
    Total_Number_of_Failures1=.......
        sum(Failures_Vector1); % The total number of failures
                               % in the face detection process.

    Error_Rate_Detection(1,kk)=.........
        (Total_Number_of_Failures1/Total_No_of_Tested_Im)*100;

    fprintf(fid,['==========================================='.....
        '========================================\r\n']);
    fprintf(fid,['** The Total Number of Successes: %0.3d '....
        'out of %0.3d (%3.4f%%) \r\n\n'],...
        Total_No_of_Tested_Im-Total_Number_of_Failures1,....
        Total_No_of_Tested_Im,.......
        ((Total_No_of_Tested_Im-Total_Number_of_Failures1)/.....
        Total_No_of_Tested_Im)*100);
    fprintf(fid,['** The Total Number of Failures: %0.3d '....
        'out of %0.3d (%3.4f%%) \r\n\n'],....
        Total_Number_of_Failures1,Total_No_of_Tested_Im,.....
        (Total_Number_of_Failures1/Total_No_of_Tested_Im)*100);
    fclose(fid);

%      close all
%      clc
%
%      disp(['Please, see the documented results of face '.....
%          'detection when q=' num2str(kk) ' in the open'])
%      disp(['text file then press any keyboard button to '.....
%          'resume the code >>>>'])
%      Text=['.\Face Detection Performance\Testing Face '.....
%          'Detection Results for Different Eigenfaces\Face '......
%          'Detection Results for Testing When q=' ......
%          num2str(kk) '.txt'];
%      open(Text) % Opening the text file which contains
%                 % the results of face detection.
%      pause
%      clc
%      open('PCA_IPCA_Testing_and_Setting_up_Thresholds.m')
end


% Plotting the error rates of face detection for different selected
% eigenfaces compared with the error rates for the PCA and IPCA
% algorithms.
clc
figure('units','centimeters','position',[0.15 1.2 35.8 16.9])
subplot(2,1,1)
Leg1=plot(1:length(Eigenvalues),Error_Rate_Detection);
```

```
hold on
Leg2=plot(1,Error_Rate_Detection(1),'kd','LineWidth',1.5,.....
    'MarkerEdgeColor','k','MarkerFaceColor','m','MarkerSize',8);
text(24.8,Error_Rate_Detection(1)+1.8,......
    {'\fontsize{10} \color{black}' Error_Rate_Detection(1)})
hold on
Leg3=plot(length(Eigenvalues),.......
    Error_Rate_Detection(length(Eigenvalues)),'kd',....
    'LineWidth',1.5,'MarkerEdgeColor','k',....
    'MarkerFaceColor','g','MarkerSize',8);
text(length(Eigenvalues)-55,......
    Error_Rate_Detection(length(Eigenvalues))-1.8,.....
    {'\fontsize{10} \color{black}' .....
    Error_Rate_Detection(length(Eigenvalues))})
hold off
axis([0 length(Eigenvalues)+(length(Eigenvalues)/40) ......
    -max(Error_Rate_Detection)/10 ..............
    max(Error_Rate_Detection)+(max(Error_Rate_Detection)/10)])
set(gca,'XTick',[1 length(Eigenvalues)/2 length(Eigenvalues)])
title(['The Error Rates of Detection for Different '.....
    'Selected Eigenfaces'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Error Rate (%)')
legend([Leg1 Leg2 Leg3],['The Error Rates of Detection for '.....
    'Different Selected Eigenfaces.'],['The Error Rate of '....
    'Detection When the First Eigenface Is Selected.'],....
    ['The Error Rate of Detection When All Eigenfaces Are '.....
    'Selected.'],'Location','NorthWest');
subplot(2,1,2)
Leg1=plot(1:length(Eigenvalues),Error_Rate_Detection);
axis([0 20 0 .......
    max(Error_Rate_Detection)+(max(Error_Rate_Detection)/10)])
Leg2=line([length(Best_Eigenvalues_PCA) ......
    length(Best_Eigenvalues_PCA)],.....
    [0 Error_Rate_Detection(length(Best_Eigenvalues_PCA))],....
    'LineStyle','--','Color','k','LineWidth',3);
line([0 length(Best_Eigenvalues_PCA)],........
    [Error_Rate_Detection(length(Best_Eigenvalues_PCA)) ......
    Error_Rate_Detection(length(Best_Eigenvalues_PCA))],....
    'LineStyle','--','Color','k','LineWidth',3)
text(length(Best_Eigenvalues_PCA)-0.9,.......
    Error_Rate_Detection(length(Best_Eigenvalues_PCA))+3.6,.....
    {'\fontsize{10} \color{black}' .........
    num2str(Error_Rate_Detection(length(Best_Eigenvalues_PCA)))})
Leg3=line([length(Best_Eigenvalues_IPCA) ......
    length(Best_Eigenvalues_IPCA)],......
    [0 Error_Rate_Detection(length(Best_Eigenvalues_IPCA))],.....
    'LineStyle','--','Color','r','LineWidth',4);
line([0 length(Best_Eigenvalues_IPCA)],.......
    [Error_Rate_Detection(length(Best_Eigenvalues_IPCA)) .....
```

```
    Error_Rate_Detection(length(Best_Eigenvalues_IPCA))],....
    'LineStyle','--','Color','r','LineWidth',4)
text(0.3,......
    Error_Rate_Detection(length(Best_Eigenvalues_IPCA))+3.6,.....
    {'\fontsize{10} \color{red} \bf' .....
    num2str(Error_Rate_Detection(length(Best_Eigenvalues_IPCA)))})
vv=[length(Best_Eigenvalues_IPCA) length(Best_Eigenvalues_PCA)];
if vv(1)==1 || vv(2)==1
    set(gca,'XTick',[0 sort(vv) 20])
else set(gca,'XTick',[0 1 sort(vv) 20])
end
title(['Explaining the Error Rates for the PCA and IPCA '.....
    'Algorithms on the Plot'])
xlabel('The Number of Selected Eigenfaces')
ylabel('The Error Rate (%)')
legend([Leg1 Leg2 Leg3],['The Error Rates of Detection for '.....
    'Different Selected Eigenfaces.'],......
    'The Error Rate for PCA Algorithm.',.....
    'The Error Rate for IPCA Algorithm.','Location','NorthEast');
```

Appendix B

Databases for the Digital and Optical Models

ALL images in Figure B.1, Figure B.2, Figure B.3, Figure B.4, Figure B.5, Figure B.6, Figure B.7, Figure B.8, and Figure B.9 form the database of the tested images. The database of the objects consists of images that have vertical faces to people's shoulders shown in Figure B.1, Figure B.4, and Figure B.7.

Figure B.1: Images for Mr. Mansour Alshammari, 1^{st} projection.

Figure B.2: Images for Mr. Mansour Alshammari, 2^{nd} projection.

Figure B.3: Images for Mr. Mansour Alshammari, 3^{rd} projection.

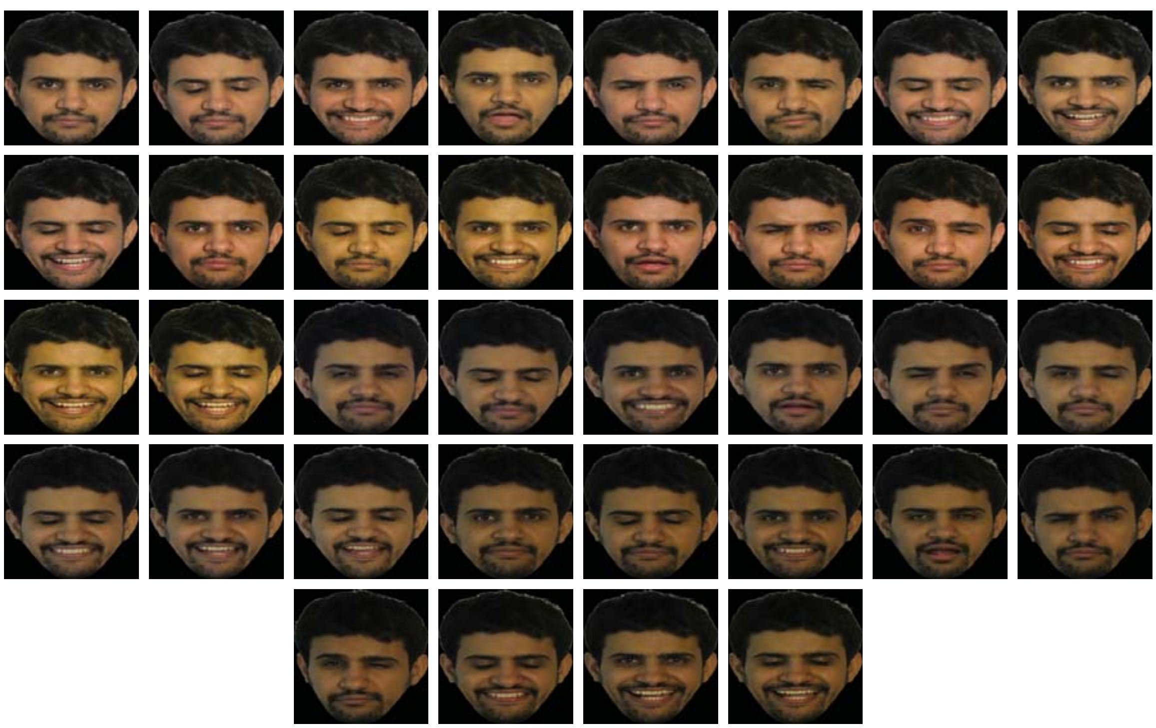


Figure B.4: Images for Mr. Methkir Alharthee, 1^{st} projection.

Figure B.5: Images for Mr. Methkir Alharthee, 2^{nd} projection.

Figure B.6: Images for Mr. Methkir Alharthee, 3^{rd} projection.

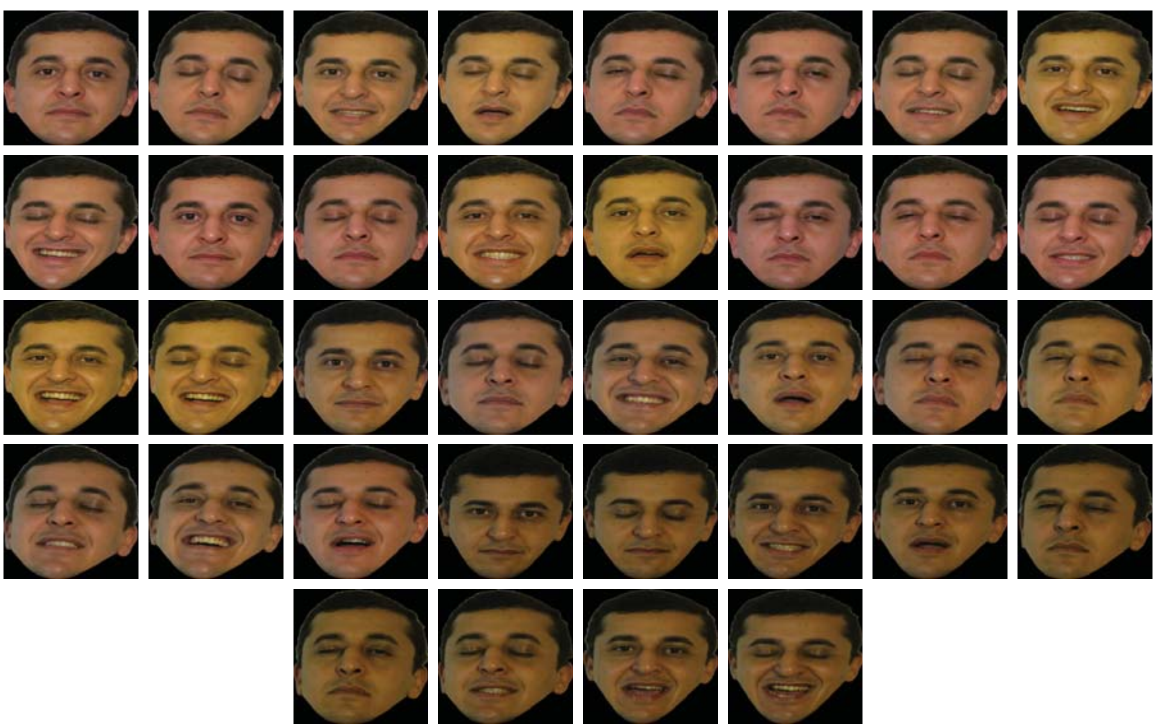


Figure B.7: Images for Mr. Mohammed Hanafy, 1^{st} projection.

Figure B.8: Images for Mr. Mohammed Hanafy, 2^{nd} projection.

Figure B.9: Images for Mr. Mohammed Hanafy, 3^{rd} projection.

Appendix C

Results of the Digital Recognition

Table C.1: The recognition of all 180 tested images by using the PCA algorithm.

Tested Image No.	Input Face	Recognized Output Face	Status
1	Mr. Mansour Alshammari	Unknown Image	Failure
2	Mr. Mansour Alshammari	Unknown Image	Failure
3	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
4	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
5	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
6	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
7	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
8	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
9	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
10	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
11	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
12	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
13	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
14	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
15	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
16	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
17	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
18	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
19	Mr. Mansour Alshammari	Unknown Image	Failure
20	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
21	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success

Continued on the next page ...

Tested Image No.	Input Face	Recognized Output Face	Status
22	Mr. Mansour Alshammari	Unknown Image	Failure
23	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
24	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
25	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
26	Mr. Mansour Alshammari	Unknown Image	Failure
27	Mr. Mansour Alshammari	Unknown Image	Failure
28	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
29	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
30	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
31	Mr. Mansour Alshammari	Unknown Image	Failure
32	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
33	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
34	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
35	Mr. Mansour Alshammari	Unknown Image	Failure
36	Mr. Mansour Alshammari	Unknown Image	Failure
37	Mr. Mansour Alshammari	Unknown Image	Failure
38	Mr. Mansour Alshammari	Unknown Image	Failure
39	Mr. Mansour Alshammari	Unknown Image	Failure
40	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
41	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
42	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
43	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
44	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
45	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
46	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
47	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
48	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
49	Mr. Mansour Alshammari	Unknown Image	Failure
50	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
51	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
52	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
53	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
54	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
55	Mr. Mansour Alshammari	Unknown Image	Failure
56	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
57	Mr. Mansour Alshammari	Unknown Image	Failure
58	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
59	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success

Continued on the next page ...

Tested Image No.	Input Face	Recognized Output Face	Status
60	Mr. Mansour Alshammari	Mr. Mansour Alshammari	Success
61	Mr. Methkir Alharthee	Unknown Image	Failure
62	Mr. Methkir Alharthee	Unknown Image	Failure
63	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
64	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
65	Mr. Methkir Alharthee	Unknown Image	Failure
66	Mr. Methkir Alharthee	Unknown Image	Failure
67	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
68	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
69	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
70	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
71	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
72	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
73	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
74	Mr. Methkir Alharthee	Unknown Image	Failure
75	Mr. Methkir Alharthee	Unknown Image	Failure
76	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
77	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
78	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
79	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
80	Mr. Methkir Alharthee	Unknown Image	Failure
81	Mr. Methkir Alharthee	Unknown Image	Failure
82	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
83	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
84	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
85	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
86	Mr. Methkir Alharthee	Unknown Image	Failure
87	Mr. Methkir Alharthee	Unknown Image	Failure
88	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
89	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
90	Mr. Methkir Alharthee	Unknown Image	Failure
91	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
92	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
93	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
94	Mr. Methkir Alharthee	Unknown Image	Failure
95	Mr. Methkir Alharthee	Unknown Image	Failure
96	Mr. Methkir Alharthee	Unknown Image	Failure
97	Mr. Methkir Alharthee	Unknown Image	Failure

Continued on the next page ...

Tested Image No.	Input Face	Recognized Output Face	Status
98	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
99	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
100	Mr. Methkir Alharthee	Unknown Image	Failure
101	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
102	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
103	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
104	Mr. Methkir Alharthee	Unknown Image	Failure
105	Mr. Methkir Alharthee	Unknown Image	Failure
106	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
107	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
108	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
109	Mr. Methkir Alharthee	Unknown Image	Failure
110	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
111	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
112	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
113	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
114	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
115	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
116	Mr. Methkir Alharthee	Unknown Image	Failure
117	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
118	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
119	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
120	Mr. Methkir Alharthee	Mr. Methkir Alharthee	Success
121	Mr. Mohammed Hanafy	Unknown Image	Failure
122	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
123	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
124	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
125	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
126	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
127	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
128	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
129	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
130	Mr. Mohammed Hanafy	Unknown Image	Failure
131	Mr. Mohammed Hanafy	Unknown Image	Failure
132	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
133	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
134	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
135	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success

Continued on the next page ...

Tested Image No.	Input Face	Recognized Output Face	Status
136	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
137	Mr. Mohammed Hanafy	Unknown Image	Failure
138	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
139	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
140	Mr. Mohammed Hanafy	Unknown Image	Failure
141	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
142	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
143	Mr. Mohammed Hanafy	Unknown Image	Failure
144	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
145	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
146	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
147	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
148	Mr. Mohammed Hanafy	Unknown Image	Failure
149	Mr. Mohammed Hanafy	Unknown Image	Failure
150	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
151	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
152	Mr. Mohammed Hanafy	Unknown Image	Failure
153	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
154	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
155	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
156	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
157	Mr. Mohammed Hanafy	Unknown Image	Failure
158	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
159	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
160	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
161	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
162	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
163	Mr. Mohammed Hanafy	Mr. Mansour Alshammari	Failure
164	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
165	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
166	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
167	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
168	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
169	Mr. Mohammed Hanafy	Unknown Image	Failure
170	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
171	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
172	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
173	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success

Continued on the next page ...

Tested Image No.	**Input Face**	**Recognized Output Face**	**Status**
174	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
175	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
176	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
177	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
178	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
179	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
180	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success

The table end.

Appendix D

Results of the Digital Detection

Table D.1: The detection of all 180 tested images by using the PCA algorithm.

Tested Image No.	Input Image	Detected Output Image	Status
1	a face	not a face	Failure
2	a face	not a face	Failure
3	a face	a face	Success
4	a face	a face	Success
5	a face	a face	Success
6	a face	a face	Success
7	a face	a face	Success
8	a face	a face	Success
9	a face	a face	Success
10	a face	a face	Success
11	a face	a face	Success
12	a face	a face	Success
13	a face	a face	Success
14	a face	a face	Success
15	a face	a face	Success
16	a face	a face	Success
17	a face	a face	Success
18	a face	a face	Success
19	a face	a face	Success
20	a face	a face	Success
21	a face	a face	Success

Continued on the next page ...

Tested Image No.	Input Image	Detected Output Image	Status
22	a face	a face	Success
23	a face	a face	Success
24	a face	a face	Success
25	a face	a face	Success
26	a face	a face	Success
27	a face	a face	Success
28	a face	a face	Success
29	a face	a face	Success
30	a face	a face	Success
31	a face	a face	Success
32	a face	a face	Success
33	a face	a face	Success
34	a face	not a face	Failure
35	a face	a face	Success
36	a face	a face	Success
37	a face	not a face	Failure
38	a face	not a face	Failure
39	a face	not a face	Failure
40	a face	a face	Success
41	a face	a face	Success
42	a face	a face	Success
43	a face	a face	Success
44	a face	a face	Success
45	a face	a face	Success
46	a face	a face	Success
47	a face	a face	Success
48	a face	a face	Success
49	a face	not a face	Failure
50	a face	not a face	Failure
51	a face	not a face	Failure
52	a face	a face	Success
53	a face	a face	Success
54	a face	a face	Success
55	a face	a face	Success
56	a face	a face	Success
57	a face	a face	Success
58	a face	a face	Success
59	a face	a face	Success

Continued on the next page ...

Tested Image No.	Input Image	Detected Output Image	Status
60	a face	a face	Success
61	a face	not a face	Failure
62	a face	a face	Success
63	a face	a face	Success
64	a face	a face	Success
65	a face	not a face	Failure
66	a face	a face	Success
67	a face	a face	Success
68	a face	a face	Success
69	a face	a face	Success
70	a face	a face	Success
71	a face	a face	Success
72	a face	a face	Success
73	a face	a face	Success
74	a face	a face	Success
75	a face	a face	Success
76	a face	a face	Success
77	a face	a face	Success
78	a face	a face	Success
79	a face	a face	Success
80	a face	a face	Success
81	a face	a face	Success
82	a face	a face	Success
83	a face	a face	Success
84	a face	a face	Success
85	a face	a face	Success
86	a face	not a face	Failure
87	a face	a face	Success
88	a face	a face	Success
89	a face	a face	Success
90	a face	a face	Success
91	a face	not a face	Failure
92	a face	a face	Success
93	a face	not a face	Failure
94	a face	a face	Success
95	a face	not a face	Failure
96	a face	not a face	Failure
97	a face	not a face	Failure

Continued on the next page ...

Tested Image No.	Input Image	Detected Output Image	Status
98	a face	a face	Success
99	a face	a face	Success
100	a face	a face	Success
101	a face	a face	Success
102	a face	a face	Success
103	a face	not a face	Failure
104	a face	a face	Success
105	a face	a face	Success
106	a face	a face	Success
107	a face	a face	Success
108	a face	not a face	Failure
109	a face	not a face	Failure
110	a face	a face	Success
111	a face	a face	Success
112	a face	a face	Success
113	a face	a face	Success
114	a face	a face	Success
115	a face	not a face	Failure
116	a face	not a face	Failure
117	a face	a face	Success
118	a face	not a face	Failure
119	a face	a face	Success
120	a face	not a face	Failure
121	a face	not a face	Failure
122	a face	a face	Success
123	a face	a face	Success
124	a face	a face	Success
125	a face	a face	Success
126	a face	a face	Success
127	a face	a face	Success
128	a face	a face	Success
129	a face	a face	Success
130	a face	a face	Success
131	a face	a face	Success
132	a face	a face	Success
133	a face	a face	Success
134	a face	a face	Success
135	a face	a face	Success

Continued on the next page ...

Tested Image No.	Input Image	Detected Output Image	Status
136	a face	a face	Success
137	a face	a face	Success
138	a face	a face	Success
139	a face	a face	Success
140	a face	a face	Success
141	a face	a face	Success
142	a face	a face	Success
143	a face	a face	Success
144	a face	a face	Success
145	a face	a face	Success
146	a face	a face	Success
147	a face	a face	Success
148	a face	not a face	Failure
149	a face	a face	Success
150	a face	not a face	Failure
151	a face	a face	Success
152	a face	not a face	Failure
153	a face	a face	Success
154	a face	not a face	Failure
155	a face	a face	Success
156	a face	not a face	Failure
157	a face	not a face	Failure
158	a face	a face	Success
159	a face	a face	Success
160	a face	a face	Success
161	a face	a face	Success
162	a face	a face	Success
163	a face	a face	Success
164	a face	a face	Success
165	a face	a face	Success
166	a face	a face	Success
167	a face	a face	Success
168	a face	a face	Success
169	a face	not a face	Failure
170	a face	not a face	Failure
171	a face	a face	Success
172	a face	a face	Success
173	a face	a face	Success

Continued on the next page ...

Tested Image No.	Input Image	Detected Output Image	Status
174	a face	a face	Success
175	a face	a face	Success
176	a face	a face	Success
177	a face	a face	Success
178	a face	a face	Success
179	a face	a face	Success
180	a face	a face	Success

The table end.

Appendix E

Derivation of $U_2(x_2, y_2)$ for the JTC

In the joint transform correlator (JTC), the derivation of the complex amplitude distribution $U_2(x_2, y_2)$ of the Fourier transformed field in the back focal plane P_2 can be found as follows,

$$
\begin{aligned}
U_2(x_2, y_2) =& \frac{1}{j\lambda f} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} U_1(x_1, y_1) \exp^{-j\frac{2\pi}{\lambda f}(x_1 x_2 + y_1 y_2)} dx_1 dy_1 \\
=& \frac{A}{j\lambda f} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h\left(x_1, y_1 - \frac{Y}{2}\right) \exp^{-j\frac{2\pi}{\lambda f}(x_1 x_2 + y_1 y_2)} dx_1 dy_1 + \\
& + \frac{A}{j\lambda f} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g\left(x_1, y_1 + \frac{Y}{2}\right) \exp^{-j\frac{2\pi}{\lambda f}(x_1 x_2 + y_1 y_2)} dx_1 dy_1
\end{aligned}
$$

Changing variables: $y_1 - \frac{Y}{2} \rightarrow a, dy_1 \rightarrow da$ &

$y_1 + \frac{Y}{2} \rightarrow b, dy_1 \rightarrow db$

$$
\begin{aligned}
U_2(x_2,y_2) =& \frac{A}{j\lambda f}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(x_1,a)\exp^{-j\frac{2\pi}{\lambda f}\left(x_1x_2+\left(a+\frac{Y}{2}\right)y_2\right)}dx_1da+\\
&+\frac{A}{j\lambda f}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x_1,b)\exp^{-j\frac{2\pi}{\lambda f}\left(x_1x_2+\left(b-\frac{Y}{2}\right)y_2\right)}dx_1db\\
=& \frac{A}{j\lambda f}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(x_1,a)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+ay_2)-j\frac{2\pi}{\lambda f}\frac{Y}{2}y_2}dx_1da+\\
&+\frac{A}{j\lambda f}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x_1,b)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+by_2)+j\frac{2\pi}{\lambda f}\frac{Y}{2}y_2}dx_1db\\
=& \frac{A}{j\lambda f}\exp^{-j\frac{\pi Y}{\lambda f}y_2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(x_1,a)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+ay_2)}dx_1da+\\
&+\frac{A}{j\lambda f}\exp^{j\frac{\pi Y}{\lambda f}y_2}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x_1,b)\exp^{-j\frac{2\pi}{\lambda f}(x_1x_2+by_2)}dx_1db
\end{aligned}
$$

Therefore,

$$
U_2(x_2,y_2) = \frac{A}{j\lambda f}\exp^{-j\frac{\pi Y}{\lambda f}y_2} H\left(\frac{x_2}{\lambda f},\frac{y_2}{\lambda f}\right) + \frac{A}{j\lambda f}\exp^{j\frac{\pi Y}{\lambda f}y_2} G\left(\frac{x_2}{\lambda f},\frac{y_2}{\lambda f}\right)
$$

Appendix F

A Code for the Optical Model

This appendix presents the joint transform correlator (JTC) code for object detection and face recognition.

```
% Testing the Joint Transform Correlator (JTC) for Object Detection
% and Recognition. Note That, Objects Here Are Known for Us in
% Order to Use Them for Testing Object Detection and Recognition
% Processes as Well as Setting up Recognition and Detection
% Thresholds.


clc
clear all
close all


Impulses_Folder=[cd .....
    '\The Black Background Impulses']; % The folder of the black
                                       % background impulses.
% Impulses_Folder=[cd ......
%     '\The White Background Impulses']; % The folder of the white
                                       % background impulses.
if isdir(Impulses_Folder)==0
    Error_Message=sprintf(['Error: The following folder does '....
        'not exist\n%s'],Impulses_Folder);
    warndlg(Error_Message);
    break
end

Impulses=dir(fullfile(Impulses_Folder,'*.jpg')); % Listing the
                                                 % folder of the
                                                 % black or white
```

```
                                                        % background
                                                        % impulses.

Total_No_of_Impulses=length(Impulses); % The total number
                                       % of the impulses.


% Imhist for setting up a threshold to work on just the pixels of a
% face and throwing the background pixels. Imhist calculates the
% number of pixels in an impulse that have the same intensity
% levels. So, if an impulse has a unified background then the
% biggest histogram of the intensity levels will be for the
% background pixels because the total number of pixels that have
% the same intensity levels are the background pixels of the
% impulse. Note that, the histogram of a digital image is defined
% as the discrete function, h(rk)=nk, where rk is the kth intensity
% level and nk is the number of pixels in the image whose intensity
% level is rk.
hist_Impulses=zeros(Total_No_of_Impulses,256);
for A=1:Total_No_of_Impulses

    One_Impulse=Impulses(A).name;
    Impulse_Location=fullfile(Impulses_Folder,One_Impulse);
    Impulse=double(rgb2gray(.....
        imread(Impulse_Location))); % The impulse response.
    hist_Impulses(A,:)=......
        imhist(uint8(Impulse)); % Note that, each impulse must be
                                % scaled between 0 to 255 before
                                % using imhist. For doing that,
                                % uint8 can be used for converting
                                % the impulse class form double to
                                % uint8.

%     plot(hist_Impulses(A,:))
%     if A==1
%         title(['The Histogram of The First Impulse for '.....
%             'Mr. Mansour Alshammari'])
%     elseif A==2
%         title(['The Histogram of The Second Impulse for '.....
%             'Mr. Methkir Alharthee'])
%     elseif A==3
%         title(['The Histogram of The Third Impulse for '.....
%             'Mr. Mohammed Hanafy'])
%     end
%     xlabel('Intensity Level r_{k}')
%     ylabel({'The Number of Pixels in the Impulse Whose '.....
%         'Intensity Level Is r_{k} Where h(r_{k})=n_{k}'})
%     axis tight
%
%     disp(['Please, press any keyboard button to explore '......
```

```
%         'the remaining histograms >>>>>>>'])
%     pause
%     clc
end

Mean_hist_Impulses=sum(hist_Impulses,1)/......
    Total_No_of_Impulses; % The average histogram
                          % for all impulses.
% plot(Mean_hist_Impulses)
% title('The Mean Histogram of All Impulses')
% xlabel('Intensity Level r_{k}')
% ylabel({'The Mean Number of Pixels from All Impulses Whose';.....
%     'Intensity Level Is r_{k}'})
% axis tight
% pause

% Setting up a threshold in order to work on just the pixels of the
% faces and blocking the pixels of the backgrounds.
Impulses_Threshold=8; % The picked threshold is based on the
                      % average histogram for all impulses when the
                      % impulses have black backgrounds. Note that,
                      % all intesity levels below the threshold
                      % represent the impulses backgrounds because
                      % these levels have the biggest histogram.
% Impulses_Threshold=180; % The Picked threshold is based on the
%                         % average histogram for all impulses when
%                         % the impulses have white backgrounds.
%                         % Note that, all intesity levels above
%                         % the threshold represent the impulses
%                         % backgrounds because these levels have
%                         % the biggest histogram.


Objects_Folder=[cd ......
    '\The Black Background Tested Objects']; % The folder of the
                                             % black background
                                             % tested objects.
% Objects_Folder=[cd .........
%     '\The White Background Tested Objects']; % The folder of the
                                             % white background
                                             % tested objects.
if isdir(Objects_Folder)==0
    Error_Message=sprintf(['Error: The following folder does '....
        'not exist\n%s'],Objects_Folder);
    warndlg(Error_Message);
    break
end

Objects=dir(fullfile(Objects_Folder,'*.jpg')); % Listing the folder
                                               % of the black or
```

```
                                                        % white background
                                                        % objects.

Total_No_of_Objects=length(Objects); % The total number
                                     % of the objects.

Objs=[36 36 36]; % Each element in this vector represents
                 % the total number of the objects that
                 % are taken for each impulse.

L1=Objs(1); % L1=60 is the total number of the
            % objects for Mr. Mansour Alshammari.
L2=L1+Objs(2); % L2=120 is the total number of the
               % objects for Mr. Methkir Alharthee.
L3=L2+Objs(3); % L3=180 is the total number of the
               % objects for Mr. Mohammed Hanafy.


% Imhist for setting up a threshold to work on just the pixels of a
% face and throwing the background pixels. Imhist calculates the
% number of pixels in an object that have the same intensity
% levels. So, if an object has a unified background then the
% biggest histogram of the intensity levels will be for the
% background pixels because the total number of pixels that have
% the same intensity levels are the background pixels of the
% object. Note that, the histogram of a digital image is defined as
% the discrete function, h(rk)=nk, where rk is the kth intensity
% level and nk is the number of pixels in the image whose intensity
% level is rk.
hist_Objects=zeros(Total_No_of_Objects,256);
for A1=1:Total_No_of_Objects

    Object_Number=[num2str(A1) '.jpg'];
    Object_Location=fullfile(Objects_Folder,Object_Number);
    Object=double(rgb2gray(imread(Object_Location))); % The object.
    hist_Objects(A1,:)=imhist(uint8(Object)); % Note that, each
                                              % object must be
                                              % scaled between 0 to
                                              % 255 before using
                                              % imhist. For doing
                                              % that, uint8 can be
                                              % used for converting
                                              % the object class
                                              % form double to
                                              % uint8.

%     plot(hist_Objects(A1,:))
%     if A1<=L1
%         title(['The Histogram of Object No.' num2str(A1) ....
%             ' for Mr. Mansour Alshammari'])
```

```
%     elseif A1>L1 && A1<=L2
%         title(['The Histogram of Object No.' num2str(A1) .....
%             ' for Mr. Methkir Alharthee'])
%     elseif A1>L2 && A1<=L3
%         title(['The Histogram of Object No.' num2str(A1) ....
%             ' for Mr. Mohammed Hanafy'])
%     end
%     xlabel('Intensity Level r_{k}')
%     ylabel({'The Number of Pixels in the Object Whose '....
%         'Intensity Level Is r_{k} Where h(r_{k})=n_{k}'})
%     axis tight
%
%     disp(['Please, press any keyboard button to explore '......
%         'the remaining histograms >>>>>>>'])
%     pause
%     clc
end

Mean_hist_Objects=sum(hist_Objects,1)/...........
    Total_No_of_Objects; % The average histogram
                         % for all objects.
% plot(Mean_hist_Objects)
% title('The Mean Histogram of All Objects')
% xlabel('Intensity Level r_{k}')
% ylabel({'The Mean Number of Pixels from All Objects Whose';....
%     'Intensity Level Is r_{k}'})
% axis tight
% pause

% Setting up a threshold in order to work on just the pixels of the
% faces and blocking the pixels of the backgrounds.
Objects_Threshold=8; % The picked threshold is based on the average
                     % histogram for all objects when the objects
                     % have black backgrounds. Note that, all
                     % intesity levels below the threshold
                     % represent the objects backgrounds because
                     % these levels have the biggest histogram.
% Objects_Threshold=180; % The Picked threshold is based on the
%                        % average histogram for all objects when
%                        % the objects have white backgrounds. Note
%                        % that, all intesity levels above the
%                        % threshold represent the objects
%                        % backgrounds because these levels have
%                        % the biggest histogram.


Max_Desired_Cross_Fields=zeros(Total_No_of_Objects,.....
    Total_No_of_Impulses); % Each element of each row in this
                           % matrix represents the maximum value
                           % of the desired crosscorrelated field
```

```
                              % between an object and one of the
                              % impulses.


for n=1:Total_No_of_Objects

    % Normalizing all the objects for removing lightening effects
    % on them then increasing the resolution of object detection
    % and recognition. Note that, the normalization will be done
    % just for the faces pixels for keeping variations among the
    % objects and impulses just in the faces without the
    % backgrounds effects.
    Object_Number=[num2str(n) '.jpg'];
    Object_Location=fullfile(Objects_Folder,Object_Number);
    Object1=........
        double(rgb2gray(imread(Object_Location))); % The object.

    T=Object1>Objects_Threshold; % The pixels bigger than the
                                 % threshold are of interest
                                 % because they represent the
                                 % pixels of a face.
%     T=Object1<Objects_Threshold; % The pixels smaller than the
%                                  % threshold are of interest
%                                  % because they represent the
%                                  % pixels of a face.
    Object=zeros(size(T,1),size(T,2)); % The normalized object.
    for R2=1:size(T,1)
        for C2=1:size(T,2)
            if T(R2,C2)==1
                Object(R2,C2)=ceil(255*(Object1(R2,C2)/......
                    max(max(Object1)))); % The normalization of the
                                         % object. This is done to
                                         % increase the dynamic
                                         % range of the object for
                                         % visualization by scaling
                                         % the intensities from 0
                                         % to 255.
            end
        end
    end
    [r c]=size(Object);


%     figure
%     subplot(2,1,1)
%     imshow(Object1)
%     if n<=L1
%         title({['This Is To Show How Good the Objects '.....
%             'Threshold Is,'];blanks(1);['Object No.' ....
%             num2str(n) ' for Mr. Mansour Alshammari']})
```

```
%     elseif n>L1 && n<=L2
%         title({['This Is To Show How Good the Objects '....
%             'Threshold Is,'];blanks(1);['Object No.' .....
%             num2str(n) ' for Mr. Methkir Alharthee']})
%     elseif n>L2 && n<=L3
%         title({['This Is To Show How Good the Objects '.....
%             'Threshold Is,'];blanks(1);['Object No.' ....
%             num2str(n) ' for Mr. Mohammed Hanafy']})
%     end
%     subplot(2,1,2)
%     imshow(Object)
%     if n<=L1
%         title(['Normalized Object No.' num2str(n) ....
%             ' for Mr. Mansour Alshammari'])
%     elseif n>L1 && n<=L2
%         title(['Normalized Object No.' num2str(n) .....
%             ' for Mr. Methkir Alharthee'])
%     elseif n>L2 && n<=L3
%         title(['Normalized Object No.' num2str(n) ....
%             ' for Mr. Mohammed Hanafy'])
%     end
%
%     figure
%     subplot(2,1,1)
%     imshow(uint8(Object1))
%     if n<=L1
%         title(['Object No.' num2str(n) .....
%             ' for Mr. Mansour Alshammari'])
%     elseif n>L1 && n<=L2
%         title(['Object No.' num2str(n) .....
%             ' for Mr. Methkir Alharthee'])
%     elseif n>L2 && n<=L3
%         title(['Object No.' num2str(n) ....
%             ' for Mr. Mohammed Hanafy'])
%     end
%     subplot(2,1,2)
%     imshow(uint8(Object))
%     if n<=L1
%         title(['Normalized Object No.' num2str(n) .....
%             ' for Mr. Mansour Alshammari'])
%     elseif n>L1 && n<=L2
%         title(['Normalized Object No.' num2str(n) ....
%             ' for Mr. Methkir Alharthee'])
%     elseif n>L2 && n<=L3
%         title(['Normalized Object No.' num2str(n) .....
%             ' for Mr. Mohammed Hanafy'])
%     end

    for m=1:Total_No_of_Impulses

```

```
        % Normalizing all the impulses for removing lightening
        % effects on them then increasing the resolution of object
        % detection and recognition. Note that, the normalization
        % will be done just for the faces pixels for keeping
        % variations among the objects and impulses just in the
        % faces without the backgrounds effects.
        One_Impulse=Impulses(m).name;
        Impulse_Location=fullfile(Impulses_Folder,One_Impulse);
        Impulse1=double(rgb2gray(......
            imread(Impulse_Location))); % The impulse response.

        T1=Impulse1>Impulses_Threshold; % The pixels bigger than
                                        % the threshold are of
                                        % interest because they
                                        % represent the pixels of
                                        % a face.
%         T1=Impulse1<Impulses_Threshold; % The pixels smaller than
%                                         % the threshold are of
%                                         % interest because they
%                                         % represent the pixels
%                                         % of a face.
        Impulse=zeros(size(T1,1),size(T1,2)); % The normalized
                                              % impulse response.
        for R1=1:size(T1,1)
            for C1=1:size(T1,2)
                if T1(R1,C1)==1
                    Impulse(R1,C1)=ceil(255*(Impulse1(R1,C1)/.....
                        max(max(Impulse1)))); % The normalization
                                              % of the impulse
                                              % response. This is
                                              % done to increase
                                              % the dynamic range
                                              % of the impulse for
                                              % visualization by
                                              % scaling the
                                              % intensities from
                                              % 0 to 255.
                end
            end
        end
        [p q]=size(Impulse);


        % Equalizing the width of the impulse response with the
        % width of the object in order to collimate them on the
        % input transparencies.
        if q>c
            if mod(q-c,2)==0
                Object=[zeros(r,(q-c)/2) Object zeros(r,(q-c)/2)];
            elseif mod(q-c,2)==1
```

```
                Object=[zeros(r,floor((q-c)/2)) Object ....
                    zeros(r,floor((q-c)/2)+1)];
            end
        elseif q<c
            if mod(c-q,2)==0
                Impulse=[zeros(p,(c-q)/2) Impulse .....
                    zeros(p,(c-q)/2)];
            elseif mod(c-q,2)==1
                Impulse=[zeros(p,floor((c-q)/2)) Impulse .....
                    zeros(p,floor((c-q)/2)+1)];
            end
        end

        % Collimating the impulse response and the object on the
        % input transparencies. Note that, the separation between
        % the impulse response and object must be bigger than
        % max{Wh,Wg}+Wg/2+Wh/2 in order to make the output
        % crosscorrelations of the impulse response and object are
        % completely separated without any overlapping.
        Wh=size(Impulse,1); % The width of the impulse response in
                            % the direction of the y1-coordinate.
        Wg=size(Object,1); % The width of the object in the
                           % direction of the y1-coordinate.
        Y=max(Wh,Wg)+((Wh+Wg)/2); % The separation between the
                                  % centers of the impulse response
                                  % and object.
        dis=10; % This distance in order to make the separation
                % between the centers of the impulse response and
                % object bigger than max{Wh,Wg}+Wg/2+Wh/2.
        Impulse_Object=[.......
            zeros(ceil(max(Wh,Wg)/2+Wh/4+3/4*Wg)+ceil(dis/2),.....
            size(Impulse,2));Impulse;.....
            zeros(max(Wh,Wg)+dis,size(Impulse,2));Object;.....
            zeros(ceil(max(Wh,Wg)/2+3/4*Wh+Wg/4)+ceil(dis/2),.....
            size(Object,2))];

        % Equalizing the dimensions of the input plane P1 by
        % padding it with zeros.
        [R C]=size(Impulse_Object);
        if R>C
            if mod(R-C,2)==0
                Impulse_Object=[.......
                    zeros(size(Impulse_Object,1),(R-C)/2) .....
                    Impulse_Object ......
                    zeros(size(Impulse_Object,1),(R-C)/2)];
            elseif mod(R-C,2)==1
                Impulse_Object=[......
                    zeros(size(Impulse_Object,1),.....
                    floor((R-C)/2)) Impulse_Object .......
                    zeros(size(Impulse_Object,1),......
```

```
                    floor((R-C)/2)+1)];
            end
        elseif R<C
            if mod(C-R,2)==0
                Impulse_Object=[......
                    zeros((C-R)/2,size(Impulse_Object,2));....
                    Impulse_Object;....
                    zeros((C-R)/2,size(Impulse_Object,2))];
            elseif mod(C-R,2)==1
                Impulse_Object=[zeros(floor((C-R)/2),......
                    size(Impulse_Object,2));Impulse_Object;......
                    zeros(floor((C-R)/2)+1,......
                    size(Impulse_Object,2))];
            end
        end


        U1=Impulse_Object; % The transmitted field from
                           % the input plane P1.
        [M N]=size(U1);

        L=10; % The physical side length of the
              % array which holds the input
              % plane P1 in meters (m).
        dx1_Input=L/N; % The sample spacing in the input plane
                       % array in the direction of the spatial
                       % space coordinate x1 in meters (m).
        dy1_Input=L/M; % The sample spacing in the input plane
                       % array in the direction of the spatial
                       % space coordinate y1 in meters (m).
        x1_Axis_Input=-floor(N/2)*dx1_Input:dx1_Input:......
            ceil(N/2)*dx1_Input-dx1_Input; % Sampling the input
                                           % plane P1 in the
                                           % direction of the
                                           % spatial space
                                           % coordinate x1.
        y1_Axis_Input=-floor(M/2)*dy1_Input:dy1_Input:.....
            ceil(M/2)*dy1_Input-dy1_Input; % Sampling the input
                                           % plane P1 in the
                                           % direction of the
                                           % spatial space
                                           % coordinate y1.


        U2=fftshift(fft2(fftshift(U1))); % The Fourier transform of
                                         % the transmitted field in
                                         % the back focal plane of
                                         % the lens L2.
        I=(abs(U2)).^2; % The intensity of the Fourier transformed
                        % field in the plane P2.
```

```
lambda=550e-9; % The wavelength in meters (m).
f=0.055; % The focal length in meters (m).
dx2=(lambda*f)/(N*dx1_Input); % The sample spacing in the
                              % plane P2 in the direction
                              % of the spatial space
                              % coordinate x2 in meters
                              % (m).
dy2=(lambda*f)/(M*dy1_Input); % The sample spacing in the
                              % plane P2 in the direction
                              % of the spatial space
                              % coordinate y2 in meters
                              % (m).
x2_Axis=-floor(N/2)*dx2:dx2:........
    ceil(N/2)*dx2-dx2; % Sampling the plane P2 in the
                       % direction of the spatial space
                       % coordinate x2.
y2_Axis=-floor(M/2)*dy2:dy2:.....
    ceil(M/2)*dy2-dy2; % Sampling the plane P2 in the
                       % direction of the spatial space
                       % coordinate y2.


U3=ifftshift(ifft2(ifftshift(I))); % The crosscorrelated
                                   % field in the back
                                   % focal plane of the
                                   % lens L4.

dx3=(lambda*f)/(N*dx2); % The sample spacing in the plane
                        % P3 in the direction of the
                        % spatial space coordinate x3 in
                        % meters (m).
dy3=(lambda*f)/(M*dy2); % The sample spacing in the plane
                        % P3 in the direction of the
                        % spatial space coordinate y3 in
                        % meters (m).
x3_Axis=-floor(N/2)*dx3:dx3:.....
    ceil(N/2)*dx3-dx3; % Sampling the plane P3 in the
                       % direction of the spatial space
                       % coordinate x3.
y3_Axis=-floor(M/2)*dy3:dy3:......
    ceil(M/2)*dy3-dy3; % Sampling the plane P3 in the
                       % direction of the spatial space
                       % coordinate y3.


% Synthesizing a desired filtering mask then filtering the
% crosscorrelated field in the plane P3.
Cen=floor(M/2)+1; % The center of the filtering mask.
Cen1=Cen-(Y+dis); % The center of the desired
```

```
                         % crosscorrelated field.
        Wh1=q; % The width of the impulse response in
               % the direction of the x1−coordinate.
        Wg1=c; % The width of the object in the
               % direction of the x1−coordinate.

        Mask=zeros(M,N);
        for P=Cen1−floor((Wh+Wg)/2):Cen1+ceil((Wh+Wg)/2)
            for Q=Cen−floor((Wh1+Wg1)/2):Cen+ceil((Wh1+Wg1)/2)
                Mask(P,Q)=1;
            end
        end

        Cross_Field=Mask.*U3; % The filtered crosscorrelated
                              % field in the plane P3.


        % For simplicity, instead of processing the entire image of
        % the filtered crosscorrelated field, we select only the
        % crosscorrelated field of interest.
        P=Cen1−floor((Wh+Wg)/2):Cen1+ceil((Wh+Wg)/2);
        Q=Cen−floor((Wh1+Wg1)/2):Cen+ceil((Wh1+Wg1)/2);
        Desired_Cross_Field=U3(P,Q);


        Max_Desired_Cross_Fields(n,m)=......
            max(max(Desired_Cross_Field));
        n


%         figure
%         subplot(2,1,1)
%         imshow(Impulse1)
%         if m==1
%             title({['This Is To Show How Good the Impulses '.....
%                 'Threshold Is,']; blanks(1);.....
%                 ['Impulse Response No.' num2str(m) .....
%                 ' for Mr. Mansour Alshammari']})
%         elseif m==2
%             title({['This Is To Show How Good the Impulses '.....
%                 'Threshold Is,'];blanks(1);.....
%                 ['Impulse Response No.' num2str(m) .....
%                 ' for Mr. Methkir Alharthee']})
%         elseif m==3
%             title({['This Is To Show How Good the Impulses '....
%                 'Threshold Is,'];blanks(1);....
%                 ['Impulse Response No.' num2str(m) ......
%                 ' for Mr. Mohammed Hanafy']})
%         end
%         subplot(2,1,2)
```

```
%           imshow(Impulse)
%           if m==1
%               title({['Normalized Impulse Response No.' ....
%                   num2str(m) ' for Mr. Mansour Alshammari']})
%           elseif m==2
%               title({['Normalized Impulse Response No.' .....
%                   num2str(m) ' for Mr. Methkir Alharthee']})
%           elseif m==3
%               title({['Normalized Impulse Response No.' .....
%                   num2str(m) ' for Mr. Mohammed Hanafy']})
%           end
%
%           figure
%           subplot(2,1,1)
%           imshow(uint8(Impulse1))
%           if m==1
%               title(['Impulse Response No.' num2str(m) .....
%                   ' for Mr. Mansour Alshammari'])
%           elseif m==2
%               title(['Impulse Response No.' num2str(m) ....
%                   ' for Mr. Methkir Alharthee'])
%           elseif m==3
%               title(['Impulse Response No.' num2str(m) .....
%                   ' for Mr. Mohammed Hanafy'])
%           end
%           subplot(2,1,2)
%           imshow(uint8(Impulse))
%           if m==1
%               title(['Normalized Impulse Response No.' .....
%                   num2str(m) ' for Mr. Mansour Alshammari'])
%           elseif m==2
%               title(['Normalized Impulse Response No.' .....
%                   num2str(m) ' for Mr. Methkir Alharthee'])
%           elseif m==3
%               title(['Normalized Impulse Response No.' ....
%                   num2str(m) ' for Mr. Mohammed Hanafy'])
%           end
%
%           figure('units','centimeters','position',[7 1.2 25 16.9])
%           imagesc(x1_Axis_Input,y1_Axis_Input,U1)
%           colorbar
%           if n<=L1
%               if m==1
%                   title({['The Transmitted Field from the '....
%                       'Input Plane P_1'];['(Impulse No.1 Is '....
%                       'for Mr. Mansour Alshammari as Well '.....
%                       'as Object No.' num2str(n) .....
%                       ' Is for Him)']})
%               elseif m==2
%                   title({['The Transmitted Field from the '.....
```

```
%                     'Input Plane P_1'];['(Impulse No.2 Is '....
%                     'for Mr. Methkir Alharthee and Object '....
%                     'No.' num2str(n) .....
%                     ' Is for Mr. Mansour Alshammari)']})
%             else
%                 title({['The Transmitted Field from the '.....
%                     'Input Plane P_1'];['(Impulse No.3 Is '....
%                     'for Mr. Mohammed Hanafy and Object '....
%                     'No.' num2str(n) .......
%                     ' Is for Mr. Mansour Alshammari)']})
%             end
%         elseif n>L1 && n<=L2
%             if m==1
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.1 Is '....
%                     'for Mr. Mansour Alshammari and Object '....
%                     'No.' num2str(n) ......
%                     ' Is for Mr. Methkir Alharthee)']})
%             elseif m==2
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.2 Is '....
%                     'for Mr. Methkir Alharthee as Well as '....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             else
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.3 Is '....
%                     'for Mr. Mohammed Hanafy and Object No.'....
%                     num2str(n) ........
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.1 Is '....
%                     'for Mr. Mansour Alshammari and Object '....
%                     'No.' num2str(n) .......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.2 Is '....
%                     'for Mr. Methkir Alharthee and '.....
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
%                 title({['The Transmitted Field from the '....
%                     'Input Plane P_1'];['(Impulse No.3 Is '....
%                     'for Mr. Mohammed Hanafy as Well as '.....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             end
%         end
```

```
%         colormap('gray')
%         xlabel('x_1 (m)')
%         ylabel('y_1 (m)')
%
%         figure('units','centimeters','position',[7 1.2 25 16.9])
%         imagesc(x2_Axis,y2_Axis,255*(I/max(max(I))))
%         colorbar
%         if n<=L1
%             if m==1
%                 title({['The Incident Intensity on the '.....
%                     'Plane P_2'];['(Impulse No.1 Is for '....
%                     'Mr. Mansour Alshammari as Well as '....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             elseif m==2
%                 title({['The Incident Intensity on the '.....
%                     'Plane P_2'];['(Impulse No.2 Is for '.....
%                     'Mr. Methkir Alharthee and Object No.'....
%                     num2str(n) ...........
%                     ' Is for Mr. Mansour Alshammari)']})
%             else
%                 title({['The Incident Intensity on the '....
%                     'Plane P_2'];['(Impulse No.3 Is for '....
%                     'Mr. Mohammed Hanafy and Object No.' ....
%                     num2str(n) ......
%                     ' Is for Mr. Mansour Alshammari)']})
%             end
%         elseif n>L1 && n<=L2
%             if m==1
%                 title({['The Incident Intensity on the '.....
%                     'Plane P_2'];['(Impulse No.1 Is for '.....
%                     'Mr. Mansour Alshammari and Object No.'....
%                     num2str(n) .......
%                     ' Is for Mr. Methkir Alharthee)']})
%             elseif m==2
%                 title({['The Incident Intensity on the '.....
%                     'Plane P_2'];['(Impulse No.2 Is for '.....
%                     'Mr. Methkir Alharthee as Well as '.....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             else
%                 title({['The Incident Intensity on the '....
%                     'Plane P_2'];['(Impulse No.3 Is for '....
%                     'Mr. Mohammed Hanafy and '......
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({['The Incident Intensity on the '....
%                     'Plane P_2'];['(Impulse No.1 Is for '.....
%                     'Mr. Mansour Alshammari and '......
```

```
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({['The Incident Intensity on the '....
%                     'Plane P_2'];['(Impulse No.2 Is for '....
%                     'Mr. Methkir Alharthee and '.....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
%                 title({['The Incident Intensity on the '.....
%                     'Plane P_2'];['(Impulse No.3 Is for '.....
%                     'Mr. Mohammed Hanafy as Well as '....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             end
%         end
%         colormap('gray')
%         xlabel('x_2 (m)')
%         ylabel('y_2 (m)')
%
%         figure('units','centimeters','position',[7 1.2 25 16.9])
%         imagesc(x3_Axis,y3_Axis,U3)
%         colorbar
%         if n<=L1
%             if m==1
%                 title({['The Crosscorrelated Field in '.....
%                     'the Plane P_3'];['(Impulse No.1 Is '.....
%                     'for Mr. Mansour Alshammari as Well as '....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             elseif m==2
%                 title({['The Crosscorrelated Field in '....
%                     'the Plane P_3'];['(Impulse No.2 Is '.....
%                     'for Mr. Methkir Alharthee and '.....
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Mansour Alshammari)']})
%             else
%                 title({['The Crosscorrelated Field in '....
%                     'the Plane P_3'];['(Impulse No.3 Is '.....
%                     'for Mr. Mohammed Hanafy and '.....
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Mansour Alshammari)']})
%             end
%         elseif n>L1 && n<=L2
%             if m==1
%                 title({['The Crosscorrelated Field in '....
%                     'the Plane P_3'];['(Impulse No.1 Is '....
%                     'for Mr. Mansour Alshammari and '.....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Methkir Alharthee)']})
%             elseif m==2
%                 title({['The Crosscorrelated Field in '....
```

```
%                     'the Plane P_3'];['(Impulse No.2 Is '.....
%                     'for Mr. Methkir Alharthee as Well as '....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             else
%                 title({['The Crosscorrelated Field in '.....
%                     'the Plane P_3'];['(Impulse No.3 Is '....
%                     'for Mr. Mohammed Hanafy and '.....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({['The Crosscorrelated Field in '.....
%                     'the Plane P_3'];['(Impulse No.1 Is '....
%                     'for Mr. Mansour Alshammari and '.....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({['The Crosscorrelated Field in '.....
%                     'the Plane P_3'];['(Impulse No.2 Is '.....
%                     'for Mr. Methkir Alharthee and '.....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
%                 title({['The Crosscorrelated Field in '....
%                     'the Plane P_3'];['(Impulse No.3 Is '.....
%                     'for Mr. Mohammed Hanafy as Well as '.....
%                     'Object No.' num2str(n) ' Is for Him)']})
%             end
%         end
%         colormap('gray')
%         xlabel('x_3 (m)')
%         ylabel('y_3 (m)')
%
%         figure('units','centimeters','position',[7 1.2 25 16.9])
%         imagesc(x3_Axis,y3_Axis,Mask)
%         colorbar
%         if n<=L1
%             if m==1
%                 title({'The Adaptive Filtering Mask';....
%                     ['(Impulse No.1 Is for Mr. Mansour '.....
%                     'Alshammari as Well as Object No.' ....
%                     num2str(n) ' Is for Him)']})
%             elseif m==2
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.2 Is for Mr. Methkir '.....
%                     'Alharthee and Object No.' num2str(n) ....
%                     ' Is for Mr. Mansour Alshammari)']})
%             else
%                 title({'The Adaptive Filtering Mask';.....
```

```
%                     ['(Impulse No.3 Is for Mr. Mohammed '....
%                     'Hanafy and Object No.' num2str(n) .....
%                     ' Is for Mr. Mansour Alshammari)']})
%             end
%         elseif n>L1 && n<=L2
%             if m==1
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.1 Is for Mr. Mansour '.....
%                     'Alshammari and Object No.' num2str(n) ....
%                     ' Is for Mr. Methkir Alharthee)']})
%             elseif m==2
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.2 Is for Mr. Methkir '.....
%                     'Alharthee as Well as Object No.' .....
%                     num2str(n) ' Is for Him)']})
%             else
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.3 Is for Mr. Mohammed '.....
%                     'Hanafy and Object No.' num2str(n) .....
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.1 Is for Mr. Mansour '.....
%                     'Alshammari and Object No.' num2str(n) ....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.2 Is for Mr. Methkir '.....
%                     'Alharthee and Object No.' num2str(n) ....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
%                 title({'The Adaptive Filtering Mask';.....
%                     ['(Impulse No.3 Is for Mr. Mohammed '.....
%                     'Hanafy as Well as Object No.' .....
%                     num2str(n) ' Is for Him)']})
%             end
%         end
%         colormap('gray')
%         xlabel('x_3 (m)')
%         ylabel('y_3 (m)')
%
%         figure('units','centimeters','position',[7 1.2 25 16.9])
%         imagesc(x3_Axis,y3_Axis,Cross_Field)
%         colorbar
%         if n<=L1
%             if m==1
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
```

```
%                     'No.1 Is for Mr. Mansour Alshammari '....
%                     'as Well as Object No.' num2str(n) ....
%                     ' Is for Him)']})
%             elseif m==2
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.2 Is for Mr. Methkir Alharthee '.....
%                     'and Object No.' num2str(n) ......
%                     ' Is for Mr. Mansour Alshammari)']})
%             else
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.3 Is for Mr. Mohammed Hanafy and '....
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Mansour Alshammari)']})
%             end
%         elseif n>L1 && n<=L2
%             if m==1
%                 title({['The Filtered Crosscorrelated '.....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.1 Is for Mr. Mansour Alshammari '.....
%                     'and Object No.' num2str(n) ......
%                     ' Is for Mr. Methkir Alharthee)']})
%             elseif m==2
%                 title({['The Filtered Crosscorrelated '.....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.2 Is for Mr. Methkir Alharthee '....
%                     'as Well as Object No.' num2str(n) .....
%                     ' Is for Him)']})
%             else
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.3 Is for Mr. Mohammed Hanafy and '....
%                     'Object No.' num2str(n) ......
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.1 Is for Mr. Mansour Alshammari '....
%                     'and Object No.' num2str(n) ......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({['The Filtered Crosscorrelated '....
%                     'Field in the Plane P_3'];['(Impulse '....
%                     'No.2 Is for Mr. Methkir Alharthee '.....
%                     'and Object No.' num2str(n) .....
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
```

```
%               title({['The Filtered Crosscorrelated '.....
%                   'Field in the Plane P_3'];['(Impulse '....
%                   'No.3 Is for Mr. Mohammed Hanafy as '....
%                   'Well as Object No.' num2str(n) ......
%                   ' Is for Him)']})
%           end
%       end
%       colormap('gray')
%       xlabel('x_3 (m)')
%       ylabel('y_3 (m)')
%
%       figure('units','centimeters','position',[7 1.2 25 16.9])
%       imagesc(x3_Axis,y3_Axis,Desired_Cross_Field)
%       colorbar
%       if n<=L1
%           if m==1
%               title({['The Crosscorrelated Field of '.....
%                   'Interest in the Plane P_3'];.....
%                   ['(Impulse No.1 Is for Mr. Mansour '....
%                   'Alshammari as Well as Object No.' ....
%                   num2str(n) ' Is for Him)']})
%           elseif m==2
%               title({['The Crosscorrelated Field of '.....
%                   'Interest in the Plane P_3'];['(Impulse'....
%                   ' No.2 Is for Mr. Methkir Alharthee '.....
%                   'and Object No.' num2str(n) ......
%                   ' Is for Mr. Mansour Alshammari)']})
%           else
%               title({['The Crosscorrelated Field of '.....
%                   'Interest in the Plane P_3'];['(Impulse'....
%                   ' No.3 Is for Mr. Mohammed Hanafy and '....
%                   'Object No.' num2str(n) ......
%                   ' Is for Mr. Mansour Alshammari)']})
%           end
%       elseif n>L1 && n<=L2
%           if m==1
%               title({['The Crosscorrelated Field of '......
%                   'Interest in the Plane P_3'];['(Impulse'....
%                   ' No.1 Is for Mr. Mansour Alshammari '....
%                   'and Object No.' num2str(n) ......
%                   ' Is for Mr. Methkir Alharthee)']})
%           elseif m==2
%               title({['The Crosscorrelated Field of '.....
%                   'Interest in the Plane P_3'];['(Impulse'....
%                   ' No.2 Is for Mr. Methkir Alharthee '.....
%                   'as Well as Object No.' num2str(n) .....
%                   ' Is for Him)']})
%           else
%               title({['The Crosscorrelated Field of '.....
%                   'Interest in the Plane P_3'];['(Impulse'....
```

```
%                     ' No.3 Is for Mr. Mohammed Hanafy and '....
%                     'Object No.' num2str(n) .....
%                     ' Is for Mr. Methkir Alharthee)']})
%             end
%         elseif n>L2 && n<=L3
%             if m==1
%                 title({['The Crosscorrelated Field of '.....
%                     'Interest in the Plane P_3'];['(Impulse'....
%                     ' No.1 Is for Mr. Mansour Alshammari '.....
%                     'and Object No.' num2str(n) ......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             elseif m==2
%                 title({['The Crosscorrelated Field of '.....
%                     'Interest in the Plane P_3'];['(Impulse'....
%                     ' No.2 Is for Mr. Methkir Alharthee '....
%                     'and Object No.' num2str(n) ......
%                     ' Is for Mr. Mohammed Hanafy)']})
%             else
%                 title({['The Crosscorrelated Field of '.....
%                     'Interest in the Plane P_3'];['(Impulse'....
%                     ' No.3 Is for Mr. Mohammed Hanafy '.....
%                     'as Well as Object No.' ......
%                     num2str(n) ' Is for Him)']})
%             end
%         end
%         colormap('gray')
%         xlabel('x_3 (m)')
%         ylabel('y_3 (m)')
%
%
%
%         %%%% Note that, "imshow" is better to be used instead
%         %%%% of "imagesc" during designing the adaptive mask
%         %%%% because "imshow" dispalays the cross-correlations
%         %%%% in the plane P3 clearer than "imagesc"!!
%
%
%
%         disp(['Please, press any keyboard button to explore '....
%             'the remaining crosscorrelated fields >>>>>>>'])
%         pause
%         clc
%         close all
    end
end


% Testing the process of object recognition.
% Note that, the objects here are known for us in order to use them
% for testing the object recognition process as well as setting up
```

```
% a recognition threshold.

% The elements in each of the following vectors represent the
% maximum values of the desired crosscorrelated fields between the
% objects and their corresponding impulse. Note that, each impulse
% and its corresponding objects have a same face so the vectors
% will include the biggest crosscorrelations.
V1=(Max_Desired_Cross_Fields(1:L1,1)).';
V2=(Max_Desired_Cross_Fields(L1+1:L2,2)).';
V3=(Max_Desired_Cross_Fields(L2+1:L3,3)).';

% The calculation of the mean and the standard deviation for each
% vector of the biggest crosscorrelations and stacking them in a
% vector for the means and another for the standard deviations.
% This is done for setting up a threshold for object recognition.
V_Mean=[mean(V1);mean(V2);mean(V3)];
V_STD=[std(V1);std(V2);std(V3)];
save('Computed Means for Object Recognition','V_Mean')
save('Computed STDs for Object Recognition','V_STD')

fid=fopen('Object Recognition Results for Testing.txt',....
    'w'); % A text file for typing
          % the object recognition
          % results for testing.
fprintf(fid,['\n ***** The Object Recognition Results '.....
    'for Testing Obtained from the Code of the *****\r\n']);
fprintf(fid,['   **** Joint Transform Correlator (JTC) for '.....
    'Testing and Setting up Thresholds ****\r\n\n']);
fprintf(fid,['The Object No.   The Object Is Originally for'......
    '   The Object Is Recognized as   The Status\r\n']);
fprintf(fid,['==============   ============================'.....
    '   ===========================   ==========\r\n']);

Failures_Vector=zeros(1,Total_No_of_Objects); % A vector for
                                              % counting the number
                                              % of failures in the
                                              % object recognition
                                              % process.

Latex_Matrix=cell(Total_No_of_Objects,4); % This matrix is used
                                          % for creating a table
                                          % in Latex.
for w=1:Total_No_of_Objects
    % The object recognition process.
    for ii=1:Total_No_of_Impulses
        if  max(Max_Desired_Cross_Fields(w,:))==.....
                Max_Desired_Cross_Fields(w,ii) && .....
                max(Max_Desired_Cross_Fields(w,:))>=....
                (V_Mean(ii,1)-V_STD(ii,1)) && .....
                max(Max_Desired_Cross_Fields(w,:))<=....
```

```
                (V_Mean(ii,1)+V_STD(ii,1))
            S=transpose(struct2cell(Impulses));
            d=sortrows(S,1);
            z=d(:,1);
            Recognized_As=char(z(ii,1));
            Recognized_Object_Location=......
                fullfile(Impulses_Folder,Recognized_As);
            Recognized_Object=im2double(rgb2gray(.....
                imread(Recognized_Object_Location)));
            break
        else
            Recognized_As='Unknown Object';
            Recognized_Object=imread('Unknown_Object.jpg');
        end
    end

    % Defining the object.
    if w<=L1
        name='Mr. Mansour Alshammari';
    elseif L1<w && w<=L2
        name='Mr. Methkir Alharthee';
    else name='Mr. Mohammed Hanafy';
    end

    Str1=strcmp(Recognized_As(1:length(Recognized_As)-6),....
        'Mr. Mansour Alshammari');
    Str2=strcmp(Recognized_As(1:length(Recognized_As)-6),.....
        'Mr. Methkir Alharthee');
    Str3=strcmp(Recognized_As(1:length(Recognized_As)-6),....
        'Mr. Mohammed Hanafy');
    F='Success';
    if w<=L1 && Str1==0;
        F='Failure';
        Failures_Vector(1,w)=1;
    elseif w>L1 && w<=L2 && Str2==0;
        F='Failure';
        Failures_Vector(1,w)=1;
    elseif w>L2 && w<=L3 && Str3==0;
        F='Failure';
        Failures_Vector(1,w)=1;
    end

%     Object_Number=[num2str(w) '.jpg'];
%     Object_Location=fullfile(Objects_Folder,Object_Number);
%     Object=im2double(rgb2gray(imread(Object_Location)));
%     subplot(2,1,1)
%     imshow(Object)
%     title({['Object No.' num2str(w) ' Is Originally for'];name})
%     subplot(2,1,2)
%     imshow(Recognized_Object)
```

```
%     if Str1==1 || Str2==1 || Str3==1
%         title({'The Object Is Recognized As';..............
%             Recognized_As(1:length(Recognized_As)-6)})
%     else title({'The Object Is Recognized As' ......
%             ['an' blanks(1) Recognized_As]})
%     end

    if Str1==1 || Str2==1 || Str3==1
        fprintf(fid,['%0.3d\t\t\t     %-23s\t    '.......
            '%-24s\t  %s \r\n\n'],w,name,......
            Recognized_As(1:length(Recognized_As)-6),F);
        Latex_Matrix(w,1:4)={num2str(w) name .....
            Recognized_As(1:length(Recognized_As)-6) F};
    else fprintf(fid,['%0.3d\t\t\t     %-23s\t    %-24s\t'.....
            '  %s \r\n\n'],w,name,Recognized_As,F);
        Latex_Matrix(w,1:4)={num2str(w) name Recognized_As F};
    end

%     disp(['Please, press Enter button to see another '......
%         'object and its recognition....'])
%     pause
%     clc
end

Total_Number_of_Failures=sum(Failures_Vector); % The total number
                                                % of failures in the
                                                % object recognition
                                                % process.

fprintf(fid,['================================================'....
    '=========================================\r\n']);
fprintf(fid,['** The Total Number of Successes: %0.3d out '......
    'of %0.3d (%3.4f%%) \r\n\n'],Total_No_of_Objects-......
    Total_Number_of_Failures,Total_No_of_Objects,......
    ((Total_No_of_Objects-Total_Number_of_Failures)/.....
    Total_No_of_Objects)*100);
fprintf(fid,['** The Total Number of Failures: %0.3d out'.....
    ' of %0.3d (%3.4f%%) \r\n\n'],....
    Total_Number_of_Failures,Total_No_of_Objects,.....
    (Total_Number_of_Failures/Total_No_of_Objects)*100);
fclose(fid);

close all
clc

disp(['Please, see the documented results of object '......
    'recognition in the open'])
disp(['text file then press any keyboard button to '.....
    'resume the code >>>>'])
Text='Object Recognition Results for Testing.txt';
```

```
open(Text) % Opening the text file which contains
           % the results of object recognition.
pause
clc
open('The_JTC_Testing_and_Setting_up_Thresholds.m')


% Testing the process of object detection.
% Note that, the objects here are known for us in order to use them
% for testing the object detection process as well as setting up a
% detection threshold.

% The calculation of the mean and standard deviation for the
% crosscorrelations between the objects and each impulse response.
% This is done for setting up a threshold for object detection.
Vectorization=reshape(Max_Desired_Cross_Fields,1,.....
    size(Max_Desired_Cross_Fields,1)*.....
    size(Max_Desired_Cross_Fields,2));
Mean=mean(Vectorization);
STD=std(Vectorization);
save('Computed Mean for Object Detection','Mean')
save('Computed STD for Object Detection','STD')

fid=fopen('Object Detection Results for Testing.txt',.....
    'w'); % A text file for typing
          % the object detection
          % results for testing.
fprintf(fid,['\n ***** The Object Detection Results '.......
    'for Testing Obtained from the Code of the *****\r\n']);
fprintf(fid,['  **** Joint Transform Correlator (JTC) for '.....
    'Testing and Setting up Thresholds ****\r\n\n']);
fprintf(fid,['The Object No.     The Object Originally '.......
    'Is     The Detected Object Is     The Status\r\n']);
fprintf(fid,['==============     ========================='.....
    '     ======================     ==========\r\n']);

Failures_Vector1=zeros(1,.......
    Total_No_of_Objects); % A vector for counting the number
                          % of failures in the object detection
                          % process.

Latex_Matrix=cell(Total_No_of_Objects,4); % This matrix is used
                                          % for creating a table
                                          % in Latex.
for w=1:Total_No_of_Objects
    % The object detection process.
    if  max(Max_Desired_Cross_Fields(w,:))>=(Mean-STD) && .....
            max(Max_Desired_Cross_Fields(w,:))<=(Mean+STD)
        Detected_As='a face';
        Detected_Object=imread('A_Face.jpg');
```

```
    else
        Detected_As='not a face';
        Detected_Object=imread('Not_a_Face.jpg');
    end

    b='a face'; % The object originally is a face.

    Str=strcmp(Detected_As,'a face');
    F='Success';
    if w<=L3 && Str==0;
        F='Failure';
        Failures_Vector1(1,w)=1;
    end

%     Object_Number=[num2str(w) '.jpg'];
%     Object_Location=fullfile(Objects_Folder,Object_Number);
%     Object=im2double(rgb2gray(imread(Object_Location)));
%     subplot(2,1,1)
%     imshow(Object)
%     title(['Object No.' num2str(w) ' Originally Is'])
%     subplot(2,1,2)
%     imshow(Detected_Object)
%     title('It Is Detected As')

    if Str==1
        fprintf(fid,['%0.3d\t\t\t       %-23s\t    %-22s\t'.....
            '   %s \r\n\n'],w,b,Detected_As,F);
        Latex_Matrix(w,1:4)={num2str(w) b Detected_As F};
    else fprintf(fid,['%0.3d\t\t\t       %-23s\t    %-22s\t'....
            '   %s \r\n\n'],w,b,Detected_As,F);
        Latex_Matrix(w,1:4)={num2str(w) b Detected_As F};
    end

%     disp(['Please, press Enter button to see another '......
%         'object and its detection....'])
%     pause
%     clc
end

Total_Number_of_Failures1=sum(Failures_Vector1); % The total number
                                                  % of failures in
                                                  % the object
                                                  % detection
                                                  % process.

fprintf(fid,['==============================================='....
    '=====================================\r\n']);
fprintf(fid,['** The Total Number of Successes: %0.3d out '.....
    'of %0.3d (%3.4f%%) \r\n\n'],Total_No_of_Objects-.....
    Total_Number_of_Failures1,Total_No_of_Objects,.....
```

```
    ((Total_No_of_Objects-Total_Number_of_Failures1)/.....
    Total_No_of_Objects)*100);
fprintf(fid,['** The Total Number of Failures: %0.3d '.....
    'out of %0.3d (%3.4f%%) \r\n\n'],Total_Number_of_Failures1,....
    Total_No_of_Objects,......
    (Total_Number_of_Failures1/Total_No_of_Objects)*100);
fclose(fid);

close all
clc

disp(['Please, see the documented results of object '.....
    'detection in the open'])
disp(['text file then press any keyboard button to '.....
    'resume the code >>>>'])
Text='Object Detection Results for Testing.txt';
open(Text) % Opening the text file which contains
           % the results of object detection.
pause
clc
open('The_JTC_Testing_and_Setting_up_Thresholds.m')
```

Appendix **G**

Results of the Optical Recognition

Table G.1: The recognition of all 108 objects by using the joint transform correlator (JTC).

Object No.	Input Face	Recognized Output Face	Status
1	Mr. Mansour Alshammari	Unknown Object	Failure
2	Mr. Mansour Alshammari	Unknown Object	Failure
3	Mr. Mansour Alshammari	Unknown Object	Failure
4	Mr. Mansour Alshammari	Unknown Object	Failure
5	Mr. Mansour Alshammari	Unknown Object	Failure
6	Mr. Mansour Alshammari	Unknown Object	Failure
7	Mr. Mansour Alshammari	Unknown Object	Failure
8	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
9	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
10	Mr. Mansour Alshammari	Unknown Object	Failure
11	Mr. Mansour Alshammari	Unknown Object	Failure
12	Mr. Mansour Alshammari	Unknown Object	Failure
13	Mr. Mansour Alshammari	Unknown Object	Failure
14	Mr. Mansour Alshammari	Unknown Object	Failure
15	Mr. Mansour Alshammari	Unknown Object	Failure
16	Mr. Mansour Alshammari	Unknown Object	Failure
17	Mr. Mansour Alshammari	Unknown Object	Failure
18	Mr. Mansour Alshammari	Unknown Object	Failure
19	Mr. Mansour Alshammari	Unknown Object	Failure
20	Mr. Mansour Alshammari	Unknown Object	Failure
21	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
22	Mr. Mansour Alshammari	Unknown Object	Failure

Continued on the next page ...

Object No.	Input Face	Recognized Output Face	Status
23	Mr. Mansour Alshammari	Unknown Object	Failure
24	Mr. Mansour Alshammari	Unknown Object	Failure
25	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
26	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
27	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
28	Mr. Mansour Alshammari	Unknown Object	Failure
29	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
30	Mr. Mansour Alshammari	Unknown Object	Failure
31	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
32	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
33	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
34	Mr. Mansour Alshammari	Unknown Object	Failure
35	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
36	Mr. Mansour Alshammari	Mr. Mohammed Hanafy	Failure
37	Mr. Methkir Alharthee	Unknown Object	Failure
38	Mr. Methkir Alharthee	Unknown Object	Failure
39	Mr. Methkir Alharthee	Unknown Object	Failure
40	Mr. Methkir Alharthee	Unknown Object	Failure
41	Mr. Methkir Alharthee	Unknown Object	Failure
42	Mr. Methkir Alharthee	Unknown Object	Failure
43	Mr. Methkir Alharthee	Unknown Object	Failure
44	Mr. Methkir Alharthee	Unknown Object	Failure
45	Mr. Methkir Alharthee	Unknown Object	Failure
46	Mr. Methkir Alharthee	Unknown Object	Failure
47	Mr. Methkir Alharthee	Unknown Object	Failure
48	Mr. Methkir Alharthee	Unknown Object	Failure
49	Mr. Methkir Alharthee	Unknown Object	Failure
50	Mr. Methkir Alharthee	Unknown Object	Failure
51	Mr. Methkir Alharthee	Unknown Object	Failure
52	Mr. Methkir Alharthee	Unknown Object	Failure
53	Mr. Methkir Alharthee	Unknown Object	Failure
54	Mr. Methkir Alharthee	Unknown Object	Failure
55	Mr. Methkir Alharthee	Unknown Object	Failure
56	Mr. Methkir Alharthee	Unknown Object	Failure
57	Mr. Methkir Alharthee	Unknown Object	Failure
58	Mr. Methkir Alharthee	Unknown Object	Failure
59	Mr. Methkir Alharthee	Unknown Object	Failure
60	Mr. Methkir Alharthee	Unknown Object	Failure
61	Mr. Methkir Alharthee	Unknown Object	Failure

Continued on the next page ...

Object No.	Input Face	Recognized Output Face	Status
62	Mr. Methkir Alharthee	Unknown Object	Failure
63	Mr. Methkir Alharthee	Unknown Object	Failure
64	Mr. Methkir Alharthee	Unknown Object	Failure
65	Mr. Methkir Alharthee	Unknown Object	Failure
66	Mr. Methkir Alharthee	Unknown Object	Failure
67	Mr. Methkir Alharthee	Unknown Object	Failure
68	Mr. Methkir Alharthee	Unknown Object	Failure
69	Mr. Methkir Alharthee	Unknown Object	Failure
70	Mr. Methkir Alharthee	Unknown Object	Failure
71	Mr. Methkir Alharthee	Unknown Object	Failure
72	Mr. Methkir Alharthee	Unknown Object	Failure
73	Mr. Mohammed Hanafy	Unknown Object	Failure
74	Mr. Mohammed Hanafy	Unknown Object	Failure
75	Mr. Mohammed Hanafy	Unknown Object	Failure
76	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
77	Mr. Mohammed Hanafy	Unknown Object	Failure
78	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
79	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
80	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
81	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
82	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
83	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
84	Mr. Mohammed Hanafy	Unknown Object	Failure
85	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
86	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
87	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
88	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
89	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
90	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
91	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
92	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
93	Mr. Mohammed Hanafy	Unknown Object	Failure
94	Mr. Mohammed Hanafy	Unknown Object	Failure
95	Mr. Mohammed Hanafy	Unknown Object	Failure
96	Mr. Mohammed Hanafy	Unknown Object	Failure
97	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
98	Mr. Mohammed Hanafy	Unknown Object	Failure
99	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
100	Mr. Mohammed Hanafy	Unknown Object	Failure

Continued on the next page ...

Object No.	**Input Face**	**Recognized Output Face**	**Status**
101	Mr. Mohammed Hanafy	Unknown Object	Failure
102	Mr. Mohammed Hanafy	Unknown Object	Failure
103	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
104	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
105	Mr. Mohammed Hanafy	Mr. Mohammed Hanafy	Success
106	Mr. Mohammed Hanafy	Unknown Object	Failure
107	Mr. Mohammed Hanafy	Unknown Object	Failure
108	Mr. Mohammed Hanafy	Unknown Object	Failure

The table end.

Appendix **H**

Results of the Optical Detection

Table H.1: The detection of all 108 objects by using the joint transform correlator (JTC).

Object No.	Input Object	Detected Output Object	Status
1	a face	not a face	Failure
2	a face	not a face	Failure
3	a face	not a face	Failure
4	a face	not a face	Failure
5	a face	not a face	Failure
6	a face	not a face	Failure
7	a face	not a face	Failure
8	a face	not a face	Failure
9	a face	a face	Success
10	a face	not a face	Failure
11	a face	not a face	Failure
12	a face	not a face	Failure
13	a face	not a face	Failure
14	a face	not a face	Failure
15	a face	not a face	Failure
16	a face	not a face	Failure
17	a face	not a face	Failure
18	a face	not a face	Failure
19	a face	not a face	Failure
20	a face	not a face	Failure
21	a face	a face	Success
22	a face	not a face	Failure

Continued on the next page ...

Object No.	Input Object	Detected Output Object	Status
23	a face	not a face	Failure
24	a face	not a face	Failure
25	a face	not a face	Failure
26	a face	a face	Success
27	a face	a face	Success
28	a face	not a face	Failure
29	a face	not a face	Failure
30	a face	a face	Success
31	a face	not a face	Failure
32	a face	not a face	Failure
33	a face	a face	Success
34	a face	a face	Success
35	a face	not a face	Failure
36	a face	a face	Success
37	a face	a face	Success
38	a face	a face	Success
39	a face	a face	Success
40	a face	a face	Success
41	a face	a face	Success
42	a face	a face	Success
43	a face	a face	Success
44	a face	a face	Success
45	a face	a face	Success
46	a face	a face	Success
47	a face	a face	Success
48	a face	a face	Success
49	a face	a face	Success
50	a face	a face	Success
51	a face	a face	Success
52	a face	a face	Success
53	a face	a face	Success
54	a face	a face	Success
55	a face	a face	Success
56	a face	a face	Success
57	a face	not a face	Failure
58	a face	a face	Success
59	a face	a face	Success
60	a face	a face	Success
61	a face	a face	Success

Continued on the next page ...

Object No.	**Input Object**	**Detected Output Object**	**Status**
62	a face	a face	Success
63	a face	a face	Success
64	a face	a face	Success
65	a face	a face	Success
66	a face	a face	Success
67	a face	a face	Success
68	a face	a face	Success
69	a face	a face	Success
70	a face	not a face	Failure
71	a face	not a face	Failure
72	a face	not a face	Failure
73	a face	a face	Success
74	a face	not a face	Failure
75	a face	not a face	Failure
76	a face	a face	Success
77	a face	not a face	Failure
78	a face	not a face	Failure
79	a face	not a face	Failure
80	a face	not a face	Failure
81	a face	not a face	Failure
82	a face	a face	Success
83	a face	not a face	Failure
84	a face	a face	Success
85	a face	not a face	Failure
86	a face	a face	Success
87	a face	not a face	Failure
88	a face	a face	Success
89	a face	a face	Success
90	a face	a face	Success
91	a face	a face	Success
92	a face	not a face	Failure
93	a face	a face	Success
94	a face	not a face	Failure
95	a face	not a face	Failure
96	a face	not a face	Failure
97	a face	not a face	Failure
98	a face	a face	Success
99	a face	not a face	Failure
100	a face	a face	Success

Continued on the next page ...

Object No.	Input Object	Detected Output Object	Status
101	a face	a face	Success
102	a face	a face	Success
103	a face	not a face	Failure
104	a face	a face	Success
105	a face	not a face	Failure
106	a face	a face	Success
107	a face	a face	Success
108	a face	a face	Success

The table end.

Appendix I

MSEs Plots of Reconstructing Some Training Faces

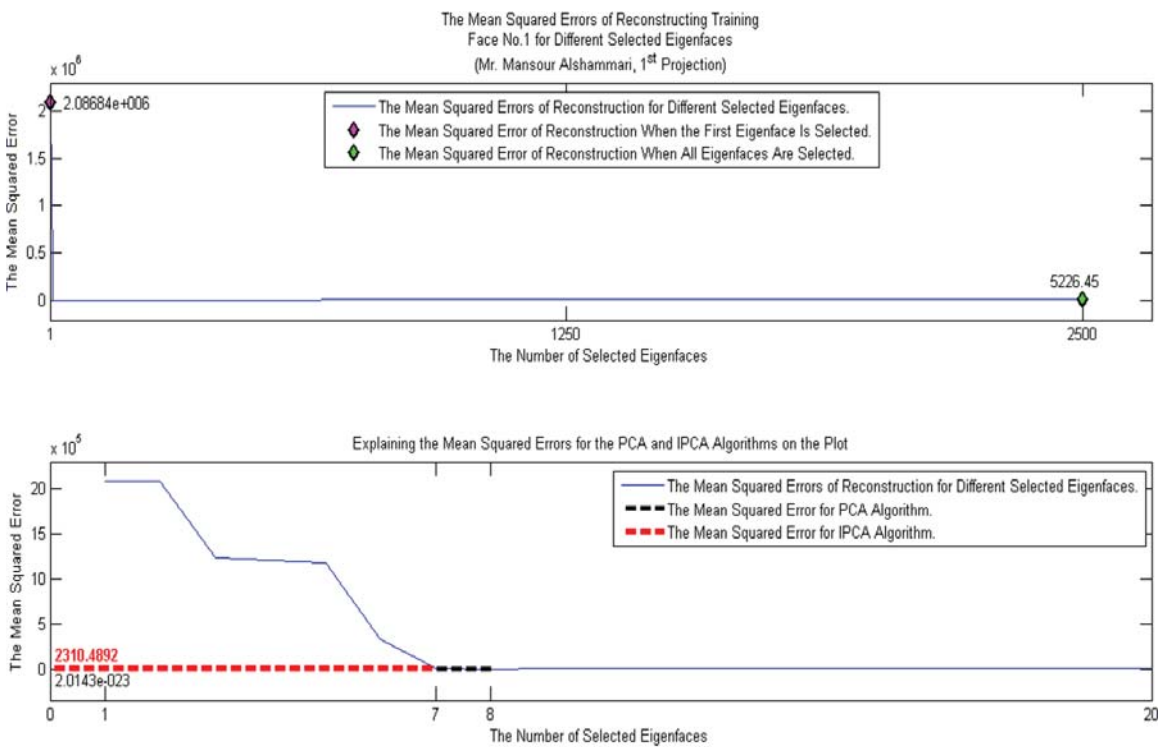


Figure I.1: The plot of the mean squared errors (MSEs) of reconstructing training face number one for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

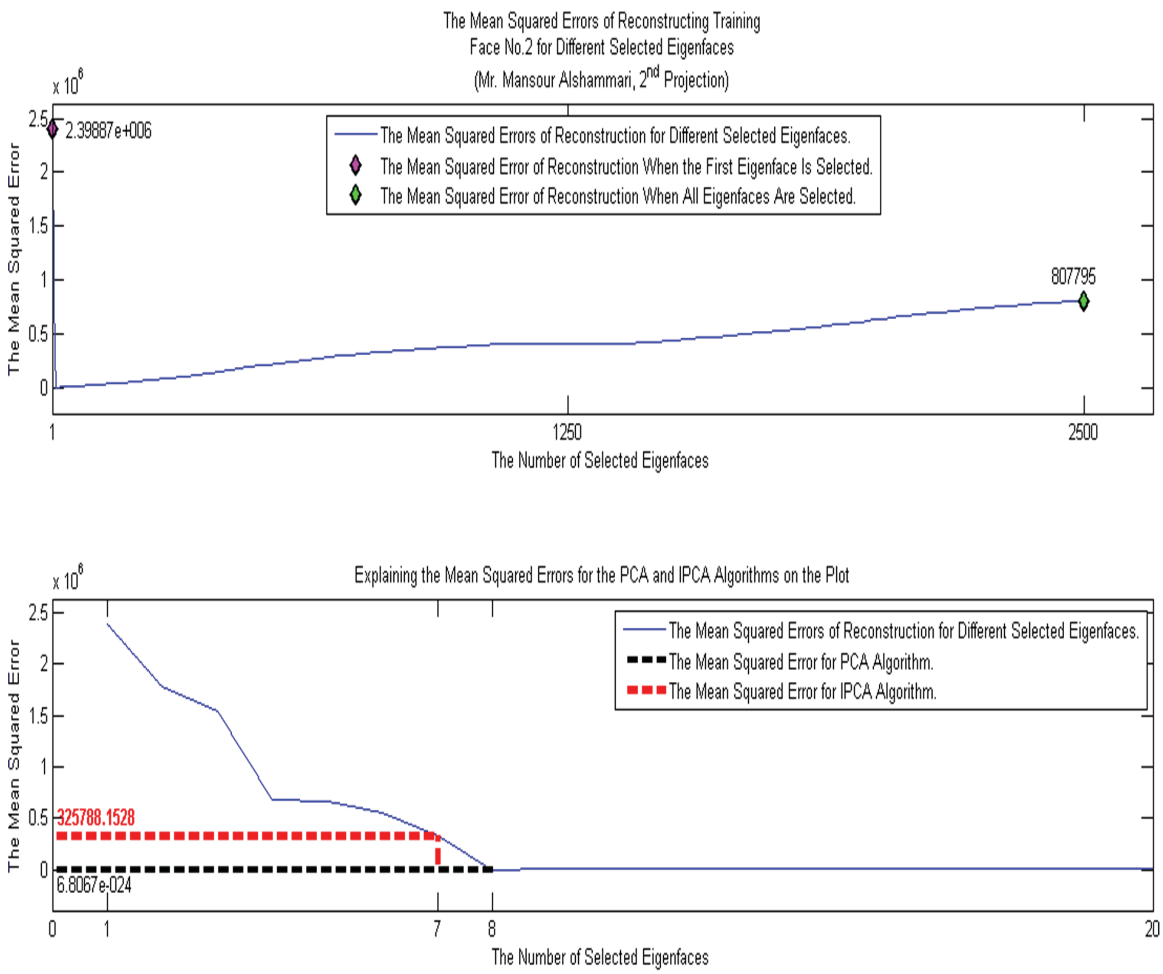


Figure I.2: The plot of the mean squared errors (MSEs) of reconstructing training face number two for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

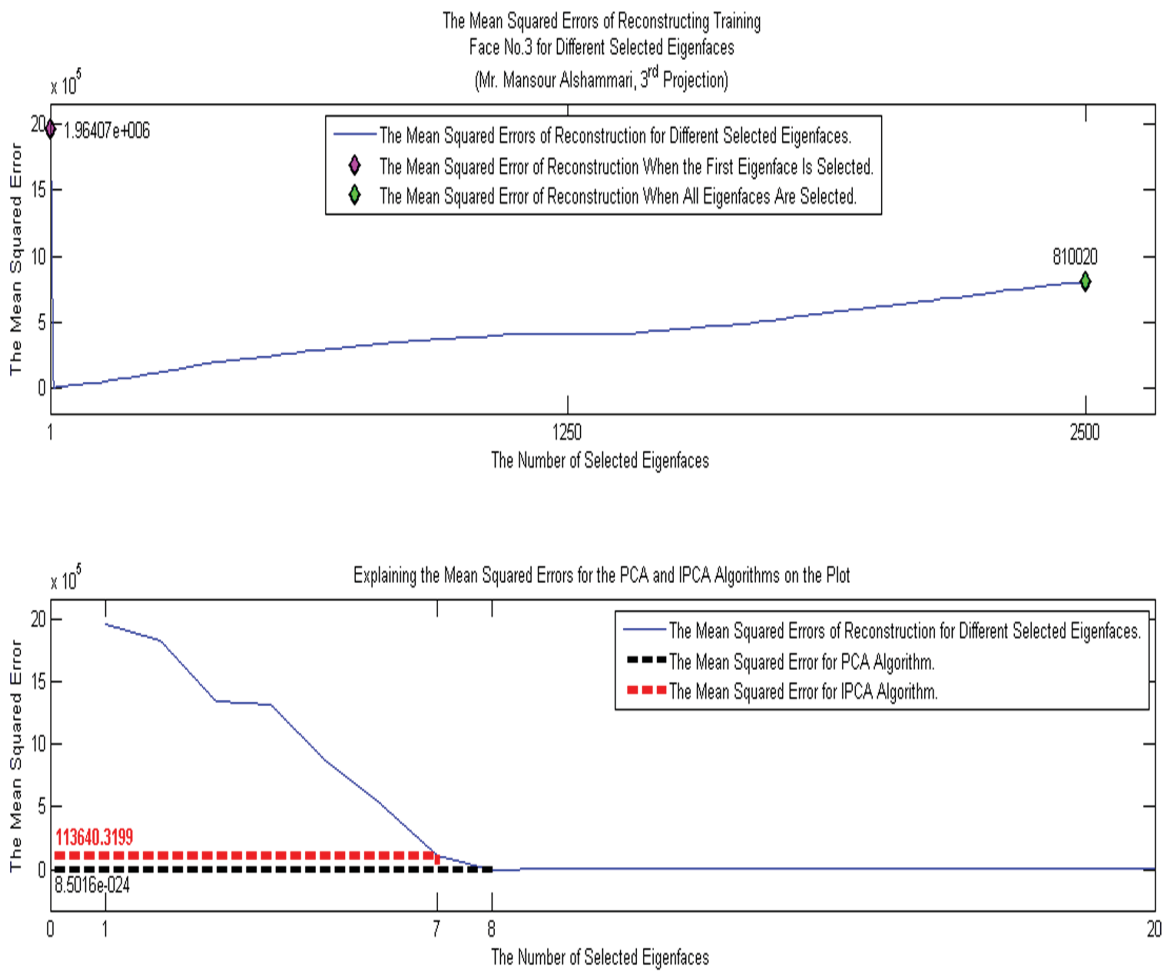


Figure I.3: The plot of the mean squared errors (MSEs) of reconstructing training face number three for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

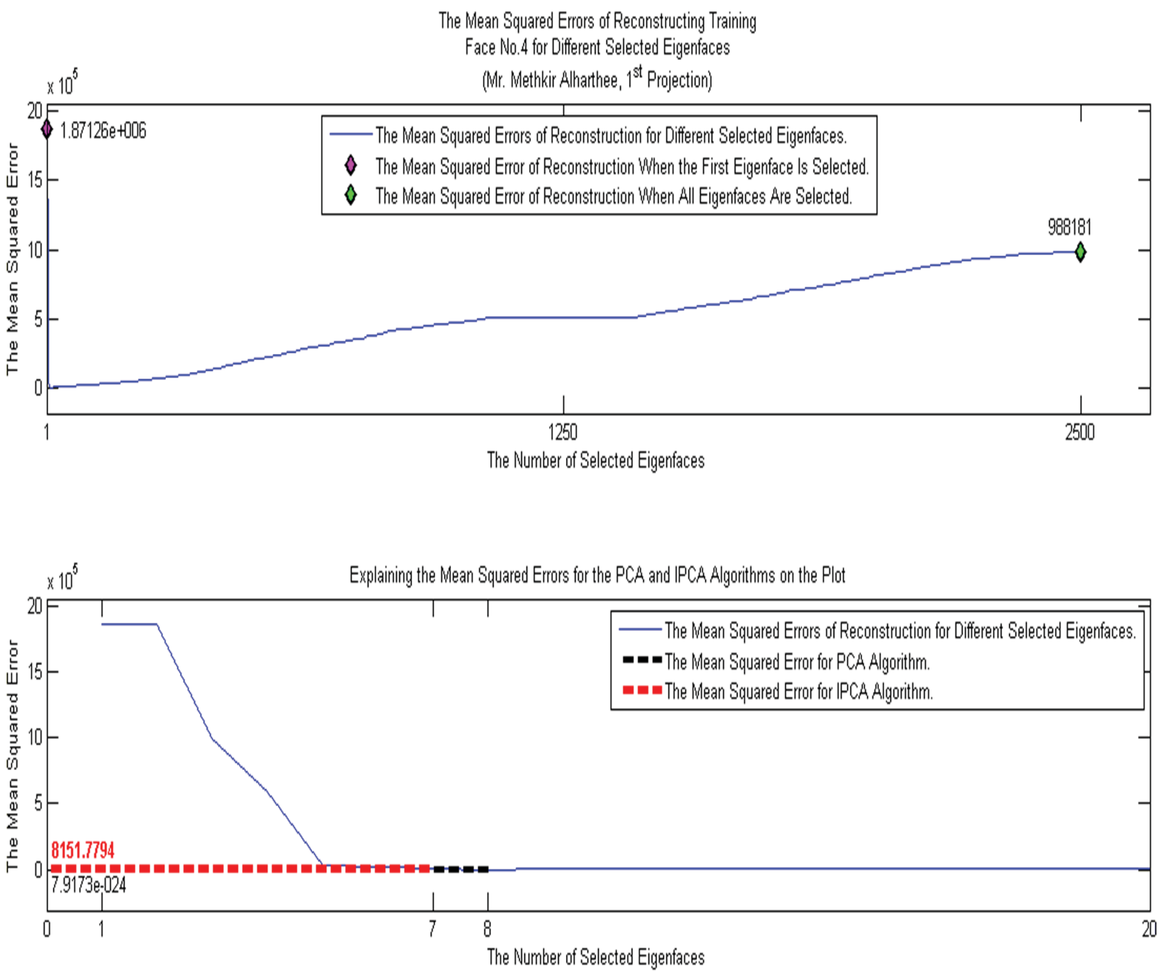


Figure I.4: The plot of the mean squared errors (MSEs) of reconstructing training face number four for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

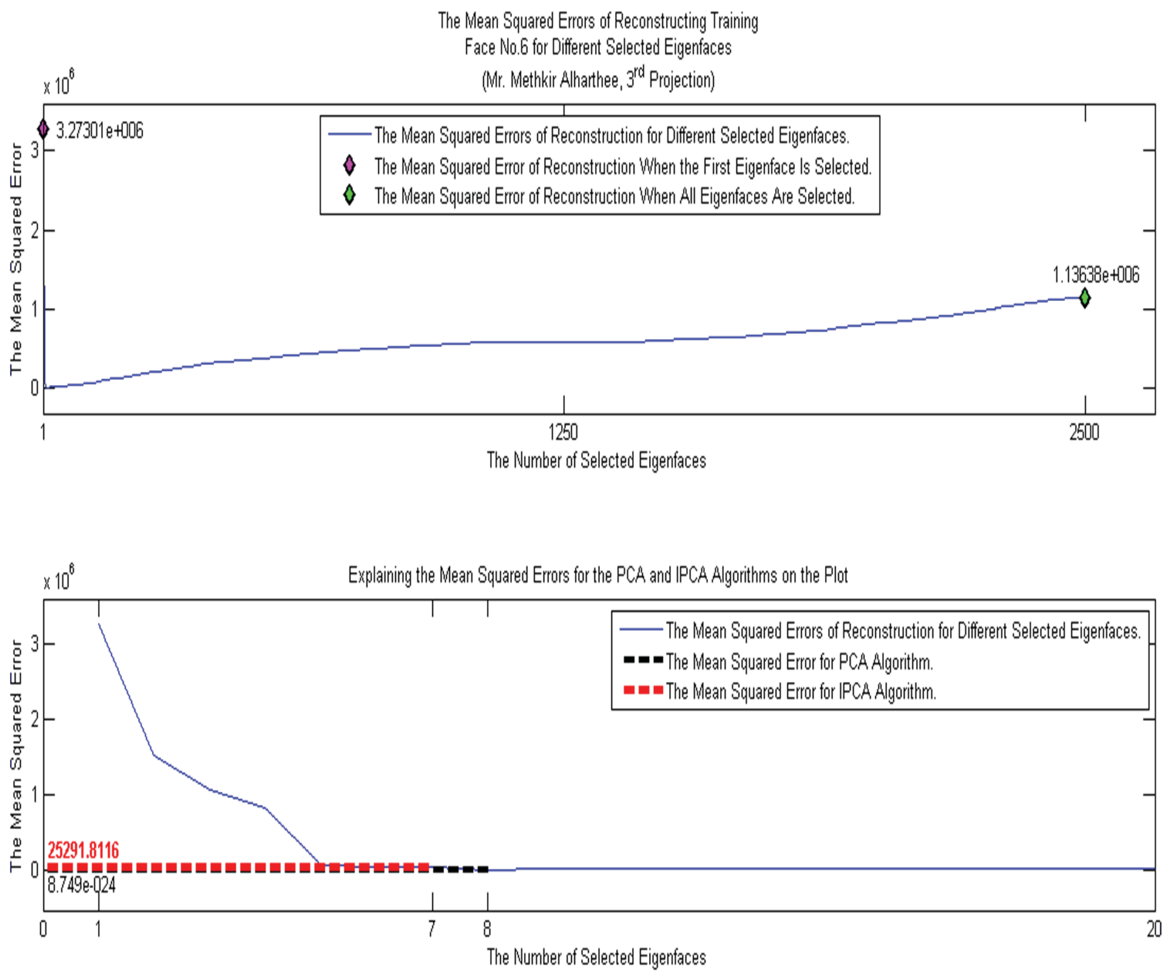
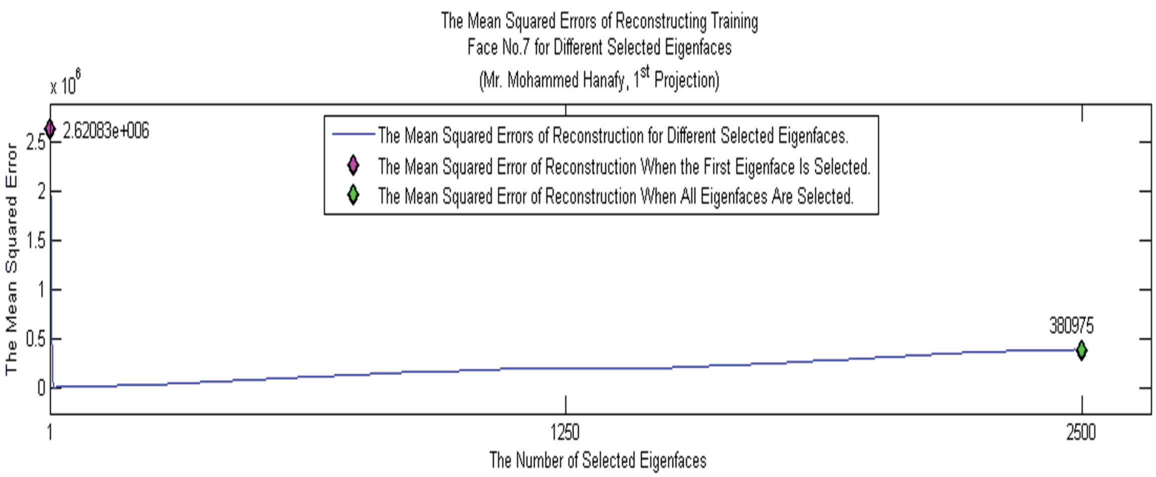


Figure I.5: The plot of the mean squared errors (MSEs) of reconstructing training face number six for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.



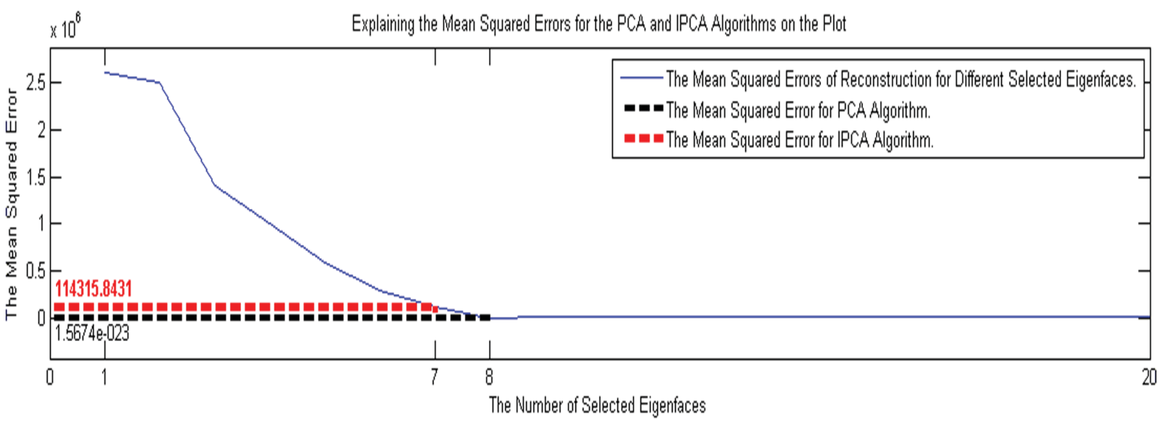


Figure I.6: The plot of the mean squared errors (MSEs) of reconstructing training face number seven for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

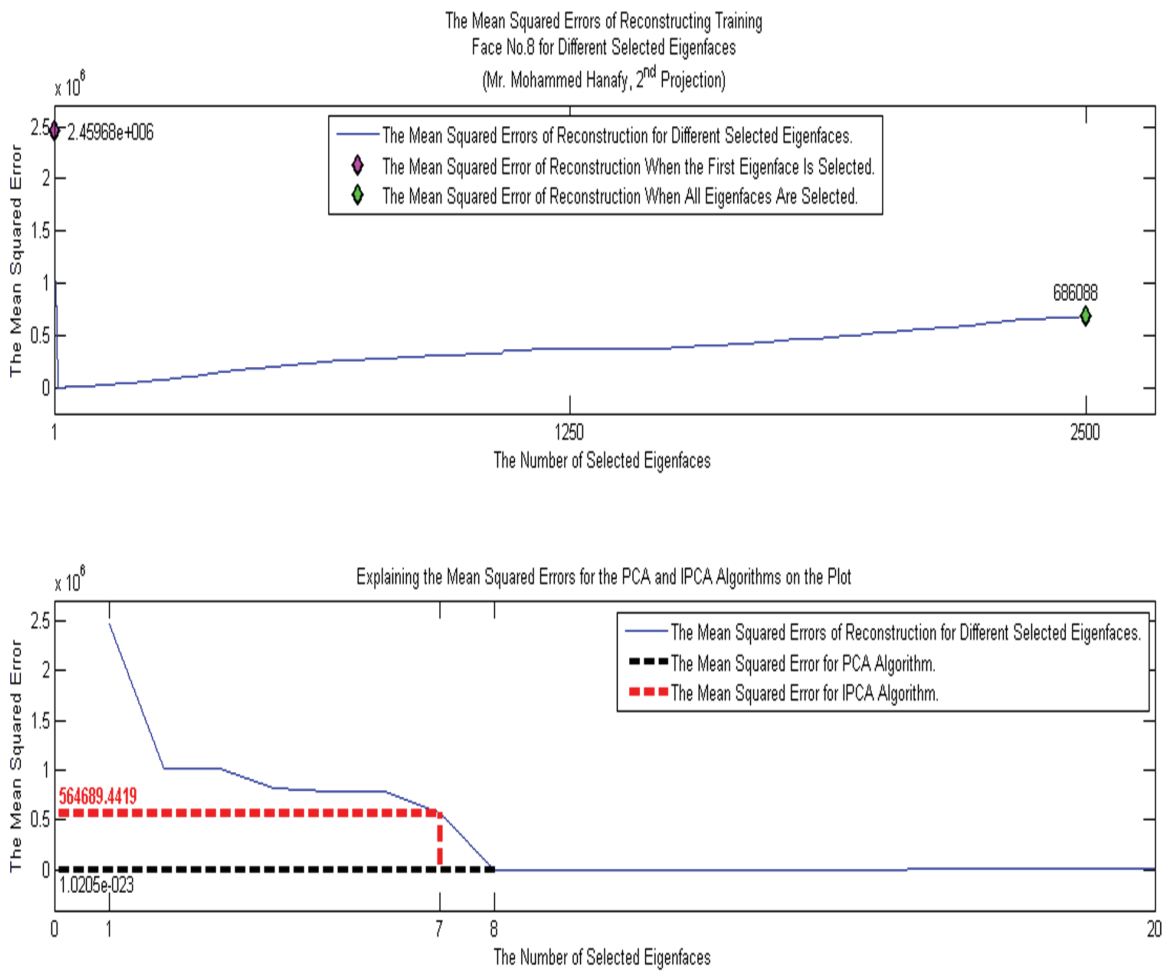


Figure I.7: The plot of the mean squared errors (MSEs) of reconstructing training face number eight for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

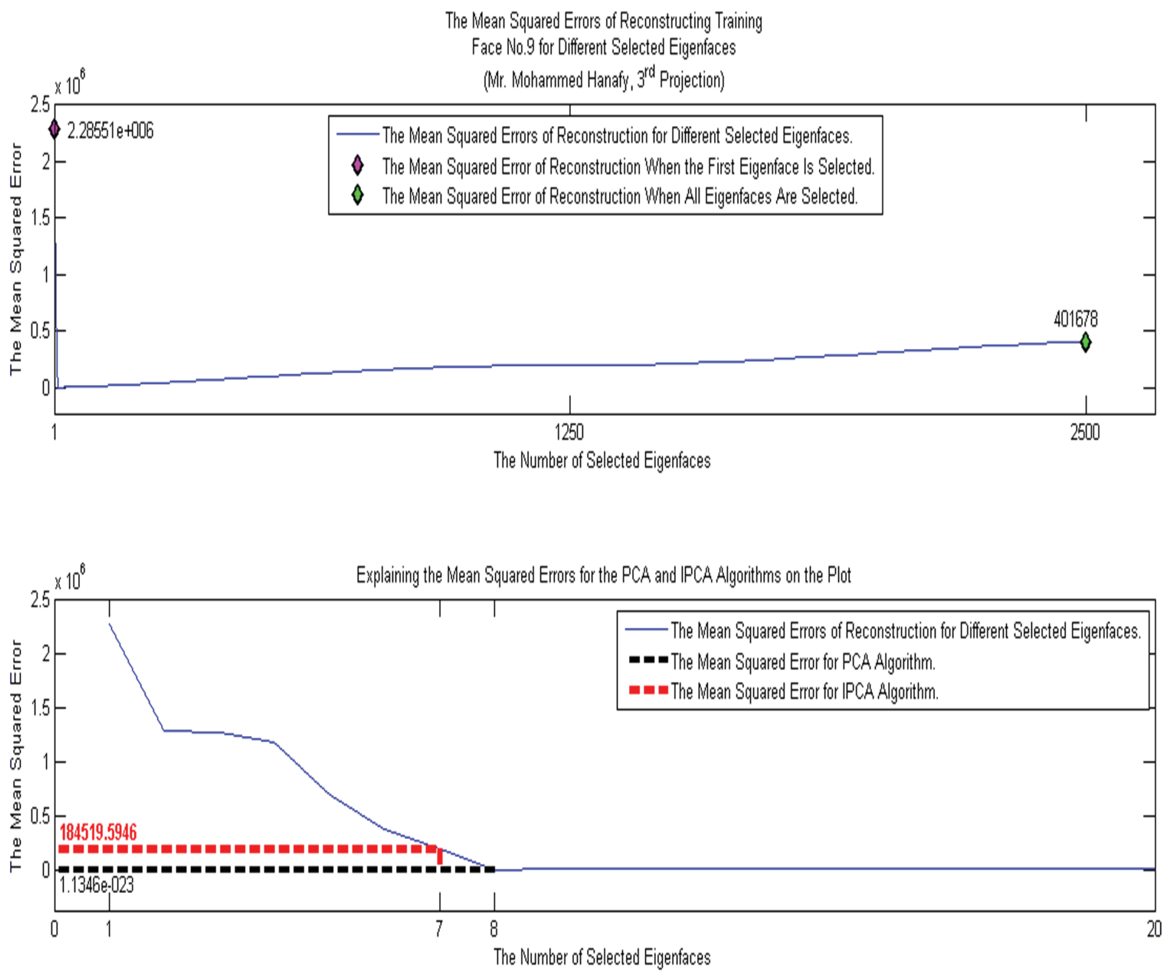


Figure I.8: The plot of the mean squared errors (MSEs) of reconstructing training face number nine for different selected eigenfaces compared with resulted mean squared errors when the PCA and IPCA algorithms are used.

Appendix J

A Code for Optimizing the Optical Model Database

THIS code is for optimizing the impulses database of the joint transform correlator (JTC) for object detection and face recognition.

```

% Optimizing the Impulses' Database of the Joint Transform
% Correlator (JTC) for Object Detection and Face Recognition.


clc
clear all
close all


Total_No_of_Impulses=3; % The total number of the impulses.


Objects_Folder=[cd ........
    '\The Black Background Tested Objects']; % The folder of the
                                              % black background
                                              % tested objects.
% Objects_Folder=[cd .........
%     '\The White Background Tested Objects']; % The folder of the
                                              % white background
                                              % tested objects.
if isdir(Objects_Folder)==0
    Error_Message=sprintf(.....
        'Error: The following folder does not exist\n%s',.....
        Objects_Folder);
    warndlg(Error_Message);
```

```
    break
end

Objects=.......
    dir(fullfile(Objects_Folder,'*.jpg')); % Listing the folder of
                                           % the black or white
                                           % background objects.

Total_No_of_Objects=length(Objects); % The total number
                                     % of the objects.

Objs=[36 36 36]; % Each element in this vector represents
                 % the total number of the objects that
                 % are taken for each impulse.

L1=Objs(1); % L1=60 is the total number of the
            % objects for Mr. Mansour Alshammari.
L2=L1+Objs(2); % L2=120 is the total number of the
               % objects for Mr. Methkir Alharthee.
L3=L2+Objs(3); % L3=180 is the total number of the
               % objects for Mr. Mohammed Hanafy.


% Imhist for setting up a threshold to work on just the pixels of
% a face and throwing the background pixels. Imhist calculates the
% number of pixels in an object that have the same intensity
% levels. So, if an object has a unified background then the
% biggest histogram of the intensity levels will be for the
% backgroubd pixels because the total number of pixels that have
% the same intensity levels are the background pixels of the
% object. Note that, the histogram of a digital image is defined as
% the discrete function, h(rk)=nk, where rk is the kth intensity
% level and nk is the number of pixels in the image whose intensity
% level is rk.
hist_Objects=zeros(Total_No_of_Objects,256);
for A1=1:Total_No_of_Objects

    Object_Number=[num2str(A1) '.jpg'];
    Object_Location=fullfile(Objects_Folder,Object_Number);
    Object=double(rgb2gray(imread(Object_Location))); % The object.
    hist_Objects(A1,:)=.....
        imhist(uint8(Object)); % Note that, each object must be
                               % scaled between 0 to 255 before
                               % using imhist. For doing that,
                               % uint8 can be used for converting
                               % the object class form double to
                               % uint8.

%     plot(hist_Objects(A1,:))
%     if A1<=L1
```

```
%         title(['The Histogram of Object No.' num2str(A1) ....
%             ' for Mr. Mansour Alshammari'])
%     elseif A1>L1 && A1<=L2
%         title(['The Histogram of Object No.' num2str(A1) .....
%             ' for Mr. Methkir Alharthee'])
%     elseif A1>L2 && A1<=L3
%         title(['The Histogram of Object No.' num2str(A1) .....
%             ' for Mr. Mohammed Hanafy'])
%     end
%     xlabel('Intensity Level r_{k}')
%     ylabel({'The Number of Pixels in the Object Whose '....
%         'Intensity Level Is r_{k} Where h(r_{k})=n_{k}'})
%     axis tight
%
%     disp(['Please, press any keyboard button to explore '....
%         'the remaining histograms >>>>>>>'])
%     pause
%     clc
end

Mean_hist_Objects=sum(hist_Objects,1)/......
    Total_No_of_Objects; % The average histogram
                         % for all objects.
% plot(Mean_hist_Objects)
% title('The Mean Histogram of All Objects')
% xlabel('Intensity Level r_{k}')
% ylabel({'The Mean Number of Pixels from All Objects Whose';....
%     'Intensity Level Is r_{k}'})
% axis tight
% pause

% Setting up a threshold in order to work on just the pixels of the
% faces and blocking the pixels of the backgrounds.
Objects_Threshold=8; % The picked threshold is based on the average
                     % histogram for all objects when the objects
                     % have black backgrounds. Note that, all
                     % intesity levels below the threshold
                     % represent the objects backgrounds because
                     % these levels have the biggest histogram.
% Objects_Threshold=180; % The Picked threshold is based on the
%                        % average histogram for all objects when
%                        % the objects have white backgrounds. Note
%                        % that, all intesity levels above the
%                        % threshold represent the objects
%                        % backgrounds because these levels have
%                        % the biggest histogram.


Max_Desired_Cross_Fields=zeros(Total_No_of_Objects,.....
    Total_No_of_Impulses); % Each element of each row in this
```

```
                              % matrix represents the maximum value
                              % of the desired crosscorrelated field
                              % between an object and one of the
                              % impulses.


Recognition_Combinations=zeros(L1*(L2-L1)*(L3-L2),.....
    Total_No_of_Impulses+1); % The first three columns of this
                             % matrix contain different
                             % combinations of impulses and the
                             % third column represents the error
                             % rates of recognition associated with
                             % those combinations.


Detection_Combinations=zeros(L1*(L2-L1)*(L3-L2),......
    Total_No_of_Impulses+1); % The first three columns of this
                             % matrix contain different
                             % combinations of impulses and the
                             % third column represents the error
                             % rates of detection associated with
                             % those combinations.


i=0;


for Im1=1:L1
    for Im2=L1+1:L2
        for Im3=L2+1:L3

            Impulses=[Im1 Im2 Im3]; % The selected impulses.

            for n=1:Total_No_of_Objects

                % Normalizing all the objects for removing
                % lightening effects on them then increasing the
                % resolution of object detection and recognition.
                % Note that, the normalization will be done just
                % for the faces pixels for keeping variations among
                % the objects and impulses just in the faces
                % without the backgrounds effects.
                Object_Number=[num2str(n) '.jpg'];
                Object_Location=.....
                    fullfile(Objects_Folder,Object_Number);
                Object1=double(rgb2gray(.....
                    imread(Object_Location))); % The object.

                T=Object1>Objects_Threshold; % The pixels bigger
                                             % than the threshold
```

```
                                              % are of interest
                                              % because they
                                              % represent the pixels
                                              % of a face.
%                  T=Object1<Objects_Threshold; % The pixels smaller
%                                               % than the threshold
%                                               % are of interest
%                                               % because they
%                                               % represent the
%                                               % pixels of a face.
                 Object=zeros(size(T,1),size(T,2)); % The normalized
                                                    % object.
                 for R2=1:size(T,1)
                     for C2=1:size(T,2)
                         if T(R2,C2)==1
                             Object(R2,C2)=.....
                                 ceil(255*(Object1(R2,C2)/max(....
                                 max(Object1)))); % The
                                                  % normalization
                                                  % of the object.
                                                  % This is done to
                                                  % increase the
                                                  % dynamic range of
                                                  % the object for
                                                  % visualization by
                                                  % scaling the
                                                  % intensities from
                                                  % 0 to 255.
                         end
                     end
                 end
                 [r c]=size(Object);

                 for m=1:Total_No_of_Impulses

                     % Normalizing all the impulses for removing
                     % lightening effects on them then increasing
                     % the resolution of object detection and
                     % recognition. Note that, the normalization
                     % will be done just for the faces pixels for
                     % keeping variations among the objects and
                     % impulses just in the faces without the
                     % backgrounds effects.
                     Impulse_Number=[num2str(Impulses(m)) '.jpg'];
                     Impulse_Location=......
                         fullfile(Objects_Folder,Impulse_Number);
                     Impulse1=double(rgb2gray(.....
                         imread(Impulse_Location))); % The impulse
                                                     % response.

```

```
T1=Impulse1>......
    Objects_Threshold; % The pixels bigger than
                       % the threshold are of
                       % interest because they
                       % represent the pixels
                       % of a face.
%  T1=Impulse1<.....
%      Objects_Threshold; % The pixels smaller
%                         % than the threshold
%                         % are of interest
%                         % because they
%                         % represent the
%                         % pixels of a face.
Impulse=zeros(size(T1,1),....
    size(T1,2)); % The normalized
                 % impulse response.
for R1=1:size(T1,1)
    for C1=1:size(T1,2)
        if T1(R1,C1)==1
            Impulse(R1,C1)=.....
                ceil(255*(Impulse1(R1,C1)/....
                max(max(Impulse1)))....
                ; % The normalization of the
                  % impulse response. This is
                  % done to increase the
                  % dynamic range of the
                  % impulse for visualization
                  % by scaling the intensities
                  % from 0 to 255.
        end
    end
end
[p q]=size(Impulse);


% Equalizing the width of the impulse response
% with the width of the object in order to
% collimate them on the input transparencies.
if q>c
    if mod(q-c,2)==0
        Object=[zeros(r,(q-c)/2) Object .....
            zeros(r,(q-c)/2)];
    elseif mod(q-c,2)==1
        Object=[zeros(r,floor((q-c)/2)) .....
            Object zeros(r,floor((q-c)/2)+1)];
    end
elseif q<c
    if mod(c-q,2)==0
        Impulse=[zeros(p,(c-q)/2) Impulse ....
            zeros(p,(c-q)/2)];
```

```
                    elseif mod(c-q,2)==1
                        Impulse=[zeros(p,floor((c-q)/2)) .....
                            Impulse zeros(p,floor((c-q)/2)+1)];
                    end
                end

                % Collimating the impulse response and the
                % object on the input transparencies. Note
                % that, the separation between the impulse
                % response and object must be bigger than
                % max{Wh,Wg}+Wg/2+Wh/2 in order to make the
                % output crosscorrelations of the impulse
                % response and object are completely separated
                % without any overlapping.
                Wh=size(Impulse,1); % The width of the impulse
                                    % response in the direction
                                    % of the y1-coordinate.
                Wg=size(Object,1); % The width of the object in
                                   % the direction of the
                                   % y1-coordinate.
                Y=max(Wh,Wg)+((Wh+Wg)/2); % The separation
                                          % between the centers
                                          % of the impulse
                                          % response and
                                          % object.
                dis=10; % This distance in order to make the
                        % separation between the centers of the
                        % impulse response and object bigger
                        % than max{Wh,Wg}+Wg/2+Wh/2.
                Impulse_Object=[...........
                    zeros(ceil(max(Wh,Wg)/2+Wh/4+3/4*Wg)+.....
                    dis,size(Impulse,2));Impulse;....
                    zeros(max(Wh,Wg)+dis,size(Impulse,2));....
                    Object;zeros(ceil(max(Wh,Wg)/2+.....
                    3/4*Wh+Wg/4)+dis,size(Object,2))];

                % Equalizing the dimensions of the input plane
                % P1 by padding it with zeros.
                [R C]=size(Impulse_Object);
                if R>C
                    if mod(R-C,2)==0
                        Impulse_Object=[.....
                            zeros(size(Impulse_Object,1),....
                            (R-C)/2) Impulse_Object ....
                            zeros(size(Impulse_Object,1),....
                            (R-C)/2)];
                    elseif mod(R-C,2)==1
                        Impulse_Object=[....
                            zeros(size(Impulse_Object,1),....
                            floor((R-C)/2)) Impulse_Object ....
```

```
            zeros(size(Impulse_Object,1),....
            floor((R-C)/2)+1)];
    end
elseif R<C
    if mod(C-R,2)==0
        Impulse_Object=[zeros((C-R)/2,.....
            size(Impulse_Object,2));....
            Impulse_Object;zeros((C-R)/2,....
            size(Impulse_Object,2))];
    elseif mod(C-R,2)==1
        Impulse_Object=[.....
            zeros(floor((C-R)/2),....
            size(Impulse_Object,2));....
            Impulse_Object;.....
            zeros(floor((C-R)/2)+1,.....
            size(Impulse_Object,2))];
    end
end


U1=Impulse_Object; % The transmitted field from
                   % the input plane P1.
[M N]=size(U1);

L=10; % The physical side length of the array
      % which holds the input plane P1 in
      % meters (m).
dx1_Input=L/N; % The sample spacing in the
               % input plane array in the
               % direction of the spatial space
               % coordinate x1 in meters (m).
dy1_Input=L/M; % The sample spacing in the
               % input plane array in the
               % direction of the spatial space
               % coordinate y1 in meters (m).
x1_Axis_Input=-floor(N/2)*dx1_Input:....
    dx1_Input:ceil(N/2)*dx1_Input-.....
    dx1_Input; % Sampling the input plane P1 in
               % the direction of the spatial
               % space coordinate x1.
y1_Axis_Input=-floor(M/2)*dy1_Input:....
    dy1_Input:ceil(M/2)*dy1_Input-....
    dy1_Input; % Sampling the input plane P1 in
               % the direction of the spatial
               % space coordinate y1.


U2=fftshift(fft2(fftshift(....
    U1))); % The Fourier transform of the
           % transmitted field in the back
```

```
                        % focal plane of the lens L2.
            I=(abs(U2)).^2; % The intensity of the Fourier
                            % transformed field in the
                            % plane P2.

            lambda=550e-9; % The wavelength in meters (m).
            f=0.055; % The focal length in meters (m).
            dx2=(lambda*f)/....
                (N*dx1_Input); % The sample spacing in the
                               % plane P2 in the direction
                               % of the spatial space
                               % coordinate x2 in meters
                               % (m).
            dy2=(lambda*f)/.....
                (M*dy1_Input); % The sample spacing in the
                               % plane P2 in the direction
                               % of the spatial space
                               % coordinate y2 in meters
                               % (m).
            x2_Axis=-floor(N/2)*dx2:dx2:ceil(N/2)*dx2-....
                dx2; % Sampling the plane P2 in the
                     % direction of the spatial space
                     % coordinate x2.
            y2_Axis=-floor(M/2)*dy2:dy2:ceil(M/2)*dy2-....
                dy2; % Sampling the plane P2 in the
                     % direction of the spatial space
                     % coordinate y2.


            U3=ifftshift(ifft2(ifftshift(.....
                I))); % The crosscorrelated field in the
                      % back focal plane of the lens L4.

            dx3=(lambda*f)/(N*dx2); % The sample spacing in
                                    % the plane P3 in the
                                    % direction of the
                                    % spatial space
                                    % coordinate x3 in
                                    % meters (m).
            dy3=(lambda*f)/(M*dy2); % The sample spacing in
                                    % the plane P3 in the
                                    % direction of the
                                    % spatial space
                                    % coordinate y3 in
                                    % meters (m).
            x3_Axis=-floor(N/2)*dx3:dx3:ceil(N/2)*dx3-.....
                dx3; % Sampling the plane P3 in the
                     % direction of the spatial space
                     % coordinate x3.
            y3_Axis=-floor(M/2)*dy3:dy3:ceil(M/2)*dy3-....
```

```
                      dy3; % Sampling the plane P3 in the
                           % direction of the spatial space
                           % coordinate y3.


             % Synthesizing a desired filtering mask then
             % filtering the crosscorrelated field in the
             % plane P3.
             Cen=floor(M/2)+1; % The center of the filtering
                               % mask.
             Cen1=Cen-(Y+dis); % The center of the desired
                               % crosscorrelated field.
             Wh1=q; % The width of the impulse response in
                    % the direction of the x1-coordinate.
             Wg1=c; % The width of the object in the
                    % direction of the x1-coordinate.

             Mask=zeros(M,N);
             for P=Cen1-floor((Wh+Wg)/2):Cen1+.....
                     ceil((Wh+Wg)/2)
                 for Q=Cen-floor((Wh1+Wg1)/2):Cen+.....
                         ceil((Wh1+Wg1)/2)
                     Mask(P,Q)=1;
                 end
             end

             Cross_Field=Mask.*U3; % The filtered
                                   % crosscorrelated field
                                   % in the plane P3.


             % For simplicity, instead of processing the
             % entire image of the filtered crosscorrelated
             % field, we select only the crosscorrelated
             % field of interest.
             P=Cen1-floor((Wh+Wg)/2):Cen1+ceil((Wh+Wg)/2);
             Q=Cen-floor((Wh1+Wg1)/2):Cen+ceil((Wh1+Wg1)/2);
             Desired_Cross_Field=U3(P,Q);


             Max_Desired_Cross_Fields(n,m)=.....
                 max(max(Desired_Cross_Field));

         end
     end


     % Testing the process of object recognition.
     % Note that, the objects here are known for us in
     % order to use them for testing the object recognition
```

```
            % process as well as setting up a recognition
            % threshold.

            % The elements in each of the following vectors
            % represent the maximum values of the desired
            % crosscorrelated fields between the objects and their
            % corresponding impulse. Note that, each impulse and
            % its corresponding objects have a same face so the
            % vectors will include the biggest crosscorrelations.
            V1=(Max_Desired_Cross_Fields(1:L1,1)).';
            V2=(Max_Desired_Cross_Fields(L1+1:L2,2)).';
            V3=(Max_Desired_Cross_Fields(L2+1:L3,3)).';

            % The calculation of the mean and the standard
            % deviation for each vector of the biggest
            % crosscorrelations and stacking them in a vector for
            % the means and another for the standard deviations.
            % This is done for setting up a threshold for object
            % recognition.
            V_Mean=[mean(V1);mean(V2);mean(V3)];
            V_STD=[std(V1);std(V2);std(V3)];

            Failures_Vector=zeros(1,.....
                Total_No_of_Objects); % A vector for counting the
                                      % number of failures in the
                                      % object recognition process.

            for w=1:Total_No_of_Objects
                % The object recognition process.
                for ii=1:Total_No_of_Impulses
                    if  max(Max_Desired_Cross_Fields(w,:))==....
                            Max_Desired_Cross_Fields(w,ii) && ....
                            max(Max_Desired_Cross_Fields(w,:))>=...
                            (V_Mean(ii,1)-V_STD(ii,1)) && ....
                            max(Max_Desired_Cross_Fields(w,:))<=...
                            (V_Mean(ii,1)+V_STD(ii,1))
                        z={'Mr. Mansour Alshammari';....
                            'Mr. Methkir Alharthee';.....
                            'Mr. Mohammed Hanafy'};
                        Recognized_As=char(z(ii,1));
                        break
                    else
                        Recognized_As='Unknown Object';
                    end
                end

                % Defining the object.
                if w<=L1
                    name='Mr. Mansour Alshammari';
                elseif L1<w && w<=L2
```

```
                    name='Mr. Methkir Alharthee';
                else name='Mr. Mohammed Hanafy';
                end

                Str1=strcmp(Recognized_As,....
                    'Mr. Mansour Alshammari');
                Str2=strcmp(Recognized_As,'Mr. Methkir Alharthee');
                Str3=strcmp(Recognized_As,'Mr. Mohammed Hanafy');
                F='Success';
                if w<=L1 && Str1==0;
                    F='Failure';
                    Failures_Vector(1,w)=1;
                elseif w>L1 && w<=L2 && Str2==0;
                    F='Failure';
                    Failures_Vector(1,w)=1;
                elseif w>L2 && w<=L3 && Str3==0;
                    F='Failure';
                    Failures_Vector(1,w)=1;
                end
            end

            Total_Number_of_Failures=.....
                sum(Failures_Vector); % The total number of
                                      % failures in the object
                                      % recognition process.

            Recognition_Error_Rate=(Total_Number_of_Failures/.....
                Total_No_of_Objects)*100; % The error rate
                                          % of recognition.


            % Testing the process of object detection.
            % Note that, the objects here are known for us in order
            % to use them for testing the object detection process
            % as well as setting up a detection threshold.

            % The calculation of the mean and standard deviation
            % for the crosscorrelations between the objects and
            % each impulse response. This is done for setting up a
            % threshold for object detection.
            Vectorization=reshape(Max_Desired_Cross_Fields,1,.....
                size(Max_Desired_Cross_Fields,1)*.....
                size(Max_Desired_Cross_Fields,2));
            Mean=mean(Vectorization);
            STD=std(Vectorization);

            Failures_Vector1=zeros(1,.....
                Total_No_of_Objects); % A vector for counting the
                                      % number of failures in the
                                      % object detection process.
```

```
                for w=1:Total_No_of_Objects
                    % The object detection process.
                    if  max(Max_Desired_Cross_Fields(w,:))>=.....
                                (Mean−STD) && .....
                                max(Max_Desired_Cross_Fields(w,:))<=....
                                (Mean+STD)
                        Detected_As='a face';
                    else
                        Detected_As='not a face';
                    end

                    b='a face'; % The object originally is a face.

                    Str=strcmp(Detected_As,'a face');
                    F='Success';
                    if w<=L3 && Str==0;
                        F='Failure';
                        Failures_Vector1(1,w)=1;
                    end
                end

                Total_Number_of_Failures1=....
                    sum(Failures_Vector1); % The total number of
                                           % failures in the object
                                           % detection process.

                Detection_Error_Rate=(Total_Number_of_Failures1/.....
                    Total_No_of_Objects)*100; % The error rate
                                              % of detection.


                Recognition_Combinations((Im3−L2)+i,:)=.....
                    [Impulses Recognition_Error_Rate];


                Detection_Combinations((Im3−L2)+i,:)=.....
                    [Impulses Detection_Error_Rate];

            end
            i=i+(Im3−L2);
        end
        Im1
    end


    save('Impulses Combinations for Recognition',....
        'Recognition_Combinations')
    save('Impulses Combinations for Detection',....
        'Detection_Combinations')
```

```


% Finding the optimal combination of impulses which obtain the
% lowest error rate of recognition.
Optimal_Combination_Recognition=0; % The optimal combination of
                                    % impulses for recognition.
Optimal_Error_Rate_Recognition=0; % The lowest error rate of
                                   % recognition that is produced
                                   % when the optimal combination
                                   % of impulses for recognition
                                   % is used.
for j=1:size(Recognition_Combinations,1)
    if Recognition_Combinations(j,Total_No_of_Impulses+1)==.....
            min(Recognition_Combinations(:,Total_No_of_Impulses+1))
        Optimal_Combination_Recognition=.......
            Recognition_Combinations(j,1:Total_No_of_Impulses);
        Optimal_Error_Rate_Recognition=.....
            Recognition_Combinations(j,Total_No_of_Impulses+1);
    end
end


% Finding the optimal combination of impulses which obtain the
% lowest error rate of detection.
Optimal_Combination_Detection=0; % The optimal combination of
                                  % impulses for detection.
Optimal_Error_Rate_Detection=0; % The lowest error rate of
                                 % detection that is produced when
                                 % the optimal combination of
                                 % impulses for detection is used.
for j=1:size(Detection_Combinations,1)
    if Detection_Combinations(j,Total_No_of_Impulses+1)==.....
            min(Detection_Combinations(:,Total_No_of_Impulses+1))
        Optimal_Combination_Detection=.....
            Detection_Combinations(j,1:Total_No_of_Impulses);
        Optimal_Error_Rate_Detection=.....
            Detection_Combinations(j,Total_No_of_Impulses+1);
    end
end
```

Appendix K

Authorizations for Using People Photos

Figure K.1, Figure K.2 and Figure K.3 show respectively the authorizations for using the photos of Mr. Mansour Thuwaini Al-Shammari, Mr. Mathkar Alawi Alharthi and Mr. Mohamed Elsayed Hanafy.

I am Mansour Thuwaini Al-Shammari. I give Abdulaziz Abdullah Alorf full authorization to use the images of my face in his researches.

Signature,

Obscured

Figure K.1: The authorization for using the photos of Mr. Mansour Thuwaini Al-Shammari.

I am Mathkar Alawi Alharthi. I give Abdulaziz Abdullah Alorf full authorization to use the images of my face in his researches.

Signature,

Obscured

Figure K.2: The authorization for using the photos of Mr. Mathkar Alawi Alharthi.

I am Mr. Mohamed Elsayed Hanafy. I give Abdulaziz Abdullah Alorf full authorization to use the images of my face in his researches.

Signature,

Obscured

Figure K.3: The authorization for using the photos of Mr. Mohamed Elsayed Hanafy.