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Face Recognition using Local Binary Pattern and Principle Component Analysis

التعرف على الوجوه باستخدام الأنماط المحلية الثنائية و تحليل المكون الرئيسي

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This Thesis was Submitted in Partial Fulfillment of the Requirements for the **Master's Degree in computer science**

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Face Recognition using Local Binary Pattern and Principle Component Analysis

التعرف على الوجوه بأستخدام الأنماط المحلية الثنائية و تحليل المكون الرئيسي

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Face Recognition using Local Binary Pattern and Principle Component Analysis

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Abstract

In the last two decades, face recognition is considered as one of the most attractive Biometric research fields. Face recognition most significant properties lie on its ability of automatic identifications without any direct user interaction, low cost, and hygienic. Due to its properties, face recognition is applied on several platforms, such as access control, surveillance, and law enforcement. In uncontrolled environments, face recognition process might suffer from several problems such as illumination, pose, occlusion, face expression and low-resolution images. Face recognition can be carried out using global features extraction or local features extraction. This thesis develops a hybrid face recognition system that handles the previously stated problems/shortcomings. The proposed system consists of five stages. In the first stage, Haar-cascade is applied to the detect face with its significant characteristics, such as the mouth, nose and eyes. In the second stage, Histogram Equalization (HE) is added to the detected face with its significant characteristics. In the third stage, the global and local features are extracted using Principal Component Analysis (PCA) and Local Binary Pattern (LBP) respectively. In the fourth stage, Frequency Partition (FP) fusion technique is used to integrate the extracted features from both PCA and LBP. Finally,

Artificial Neural Network (ANN) is applied as classifier. In this thesis, experimental results are divided into two phases. In the first and the main phase, the system is trained with the entire face problems scenario. The resulted recognition rate yields (95.721) with LBP and (96.102) with PCA. However, the proposed system yields (97.0829). In the second phase of the experiment, the dataset is separated based on each face problems scenario, then the proposed system is tested on each one of them separately. When the proposed system is tested on a dataset of face images with different poses. The recognition rate yields (95.187) for LBP and (95.301) for PCA. On the other hand, the proposed system yields (97.020). When the proposed system is tested on dataset of face images that contains virous face expression. The recognition rate yields (95.235) with LBP and (96.997) with PCA. However, the proposed system yields (98.373). When the proposed system is tested on a dataset of face images with illumination. The recognition rate yields (95.274) with LBP and (95.809) with PCA. Where, the proposed system yields (96.746). When the proposed system is tested on a dataset of images with occlusion. The recognition rate yields (95.75) with LBP and (95.552) with PCA. Similarly, the proposed system yields (96.628). when the proposed system is tested on a dataset of images with low resolution. The recognition rate yields (95.274) with LBP and (95.809) with PCA, while the proposed system yields (96.746).

التعرف على الوجوه بأستخدام الأنماط المحلية الثنائية و تحليل المكون الرئيسي

رسالة ماجستير قُدِّمت من قبل
محمد ابراهيم حسن نصير

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د فيصل السقار.

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قسم علم الحاسوب، جامعة آل البيت، 2018م

ملخص

في اخرعقدين أصبحت أنظمة التَّعرف على الوجوه من أكثر مجالات البحث جذبًا, هذه المختصَّة في البصمات الرقمية. وأهم خصائص أنظمة التَّعرف على الوجوه تتمثلُ في قدرتِها على كشف هوية المستخدمين بشكل تلقائي, من غير الحاجة للتفاعل المباشر مع النظام, ذي تكلفة قليلة, و لا يساهم في نقل الامراض. بسبب خصائصه الفريدة, تم تطبيق أنظمة التَّعرف على الوجوه في الكثير من البرامج, مثل أنظمة التحكم في الوصول, المراقبة, والعديد من الأنظمة القانونية. في البيئة غير المتحكم بها (العالم الخارجي), فإنَّ أنظمة التَّعرف على الوجوه تعاني من عدد من المشكلات التي تساهم في خفض دقة التعرف على الوجوه مثل تبيان الإضاءة في الصورة, زاوية نظر الوجه في الصورة, الانسداد, تعبير الوجه, وجودة الصورة الملتقطة. في أي نظام للتعرف على الوجوه يمكن التعرف على الوجوه بأستخدام المعالم العالمية للوجه أو عن طريق استخدام المعالم المحلية للوجه. وفي هذه الاطروحة تمَّ تطوير نظام هجين للتعرف على الوجوه, ولديه القدرة في التعامل مع المشكلات التي ذكرناها سابقًا. النظام المقترح مكونٌ من خمسة إجراءات رئيسية. في الإجراء الأوَّل تمَّ تطبيق متتالية هار لتحديد الوجه و بعض المعالم المميزة للوجه مثل العينين, الأنف, والفم. في الاجراء الثاني تمَّت إضافة مساوية الرسم البياني على نسخة من الوجه و بعض المعالم المميزة للوجه, والتي تم تحديدها في الإجراء السابق. في الإجراء الثالث تمَّ استخراج المعالم العالمية عن طريق استخدام خوارزمية تحليل المكون الرئيسي, بالإضافة الى ذلك, تم استخراج المعالم المحلية باستخدام الأنماط المحلية الثنائية. في الإجراء الرابع تمَّ تطبيق طريقة تقسيم التردد, وذلك من أجل الدمج ما بين المعالم العالمية والمحلية. وفي الإجراء الخامس و الأخير استخدمنا الشبكات العصبية لتصنيف الوجوه. في هذه الأطروحة تمَّ تقسيم نتائج التجربة إلى جزأين. في الجزء الاول تمَّ أختبار النظام على جميع المشكلات المذكورة سابقا, وقد نتج لدينا معدل تعرُّف على الوجوه بمقدار (95.721) للأنماط الثانئية المحلية,

(96.102) للتحليل المكون الرئيسي, و (97.0829) للنظام المقترح. في الجزء الثاني من التجربة قمنا بفصل كل مشكلة من المشاكل التي ذكرنها سابقًا إلى مجموعات مستقلة, ومن ثمّ قمنا بتجريب النظام المقترح على كل مجموعة من هذه المجموعات على حِدة. وعند تجريب النظام على مجموعة الوجوه المنحرفة بزاوية معينة, فقد نتج لدينا معدل تعرف على الوجوه بمقدار (95.187) للأنماط الثائنية المحلية, (95.301) لتحليل المكون الرئيسي, و(97.020) للنظام المقترح. وعند تجريب النظام على مجموعة الوجوه التي يمثل فيها تعبيرات و انفعالات الوجه الآدمي, فقد نتج لدينا معدل تعرف على الوجوه بمقدار(95.235) للأنماط الثائنية المحلية, (96.997) لتحليل المكون الرئيسي, و (98.373) للنظام المقترح. وعند تجريب النظام على مجموعة الوجوه التي يمثل فيها تباين الإضاءة في الصورة, فقد نتج لدينا معدل تعرف على الوجوه بمقدار (95.274) للأنماط الثائنية المحلية, (95.809) لتحليل المكون الرئيسي, و(96.746) للنظام المقترح. وعند تجريب النظام على مجموعة الوجوه التي يمثل فيها الانسداد, قد نتج لدينا معدل تعرف على الوجوه بمقدار (95.75) للأنماط الثائنية المحلية, (95.552) لتحليل المكون الرئيسي, و (96.628) للنظام المقترح. وعند تجريب النظام على مجموعة الوجوه التي يمثل فيها الصور قليلة الجودة, فقد نتج لدينا معدل تعرف على الوجوه بمقدار (95.274) للأنماط الثائنية المحلية, (95.809) لتحليل المكون الرئيسي, و (96.746) للنظام المقترح.

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ABBREVIATIONS

Ada Boost	Adaptive Boosting
ANN	Artificial Neural Network
BP	Back Propagation
DCT	Discrete Cosine Transform
FP	Frequency Partition
FT	Fourier Transform
FFN	Feed Forward Network
GWT	Gabor Wavelet Transform
HE	Histogram Equalization
IDCT	Inverse Discrete Cosine Transform
PCA	Principal Component Analysis
LBP	Local Binary Pattern
LDA	Linear Discriminate Analysis
LF	Low Frequency
MLP	Multiple Layer Perceptron
RN	Recurrent Network
SFC	Spatial Frequency Criteria
SD	Standard Deviation
HF	High Frequency

Chapter 1

Introduction

1.1. Background

Biometric-based technologies mainly use physiological characteristics such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear, and voice, to identify/verify the system users (Bolle et al, 2013). Face recognition is a computer application applied to distinguish or verify a human face using face distinguishing features (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). Now, face recognition becomes a major attractive research fields in computer vision because of its usefulness compared to different biometric systems (Jafri et al, 2009). Almost all Biometric technologies require some volunteer action from its user, but face recognition doesn't require any type of user participation, since the photograph could be taken from far distance by digital camera. Data acquisition, in general, suffer from many problems in Biometric technologies, for instance, the Biometric techniques that relay on hand or fingerprint will not work properly when the user hand/fingerprint tissues are damaged totally or partially. Moreover, Biometric techniques that relay on iris and retina require expensive equipment and are too much sensitive to body mutation. However, facial images can be easily obtained using a couple of inexpensive fixed cameras. Biometric technologies that require multiple users to use the same equipment to capture their physiological characteristics are not hygienic and may expose users to health risk. Though, face recognition is safe, healthy and non-intrusive. Due to its advantages over other Biometric technologies, face recognition is employed in numerous application platforms such as security, surveillance, low enforcement and

Entertainment. Generally speaking, there are three main stages of face recognition systems (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). Firstly, Face detection stage scans the image to find faces and their exact location. Secondly, Features extraction stage where the special facial features are calculated to select the best set of features for facial distinction. Also, image dimensions should be reduced without losing any important information. There are two types of features that mostly extracted from any face image; the first type are the global features and the second type is the local features. Lastly, the recognition that depends on the outcomes of the two former procedures. The main goal of this stage is to recognize a specific person by comparing the given input image with the already obtained dataset. In this thesis, we propose a novel Face Recognition system based on extracting global and local features using Principle Component Analysis (PCA) and Local Binary Pattern (LBP) applying a fusion technique called Frequency Partition (FP).

1.2. Problem Statement

In controlled environment where the image of the face is in a frontal position, the illumination of the image is fixed, and there is nothing covering the face image, face recognition technologies give optimal result (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). Where, in uncontrolled environment, face recognition technologies give a degraded recognition results compared to the controlled environment (De Carrera and Ion Marques, 2010). This research addresses the following gaps/problems in uncontrolled environments:

1. Face Pose: the pose variation normally happens due to camera angles and subject movement during the image acquisition process. The relation of facial features is affected by pose variations which causes a serious of misrepresentation of the image features that affects the overall system accuracy.
2. Illumination: the variation in illumination might happen for the diversity of lighting environments. The effect of this illumination leads to dramatically change in facial appearance which effects the overall system accuracy.
3. Image resolution: which could occur due to the camera type and the environmental conditions. Images with low resolutions can affect the overall system accuracy.
4. Occlusion: occlusion may be deemed as the most challenging problem among all previously mentioned challenges, because some important parts of the face might be partially covered or hidden in a given image. An example of such issue is the presence of beards, glasses, or hats.
5. Face Expression: human beings express their emotion, or temper using different facial expressions. When human face expression changes, the shape of the feature is also change as well and will also cause a shift in the location of facial features. Thus, affecting the performance of the face recognition system.

Each of these problems is shown in Figure 1.1.

Figure 1.1: Examples of Face image problems

1.3. Research Questions

In this research, we want to answer the following research questions:

1. Is it possible to develop an integrated face recognition system using local and global features?
2. What is the best fusion technique that can be used to integrate the global and local features?
3. Which is the best well-known dataset, that can be used in the proposed system?
4. Is possible to use Artificial Neural Network to train and test the proposed system?
5. Does the proposed system give better results than face recognition systems that use local or global features only?

1.4. Research Objectives

In this research, our target is:

1. To develop a face recognition system based on the fusion of Global and Local features using Principle component analysis and Local Binary Pattern.
2. To use Frequency Partition approach to integrate global and local features.
3. To train and test the proposed system using Artificial Neural Network.
4. To test the proposed system efficiency against Pose, Illumination, Expression, Resolution, and Occlusion using AT & T Dataset.

1.5. Research Contribution

Developing a robust face recognition system that minimizes the pose, illumination, expression, resolution, and occlusion effects and gives better recognition rate than PCA and LBP, using frequency partition approach.

1.6 Research Outlines

The over-all structure of this research is shown in Figure 1.2. Chapter 1, gives a brief introduction to face recognition system and illustrates the main gaps that face recognition system suffer from. Chapter 2 addresses the necessary background literature to put the audience in the right context. In this chapter, a brief discussion regarding face recognition general framework is presented. After that a comprehensive discussion of face recognition pervious works is illustrated. Chapter 3 introduces the AT&T dataset. Thereafter, an explanation of the proposed system flow diagram stages is illustrated. The steps followed at each stage of the proposed system will also be clarified along with the training and testing mechanism. Chapter 4 illustrates the way which our experiments were conducted. Also, it presents the overall recognition rate when the proposed system trained on the entire AT&T dataset. This chapter also presents the recognition rate of the proposed system according to different image scenarios in uncontrolled environment. Chapter 5 ends up the thesis with concluding remarks and future directions.

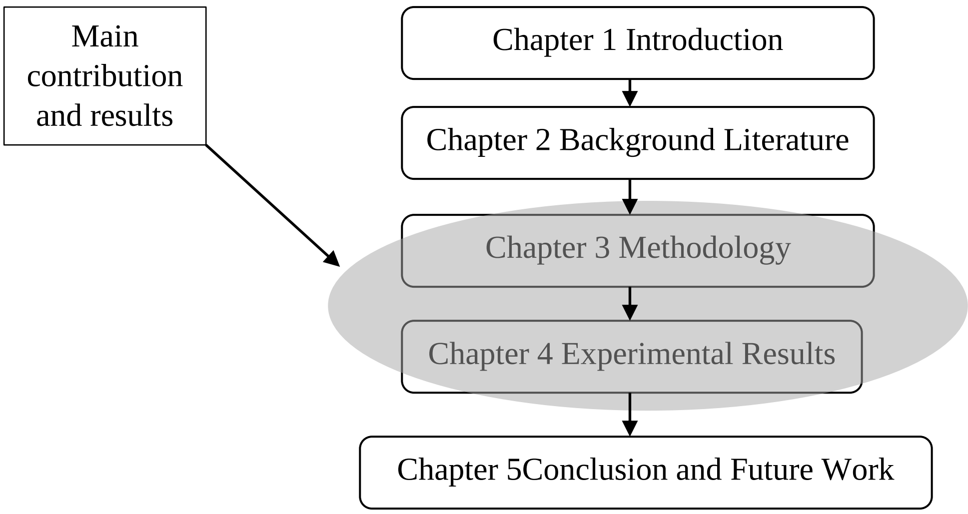


Figure 1.2: Research Structure

Chapter 2

Background Literature

2.1. Introduction

This chapter addresses the necessary background literature to put the audience in the right context. In this chapter, a brief discussion regarding face recognition general framework is presented. After that a comprehensive discussion of face recognition pervious works is illustrated.

2.2. Face Recognition General Frame Work

Face recognition is a computerized application used to determine the user identity based on their distinguishing facial features (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). The input of face recognition system usually is an image or video form, where the output of face recognition system usually is in the form of identification or verification of a specific subject (s). Identification in face recognition term means, given a face dataset guess the identity of input image. Verification in face recognition term means, given an input image, the system decides whether the identity of the servant is true or not.

Face recognition general framework usually consists of three main stages (De Carrera and Ion Marques, 2010) (Zhao et al, 2003): Face detection, Feature extraction, and Recognition / Classification. Figure 2.1 shows the generic face recognition system diagram.

Figure 2.1: The generic face recognition system diagram

2.1.1. Face Detection

This stage aims to discover if face exists in a given image and locate the face and/or its special characteristics such as mouth, nose and eyes (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). The expected output of face detection stage is a bounding box surrounding the face and/or its special features. Face detection approaches are divided into four main categories (De Carrera and Ion Marques, 2010) (Bakshiand Singhal, 2014) (Yang et al, 2002): Knowledge – based approach, Feature Invariant approach, Template Matching approach, and Appearance – based approach.

2.1.1.1. Knowledge – based approach

The basic idea behind knowledge-based approach is to learn about a typical human face structure, then it translates the gained knowledge to place some rules. Some of these rules are simple that can be guessed easily. For example, all human has symmetric eyes. Also, the eyes area is darker than the cheeks area. The main disadvantages of knowledge-based approach lie on the difficulty of building an adequate set of rules. For instance, if these rules are broad, this will lead to many false positive results, instead if the rules are detailed this could lead to many false negative results. Similarly, this approach cannot detect multiple faces in complex image (Yang et al, 2002). To reduce these effects, a based method hierarchal knowledge is suggested (Yang and Huang, 1994). This method consists of images of multi-resolution hierarchy with specific rule defined at each level of the hierarchy. The hierarchy is built by sub sampling and averaging. The face detection is based on a general look at the face. The hierarchal knowledge-based approach starts by extracting face candidates. Extraction of face candidates begins from the highest layer of the hierarchy which normally contains low resolution image. The middle and bottom layers of the hierarchy carry rules with more details such as the alignment of the features of the face plus verifying each candidate. Hierarchal knowledge – based approach accuracy might suffer from variation in lighting, pose, and occlusion (Yang et al, 2002).

2.1.1.2. Feature Invariant approach

Feature Invariant approach aims to find structural features such as, color and texture, which exist even if there is a pose or variation in lighting in the image. After that, this approach uses these structural features to detect faces. The point of difference between knowledge-based approach and Feature Invariant approach is in features invariant approach the detection starts at feature extraction and finding face candidates, and later on, it verifies each candidate by the spatial relationships among these features. However, the knowledge-based approach usually exploits data from the entire image as a whole. And its sensitivities to a complex image background. The main disadvantage of features invariant approach is that when there is a noise or occlusion in the face image, the accuracy of the detection will drop severely (Yang et al, 2002). To manage the occlusion problem in features invariant approach, a different kind of invariant features is utilized such as, skin color, to detect face in an input image. However, face detection based on skin color doesn't work well when illumination vary. Moreover, to make face detection based on skin color activate well in illumination scenario, it is combined with other methods like; local symmetric or structure and geometry (De Carrera and Ion Marques, 2010).

2.1.1.3. Template Matching approach

This approach stores a standard pattern of the face for face detecting stage. Different face features can be defined independently. For instance, face may be splits into face counter, eyes, nose, and mouth. In this approach, the connection among the input image plus stored pattern is computed for face detection. It is easy to implement this approach, but it is inadequate for face detection due to its sensitivity for pose and scale variation (Yang et al, 2002). Several studies were conducted on template-based approach such as (Cootes et al, 1995) work. In their proposed work, they exploited information from training data to produce deformable constraints. Then they applied PCA to clarify the possible variation of object shapes.

2.1.1.4. Appearance – based approach

Contrasting to template matching approach, the template in appearance-based approach is clarified from several training images. In general, appearance-based approaches rely on machine learning and statistical analysis techniques to locate relevant characteristic of face image. Appearance-based approaches are considered as the most successful approaches compared to other approaches (Yang et al, 2002). The major issue with the appearance – based approaches is its implementation complexity, and it requires large training example. To solve this problem, (Viola and Jones, 2001) proposed a rapid object detection technique using boosted Haar-Cascade. Unlike other face detection approaches that rely on pixel analysis, Viola and Jones use Haar-classifier that relies on Haar-likes features. The classification of the Haar-Cascade can be defined as machine learning algorithm that is trained on many negative and positive samples to detect objects in images input. Viola and Jones algorithm is debated with great details in chapter 3.

2.1.2. Feature Extraction

Feature Extraction is considered as the most important stage in any face recognition system**.** In fact, face recognition core problem is to extract relevant information from an image. The extracted information must be valuable to the next stage of recognition/ classification with an acceptable error rate. Generally, feature extraction consists of three steps (De Carrera and Ion Marques, 2010) (Zhao et al, 2003): Dimensionality Reduction, Feature extraction and feature selection. Figure 2.2 shows the feature extraction process. The dimensionality reduction could be seen as a consequence of feature extraction and features selection. Dimensionality reduction brings out useful information that can be revealed in lower dimensions. The output of this stage is a vector or set of facial points and their corresponding locations. There are two type of features that can be extracted from any face image such as, global feature and local feature.

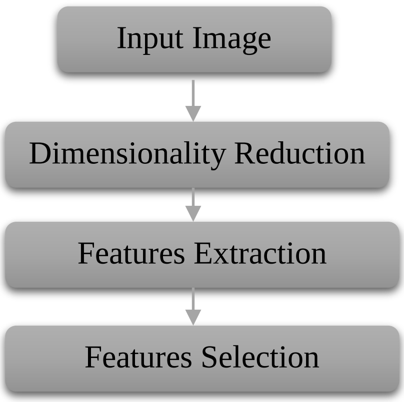


Figure 2.2: Feature Extraction Process

2.1.2.1. Global-based Feature Extraction approaches

Global-based feature extraction uses the holistic texture features and is applied to either the whole face or specific region in the face (Delac et al, 2005). In this approach, image is represented as 2D array of intensity values and recognition is performed by direct correlation comparisons between input face and all other faces in the dataset. Global feature extraction has gain more attraction in the last few decades because it does not destroy any data related to the image (Jafri and Arabnia, 2009). It thus focuses on specific regions and point of interest in the image. On the other hand, Global feature extraction approaches suffer from several drawbacks such as (Jafri and Arabnia, 2009):

1. These approaches assume that pixel in image and all data are of quite significance.
2. These approaches are computationally expensive.
3. These approaches require high correlation among training and testing of the images.
4. These approaches are not working well when they are applied to images with high degree of poses and illumination.

2.1.2.1.1. Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA)

PCA is a statistical method that performs dimensionality reduction by extracting the principal component of multi-dimensional data. The first principal component is the linear combination of the authentic dimensions that has the highest variability. (Kirby and Sirvich, 1990) are considered to be the first researchers that use the PCA method to represent a digital image. While, (Turk and Pentland, 1991) proposed a face recognition algorithm that uses eigen-faces to recognize facial image. After that, (Zhao et al, 1998) suggested a method for face recognition based on PCA and LDA. Moreover, (El-Bashir, 2012) proposed a multi-classifiers face recognition model. In his model, he applied PCA to extract global features then he recognized faces using decision tree. In this thesis, PCA will be discussed in more details in chapter 3.

LDA is a statistical method developed by (Fisher, 1936). It is used to reduce the dimensions like PCA. The basic idea behind LDA is that similar classes are clustered together. While, different classes are scattered far away from each other. (Belhumer et al, 1993) have successfully applied LDA on facial recognition. LDA and PCA differs in some aspects. For example, in LDA the inner class information is applied to classify faces. Further, LDA uses multiple faces of the same individual to establish in – class variation. On the other hand, PCA method uses one image per-person. Thus, applying the variation in particular image with the entire recognition process. The unwanted consequence of spreading the total variance in PCA leads to conserve the undesirable effects such as illumination or face expression. According to (Dacal et al, 2005), when LDA is trained on large dataset, it yields a better recognition rate compared to PCA. However, PCA yields a better result than LDA when the training dataset is small.

2.1.2.2. Local-based Feature Extraction approaches

In the local-based feature extraction approaches, the input image is processed to extract and determine essential face special features such as, the nose, mouth, forehead, and eyes…etc. After that, the geometric relationship between those features are computed. Therefore, reducing the input facial image to a vector of geometric feature (Dacal et al, 2005). To classify faces using these extracted measurements, standard statistical pattern recognition techniques are employed. The local feature extraction approaches have the following advantages (Jafri and Arabnia, 2009):

1. Feature-based approach is robust against different lightening condition and pose variation.

2. Feature-based approach includes high-speed matching and compaction of representation of face images.

Local feature extraction approaches suffer from various problems (Jafri and Arabnia, 2009).

1. In local feature extraction approaches, it is difficult to automatically detect features.
2. Due to this difficulty, the implementer of the local feature extraction approaches makes an arbitrary decision about which one of those features is essential. There are many researches are conducted in face recognition area that uses local features extraction.

One of the most popular local-based approaches is LBP, which is a texture-based method. It provides a powerful simple approach aims to characterize local structure. The texture of the image provides important information about physical properties of the certain object such as smoothness, roughness, and difference in surface reflectance (color). The most important properties of LBP are its exceptional ability to resist the change of the illumination and its computational simplicity (Huang et al, 2011). To compute LBP method, first divide the image into 3x3 Square cells. Second, compute the LBP operator by comparing the cell blocks with a specific threshold (the central block pixel). The third step is to concatenate the resulted value in the former step to get eight-pixel block in binary code form. The fourth step, is calculating the decimal number of the resulted binary code and computing the histograms of LBP values for all rectangular cells over the entire image. In this thesis, we will only address local feature extraction based on LBP.

(Wang and He, 1990) are considered as the first researchers that use textures to capture some physical properties of set of objects in an image. Then, (Ojala et al, 1996), proposed LBP operator that encode shape and texture of digital image. After that, (Ahonen et al, 2004) applied LBP operator in face recognition. In chapter 3, LBP will be discussed in more details.

There are many researchers that used combination of global and local features extraction methods in their work such as, the work of (Su et al, 2009). On their research, they proposed a genuine face recognition method depending on Fourier Transform (FT) **(**Lai et al, 2001**)** to extract global feature and Gabor Wavelet Transform (GWT**)** **(**J. Daugman, 1985) to extract local feature. Later, on (Mirza, A.M et al, 2013), they proposed a gender recognition system based on the fusion of local and global facial features. In this work, they extracted the global features using PCA and Discrete Cosine Transform (DCT) (Nasir et al, 1974). On the other hand, the local features are extracted using LBP approach augmented with a two-dimensional DCT. Moreover, they employ the K-nearest neighbors to classify faces. The training and testing are established using FERET dataset. After that, (Ghahramani, 2015) suggested a new approach of face recognition. In their work, they used a face segments as an input such as left eye, right eye, nose, and mouth. Then they used three well-known classification algorithms namely: PCA, LDA & LBP to classify faces. Their experiment shows that, using segments of the face as input, the accuracy of face recognition is increased. Thereafter (Boodoo et al, 2015) proposed a different face recognition approach based on fusion global and local features. In their work, they extracted global and local features using PCA & LBP respectively then the features are fused based on the majority vote rule. They also used UMO dataset for training and testing. In our proposed system, we use the HE to enhanced the input image. In addition, we develop an image fusion algorithm which integrates both PCA and LBP using FP approach. After that, we use Artificial Neural Network (ANN) to train and test the proposed system.

Finally, (Liu et al, 2016) proposed a method for recognition of facial expression. PCA is used in this method, to decrease dimensions of the characteristics that were combined by the gray pixel value and LBP features.

2.1.3.Recognition

Once the features are extracted and selected, classifying face image was the next step. Classification algorithm usually involves two types of learning: supervised and unsupervised (De Carrera and Ion Marques, 2010). In unsupervised leaning, the desired output is unknown. This type is trying to learn the distribution of possible categories of feature vectors in the training dataset. On other hand, supervised learning knows the desired output. This type is trying to model the relationship between the feature vectors and their corresponding desired output. Recognition is a measure of similarity between an input face image and a set of previously observed faces in the training dataset. Similarity can be established by computing the difference in the distance between the input image and training dataset. When the difference is small, the input image is considered to be similar to one of the images in the dataset. Accordingly, it would be classified as recognized. However, if the difference is large, the input face image would be considered as dissimilar to the image in dataset, and it would be classified as unrecognized. In this thesis, we employ the Artificial Neural Network (ANN) as classifier to recognize face image.

ANNs provide information processing, which is similar to the information processing in the human brain (Gardner and Dorling, 1998). ANNs are powerful and robust tool in pattern recognition due to its learning ability, fault tolerance, parallel and distributed computation. ANN is composed of a network consists of artificial neurons also known “neurons” or “nodes” (Jain et al, 1996). These nodes have three types: Input node, output nodes and hidden nodes. There are two types of topologies in ANN. The first and most common is Feed Forward Network (FFN). In FFN, the network graph has no loops which means that the input signal travels in single direction to find the desired output. The second type is Feedback / Recurrent Network (RN). In RN, the network graph has loops, which means the input signal travels through one or more hidden layers with at least single feedback loop to find the desired output. Figure 2.3 shows the graph of FFN and RN (Jain et al, 1996).

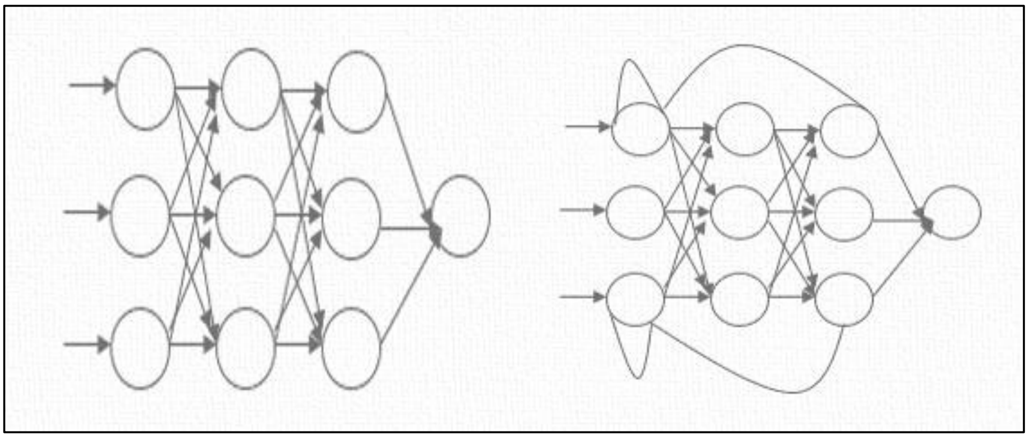


Figure 2.3: FFN and RN graph

The back-propagation algorithm (Rumelhart et al, 1986) is used to find the minimum point of error surface. Back propagation algorithm is the most computationally straightforward algorithm for training ANN (Gardner and Dorling, 1998).

There are many researchers conducted in face recognition area that uses ANN to recognize face images such as:

- (Reda et al, 2004) designed a face recognition system. In their work, instead of calling the training function, the network was trained several times on various input ideal and noise image.

- (Rizon et al, 2006) proposed a computational model to identify face image. In their work, the Eigen face is employed to extract the global features of the input image. Then, the back-propagation ANN that utilizes the Euclidean distance is used for recognition.
- (Endeshaw and Raimond, 2008) proposed two face recognition systems based on ANN. In the first system, PCA is used to extract the features from face image then classify these images using ANN. In the second system, PCA and Gabor filter collection (V. Kyrki et al, 2004) were used for feature extraction. After that, ANN is used for classification.
- (Agrawal et al, 2010) proposed a method for facial recognition that is based on information theory approach of coding and decoding the image of the face. Their proposed approach consists of two phases. The first phase, PCA is used to extract the features from the input face image. In the second phase, the feed forward back-propagation ANN is used to classify the input image.
- (Shivdas, 2014) proposed a novel face recognition method that integrated PCA, ANN and Discrete Cosine Transform (DCT) to enhance performance of the face recognition.
- (Patial et al, 2015) proposed a face recognition system based on extracting the local face features using LBP then classifying the face image using feed forward back-propagation ANN.

2.3. Fusion Techniques

Image Fusion is a process that integrates relevant information from two or more than one image into a single image (Haghighat et al, 2011). The fused image must contain more complete information and should be more suitable for human visual perception and object recognition than the original image. Image fusion consists of three main levels namely; pixel level, features level, and decision level (Jagalingam and Hegde, 2014). Pixel image fusion level is considered as the most common of the other two levels. It depends on pixel location to combine the visual information from input images to create single image based on the authentic image information. Also, pixel level preserves more information in comparison with the other two levels. Features level image fusion uses set of different features to combine the original images in order to generate the fused image. Fusion at features level have high flexibility but a classification problem could emerge due to high dimensionality of these features. Decision level image fusion integrates image details directly such as the form of relational graphics. This thesis addresses a couple of image fusion studies that is based on Discrete Cosine Transform (DCT).

DCT expresses a sequence of data points for the sake of sum cosine function oscillating at different frequency (Nasir et al, 1974). DCT have a strong energy compaction property. Therefore, it can be utilized in transform images, compacting the variations, and allowing an effective dimensionality reduction (De Carrera and Ion Marques, 2010). When DCT is performed over an image, the image energy is compacted in the upper-left corner. Figure 2.4 shows an example of DCT image compaction. Due to its compaction property, DCT was used in many techniques regarding image fusion such as:

- (Naidu, 2013) proposed a novel fusion technique that is based on DCT. Her proposed fusion technique first converts the 2D input data into 1D vector by concatenating the input data row/column wise. Then DCT is applied on the 1D vector which produce DCT coefficient. After that, a fusion rule is used to produce an enhanced fused image. In this thesis, we will follow this approach.
- (Kaur et al, 2015) proposed a novel fusion method regarding digital image. In their proposed method, the decomposition levels are selected using Frequency partition (FP).

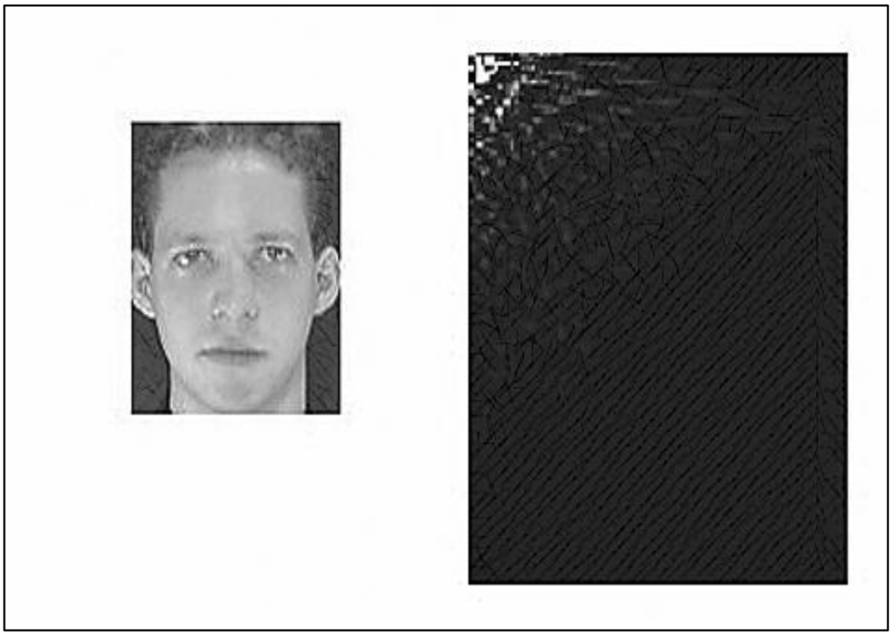


Figure 2.4: Input Face Image and it's corresponding DCT

2.4. Chapter Summary

This chapter is a revision of the previously existing techniques regarding facial recognition. Based on these previous facial recognition techniques, we propose a novel facial recognition system. The proposed system works by integrating both global and local features to produce a new enhanced image, which minimizes the error rate, plus maximizes the recognition rate.

Chapter 3

Methodology

3.1 Introduction

This chapter illustrate the AT&T dataset characteristics. After that, an explanation of the proposed system flow diagram stages is done. The steps followed at each stage of the proposed system will also be clarified along with the training and testing mechanism.

3.2 Dataset

All our results are done on the (AT&T dataset). AT&T, also known as ORL, is a well-known and widely used dataset in face recognition field. The dataset contains 40 classes. Each class has 10 different images, 4 subjects are female and the other 36 contain male subjects. The images in the AT&T dataset are taken at different times for different reasons, that's why they varied in the lighting, facial expressions: (closed/open eyes, smiling / not smiling), occlusion (glasses /no glasses), slightly different change in faces pose, and some images had a resolution problem. All images were taken against dark homogeneous background with the subjects in an upright, frontal position. The images were all grayscale with a resolution of (92 x 112) pixels. Figure 3.1 shows all the subjects images in AT&T data set.

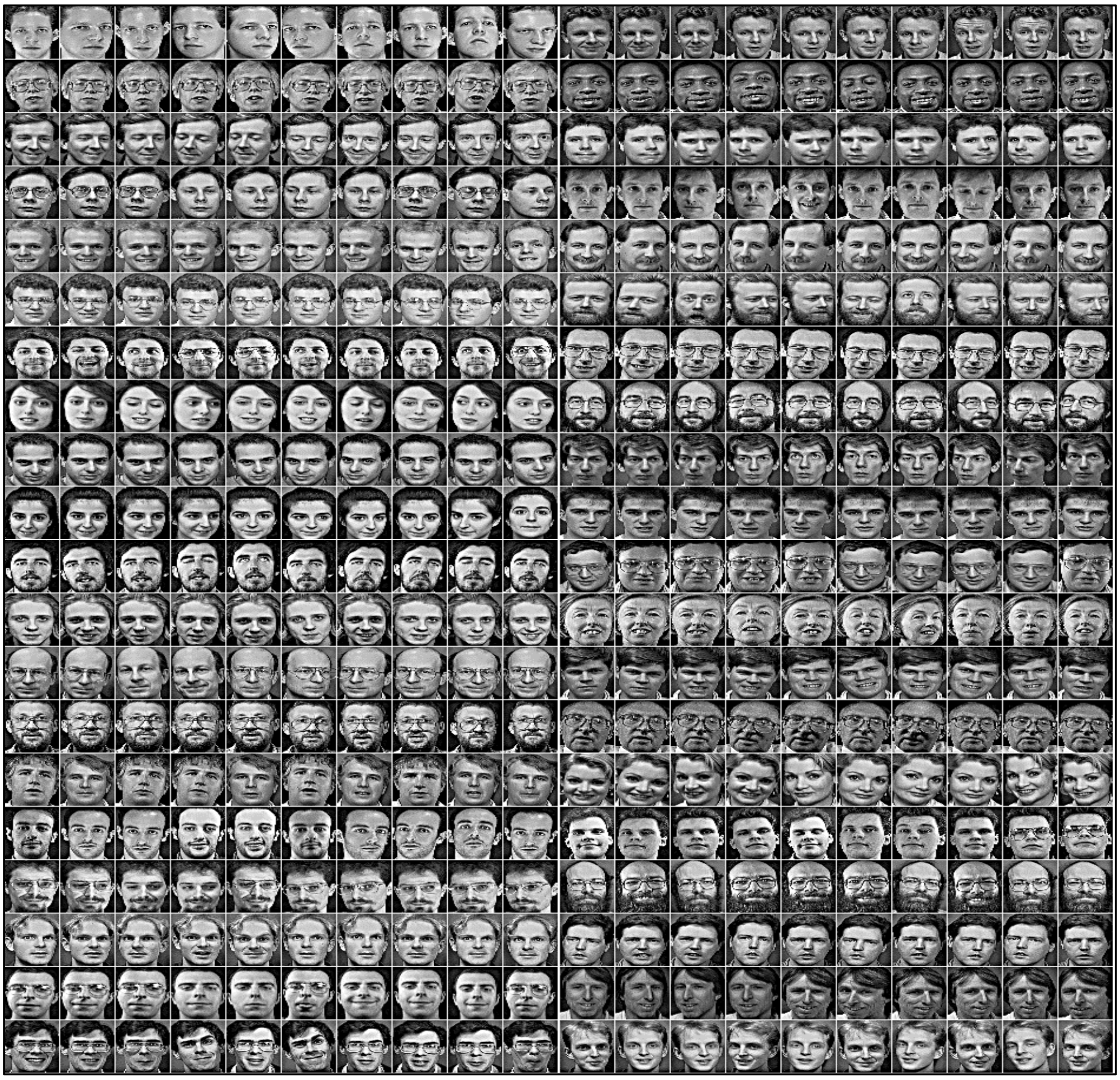


Figure 3.1: AT&T dataset

3.3 The Proposed System

As shwon in Figure 3.2, The proposed model diagram consists of five main stages. The first stage is face detection using Haar-cascade algorithm. The second stage is preprocessing using Histogram Equalization (HE). The third stage is feature extraction using both PCA & LBP. The fourth stage is features integration using FP. The fifth and final stage is recognition using ANN.

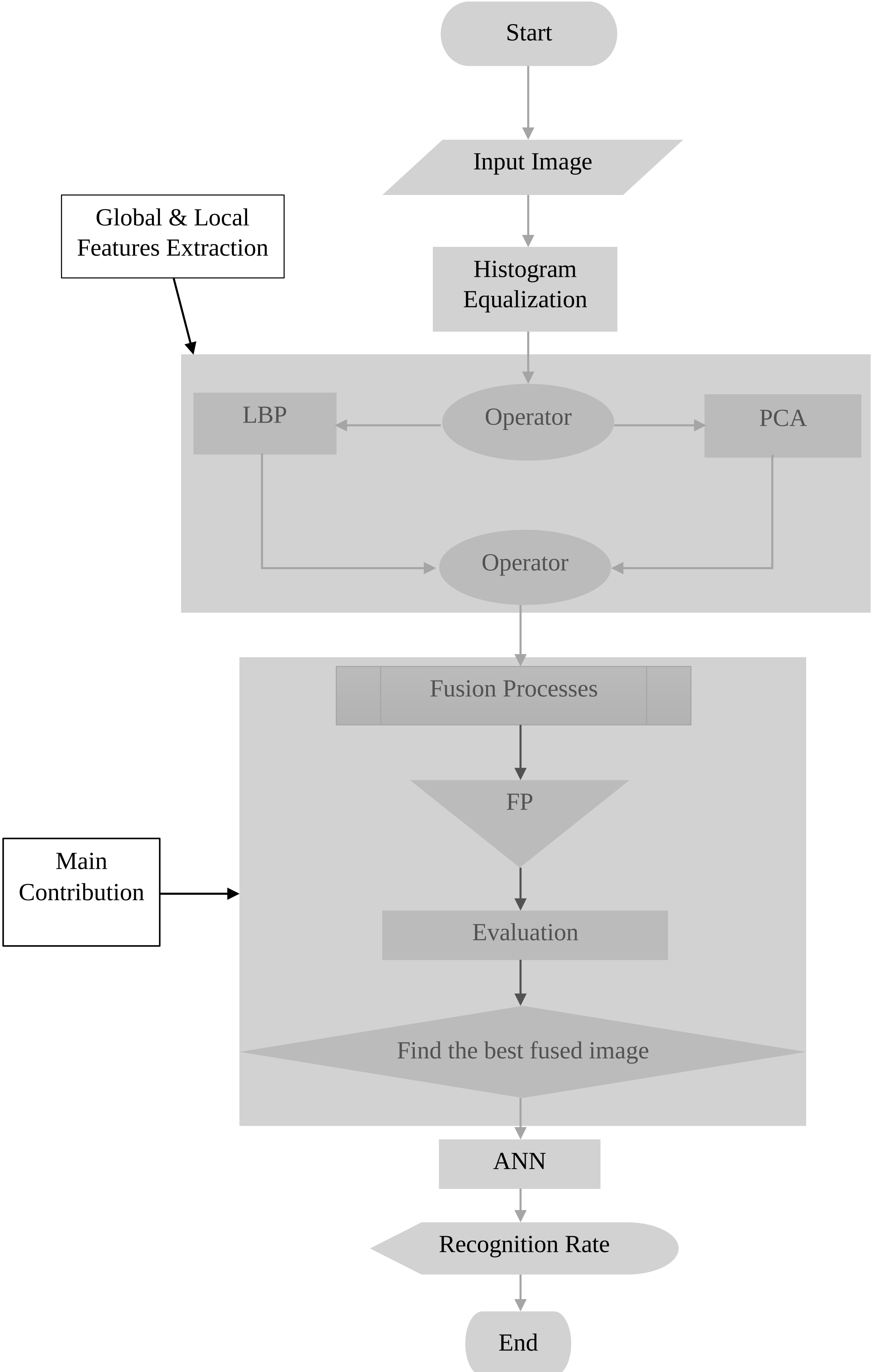


Figure 3.2: The Proposed system diagram

3.3.1 Face detection using Haar - Cascade:

Haar-cascade is an appearance-based face detection algorithm. It is originally proposed by (Viola and Jones, 2001). The haar-cascade algorithm can be considered as one of the finest algorithms regarding face detection, due to its real-time speed and high detection precision (De Carrera and Ion Marques, 2010) (Zhao et al, 2003). Unlike the prior face detection algorithms that relied on pixel analysis, (Viola and Jones, 2001) uses Haar classifiers that relied on Haar-like features. The Haar-like features are a rectangular shape features that passed over the input image to find the relevant characteristics that represent the target object. Some paradigm of Haar-like features are shown in Figure 3.3. The Haar-like features are trained to find relevant characteristics by summing all the pixels in the black and white region. After that, subtract the average of the black and white region. Then, the resulted value will be compared with a given threshold. If the resulted value is bigger than the threshold value, the Haar-like feature considers it a face candidate. However, if the resulted value is smaller than the given threshold, the Haar-like feature simply ignores it and continue searching for relevant characteristics. Using the Haar-like feature to find relevant characteristics is competently expensive. This is because of the huge number of the rectangle features that are required for scanning an image to find the relevant characteristics. To solve this problem (Viola and Jones, 2001) employed three elements namely, Integral image, Adaptive Boosting (AdaBoost), And Attentional Cascade.

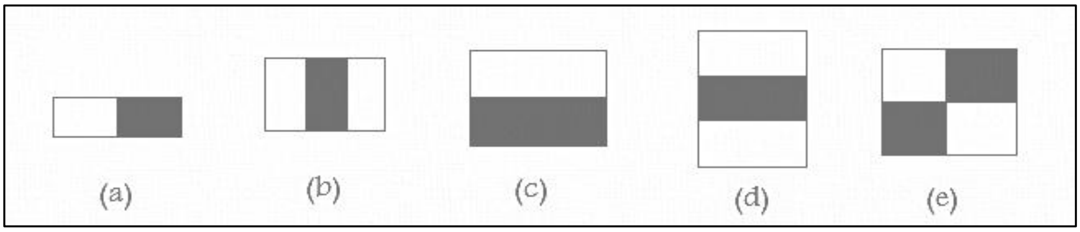


Figure 3.3: Haar-like features

In this section, the integral image, AdaBoost, and Attentional Cascade will be discussed:

3.3.1.1 Integral image

The Integral image is an algorithm that computes the Haar-like features with a low computational cost contrast to sum up all the pixels in Haar-like features. The complete agorithm of the integral image can be found in the work of (Wang, 2014).

3.3.1.2 Ada Boost algorithm

In Viola-Jones algorithm (Viola and Jones, 2001), AdaBoost is used to select the Haar-like feature that most likely contains relevant face characteristics. AdaBoost trained number of weak classifiers in order to generate a strong classifier. The strong classifier is used to select the superior subset of Haar-like features that detect the most likely desired object such as face. The detalied Ada boost agorithm can be found in the work of (Wang, 2014).

3.3.1.3 The Attentional Cascade

Ada Boost trains a set of a linear combination of weak classifiers to find the desired features in N×N sub-windows in a given input image. But few of those sub-windows contains the desired features. Moreover, computing all sub-windows to find the desired features is considered as time consuming. To fix this problem, Attentional Cascade is employed. In any input image, there are some sub-windows that deserve more attention than the others. Attentional Cascade, employs more resources on the sub-window that more likely have the desired features. Thus, instead of exploring if a face features exist in all sub-windows, the Attentional cascade allows identifying the desired features by simply testing the first few features on sub-windows. Figure 3.4 shows

Attentional Cascade; multiple classifiers is applied on each sub-window. The first classifiers exclude massive number of negative examples with less effort. The second layer excludes the remaining negative example but it requires additional computation. After several stages of processing, the number of sub-windows will be reduced. The detailed agorithm regrding the Attentional Cascade can be found in the work of (Wang, 2014).

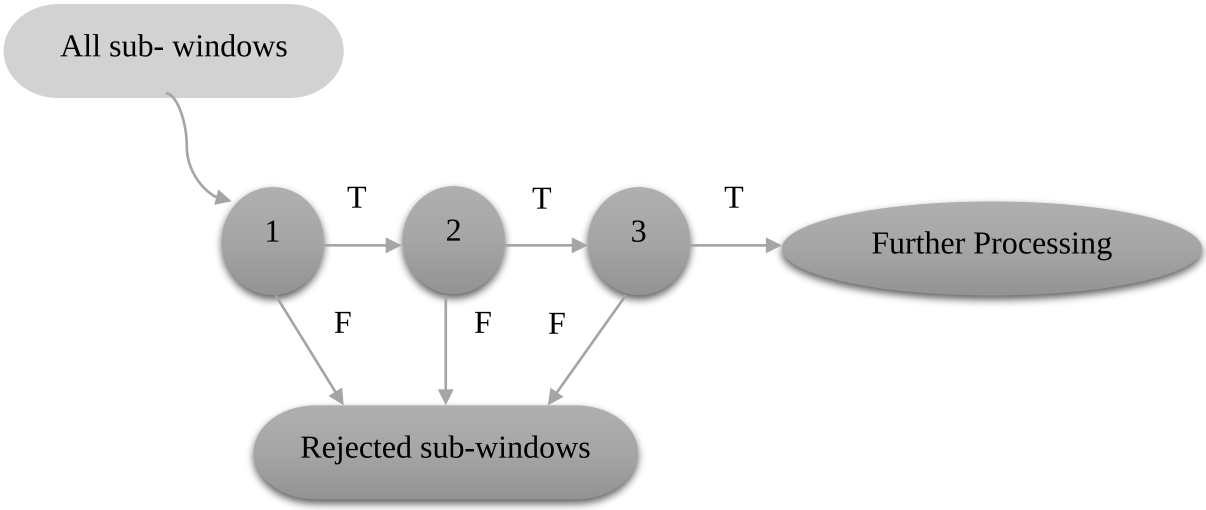


Figure 3.4: The Attentional Cascade (Viola and Jones, 2001)

The proposed system used the improved Viola-Jones algorithm in (Wang, 2014) to detect the desired features of input image as follows:

1. Detect face and return bounding box surrounding the detected face.
2. Detect nose and return bounding box surrounding the detected nose.
3. Detect mouth and return bounding box surrounding the detected mouth.
4. Detect eyes and return bounding box surrounding the detected eyes.

The output of this procedure is a square patch surrounding the desirable features. Figure 3.5 shows the detection result of Viola-Jones algorithm in the propsed system.

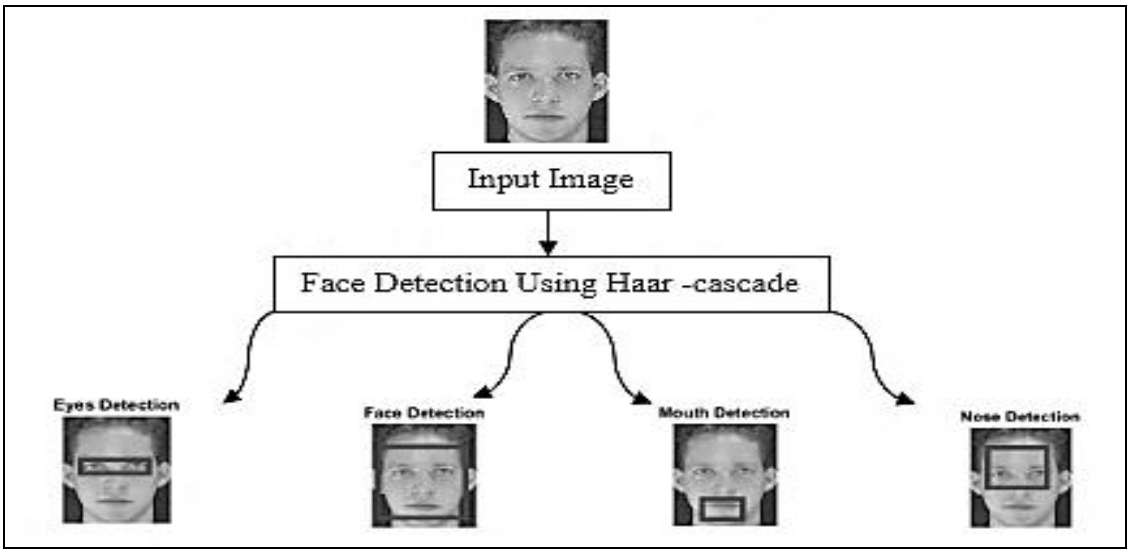


Figure 3.5: The Output of Face Detection Stage

3.3.2. Histogram Equalization (HE)

Face recognition algorithms are experiencing unwanted effects such as misclassification and decreased in performance due to illumination, image with low resultion, occlusion…etc. To minimize these effects, on the proposed system performance, the HE is employed. HE is one of the most common methods regarding image contrast enhancement (Cheng and Shi, 2004). The image histogram is manufactured by a count of the pixel values in the domain of 0-255. If the majority of the high bins are on the right side of the histogram, that means the image is bright. In contrast, if the majority of high bins are on the left side of the histogram, that means the image is dark. HE works by spreading the bins equally across the image, giving it a decent contrast. HE is mainly used for handling the illumination problem (Acharya andRay, 2005). Figure 3.6 (a) shows the input image and its histogram. Figure 3.6 (b) shows how HE spread the intensity of the dark region equally across the image.

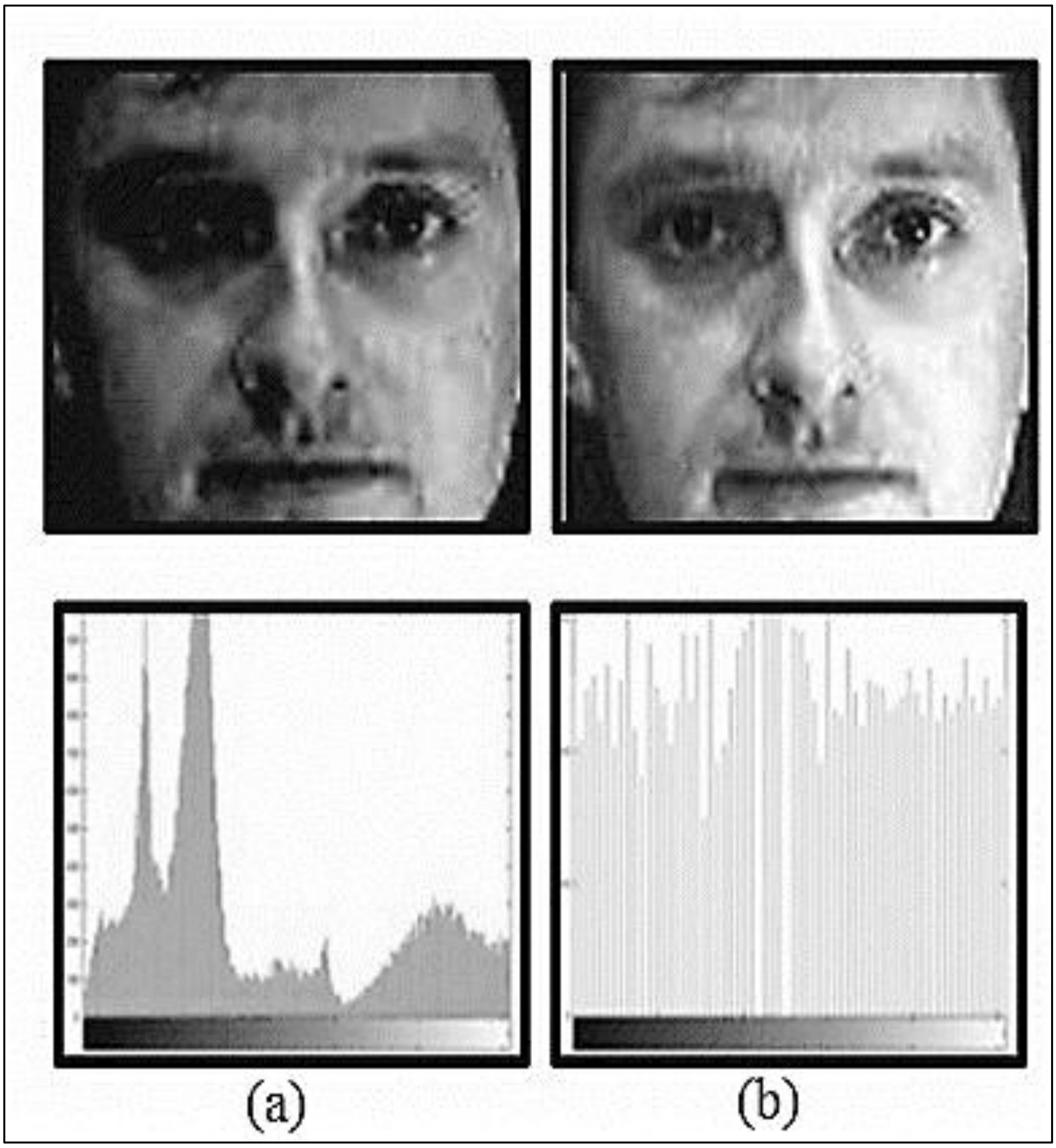


Figure 3.6: HE example. (a) shows an image from AT&T dataset and its corresponding histogram. (b) shows the image after applying the HE and its corresponding histogram

In the proposed system, a copy of the face patch, eyes patch, nose patch, and mouth patch is taken. After that, HE is applied on the copy of the face patch and to the remaining features to increase the efficiency of the image. Finally, the system replaces the histogram copy of the face image and its special features with the original input image. Figure 3.7 shows the preprocessing stage and its outcome.

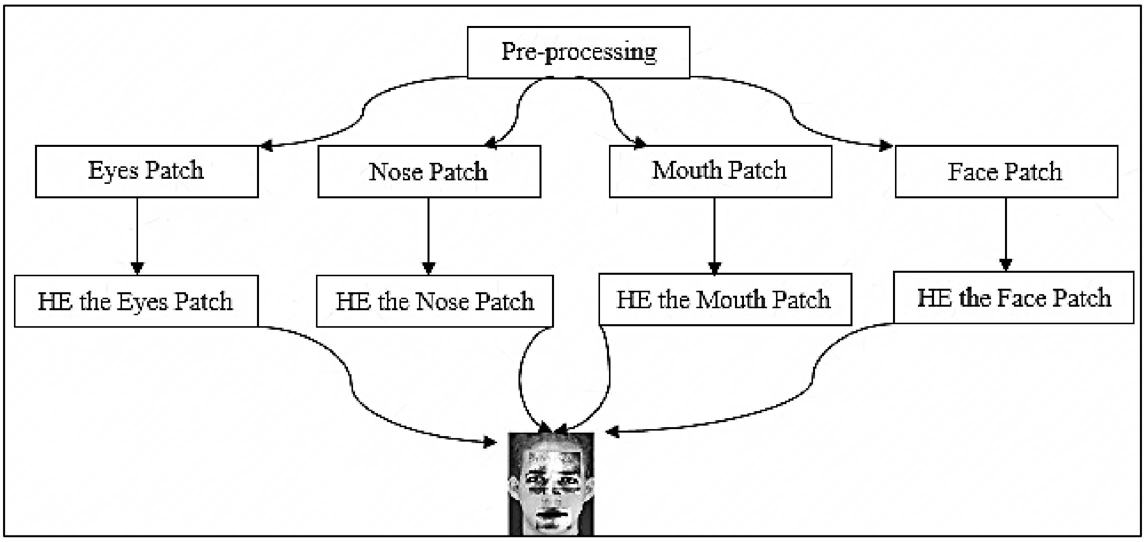


Figure 3.7: The Histogram Equalization stage

3.3.3. Feature Extraction

In the proposed system, feature extraction consists of two stages. In the first stage, PCA is used to extract global features. In second stage, LBP is used to extract local features. In this section, the details of these two stages are discussed.

3.3.3.1. Global features extraction using PCA

PCA is a Holistic-based algorithm. It is originally proposed by (Matthew and Pentl and, 1991). It is widely used for identifying patterns in high dimensional data where the luxury of the graphical representation is not available. Furthermore, PCA expresses data in a unique way, which highlights their resemblance and divergence. The main advantage of PCA is that once patterns in data are found, the dimensionality of data will be reduced without losing any significant information. The basic idea behind PCA is finding an optimal linear transformation that maps the original N-dimensional data space into M-dimensional feature space. The new subspace is supposed to be reduced dimension.

➢ PCA Algorithm

The 2D-facial image can be transformed to 1D vector by concatenating each row (or column) in the 2D matrix to form long vector. Suppose we have M vector of size N representing a sample image collection.

$$X_i = [p_1 \ldots p_N]^T, i = 1, \ldots, N \qquad (3.1)$$

Where X_i is one of thevectors in the trans set, p_N is the pixel value in vector X_i, T is the tanspose of the vector set.

- Find the mean across all image. The mean µ is given in the following equation:

$$\mu = \frac{1}{m} \sum_{i=1}^{m} x_i \qquad (3.2)$$

- Find the mean center image. The mean center w_i is given by the following equation:

$$w_i = X_i - \mu \qquad (3.3)$$

- Compute the covariance matrix. The covariance matrix measures the relationship between two or more dimensions i.e. the covariance matrix measures how much the dimensions vary from the mean with respect to each other (Matthew and Pentl and, 1991). The covariance matrix S is given by the following equation:

$$S = \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu)(x_i - \mu)^{T_i} \qquad (3.4)$$

- Compute the Eigenvalue and the Eigenvector of the Covariance Matrix S by the following equation:

$$SV_i = \lambda_i V_i, for\ i = 1,2 \ldots n. \qquad (3.5)$$

The eigenvector is a special case of matrix multiplication. Where the resulted vector from the multiplication must be an integer multiple from the original vector

(Smith and Lindsay, 2002). Whereas, the eigenvalues are the amount by which the original vector was scaled after multiplication take a place ((Matthew and Pentl and, 1991).

- Project all training images into PCA subspace.
- Project the input images into PCA subspace.

PCA projecting matrix creates N-dimensional face space. The Eigenvectors look like the ghostly face which is named Eigenface. Any single face can be represented in terms of a linear combination eigenface. The best M eigenfaces that have the largest eigenvalues, can be used for the approximation of the face. Figure 3.8 shows the face and its corresponding Eigenface.

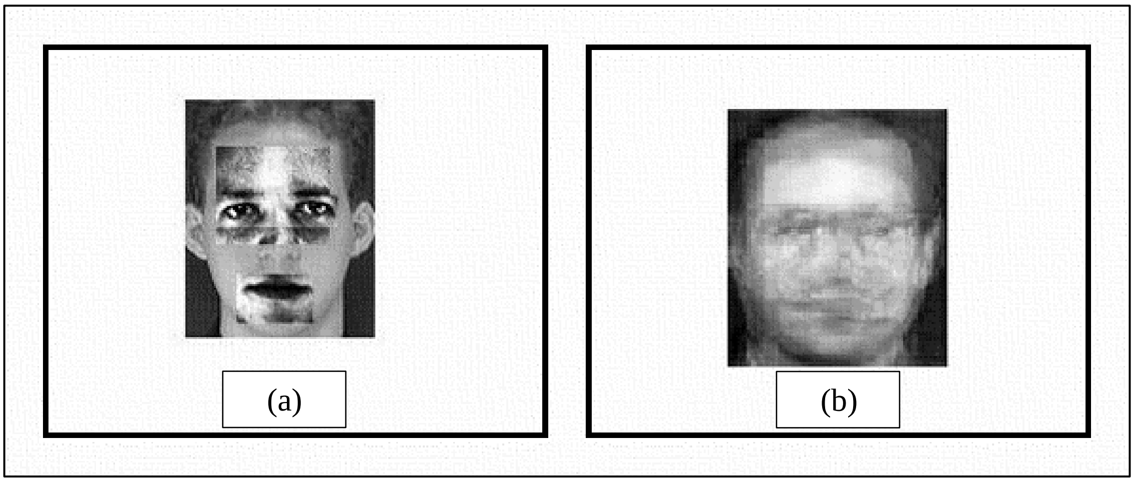


Figure 3.8: Global feature extraction stage input/output. (a) The input image, (b) The Eigenface

3.3.3.2. Local features extraction using LBP

LBP operator, originally proposed by (Ojala et al, 1996), is a powerful texture analysis algorithm used to describe the texture of the digital image, as shown in Figure 3.9. The LBP works in a 3x3 pixel block of an image. These pixel blocks are threshold using its central pixel value. If the pixel value block is larger than the threshold (central pixel value) the value of the pixel block will be encoded to 1. Otherwise, the block is going to be encoded to 0. After encoding all the pixel block, some binary values will be obtained by concatenating all these binary codes in clockwise direction from the top-left. After the binary code is obtained, it will be converted into decimal number which is used for labeling. Since the surrounding pixel block consists of 8-pixel block which gives a sum of (2^8=256) different labels that can be gained depending on the relative gray-scale values.

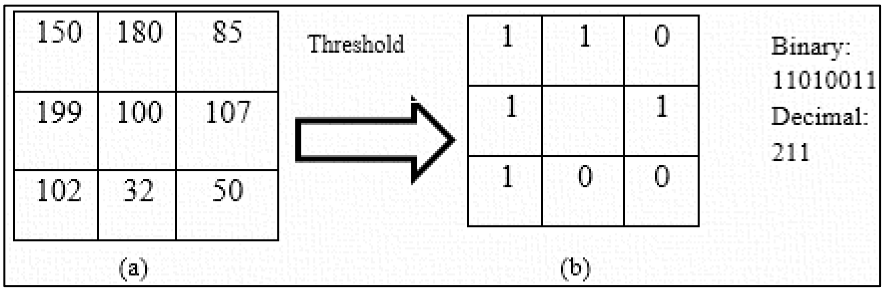


Figure 3.9: Basic LBP operator, (a) Gray-scale value, (b) Corresponding Binary Pattern

➢ LBP Algorithm

LBP extracts and trains visual features, then summarizes their distribution. LBP algorithm consists of the following steps:

- Divide the image into cells of size $3x3$ pixel block.
- For all pixel block of the image, compute LBP values by comparing the surrounding pixel, $p_{xi}, i = 0,1,..,7$. with the centric pixel p_{xc}.

$$LB(p_{xi} - p_{xc}) = \begin{cases} 1, & if\ p_{xi} \geq p_{xc} \\ 0, & if\ p_{xi} < p_{xc} \end{cases} \qquad (3.6)$$

- Calculate the resulting binary number from the previous step and convert it into decimal form.

$$LBP = \sum_{i=0}^{7} LB(p_{xi} - p_{xc}). 2^i \qquad (3.7)$$

- Compute the histogram of LBP values for all rectangular cells across the entire image. Figure 3.10 shows the local features and their corresponding LBP label images.

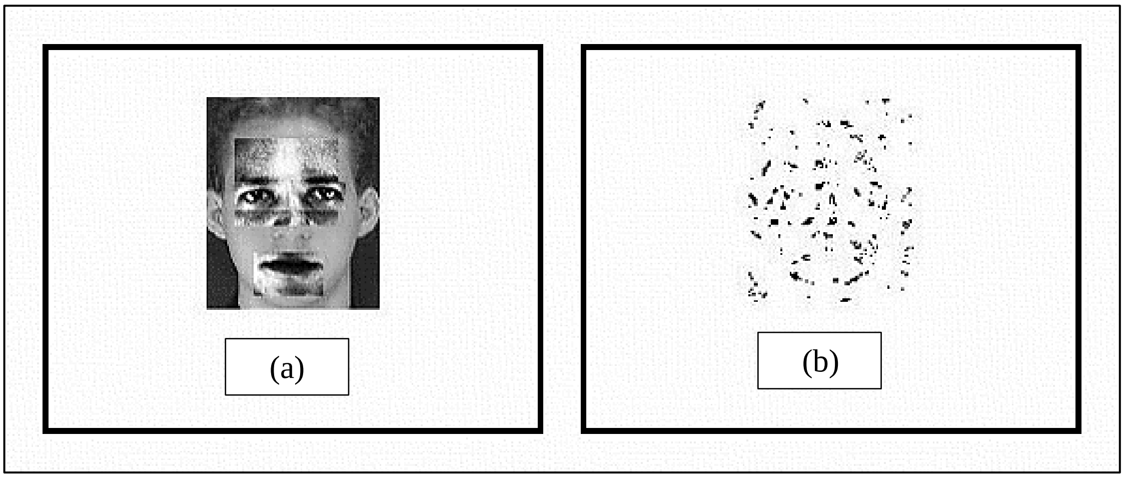


Figure 3.10: Local feature extraction stage input/ output. (a) The input image, (b) LBP label image

3.3.4. Fusion techinque

In the proposed system, a pixel level fusion technique is employed namely FP (0.0:1.0). The advantages of using the fusion techniques are their overall computational simplicity and their suitablity for real-time application. Since FP (0.0:1.0) is based on DCT, there is a need to discuss DCT in details:

DCT, originally proposed by (Nasir et al, 1974). It is a linear data transformation method used to transform a set of data $(x1..xn)$ into a coefficient in frequency domain $(w1 \ldots wn)$. DCT advantage lies in its compaction properties i.e. DCT is able to observe the energy of the original data in the first few DCT coefficients. The correlation of the data plays a major role in DCT because if data is not correlated, then the compaction properties will suffer. i.e., in the first few DCT coefficients, the energy of the original data will not be stored in the first few coefficients. Instead of that, it will be spread through all DCT coefficients. To solve this problem rearrange the value of the original data in a way that makes data correlated as possible. DCT is divided into two types according to the data dimensionality:

- 1D-DCT

To apply 1D-DCT on a 2D image ($Z(x, y)$) of size MxN, there is a need to convert the input image into 1D vector ($Z(x)$) by dividing the image into rows/columns. Then, concatenating these rows/columns to form 1D vector ($Z(x)$). As shown in Figure 3.11 (a) (b). In 2D data, the rows/columns are concatenated to form 1D vector. In the fusion processes, 1D-DCT is applied on both the rows vector and the columns vector separately. After that, the average of both rows and columns is taken to avoid any noise or distortion. The 1D-DCT vector or 1D signal $Z(x)$ of size M is defined in the following equation:

$$Z(u) = a(u) \sum_{x=0}^{M-1} z(x) \cos\left(\frac{\pi(2x+1)u}{2M}\right), 0 \leq u \leq M-1 \qquad (3.8)$$

Where $a(u)$ is the orthogonality, and can be one of two values:

$$a(u) = \begin{cases} \sqrt{\frac{1}{M}} & u = 0 \\ \sqrt{\frac{2}{M}} & u \neq 0 \end{cases} \qquad (3.9)$$

When the value of $u = 0$ the DCT is defined as follows:

$$Z(0) = \sqrt{\frac{1}{M}} \sum_{x=0}^{M-1} Z(x) \qquad (3.10)$$

Which is the first DCT coefficient, and it is called Direct Current (DC). But, when $u \neq 0$, the resulted transformation coefficient is called Alternative Current (AC). The first few coefficient of DCT will hold the most energy and represent Low Frequency (LF). However, the rest DCT coefficients hold low energy and represent High Frequency (HF).

To reconstruct data from 1D-DCT coefficient, the Inverse DCT (IDCT) is used. IDCT is defined as:

$$Z(x) = \sum_{u=0}^{M-1} a(u)Z(u)\cos(\frac{\pi(2x+1)k}{2M}), 0 \leq x \leq M-1 \qquad (3.11)$$

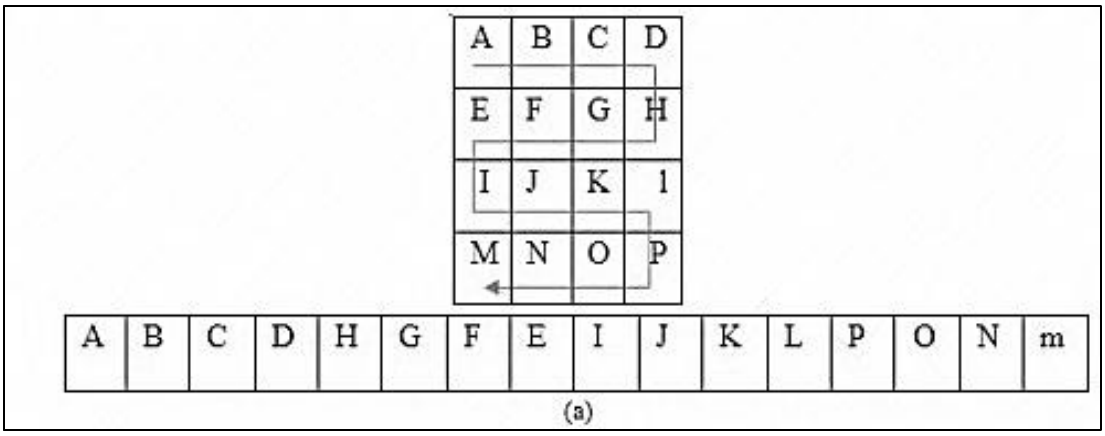


Figure 3.11 (a): Row-wise concatenating the 2D data into a 1D vector

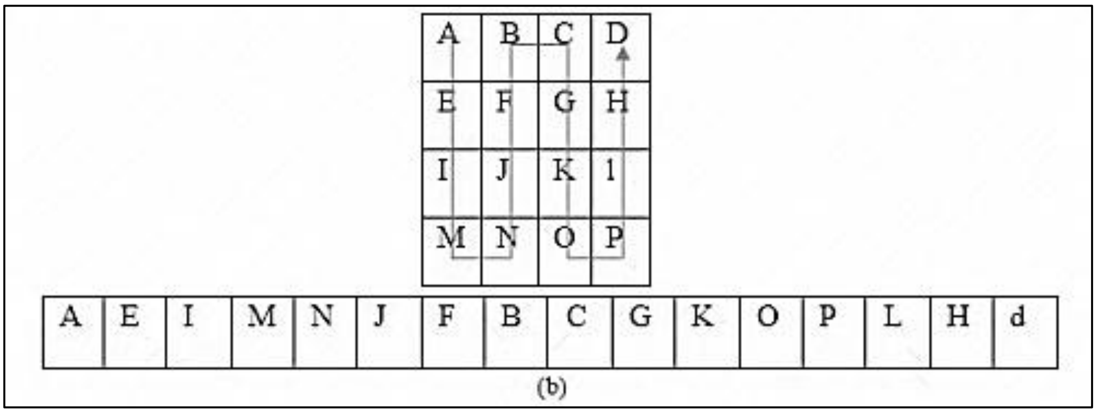


Figure 3.11 (b): column -wise concatenating the 2D data into a 1D vector

- 2D-DCT

The 2D-DCT $Z(u,v)$ of an image or 2D signal $Z(x,y)$ of size MxN is defined as follows:

$$Z(u,v) = a(u)a(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} z(x,y)\cos(\frac{\pi(2x+1)u}{2M})\cos\left(\frac{\pi(2y+1)v}{2N}\right).0 \leq u \leq M-1, 0 \leq V \leq N-1$$

(3.12)

Where u, v are the discrete frequency variables (x, y) pixel index.

$$where\ a(u) = \begin{cases} \sqrt{\frac{1}{M}} & u = 0 \\ \sqrt{\frac{2}{M}} & 1 \leq u \leq M-1 \end{cases} \quad and\ \ a(u) = \begin{cases} \sqrt{\frac{1}{N}} & v = 0 \\ \sqrt{\frac{2}{N}} & 1 \leq v \leq N-1 \end{cases} \qquad (3.13)$$

To reconstruct data from 2D-DCT coefficient, the Inverse DCT (IDCT) is used, IDCT is defined as:

$$Z(x,y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} a(u)a(v)z(u,v)\cos\left(\frac{\pi(2x+1)u}{2M}\right)\cos\left(\frac{\pi(2y+1)v}{2N}\right), 0 \leq x \leq M-1, 0 \leq y \leq N-1$$

(3.14)

3.3.4.1. Frequency Partition (FP)

(Nadiu, 2013) proposed a novel image fusion technique based on 1D-DCT to integrate digital images. The FP divides the digital image of the size MxN into rows/ columns. Then, it concatenates these rows/ columns to produce 1D vector. After that, it applies the 1D-DCT on the resulted vector. Afterwards, it will produce two types of coefficient; the LF coefficient and the HF coefficient with a partitioning factor f. The idea behind the partition factor f is, it exploits the concentration property of DCT coefficients. LF contains the most important information about data. While, HF contains less information about data. Figure 3.12 shows the LF and HF coefficients. LF and HF separation has the following as in equation:

$$\mathrm{z(u) = DCT\big(Z(x)\big), x, u = 0,1,2 \ldots. MN - 1} \qquad (3.15a)$$

$$\mathrm{ZL(u) = Z(u), u = 0,1,2 \ldots.., MNf - 1} \qquad (3.15b)$$

$$ZH(u), u = MNf, MNf + 1, \ldots, MN - 1 \qquad (3.15c)$$

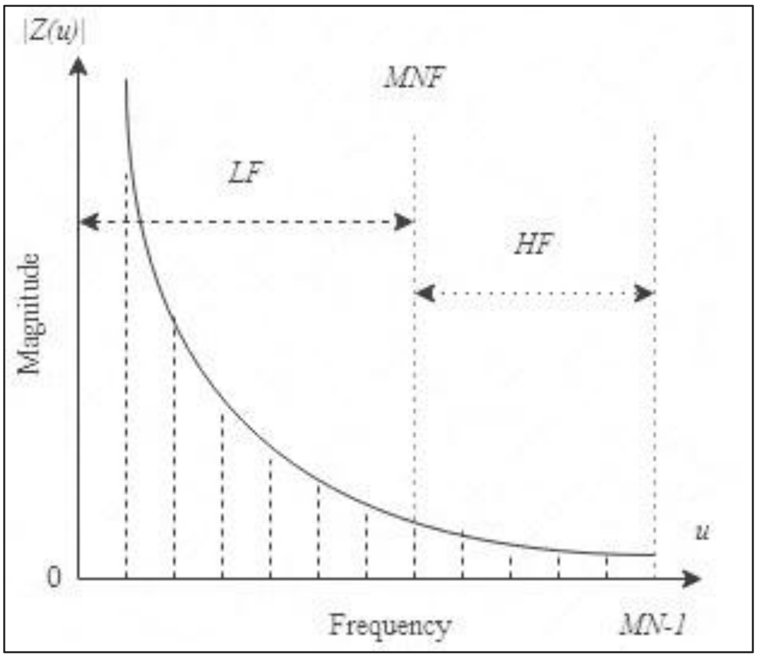


Figure 3.12: LF and HF coefficients and their separation

The integration of the image $z_1(x,y)$ and image $z_2(x,y)$ using FP is established as follows:

- Convert images $z_1(x,y)$ and $z_2(x,y)$ into 1D vector $z_1(x)$ and $z_2(x)$.
- Apply the 1D-DCT on the $z_1(x)$ and $z_2(x)$ vectors to find the DCT coefficients of $z_1(x)$ and $z_2(x)$.
- Using the equation 3.15, the fused DCT is found as follows:
  - ✓ Get the average of LF of both image coefficients.

$$ZL_f(u) = \frac{1}{2}\big(ZL_1(u) + ZL_2(u)\big), u = 0,1, \ldots, MNf - 1 \qquad (3.16)$$

  - ✓ HF is fused as follows:

$$ZH_f(u) = \begin{cases} ZH_1(u) \ if \ |ZH_1(u)| \geq |ZH_2(u)| \\ ZH_2(u) \ if \ |ZH_1(u)| < |ZH_2(u)| \end{cases}, u = MNf, MNf + 1, \ldots, MN - 1 \ (3.17)$$

✓ The resulted fused coefficients are:

$$ZL_f(u) = [ZL_f(u) \ ZH_f(u)] \qquad (3.18)$$

- ✓ To reconstruct the fused coefficient, 1DCT is used as in the following equation:

$$Z_f(x) = IDCT\left(Z_f(u)\right), 0,1, \dots, MN-1 \qquad (3.19)$$

- ✓ The fused image is:

$$I_f = IDCT\left(Z_f(x), M, N\right) \qquad (3.20)$$

3.3.4.2. Fusion Implementation

In this section, we illustrate the main contribution of the proposed system. In the proposed system, we employ the fusion processes as follows: The first process, contains several gathered features like the face, the eyes, the nose, and mouth. In the second process, a sub-fusion based on FP technique is established using the gained features from the first process. In the second process the sub-fusion is done as follows: the first two fused features are the face with the edge surrounding the face. After that, the face with the eyes is fused. Then, the face with the nose is fused. Finally, the face with the mouth is fused, the reason of the sub-fusion in the second process is to increase the information which in turn will increase the accuracy (Ghahramani, 2015). Thereafter, the FP is applied to both processes independently, the purpose of doing this is to increase the accuracy of the fused image. After that, the best-fused image that has the best resolution between the first process and second is automatically chosen based on standard Deviation and spatial Frequency Criteria for Recognition stage. Moreover, the proposed system, PCA, and LBP are evaluated using SFC according to (Blum et al, 2005). Figure 3.13 represents the first and second processes and their fusion.

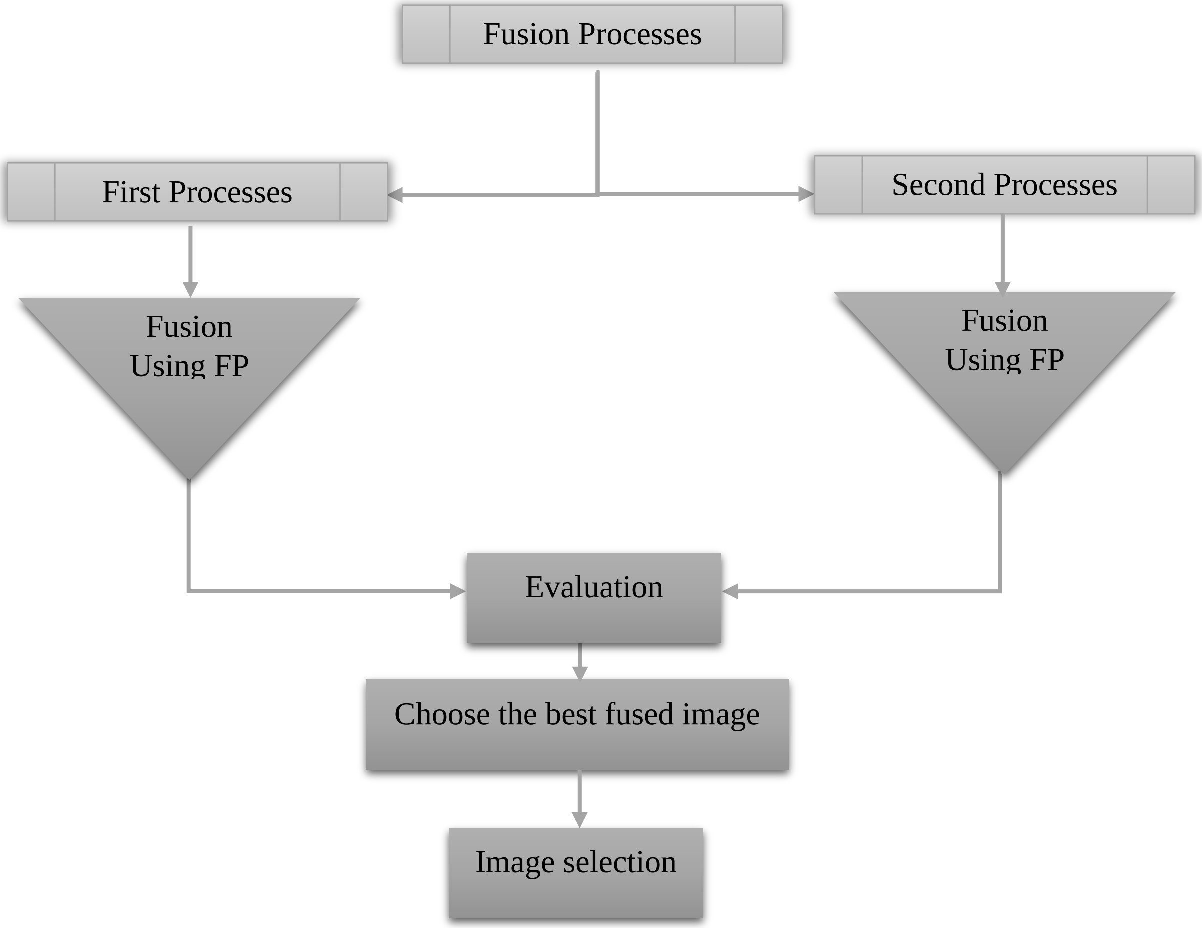


Figure 3.13: The proposed fusion method diagram

3.3.4.3. Evaluation of Fused Image

In the proposed system, the quality of the fused images is measured using SD and SFC this due to their abilities to evaluating the spectral and spatial similarities between the fused image and raw input images (Jagalingam, P. and Hegde, 2015). This section illustrates these quality metrics as follows:

3.3.4.3.1 Standard Deviation (SD)

SD is used to measure the contrast in the fused image. When the value of SD is high, it indicates that the fused image as high contrast.

$$\sigma = \sqrt{\sum_{i=0}^{L}(i - i^{\sim})^2 h_{i_f}(i)}\, , i^{\sim} = \sum_{i=0}^{L} i\, h_{i_f} \qquad (3.21)$$

Where, $h_{i_f}(i)$ is the normalized histogram of the fused image I_f and L is the number of frequency bins in the histogram.

3.3.4.3.2 Spatial Frequency Criteria (SFC)

SFC Indicates the overall activity level in the fused image. SFC is computed by calculating the row and column fused image frequency. A higher value of SFC indicates that the input images and fused image are similar (Jagalingam, P. and Hegde, 2015) (Blum et al, 2005). The SFC is defined as:

$$SFC = \sqrt{(RF)^2 + (CF)^2} \qquad (3.22)$$

Where

$$RF = \sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[F(m,n) - F(m,n-1]^2} \qquad (3.23)$$

$$CF = \sqrt{\frac{1}{MN}\sum_{n=0}^{N-1}\sum_{m=0}^{M-1}[F(m,n) - F(m-1,n]^2} \qquad (3.24)$$

CF and RF are respectively presented, column and row frequency of the image. M & N are the rows and columns number, while $F(m,n)$ is the value of the pixel (m,n) of the fused image.

3.3.5. Face Recognition using ANN

As time progresses, the interest of applying ANN on face recognition system is increased rapidly due to its Desirable advantages such as its learning and adoption ability, parallel distributed computation, and robustness (Jain et al, 1996). ANN is a collection of node or neurons interconnected together performing a specific task in parallel. ANN is a powerful classification technique that applied to wide variety of tasks such as prediction, approximation, and pattern classification. In the proposed system, a Multiple Layer Perceptron (MLP), a Multiple Layer Perceptron (MLP) trained based on Back Propagation Algorithm (BP) has been chosen for classification due to its capability of learning and solving difficult and diverse problems (Rumelhart et al, 1986). The MLP consider an FFN i.e. the network nodes are unidirectional and the network contains no cycles (loops) (Rumelhart et al, 1986). MLP is trained and tested on AT&T dataset. Figure 3.14 shows the component of MLP network. MLP contains the Input layer, multiple hidden layers and an output layer, the input layer of MLP has N units for the N-dimensional vector. The input layer is fully connected to the hidden layer, likewise, the hidden layer is fully connected to the output layer. Since the proposed system involves supervised learning, that means there is a teacher who knows the correct answer (desired output) (Gardner and Dorling, 1998). In the proposed system, AT&T dataset is used for training and testing the MLP. The following is the list steps for training and testing of MLP (Hagan et al, 1996):

1. Initialized the ANN:

1.1 set the parameters for ANN.

2. Read all the image in the dataset.
3. Normalize the ANN and its parameter.
4. Define the ANN.
5. Define training and testing process.
6. Build the ANN.
7. Training and testing of the ANN.

7.1 Define input feature vectors, from training data to the network. Where $[x_1, x_2, \dots, x_i]^T$ is the input vector or the feature vectors of a given image.

7.2 Initialize all weights with small random numbers between -0.1 and 0.1

$$[w_{1j}, w_{2j}, \dots, w_{ij}] = random\ virable$$

7.3 Propagate the input vector through the network to obtain the output.

$$y_i = sig\left[\sum_{j=1}^{i} w_{ij}\, x_j + \theta_i\right] \qquad (3.25)$$

Where θ_i is the threshold, and y_i is the actual output, then the activation function is used to calculate the node output y_i , the most common activation function used in classification is sigmoid, as follows:

$$\mathrm{Sig}(y_i) = \frac{1}{1 + e^{-y_i}} \qquad (3.26)$$

7.4 Calculate the error signal by comparing the actual output with the desired output, if y_i=y_{di} then the MLP recognizes the input image, but if $y_i \neq y_{di}$ the MLP miss recognizes the input image. It is important to calculate the error gradient δ_i between the gained output y_i and the desired output y_{di}. If the error between these two outputs is not equal to the desired error, then update the weight w_{ij}, otherwise, don't change the weight w_{ij}. The equation of the error gradient is defined as follows:

$$e_i(t) = y_{di}(t) - y_i(t) \quad (3.27)$$

$$\delta_i(t) = y_i(t)[1 - y_i(t)].e_i(t) \quad (3.28)$$

7.5 Adjust the weights to minimize the overall error. Then calculate the magnitude of change in weight w_{ij}, as follows:

$$\Delta w_{ij} = \alpha.y_i(t)\,\delta_i(t) \quad (3.29)$$

Where α is the lerarining rate. After calculating the maginatude of change in w_{ij}, the wieght is update as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} \quad (3.30)$$

MLP repeats steps 4.3-4.5 until the overall error is equal to the desired error which is in our case eqauls to10^{-5}.

7.6 The recognition rate of the proposed system is calculated as follows:

$$\text{Recognition Rate} = \left(\frac{\text{Number of correctly identified images}}{\text{Total number of images}}\right) * 100 \quad (3.31)$$

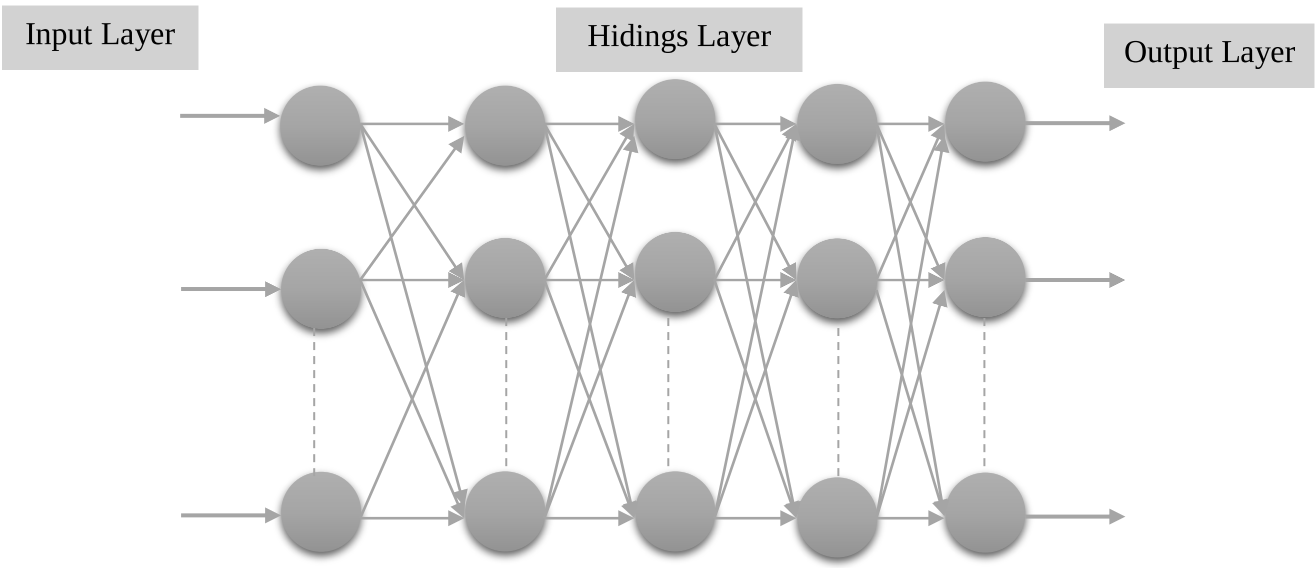


Figure 3.14: Five-layer MLP Architecture

Chapter 4

Experimental Results

4.1. Introduction

This chapter illustrates the way which our experiment was conducted. Also, it presents the overall recognition rate when the proposed system trains on the entire AT&T dataset. This chapter also presents the RR of the proposed system according to different image scenario in uncontrolled environment.

4.2. Comprehensive Example of The Proposed System

The following is a step by step example of the proposed system:

1. The user selects an input image of size (112 x 92) from AT&T dataset to test the proposed system.

2. The input image is passed to the detection stage, where the detection algorithm (Haar- Cascade) detects the face, eyes, nose, and mouth. The output of this stage is an of (1 x 4) point, that represents the boundaries of the detected features. After that, a copy of the detected features is passed to the preprocessing stage.

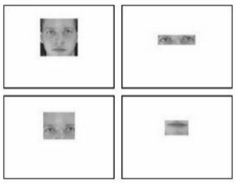
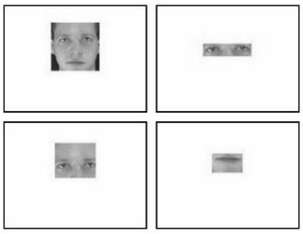
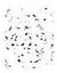
3. In preprocessing stage, the HE is applied to the copy of the detected features. Then, the detected features are gathered together and passed to the feature extraction stage. The final output of this procedure is a 2D image with better contrast and resolution of a size (112 x 92).

4. The features extraction stage is divided into two steps. In the first step, PCA is used to extract the global features. In the second step, LBP is used to extract the local features. The output of these steps is two images of size (112 x 92). The resulted images are passed to the fusion stage.

5. In the fusion stage, the images are integrated using FP. The output of this stage is a high-resolution image of size (112 x 92). The output of the fusion stage is passed to the recognition stage.

6. In the recognition stage, the ANN is applied to recognize the input image and return a recognition rate. Table 4.1 shows a comprehensive example of each stage input/output.

Table 4.1: A comprehensive of the proposed system.

Input	Input Size	Procedure	Output	Output Size
	112 x 92	Face Detection		1 x 4
	78 x 78 15 x 59 46 x 55 23 x 37	Prepressing	 	112 x 92
	112 x 92	Feature Extraction	 	112 x 92
 	112 x 92	Fusion		112 x 92
	112 x 92	Recognition	Recognition Rate	end.

4.3. Proposed System Results

The proposed system was trained on AT&T dataset which contains (400) gray scale images. Each image in the dataset was distorted by less than ten percent using Gaussian Noise, Poisson Noise, Salt and pepper noise, and Speckle Noise (Janani et al, 2015) (Farooque et al, 2013). Then, it produces (10000) distorted images that differ from each other. The proposed system is trained and tested based on these (10000) distorted images where 70% (7000) of these images used for training and 30% (3000) used for testing.

The results are given in terms of both: recognition rate and Receiver Operating Characteristic Curve (ROC). recognition rate is the correct identification percentage of a face. ROC is a technique for organizing, visualizing, and selecting classifiers with the best performance. It is also considered as an accepted method for summarizing the performance of detection & pattern matching (Fawcett, 2006). ROC is threshold independent, enabling performance comparison of multiple systems under. similar conditions, or of a single order under different conditions (Fawcett, 2006). In order to evaluate the effectiveness of the proposed system, it will be compared with PCA & LBP. The experimental experiments are divided into two stages in the main stage of the experiment, the proposed system is tested on all the previously discussed face image problems. However, in the second experiment, the robustness of the proposed system is tested by detaching each image problems in an independent dataset and test the proposed system according to each one of those datasets separately.

4.3.1. The main Experiment Results:

The training and testing of the proposed system are triggered after the input image selected and inserted into the system. In the main experiment, the proposed system was able to recognize (2913) images out of (3000) test images. However, PCA was able to recognize (2883) images out of (3000) test images. Moreover, LBP was able to recognize (2872) images out of (3000) test images. After that, the recognition rates are calculated according to the number of correctly recognized images. Moreover, the proposed system will also return the position number of the most similar image to the input image. Figure 4.1 Shows the main experiment steps.

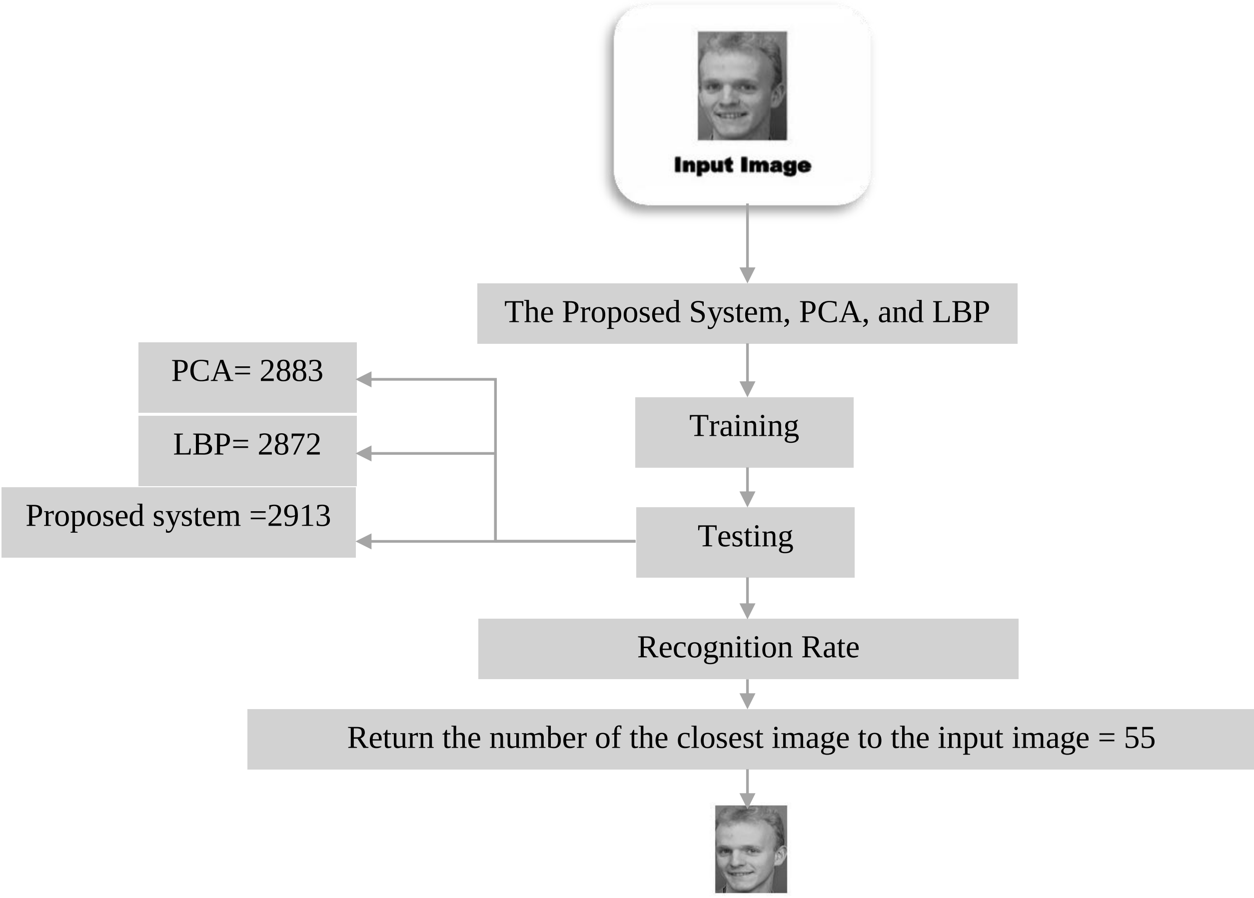


Figure 4.1 The main experiment steps

To compute the efficiency of the proposed systems, we compute the recognition rate, the results are shown as follows:

1. PCA gives (96.102) recognition rate.
2. LBP gives (95.721) recognition rate
3. The recognition rate of the proposed system using FP fusion technique is represented using table 4.2:

Table 4.2: recognition rate of the proposed system using FP (0.0: 1.0)

FP	***0.0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1.0***
Recognition Rate	*96.9327*	*96.0238*	*96.2450*	*96.0314*	*96.7504*	*96.2156*	*96.3965*	*96.6649*	*97.0755*	***97.0829***	*96.2756*

As shown in table 4.2. The propsed system, gives the best recognition rate in (0.9) partition and its equal to (97.0829). Figure 4.2 shows the ROC curve of the proposed system recognition rate compared to PCA and LBP recognition rate.

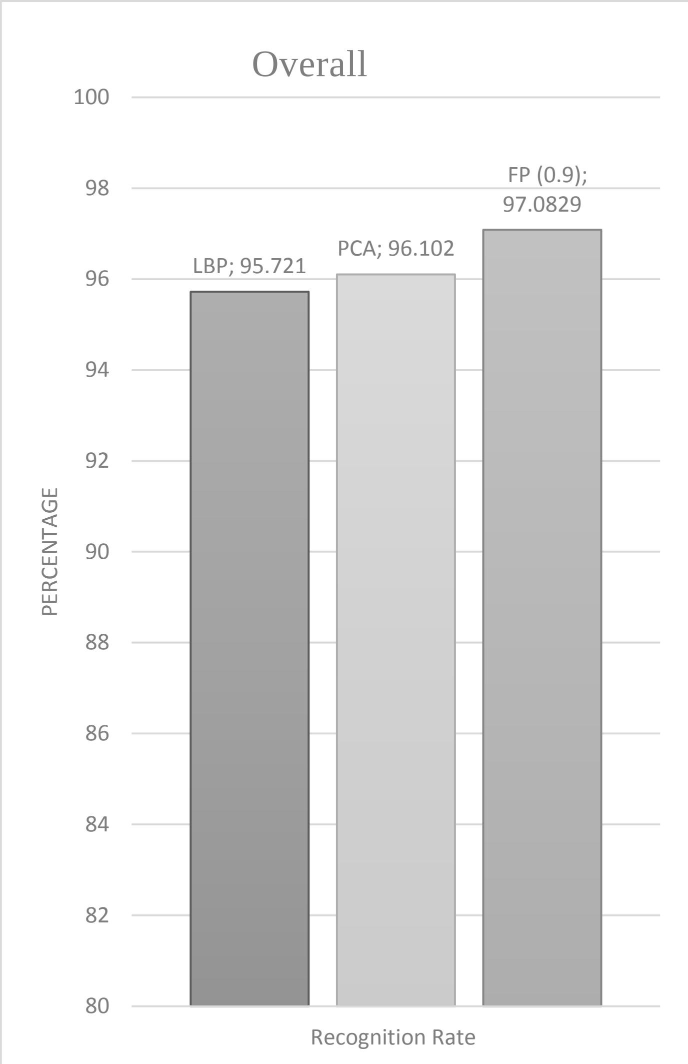


Figure 4.2: The overall recognition rate of the proposed system compared to the PCA and LBP

Notice that the proposed system optimazes the recognition rate over PCA by (0.9809)% and over LBP by (1.3619)%.

4.3.2 Testing the Robustness of the proposed system

To verify the results of the proposed system, the images in the AT&T dataset are divided based on each scenario of the uncontrolled environment such as pose, expression…etc. Then, the previously stated distortion methods are employed in order to produce (10000) distorted images for each detached datasets. After that, the proposed system is traind and tested based on each problem separately. Afterword, the proposed system is compared with PCA & LBP to observe if the proposed system optimizes the recognition rate or not. The Experimental results according to each scenario are shown below.

4.3.2.1 The Experimental Results for Pose Scenario

Our experimental results prove that the recognition rate of the proposed system is higher than PCA and LBP when they are tested on images with pose. Table 4.3 shows the recognition rate of the proposed system using FP. When its tested-on pose scenario.

Table 4.3 shows the recognition rate of the proposed system using FP. When its tested-on pose scenario

FP – Pose	*0.0*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*1.0*
Recognition Rate	*96.381*	*95.256*	*95.568*	*95.728*	*96.553*	*953692*	*95.692*	*96.382*	*96.14*	***97.02***	*95.33*

As shown in Table 4.3. The proposed system gives the best recognition rate on 0.9 partitions and its equal to (97.020) recognition rate. While PCA has (95.301) recognition rate and LBP has (95.187) recognition rate. Figure 4.3 shows the recognition rate of the proposed system compared to PCA & LBP.

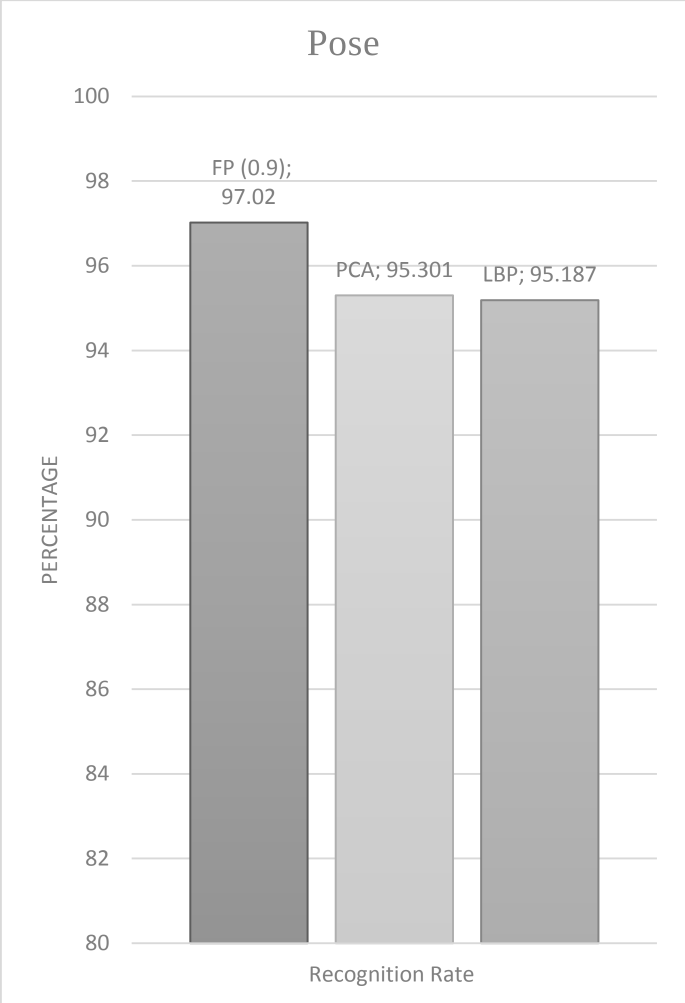


Figure 4.3: The recognition rate of the proposed system compared to PCA & LBP recognition rate when the face image has pose

Notice that the proposed system optimaze the recognition rate by (1.719)% over PCA and (1.833)% over LBP.

4.3.2.2 The Experiment Result for Expression Scenario

Our experiment result proves that the recognition rate of the proposed system is higher than PCA and LBP when they are tested on images with facial expression. Table 4.4 shows the recognition rate of the proposed system using FP. When its tested-on expression scenario.

Table 4.4: shows the recognition rate of the proposed system using FP when its tested-on expression scenario

FP-Expression	***0.0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1.0***
Recognition Rate	*97.504*	*96.515*	*96.720*	*96.971*	*97.440*	*97.066*	*97.208*	*96.941*	***98.373***	*97.724*	*97.305*

As shown in Table 4.4. The proposed system gives the best recognition rate on 0.8 partitions and its equal to (98.373) recognition rate. While PCA has (96.997) and LBP has (96.235) recognition rate. Figure 4.4 shows the recognition rate of the proposed system compared to PCA & LBP.

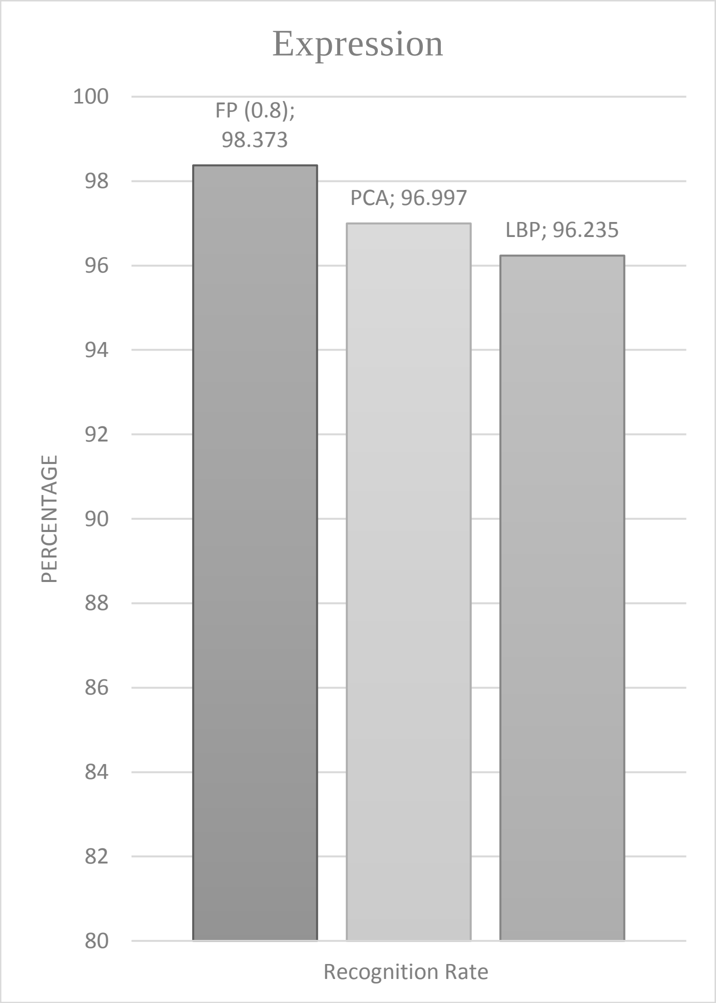


Figure 4.4: The recognition rate of the proposed system compared to PCA & LBP recognition rate when the face image has expression

Notice that the proposed system optimazes the recognition rate by (1.376) % over PCA and (2.138) % over LBP in Expression scenario.

4.3.2.3 The Experiment Result Illumination scenario

Our experimental results prove that the recognition rate of the proposed system is higher than PCA and LBP when they are tested on images with variattion in illumination. Table 4.5 shows the recognition rate of the proposed system using FP. When it is tested on illumination scenario.

Table 4.5: The recognition rate of the proposed system using FP when it is tested-on illumination scenario

FP-Illumination	***0.0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1.0***
Recognition Rate	*96.668*	*95.92*	*95.78*	*95.652*	*95.919*	*95.896*	*95.695*	*96.478*	*96.436*	***96.746***	*95.75*

As shown in Table 4.5, the propsed system gives the best recognition rate on 0.9 partition and its equal to (96.746) recognition rate. While PCA has (95.809) recognition rate and LBP has (95.274) recognition rate. Figure 4.5 shows the recognition rate of the propsed system compared to PCA & LBP.

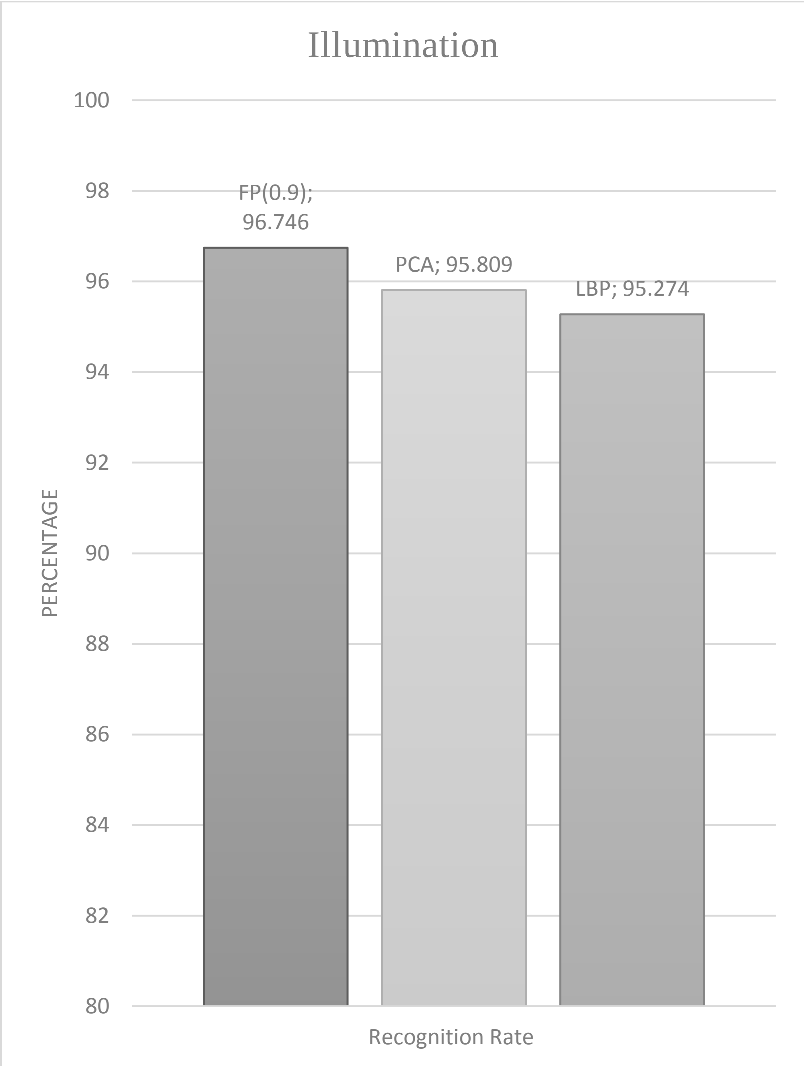


Figure 4.5: The recognition rate of the proposed system compared to PCA & LBP recognition rate when the image has illumination

Notice that the proposed system optimazes the recognition rate by (0.937)% over PCA and (1.472)% over LBP in Expression scenario.

4.3.2.4 The Experiment Result for Occlusion Scenario

Our experimental results prove that the recognition rate of the proposed system is higher than PCA and LBP when they are tested on images with occlusion. Table 4.6 shows the recognition rate of the proposed system using FP when it is tested on Occlusion scenario.

Table 4.6: The recognition rate of the proposed system using FP when it is tested-on Occlusion scenario

FP-Occlusion	***0.0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1.0***
Recognition Rate	*96.628*	*95.949*	*96.254*	*95.203*	*96.472*	*95.906*	*96.253*	*96.509*	*96.147*	***96.175***	*95.82*

As shown in Table 4.6, the propsed system gives the best recognition rate on 0.9 partition and it is equal to (96.175) recognition rate. While PCA has (95.552) recognition rate and LBP has (95.750) recognition rate. Figure 4.6 shows the recognition rate of the propsed system, PCA & LBP.

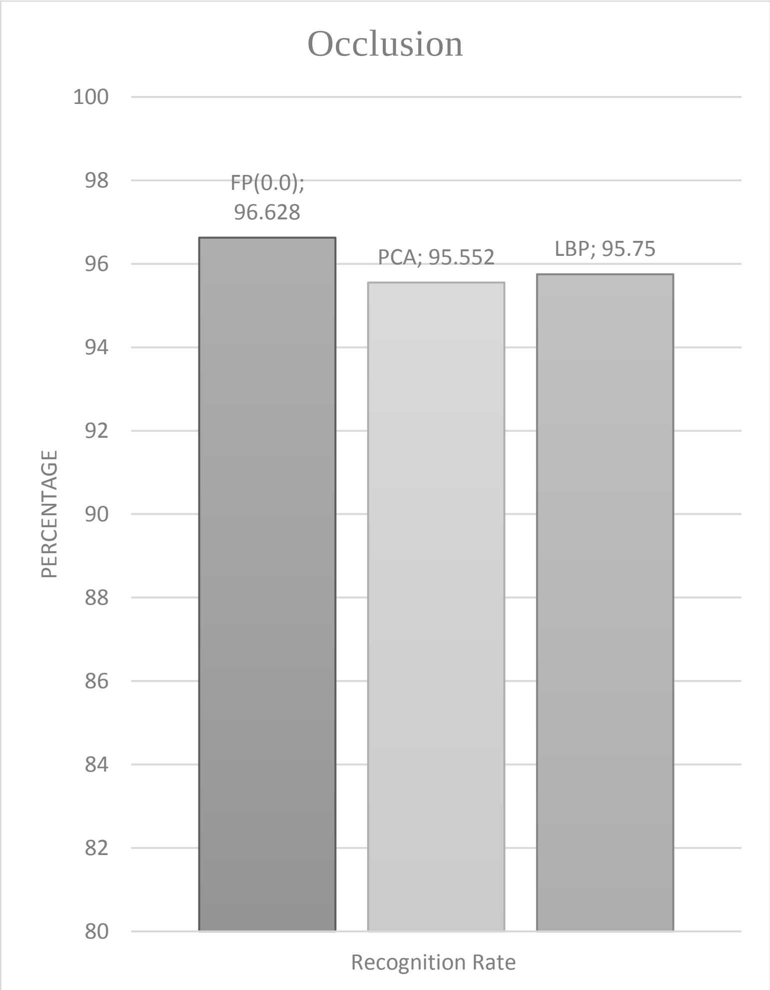


Figure 4.6: The recognition rate of the proposed system compared to PCA & LBP recognition rate when image has occlusion

Notice that the proposed system optimazes the recognition rate by (1.076)% over PCA and (0.878)% over LBP in Expression scenario.

4.3.2.5 The Experiment Result for Low-Resolution scenario

Our experimental results prove that the recognition rate of the proposed system is higher than PCA and LBP when they are tested on images with low-resolution problem. Table 4.7 shows the recognition rate of the proposed system using FP when it is tested on low-resolution scenario.

Table 4.7: The recognition rate of the proposed system using FP when its tested-on low-resolution scenario

FP-Occlusion	***0.0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1.0***
Recognition Rate	*96.572*	*95.66*	*96.002*	*95.101*	*95.933*	*95.349*	*95.516*	*96.594*	*96.277*	***96.991***	*95.404*

As shown in Table 4.7. the propsed system gives the best recognition rate on 0.9 partition and it is equal to 96.991. While PCA has 95.461 recognition rate and LBP has 95.063 recognition rate. Figure 4.7 shows the recognition rate of the propsed system compared to PCA & LBP.

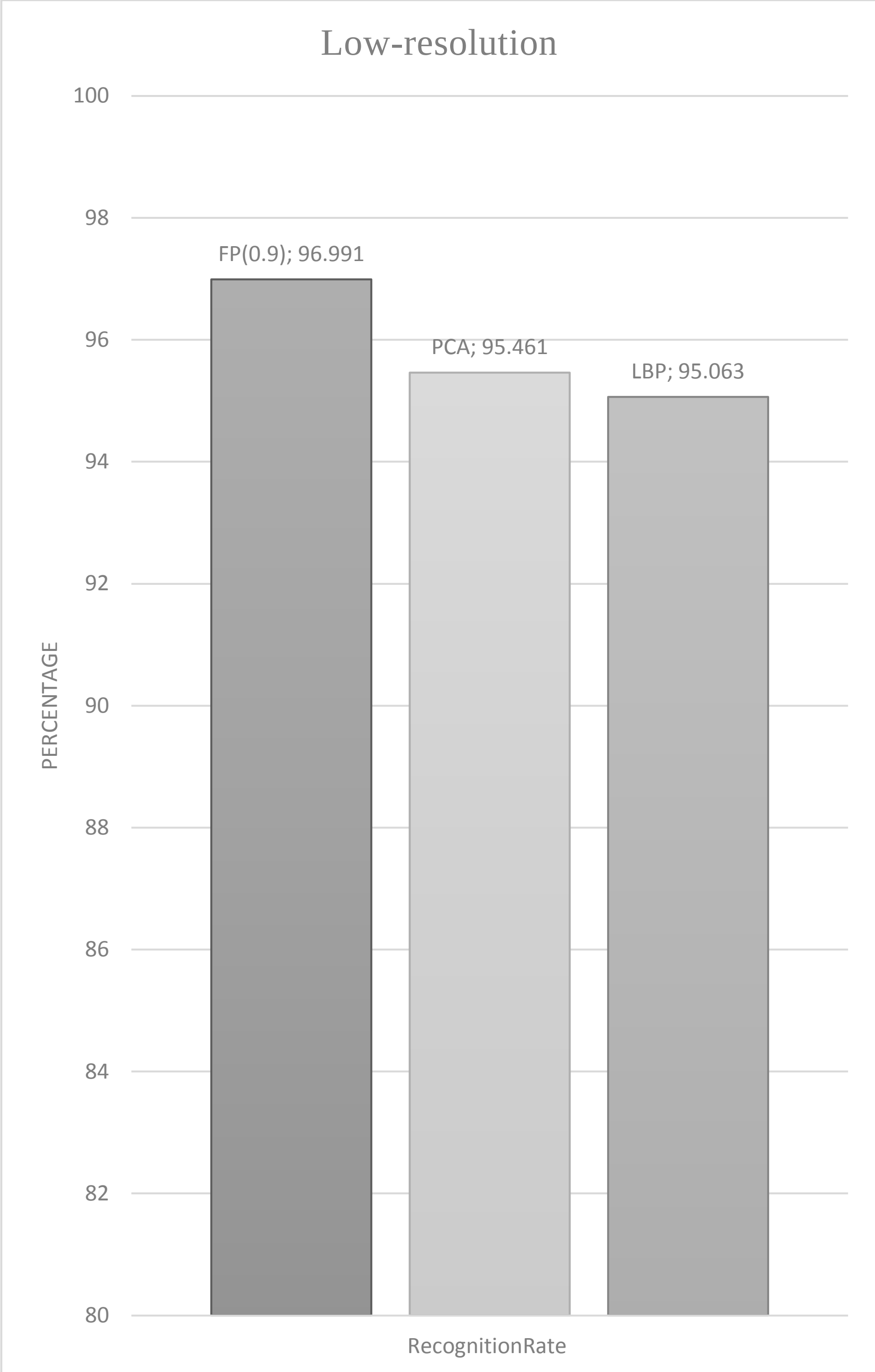


Figure 4.7: The recognition rate of the proposed system compared to PCA & LBP recognition rate when the image has low-resolution

Notice that the proposed system optimazes the recognition rate by (1.53) % over PCA and (1.928)% over LBP in low resolution scenario. Table 4.8 shows the entire recognition rate of the proposed system compared with PCA & LBP.

Table 4.8: The experimental results of the proposed system, PCA & LBP

IMAGE SCENARIO \ METHOD	THE PROPOSED METHOD-Recognition Rate	PCA-Recognition Rate	LBP-Recognition Rate
ALL	97.0829	96.102	95.721
FACE EXPRESSION	98.373	96.997	95.235
FACE POSE	97.020	95.301	95.187
LOW-RESOLUTION	96.991	95.461	95.063
OCCLUSION	96.628	95.552	95.75
ILLUMINATION	96.746	95.809	95.274

Figure 4.8 shows a comparison between the proposed system and PCA according to their recognition rate.

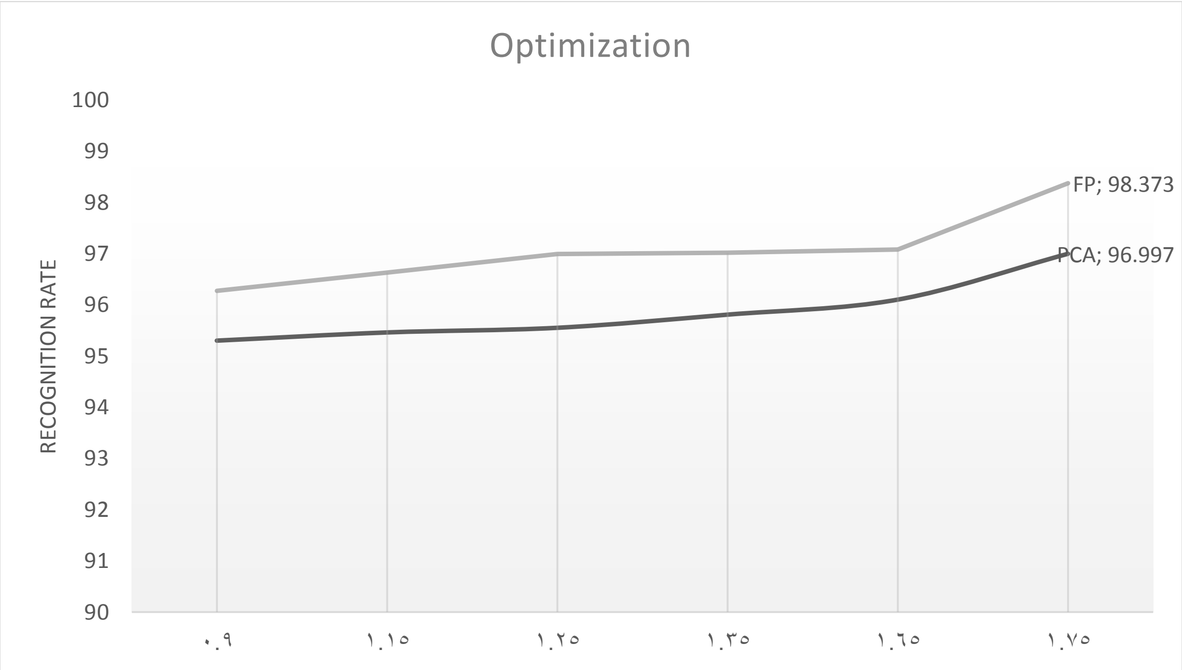


Figure 4.8: The proposed method vs. PCA

Figure 4.9 shows a comparison between the proposed system and LBP according to their recognition rate.

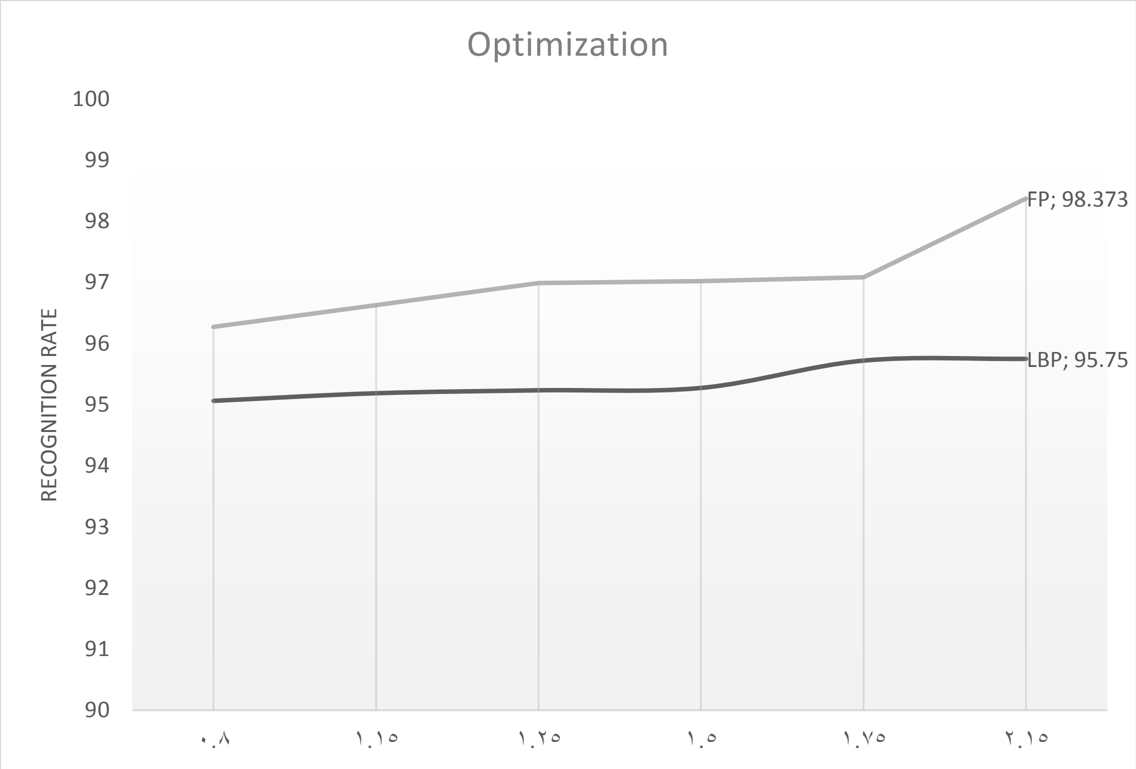


Figure 4.9: The proposed method vs. LBP

Table 4.9 shows the proposed system accuracy optimization percentage compared to PCA & LBP.

Table 4.9: Summary of optimization percentage

IMAGE SCENARIO	*IMROVEMENT OVER PCA*	*IMROVEMENT OVER LBP*
ALL	*0.9809*	*1.3619*
FACE EXPRESSION	*1.376*	*2.138*
FACE POSE	*1.719*	*1.833*
IMAGE RESOLUTION	*1.53*	*1.928*
OCCLUSION	*1.076*	*0.878*
ILLUMINATION	*0.937*	*1.472*

Figure 4.10 shows optimization percentage over PCA and LBP.

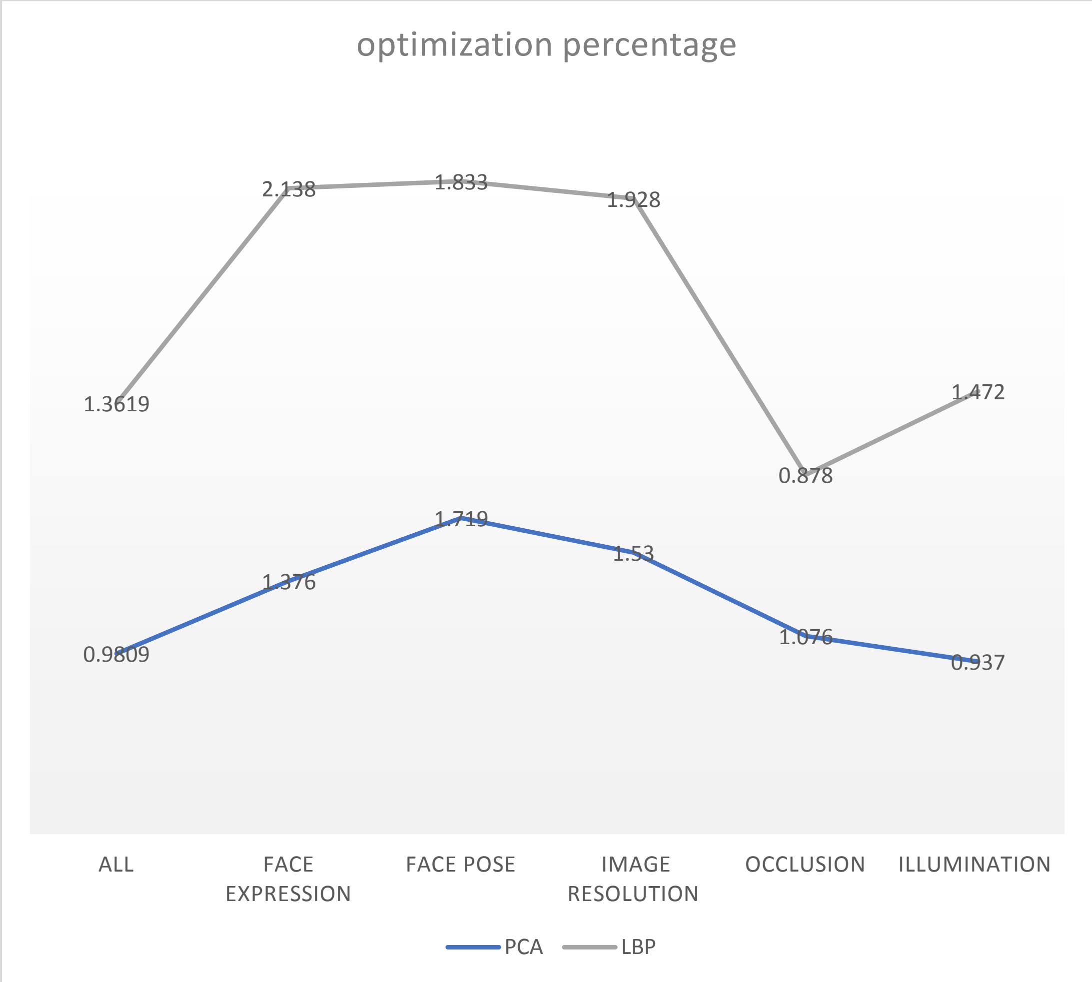


Figure 4.10: The proposed system optimization percentage

4.4 Proposed System Quality Measure

To measure the quality of the proposed system effectiveness and accurately, the SFC is used as in (Blum et al, 2005). The SFC calculation was performed on the entire proposed system, PCA & LBP, in order to measure the system's quality. Table 4.10 shows the obtained results:

Table 4.10: The obtained result from SFC quality measure after applying it over the entirety of the proposed system, PCA & LBP

Methods	*SFC*	*CF*	*RF*
The proposed system	*135.640*	*95.721*	*96.102*
PCA	*122.336*	*86.332*	*86.676*
LBP	*117.7*	*83.01*	*83.43*

The SF, CF, and RF result represent the overall proposed system work, which represents the performance of the proposed system, PCA & LBP as a single unit.

4.5 Chapter Summary

In this thesis, the results are divided into two phases. In the main phase, the proposed system is tested on all image scenarios in AT&T. The experimental results show that the proposed system gives a better recognition rate, (97.0829), compared to PCA and LBP which has (96.102) and (96.102) respectively. In the second phase of the result, the proposed system, PCA & LBP are tested on different face image scenario separately such as Pose, Expression, Illumination, Image Resolution, and Occlusion. The proposed system gives the best recognition rate in Expression scenario with (98.373) recognition rate. Then, it's compared with PCA & LBP which have (96.997) recognition rate and (95.235) recognition rate respectively. The second-best result of the proposed system goes to face Pose scenario with (97.02) recognition rate. afterward, it is compared with PCA & LBP which have (95.301) and (95.187) recognition rate respectively. The third-best result of the proposed system goes to face Image resolution scenario with (96.991) recognition rate. After that, its compared with PCA & LBP which have (95.461) and (95.063) recognition rate respectively. The fourth-best result of the proposed system goes to face occlusion scenario with (96.628) recognition rate. Thereafter, it is compared with PCA & LBP which have (95.552) and (95.75) recognition rate respectively. The fifth and final result of the proposed system goes to illumination scenario with (96.746) recognition rate. Subsequently, its compared with PCA & LBP which have (95.809) and (95.274) recognition rate respectively.

Chapter 5

Conclusion and Future Work

5.1. Conclusion

Researches on face recognition have produced quite satisfactory recognition rate. However, the face recognition system performance degrades when there is a pose variation, illumination, Expression, low image occlusion and resolution. The existing face recognition system performance can be further improved throughout integrating both global and local features. In this thesis, a hydride face recognition method that handles the previously stated problems is proposed. The proposed system consists of five stages. In the First stage, Haar-cascade is applied to detect face with its significant characteristics, such as the mouth, nose and eyes. In the second stage, HE is added to a copy image of the detected face with its significant characteristics. In the third stage, the global and local features are extracted using PCA & LBP respectively. In the fourth stage, FP fusion technique is used to integrate the extracted features. In the final stage, ANN is used for training and testing. The AT&T dataset is employed to train and test that proposed system. The experimental results show that the global and local features integration yields a higher recognition rate compared to global and local features extraction approaches.

5.2. Future Work:

In the future work, the proposed system can be enhanced as follows:

- Face detection is important stage that affects the accuracy of the proposed system. In order to improves the accuracy of the proposed system, we highly recommend to choose a face detection technique that is more robust than Haar-Cascade.
- The accuracy of the proposed system can be improved by choosing different integration techniques.
- The accuracy can be also improved by using a different or improved classification techniques rather than ANN.

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Appendix I

MATLAB R2015a is used to implement the proposed system. The program code of the proposed system is as follows:

➢ Face Detection using Haar-Cascade program code:

```
function Out = Haar(I,FigV) %Detect objects using Viola-Jones Algorithm
[a,b,c]= size(I);
if c > 1
%%%%%%%%%%%%%%%%%% To detect Face
FDetect = vision.CascadeObjectDetector;
%Returns Bounding Box values based on number of objects
BB = step(FDetect,I);
Fout(BB,I,'Face Detection',FigV);
Pf(1)= BB(2);Pf(2)= BB(4)+BB(2);Pf(3)= BB(1);Pf(4)= BB(3)+ BB(1);
    %%%%% To detect Nose
    % vision.CascadeObjectDetector('Nose');
    NoseDetect = vision.CascadeObjectDetector('Nose','MergeThreshold',16);
    BB=step(NoseDetect,I(Pf(1):Pf(2),Pf(3):Pf(4)));
    BB(:,1) = BB(:,1) + Pf(3) ; BB(:,2) = BB(:,2) + Pf(1) ;
    [a,b,c] = size(BB); BB = BB(a,:);
    Fout(BB,I,'Nose Detection',FigV);
    Pn(1)= BB(2);Pn(2)= BB(4)+BB(2);Pn(3)= BB(1);Pn(4)= BB(3)+ BB(1);
    %%%% To detect Mouth
    MouthDetect = vision.CascadeObjectDetector('Mouth','MergeThreshold',16);
    BB=step(MouthDetect,I(Pf(1):Pf(2),Pf(3):Pf(4)));
    BB(:,1) = BB(:,1) + Pf(3) ; BB(:,2) = BB(:,2) + Pf(1) ;
    [a,b,c] = size(BB); BB = BB(a,:);
    Fout(BB,I,'Mouth Detection',FigV);
    Pm(1)= BB(2);Pm(2)= BB(4)+BB(2);Pm(3)= BB(1);Pm(4)= BB(3)+ BB(1);
    %%%%%%%%%%%%%%%%%% To detect Eyes
    EyeDetect = vision.CascadeObjectDetector('EyePairBig');
    BB=step(EyeDetect,I(Pf(1):Pf(2),Pf(3):Pf(4)));
    BB(:,1) = BB(:,1) + Pf(3) ; BB(:,2) = BB(:,2) + Pf(1) ;
    [a,b,c] = size(BB); BB = BB(a,:);
    Fout(BB,I,'Eyes Detection',FigV);
    Pe(1)= BB(2);Pe(2)= BB(4)+BB(2);Pe(3)= BB(1);Pe(4)= BB(3)+ BB(1);
    % Eyes=imcrop(I,BB);
    % figure,imshow(Eyes);
    Out.f = Pf;
    Out.m = Pm;
    Out.n = Pn;
```

```
    Out.e = Pe;
    else
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    To detect Face
    FDetect = vision.CascadeObjectDetector;
    %Returns Bounding Box values based on number of objects
    BB = step(FDetect,I);
    Fout(BB,I,'Face Detection',FigV);
    [a,b] = size(BB);
    if a
    Pf(1)= BB(2);Pf(2)= BB(4)+BB(2);Pf(3)= BB(1);Pf(4)= BB(3)+ BB(1);
    else
        Pf = [] ;
    end
    %%% To detect Nose
    % vision.CascadeObjectDetector('Nose');
    NoseDetect=vision.CascadeObjectDetector('Nose','MergeThreshold',16);
    BB=step(NoseDetect,I);
    [a,b,c] = size(BB);
    if a
        BB = BB(a,:); Fout(BB,I,'Nose Detection',FigV);
        Pn(1)= BB(2);Pn(2)= BB(4)+BB(2);Pn(3)= BB(1);Pn(4)= BB(3)+ BB(1);
    else
        Fout(BB,I,'Nose Detection',FigV);
        Pn = [] ;
    end
    %%%%%%%%%%%%%%%%%% To detect Mouth
    MouthDetect = vision.CascadeObjectDetector('Mouth','MergeThreshold',16);
    BB=step(MouthDetect,I);
    [a,b,c] = size(BB);
    if a
        BB = BB(a,:); Fout(BB,I,'Mouth Detection',FigV);
        Pm(1)= BB(2);Pm(2)= BB(4)+BB(2);Pm(3)= BB(1);Pm(4)= BB(3)+ BB(1);
    else
        Fout(BB,I,'Mouth Detection',FigV);
        Pm = [] ;
    end
    %%%%%%%%%%%%%%%%%% To detect Eyes
    EyeDetect = vision.CascadeObjectDetector('EyePairBig');
    BB=step(EyeDetect,I);
    [a,b,c] = size(BB);
    if a
         BB = BB(a,:);Fout(BB,I,'Eyes Detection',FigV);
         Pe(1)= BB(2);Pe(2)= BB(4)+BB(2);Pe(3)= BB(1);Pe(4)= BB(3)+ BB(1);
    else
         Fout(BB,I,'Eyes Detection',FigV);
         Pe = [] ;
    end
```

```
% Eyes=imcrop(I,BB);
% figure,imshow(Eyes);
Out.f = Pf;
Out.m = Pm;
Out.n = Pn;
Out.e = Pe;
end
end
function Fout(BB,I,T,FigV)
if FigV
figure('Name','HAAR-Cascade');imshow(I); hold on
for i = 1:size(BB,1)
 rectangle('Position',BB(i,:),'LineWidth',4,'LineStyle','-','EdgeColor','r')
end
title(T);hold off;
end
end
```

- Histogram Equalization program code:

```
function HIm = Histogram(A,FigV)
[a,b,c] = size(A) ;
if c > 1
    A = rgb2gray(A);
end

%Specify the bin range[0 255]
bin=255;
%Find the histogram of the image.
Val=reshape(A,[],1);
Val=double(Val);
I=hist(Val,0:bin);
%Divide the result by number of pixels
Output=I/numel(A);
%Calculate the Cumulative sum
CSum=cumsum(Output);
%Perform the transformation S=T(R) where S and R in the range [ 0 1]
HIm=CSum(A+1);
%Convert the image into uint8
HIm=uint8(HIm*bin);

if FigV
    %figure('Name','Histogram'),imshow(A);
    figure('Name','Histogram'),imshow(HIm);
end

End
```

- Features Extraction using Principle Component Analysis program code:

```
function Out = PCA(I,FigV)
[a,b,c] = size(I) ;
if c > 1
    Data_gray = rgb2gray(I);
else
    Data_gray = I;
end
Data_grayD = im2double(Data_gray);
if FigV
        figure,
        set(gcf,'numbertitle','off','name','Grayscale Image'),
        imshow(Data_grayD)
    end
    Data_mean = mean(Data_grayD);
    [a b] = size(Data_gray);
    Data_meanNew = repmat(Data_mean,a,1);
    DataAdjust = Data_grayD - Data_meanNew;
    cov_data = cov(DataAdjust);
    [V, D] = eig(cov_data);
    V_trans = transpose(V);
    DataAdjust_trans = transpose(DataAdjust);
    FinalData = V_trans * DataAdjust_trans;
    % Start of Inverse PCA code,
    OriginalData_trans = inv(V_trans) * FinalData;
    OriginalData = transpose(OriginalData_trans) + Data_meanNew;
    if FigV
        figure,
        set(gcf,'numbertitle','off','name','RecoveredImage'),
        imshow(OriginalData)
    end
    % End of Inverse PCA code
    Out = OriginalData;
    End
```

- Features Extraction using Local Binary Pattern program code:

```
function Im = LBP(Input_Im, R,FigV)
if size(Input_Im, 3) == 3
    Input_Im = rgb2gray(Input_Im);
end;
L = 2*R + 1; %% The size of the LBP label
C = round(L/2);
Input_Im = uint8(Input_Im);
row_max  = size(Input_Im,1)-L+1;
col_max  = size(Input_Im,2)-L+1;
    Im        = zeros(row_max, col_max);
    for i = 1:row_max
        for j = 1:col_max
```

```
            A = Input_Im(i:i+L-1, j:j+L-1);
            A = A+1-A(C,C);
            A(A>0) = 1;
            Im(i,j) = A(C,L) + A(L,L)*2 + A(L,C)*4 + A(L,1)*8
 + ...
                A(C,1)*16 + A(1,1)*32 + A(1,C)*64 +
 A(1,L)*128;
        end;
    end;
    if FigV
        figure('Name','LBP') ; imshow(Im) ;
    end
    end
```

- Frequency partition Program code:

```
function[imf] = fpdctf(im1,im2,f)
% Freqency partition 1D DCT based image fusion
% Developed by : VPS Naidu, MSDF Lab

imfr = mrdctif(im1,im2,f);
imfc = mrdctif(im1',im2',f)';
imf = 0.5*(imfr+imfc);

function[imf] = mrdctif(im1,im2,f)
    [m,n] = size(im1);
    f = round(m*n*f);
    mr1 = mrdct(im1,m,n);
    mr2 = mrdct(im2,m,n);
    D = (abs(mr1)-abs(mr2)) >= 0;
    IMFR = D.*mr1 + (~D).*mr2;
    IMFR(1:f) = 0.5*(mr1(1:f)+mr2(1:f));
    imf = imrdct(IMFR,m,n);

    function[IMR] = mrdct(im,m,n)
    mn = m*n;
    R = im;
    R(2:2:end,:)=R(2:2:end,end:-1:1);
    R = reshape(R',1,m*n);
    IMR = dct(R,mn);

    function[R] = imrdct(R,m,n)
    mn = m*n;
    imhr = idct(R,mn);
    R = reshape(imhr,n,m)';
    R(2:2:end,:)=R(2:2:end,end:-1:1);
```

- Neural Network Program code:

```
function Out = NN_test(I,My_test)

%clear memory
%clear all
%clc
%%%%load('MData.mat')
```

```
%%%I = MData.I;%%% the real image with gray scale
nump=40;  % number of classes
n=10;     % number of images per class
      % training images
      %%%% the length of each image 10304
      P=[] ;
      for i = 1 : length(I)
          var = I{i};
          var = var(:)';
          P=[P ; var];
      end
      P = P'; % with size of 10304 × 400
      % testing images
      N = [] ;
      for i = 1 : length(I)
          N = [ N ; My_test(:)'] ;
      end
      N = N';
      % Normalization
      P=P/256;
      N=N/256;
      P=double(P);
      N=double(N);
      % display the training images
      % targets
      T = zeros(40,400);
      for i = 1 : 40
      for j = 1 : 10
      T(i,(((i-1)*10) +j)) = 1 ;
      end
      end
      %%%%T size 40 × 400
      %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
      S1=5;    % numbe of hidden layers 5
      S2=40;   % number of output layers (= number of classes)3

      [R,Q]=size(P);        % 10304 × 400
      epochs = 10000;       % number of iterations
      goal_err = 10e-5;     % goal error
      a=0.1;               % define the range of random variables
      b=-0.1;

      W1=a + (b-a) *rand(S1,R);     % 5 × 10304 Weights between Input and Hidden Neurons
      W2=a + (b-a) *rand(S2,S1);    % 40 × 5    Weights between Hidden and Output Neurons
      b1=a + (b-a) *rand(S1,1);     % 5 × 1     Weights between Input and Hidden Neurons
      b2=a + (b-a) *rand(S2,1);     % 40 × 1    Weights between Hidden and Output Neurons

      n1=W1*P;                      %  (5 × 10304) × (10304 × 400) = 5 × 400
```

```
    A1=logsig(n1);                % 5 × 400
    n2=W2*A1;                     % (40 × 5) × (5 × 400) = 40 × 400
    A2=logsig(n2);                % 40 × 400
    e=A2-T;                       % 40 × 400
    error =0.5* mean(mean(e.*e)); % 40 × 400
    nntwarn off
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    for  itr =1:epochs            % 10000
        if error <= goal_err
            break
        else
            for i=1:Q             % 400
                df1=dlogsig(n1,A1(:,i));    % 5 × 400
                df2=dlogsig(n2,A2(:,i));    % 40 × 400
                s2 = -2*diag(df2) * e(:,i);% (40 × 40) × (40 × 1) = 40 × 1
                s1 = diag(df1)* (W2'* s2); % (5 × 5) × (5 × 40)×(40 × 1)= 5 × 1
                W2 = W2- (0.1 * s2 * A1(:,i)');% (40 × 5) - (40 × 1)×(1 × 5)= 40 × 5
                b2 = b2-0.1*s2;             % (40 × 1)- (40 × 1)= 40 × 1
                W1 = W1- (0.1 * s1 * P(:,i)');% (5 × 10304) - (5 × 1)×(1 × 10304)= 5 × 10304
                b1 = b1-0.1*s1;             % (5 × 1)-(5 × 1)= 5 × 1
                A1(:,i)=logsig(W1*P(:,i),b1);% (5 × 10304)×(10304 × 1)= 5 × 1
                A2(:,i)=logsig(W2*A1(:,i),b2);% =40 × 1
            end
                e = T - A2;                  % (40 × 400) - (40 × 400)= 40 × 400
                error =0.5*mean(mean(e.*e)); %= 40 × 400
                % disp(sprintf('Iteration :%5d        mse :%12.6f%',itr,error));
                mse(itr)=error;
        end
    end
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %%%%%  N , W1, W2, T , mse

    threshold=0.9;   % threshold of the system (higher threshold = more accuracy)

    % training images result

    %TrnOutput=real(A2)
    TrnOutput=real(A2>threshold)
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    % applying test images to NN
    n1=W1*N;          % (5 × 10304)×(10304 × 400) = 5 × 400 >>> N = (10304 × 400)
```

```
A1=logsig(n1);      %  = 5 × 400
n2=W2*A1;           %  = 40 × 400
Astest=logsig(n2); %  = 40 × 400

Out = find(max(Astest)== Astest);
% testing images result
figure ; imshow(uint8(A2));
figure ; imshow(uint8(A1));
figure ; imshow(uint8(A2test));
%TstOutput=real(A2test)
TstOutput=real(Astest>threshold)
% recognition rate
wrong=size(find(TstOutput-T),1);
recognition rate=100*(size(N,2)-wrong)/size(N,2)
```