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عنوان الرسالة: Evaluation of Automatic Human Identification Algorithms Using Facial Features

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EVALUATION OF AUTOMATIC HUMAN IDENTIFICATION ALGORITHMS USING FACIAL FEATURES

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This Thesis was Submitted in Partial Fulfillment of the Requirements for the Master's Degree of Computer Science

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DEDICATION

To my beloved parents

who have never failed to give me their support

and encouragement all the way since the beginning

of my studies

To my family and best friends

who were a continuous and great source of

inspiration and motivation

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LIST OF ABBREVIATIONS

Abbreviation	Expression
AI	Artificial Intelligence
AMP	Advanced Multimedia Processing
DWT	Discrete Wavelet Transform
FR	Face Recognition
GA	Genetic Algorithm
JAFFE	Japanese Female Facial Expressions
PCA	Principle Component Analysis
SVM	Support Vector Machines

EVALUATION OF AUTOMATIC HUMAN IDENTIFICATION ALGORITHMS USING FACIAL FEATURES

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ABSTRACT

Recently, the use of human physiological characteristics for identification and verification purposes has gained an increasing interest. These so called "Biometric" techniques for human identification have proved to outperform the original classic methods such as signatures or passwords which can be easily lost, forgotten or even forged by others.

Among the various biometric techniques used for human identification such as iris, retina scan and hand recognition; Face Recognition (FR) has a major advantage of being non-intrusive and not requiring users' collaboration. It gives a quite accurate recognition results although it is simple to implement and its cost is even less than other biometric techniques.

FR algorithms generally consist of three main steps. The first step is the automatic detection of the human face from the background. After that, a set of discriminating facial features must be extracted from the face. Finally, a new unknown face image is recognized using a classifier that matches the image features set with features of other images stored in an existing database of known human images.

A lot of techniques exist to address the problem of features extraction; some of these techniques utilize the whole face to extract a distinguishing set of features, while others use only parts of the face in order to reduce the amount of information involved in the recognition process.

During the features extraction step, one of the issues that needs to be considered is to balance between including the face's most discriminating features while avoiding the need to store a huge amount of information in the database.

In this research a comparative study is provided to show that not all facial features extracted from a human face can have a positive effect on the recognition rate achieved. A comparison between the use of all features set extracted from a face against using Genetic Algorithms (GA) for selecting only a subset of the whole features is provided. The study shows how selecting a features subset strongly outperforms the use of the whole features.

In light of the previous study, knowing that not all facial features are effective in FR, a FR technique is proposed in this research to conduct a set of experiments for testing the performance of FR algorithms once on the whole face and another time on a small part of the face containing only the eyes.

The proposed FR algorithm combines the power of Wavelet transforms for representing human faces, with the simplicity of the Average Intensity method used for extracting facial features. Three datasets were used for experiments extracted from JAFFE and AMP databases. It was found that using the proposed FR algorithm and depending solely on the eyes for recognizing human faces can significantly reduce the amount of information needed in the recognition process while preserving a very good recognition rate that ranged from 94% up to 100% on the experienced datasets.

1. INTRODUCTION

This chapter describes the motivation behind this research. The problem being investigated as well as the contributions gained from the study are also discussed. After that, the methodologies used in this research are listed. And finally, the chapter ends with the thesis organization.

1.1 Motivation

In the past two decades the trend towards human authentication using biometric techniques has gained increasing attention. A lot of systems depending on iris, fingerprint, hand or face for human identification purposes have been developed so far, each of them having its own advantages and disadvantages.

Biometric characteristics of humans are different from classical identification methods such as passwords, PIN (Personal Identification Number) numbers and smart cards in that they are unique and they cannot be transferred, lost, stolen or broken. Although they all share these common characteristics, still there are certain variations between them in terms of user acceptance, degree of security, accuracy, cost and time; giving advantage to some of them over the others (Ramesha et al., 2009).

Face Recognition (FR) provides a preferable choice over other biometric authentication techniques in many applications. The advantages of FR techniques lie in their ease of use, low cost and most importantly their non-intrusiveness. Although other biometrics such as iris, retina scan and fingerprint can provide more accurate recognition results, they are complex and require users' collaboration which makes them unsuitable for all applications (Akarun et al., 2005).

For the many advantages of FR techniques, they have been used in a variety of applications starting from entertainment and ending with law enforcement and surveillance systems. The use of FR can be divided into two categories: commercial and law enforcement applications. Commercially, FR is used for static matching of photographs on credit cards, ATM cards, passports and driver's licenses, as well as for access control in still or video images. In law enforcement field, FR is used for mug shots albums (static matching) and video surveillance (Pal et al., 2004).

1.2 Problem Statement

FR is a biometric technique that aims to identify/verify humans based on their facial features. It has a wide variety of applications in real life especially in systems that require security and access control.

In order to identify a human face image from an existing set of images stored in a database, three steps are required: first, the face in the image must be accurately detected from the background. Second, the discriminating features of the face must be extracted. Finally, the recognition decision is made using a classifier that matches between the features of the new face image and the features of the already existing images in the database.

Among the previous three steps, facial features extraction has its significant effect on the performance and accuracy of any FR system. In this step, the face must be represented as a set of features that can accurately distinguish different people as well as variations of the same person due to inconsistent lighting conditions or facial expressions and other factors.

A lot of techniques exist to address the problem of features extraction; some of these techniques exploit the whole face to extract a distinguishing set of features, while others use only parts of the face trying to reduce the amount of information involved in the recognition process.

Including the face's most discriminating features while reducing the amount of information that must be extracted and stored in the database, is still an insisting need in FR systems. This balance between the amount of information exploited and the FR accuracy will provide a compromised solution to achieve both reliability and low cost in terms of memory and computations. These two factors are vital to many real-time applications where an accurate yet fast decision needs to be made.

1.3 Contributions

A lot of FR techniques have been proposed in the last two decades, each new technique tries to address a certain challenge in the FR problem or to compensate for the deficiencies existing in the previously proposed algorithms. However; despite the huge number of FR techniques available, there is still a need for a robust FR system that can give accurate results taking into consideration the variations of human faces, while keeping computational complexity and memory requirements as minimum as possible to fit in current real time applications.

In this research a FR algorithm is proposed for conducting several experiments on different datasets in an effort to prove that not all facial features extracted from a human face can have a positive effect on the recognition results. In each one of the experiments a comparison between the use of all features set against using Genetic Algorithms (GAs) for selecting a subset of the whole features in the recognition process is provided. The results clearly show that the use of the whole features reduces the accuracy of the FR algorithm being evaluated.

Additionally, knowing that using only a subset of features from a human face can enhance FR performance, another set of experiments were conducted using the proposed FR algorithm but this time using only the two eyes as input rather than the whole face.

The main reason for choosing the eyes is that they are considered a valuable discriminating region in the human face. Studies show that even humans rely on eyes on the first place for recognizing each other's faces. Another reason for using the eyes is that they are quite robust to facial expressions variations and they are unaffected by the existence of facial hair such as a beard or mustaches.

The proposed FR algorithm exploits Wavelet Transforms for multi-resolution data analysis, with the simple Average Intensity feature extraction method provided by (Fan and Verma, 2009). It was found that using the proposed FR algorithm and depending solely on the eyes for recognizing human faces can significantly reduce the amount of information needed in the recognition process, while preserving a very good recognition rate. This reduction in the amount of information consequently leads to less costing FR systems.

Despite the existence of various facial expressions for people in the tested databases, a very good recognition rate was achieved that ranged from 94% and up to 100% compared to the small number of features needed to achieve such rate in the three datasets used in the experiments.

1.4 Research Methodology

1. Studying FR as one of the biometric methods recently used for human identification and verification.
2. Studying the need for automatic FR and its applications in different life aspects especially those involving security and access control.
3. Building a strong background in different FR techniques.
4. Investigating the current categories of FR algorithms.
5. Defining the problems and challenges currently facing the existing FR techniques.
6. Collecting related information about the problem and organizing them in a scientific manner.
7. Implementing and executing the algorithm used in the evaluation using MATLAB.
8. Studying and analyzing the results and comparing them with related works.
9. Writing and documenting this research including the entire previous steps combined with the results.

1.5 Thesis Organization

The rest of this thesis is organized as follows: Chapter 2 presents the literature review; a background about FR systems, their problems and challenges, and their types are provided with the listing of the important techniques proposed in the literature so far. The proposed system is discussed in details in Chapter 3. All the experiments and the datasets used in these experiments are discussed in Chapter 4 with the recognition results obtained from each of these experiments. Finally, a conclusion is drawn in Chapter 5 together with the future work.

2. Literature Review

This chapter consists of two main sections which are the background and the related works. The background section provides a general knowledge about FR systems while the related works section lists the most well known algorithms in this field.

2.1 Background

In this section, a background about FR is provided with a brief discussion related to the current problems and challenges facing FR systems. Additionally, the steps of most FR algorithms are explained. And finally, the section describes the classification of FR techniques existing in the literature.

2.1.1 Face Recognition

FR is one of the biometric techniques used for automatic human identification based on physiological characteristics. During the last two decades it has been an active research area that has many important applications in surveillance systems, bank card systems, security monitoring and many others (Young and Rhee 2008).

A FR system is a computer application that is concerned in automatically identifying or verifying humans from their faces in still images or video frames. It is a branch of a more general topic called "Biometrics" in which humans are identified using characteristics such as iris, DNA, face or fingerprints (Nagamalla and Dhara, 2009).

Recognizing people based on biometrics is an interesting approach that can be efficiently used in applications that require security or access control. Such approaches eliminate the risk of depending on what a person has or know instead of who he really is. However; biometrics have some disadvantages; for example, the iris can give highly accurate recognition rates but unfortunately it is complex when implemented and it is not very acceptable by people. Fingerprint also gives accurate recognitions rates although it is hard to use with non-collaborative people (Abate et. al, 2007).

Being non-intrusive, the use of human faces in the recognition process is considered a compromise between achieving recognition reliability while being socially accepted. Table 1 shows some of the important applications of FR (Zhao et al., 2003).

Table 1: FR applications

Areas	Specific applications
Entertainment	Video game, virtual reality, training programs
	Human-robot-interaction, human-computer-interaction
Smart cards	Drivers' licenses, entitlement programs
	Immigration, national ID, passports, voter registration
Information security	TV Parental control, personal device logon, desktop logon
	Application security, database security
	Intranet security, Internet access, medical records
	Secure trading terminals
Law enforcement and surveillance	Advanced video surveillance, CCTV control
	Portal control, post event analysis
	Shoplifting, suspect tracking and investigation

There are two modes in which a FR system can operate: it is either required to do a one-to-one match between a test image and a database image of claimed identity (in which case is called a face verification or authentication system). Or it is required to do a one-to-many match between a test image and database images from which the test image must be identified (Nagamalla and Dhara, 2009). The latter mode is knows as face identification or recognition system and is the main focus in this research.

2.1.2 Challenges and Problems

While humans can easily recognize faces, it is considered a nontrivial task for computers. The FR problem has been widely explored by researchers along the last years. However; it still has many difficulties. Some of the factors that make the recognition process a big challenge for computers are the variations in illumination, face poses and facial expressions (Bours and Helkala, 2008). Other problems such as natural aging or the existence of some items such as wearing a hat or facial hair can cause variations in people's faces making it harder to accurately identify them (Chellappa et al., 2010).

Illumination variations can happen due to changes in lighting during the day or between indoor and outdoor environments. A lighting source directed to a face can cause shadowing effects that may result in unclear facial features in the facial image. Studies for techniques based on Principle Component Analysis (PCA) show that the variations in a human face appearance due to illumination can be more than the differences between distinct individuals (Abate et al., 2007).

Variations in poses can also be a problem in FR systems because it is hard to control the imaging direction of the face when acquiring images. The problem becomes how to handle the appearance variations of human faces due to variations in viewing directions (NG, 2006).

Human faces vary significantly over long periods of time which makes it harder to recognize them. This problem occurs when a considerable amount of time passes between the training and testing images. Hence, if the FR mechanism will not take these variations into consideration the solution would be to update the images gallery in the existing databases or to retrain the system periodically which is not practically applicable in most applications (Abate et al., 2007).

Finally, facial expressions variations can lead to a great drop in the performance of a FR algorithm. Most to date algorithms focus on pose and illumination while less effort exists for solving facial expressions variations (Hsieh et al., 2010). The focus in this research is on the role of eyes as discriminating features of humans despite the existence of facial expressions variations.

2.1.3 Face Recognition Steps

FR is considered a supervised pattern recognition problem. Given a set of M previously known classes and a new example, the problem is to label this new example as either belonging to one of the M classes or not to any of them at all. When a new example is received, some measurements known as features are extracted out of it and then fed into the pattern recognition machine known as the classifier (Ripley, 1996).

Most of FR algorithms mainly consist of three steps (see Figure 1). The first step is to allocate the human face from the background of an image. A huge number of face detection techniques has been introduced in the literature, however; this problem is beyond the scope of this research as the main concern here is in the second and third steps of FR.

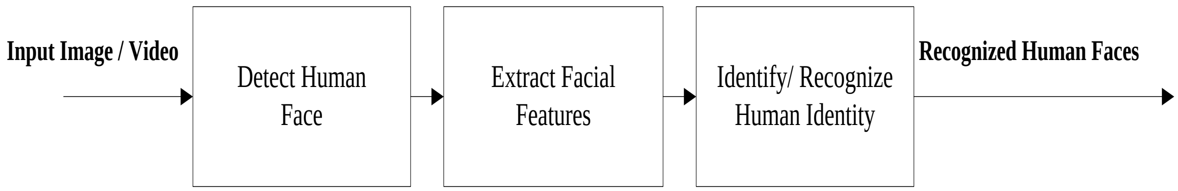


Figure 1: General FR system steps

After detecting the face, a feature extraction method is used to select the most discriminating features in the face. The accuracy of the FR algorithm is highly dependent on the method used for extracting the features. Different FR approaches require different feature extraction methods.

Finally, a classification method is used to identify or recognize humans based on the features extracted from their faces. A wide variety of classifiers are currently used for FR, they range from simple distance functions such as Euclidean distance to a more complicated Artificial Intelligence (AI) techniques such as neural networks or GAs.

2.1.4 Types of Face Recognition Techniques

During the past 30 years, a huge number of FR systems have been proposed. A lot of these systems combine multiple techniques motivated by different principles rather than depending on a single one. This mixture of techniques makes it hard to classify these systems according to the types of techniques they use. A clear classification can be obtained following what psychological research suggest about how humans recognize faces using holistic or local features (Zhao et al., 2003).

The holistic FR techniques use statistical methods taking the whole images in the training set rather than separate features to extract statistical characterizations of facial images (Wei et al., 2009).

Holistic techniques are also known as template matching. They have many forms; the simplest among them is to compare a single template representing the whole face with the face image that is considered a bi-dimensional intensity values array. The comparison is performed based on some metric such as Euclidean distance. More complicated template matching techniques also exist to recognize faces from different viewpoints like using several full templates for each face or even using several templates for each viewpoint (Brunelli and Poggio, 1993).

Feature-based approaches depend on local features. It includes methods where facial features such as eyes, mouth and nose, are located in the face and then extracted from the image. After locating these features, various extraction methods can be used to get the vectors representing these facial features (Wei et al., 2009). Depending on local features make the recognition process less affected by illumination and viewpoint variations, as well as inaccuracy in localizing the face (Zhao et al., 2003).

Each of the previously mentioned approaches has its own advantages and disadvantages as shown in Table 2 (Lu, 2003). Accordingly, some researchers add the hybrid methods in a third category. Just the way our brains recognize faces depending on the whole region of the face as well as on local features, these methods combine both holistic and feature-based techniques in the recognition process (Zhao et al., 2003).

Table 2: Advantages and disadvantages for holistic and feature-based methods

	Holistic approach	Feature-based approach
Advantages	1. FR problem can be transformed to a face space analysis problem where statistical methods can be used. 2. Good to use in situations where low resolution images with poor quality exist.	1. This approach has actual physical relationship with real faces. 2. Face variations due to illumination, pose or expressions can be handled using explicit modelling for each of these variations. 3. Prior human knowledge can be integrated.
Disadvantages	1. To sample the underlying distribution successfully, sufficient representative data must be available. 2. Prior knowledge about human faces cannot be utilized. 3. Significantly affected with facial variations such as illumination, pose and facial expressions.	1. Facial features exact positions are hard to be automatically extracted with robustness. 2. A good quality images with relatively high resolution are needed.

2.2 Related Works

This section lists the most important FR algorithms reported in the literature including techniques exploiting only parts of the face as well as some of the techniques that use AI principles and Wavelet Transforms.

2.2.1 Face Recognition Techniques

Many FR techniques that come under the classifications mentioned in Section 2.1.4 have been developed so far. Among the most known holistic FR techniques is the "eigenfaces" method (Turk and Pentland, 1991). The authors proposed what is called "eigenfaces" which are small images representing the characteristics feature of the original image. Their approach is based on the PCA.

The eigenfaces are used as the component analysis of the facial images initial training sets. A new image is projected into the subspace spanned by the eigenfaces then a comparison between the position of the face in the face space and the positions of known individuals is performed.

Another technique proposed by (Belhumeur et al., 1997) is called Fisherfaces. It is based on the Fisher's Linear Discriminant. This technique compared with the eigenfaces proved to have a lower error rate while they both aim to project the image space into a low-dimensional subspace. Fisherfaces technique performs well under illumination and facial expressions variations.

Support Vector Machines (SVM) were applied to FR in (Phillips, 1998). SVMs are binary classification methods that are used to solve the problem of classical two classes pattern recognition. The authors represented FR as a two classes problem; they used two classes as the input for the SVMs: the first class represents the dissimilarities between images of the same person while the second class represents the dissimilarities between different people images. The experimental results showed that the human identification rates are better than those rates given by the PCA techniques.

Many efforts have been made for improving the performance of holistic FR techniques. Tenllado et al. (2010) studied the effect of combining scores from two different classifiers; one that uses a holistic technique on natural human face images, and the other applies the same holistic technique on the Gabor representation of the image. The results showed an improvement of at least 10% in all tested methods.

Another holistic technique proposed by (Chitaliya and Trivedi, 2010) depends on two dimensional discrete wavelet sub band spaces and Eigen vectors. Wavelet decomposition is applied to the whole face image resulting in four subbands coefficients representing the average, horizontal, vertical and diagonal information. PCA method is then used for dimensionality reduction of the previously obtained data and for selecting the most representative features of the features set.

Feature-based methods have also gained a great interest from researchers. One of the very successful systems in this category is the Elastic Bunch Graph Matching (EBGM) system (Wiskott et al., 1997). In this system, the authors used an object adapted graph whose nodes represent special landmarks in the face called fiducial points. Using this technique a correct match between two faces can still be found despite the existence of variations in the viewpoint.

Fan and Verma (2009) proposed a feature-based FR method which extracted four sub images from each facial image. These images contain the two eyes, mouth and nose. They divided each of the four images into small blocks and calculated the Average Intensity values for each block. A final feature vector representing features from all sub images is created by concatenating the feature vectors of each one.. Their technique achieved a very good classification rate of 94%.

Hybrid FR techniques combine both holistic and local features of human faces for better FR performance. Pentland et al. (1994) extended the eigenface technique to the coding of facial features which results in eigeneyes, eigennose and eigenmouth. Their technique provided a layered representation of the face where the low-resolution description of the whole face is supported with further higher-resolution details provided by facial features. This combination of information from the whole face as well as from distinct facial features outperformed the use of the whole face or the facial features separately.

Kwak and Pedrycz (2005) also used a hybrid technique for FR, in which the results of two different classifiers were combined. The first classifier is template based (global face), while the other is feature based where local features such as eyes, nose and mouth are extracted and used. The proposed method also gave better performance when combining both approaches rather than using either the whole face or the extracted features.

Similarly, Zhou et al. (2006) proposed a hybrid method to increase the accuracy of FR constrained by various conditions. In their method, the authors divided each facial image into small sub-images containing the eyes and nose facial features. After that, the Discrete Cosine Transform (DCT) was applied on the whole image as well as on the small features images to obtain holistic and local features. Their technique proved to outperform classical FR techniques such as Eigenfaces and Fisherfaces.

2.2.2 Using AI Techniques in Face Recognition

The field of AI has been intensively exploited in the FR algorithms. Researchers have developed a great number of FR algorithms where one or more AI techniques were used either for features extraction or classification. GAs, Neural Networks, fuzzy logic and many other AI techniques are found to be useful for improving the performance of FR algorithms.

Lin and Wu (1999) used GA for solving one of the most complex tasks of features extraction which is the template matching. The complexity of feature templates lies in their use in calculating the matching value of every possible feature point in a facial region. A GA was adopted to solve the problem of template matching as a fast search algorithm instead of evaluating all pixels in a facial region trying to find the best among them. Using GA, a good performance of template matching is achieved in terms of matching error and speed.

Another technique where GA is used in template matching problems is proposed by Yen and Nithianandan (2002). To extract the facial features using features templates, the authors proposed to use GA in the context of finding the global maximum point where the facial feature is best matched with the template. The template that achieved the best fitness in terms of its density is selected as the best template for the facial feature.

Besides feature extraction, GA can be used for classification. Anam et al. (2009) used GA after extracting the set of features. The recognition of a new unknown face image is done using GA by comparing the pattern of the extracted features from the new image with the pattern of an already built image module. The authors also used Neural Networks for the same purpose as GA to compare their performance. However; this time the extracted features were fed into a multilayer Neural Networks instead of GA to create a knowledge base that will be used for recognition. Their experiments showed that Neural Networks gave a better recognition results when used in the same context as GA for classification.

Neural Networks were also intensively used in the field of FR. (Haddadnia and Ahmadi, 2004) used radial basis function (RBF) neural networks classifier with different learning algorithms seeking to build a FR system with high accuracy. The RBF neural network is built in the unsupervised learning phase of the algorithm using clustering techniques including k-mean clustering, fuzzy clustering and iterative optimization.

Other techniques which are based on the combination of fuzzy logic with neural networks are also used in FR. Neagoe and Iatan (2002) introduced a neuro-fuzzy FR classifier called Fuzzy-Gaussian Neural Network (FGNN). Their approach depends on extracting the facial features using either PCA or Discrete Cosine Transform (DCT) and then using the FGNN for pattern classification.

2.2.3 Using Parts of the Face for Face Recognition

Another important type of FR research has been investigated which adopts the idea of involving only parts of the face for FR instead of depending the whole face. The idea is to build reliable yet fast FR system, especially in real-time applications and other applications constrained by memory and time requirements. Surprisingly, some of those proposed algorithms outperformed the ones involving the whole face.

Harguess and Aggarwal (2009) studied the effect of using the average half face as an input to some of the existing famous FR techniques. Based on the fact that human faces are roughly symmetric, the images are centered around the nose and then they are divided into two right and left parts which are averaged together. The study shows that in most of the tested FR techniques, using the average half face gives more accurate recognition rate than using the whole face.

Another FR techniques use the eyes for FR. Quintiliano and Santa-Rosa (2003), applied the Eigenfaces method on the part of the face that contains only one of the two eyes. The maximum recognition rate achieved was 87.5% when the number of Eigenfaces used was 50, whereas the whole face achieved a 98.3% recognition rate using 30 Eigenfaces.

2.2.4 Using Wavelet Transforms in Face Recognition

Wavelet transforms have been widely used in analyzing data in multi-resolutions. Many methods have been introduced that take the advantages of wavelets to build FR techniques with better performance. Garcia et al. (2000) used wavelet packet decomposition in a new FR algorithm. They created several band filtered images from the original image, each of which containing a wavelet coefficient. These wavelet coefficients describing the texture of the face are used to create a feature vector which is then used in the recognition process. Depending on the facts conducted from the psycho-visual research that humans use multi-scale way to analyze images, multi-resolution analysis of images using wavelet decomposition are proven to be efficient in analyzing texture features of the face.

The algorithm is a generalization of the classic wavelet decomposition. While in classical wavelet decomposition each image is decomposed into one approximation image created by a low pass filter and another three details images obtained by bandpass filtering in one of the three directions (horizontal, vertical and diagonal), this algorithm further splits the approximation and details images providing a richer details analysis over the classic wavelets.

Also, Lai et al. (2001) used both wavelet transform and Fourier transform in a new holistic face representation method named spectroface that handles the alignment limitation of face-based methods.

Li and Liu (2002) introduced a method for face recognition that combines eigenfces with wavelets. The authors used wavelet multi-resolution decomposition where images are decomposed into several components, basically approximation and details components, each of which is separately studied. Image approximations are constructed using scaling functions while wavelets are used for constructing details components of the image in vertical, horizontal and diagonal directions. In this algorithm, three approximations of each image are created and the vectors of these approximations are combined to form a single vector used to create the eigenfaces.

The experiments showed that the use of wavelet decomposition to create several approximations and details components of the image has provided a better and more consistent performance than the original eigenfaces method where wavelets were not used.

Kinage and Bhirud (2009) proposed a new technique for FR that applies 2D PCA on wavelets subbands. In their proposed technique the authors decomposed the face images in subbands one to eight to extract the features. They repeated the same experiments using different wavelet transforms (Haar, Daubechies, Coiflet, Symlet and Biothogona). 2D PCA were used to analyze the wavelet features. The experiments showed that third level wavelets gave the most accurate results, and Symlet 7 wavelet transform was found to be the best of the transforms giving 95% recognition rate on the tested database.

3. Proposed Work

FR is considered one of the very important biometric-based methods used for automatic human identification and verification. Due to its significant importance and its various applications in real life, a FR algorithm is proposed and evaluated in this research to show how selecting a suitable subset from the whole set of facial features can dramatically affect the performance of FR systems. Furthermore, experiments on different datasets of human face images were conducted to prove that some facial regions such as the eyes regions contain the most discriminating features that can alone give a high recognition rate while reducing the amount of memory and computations needed in such huge operations.

The main objective of this research is to emphasize the fact that not all facial features have the same effect in discriminating human faces. On the contrary, some features might negatively affect the recognition process giving bad classification results. For this reason, the proposed FR technique is evaluated to compare between its performance using the whole set of facial features against its performance when GA is used to select a subset of facial features for identifying human faces. The results show that a subset of features strongly outperforms the whole features set.

Based on the fact that not all facial features are good to use in FR, it was concluded that some small parts of the face might be sufficient to be used alone in recognizing human faces.

Depending on a small part of the face to obtain good recognition results is helpful in many ways; first of all, it reduces the amount of information needed to be stored about each image in the database. Consequently, the cost needed to recognize a new human face in terms of memory and computations is reduced. Also, as FR is considered a non-intrusive technique, it is not always guaranteed that a full view of the human face is available, so it would be helpful if a good recognition rate can be achieved using only small parts.

In this research the eyes were chosen to test the performance of the proposed FR algorithm on a small part of the face. Choosing the eyes was due to many reasons; first of all, they are considered among the very discriminating features of humans. A lot of FR techniques are inspired by the actual FR in humans' brains, and in a recent study, it was revealed that our brains extract the needed information for FR mainly from the eyes and then from the mouth and nose (Public Library of Science, 2009).

Another reason for using the eyes is that they are quite robust to facial expressions variations and they are unaffected by the existence of special hair such as a beard or mustaches (Rajagopalan et al., 2006).

The proposed FR algorithm combines the use of Wavelet Transforms for decomposing facial images, with the Average Intensity feature extraction method proposed by (Fan and Verma, 2009). Wavelet Transforms are very powerful tools for analyzing data and signals in multi-resolutions, and they proved to enhance many FR techniques. Additionally, the Average Intensity feature extraction method is very simple and can provide a very good recognition rate. Figure 2 illustrates the steps followed in the evaluation, with each of them being explored in more details in the following subsections of this chapter.

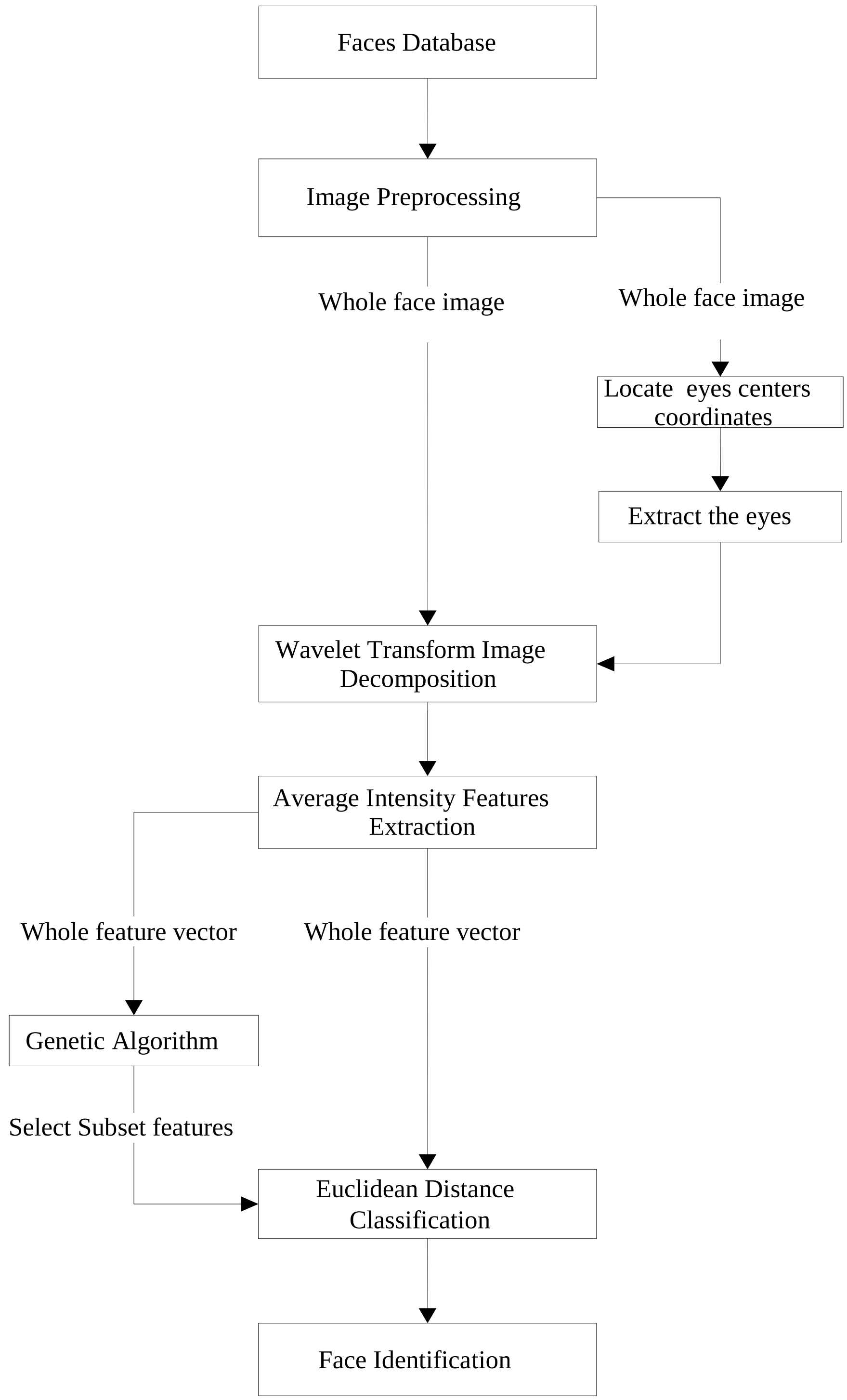


Figure 2: Evaluation steps

This chapter is organized as follows: Section 3.1 illustrates the preprocessing operations applied to images before running the experiments. Section 3.2 describes the steps needed to extract the eyes regions from a human facial image. In Section 3.3 the use of Discrete Wavelet Transform is discussed. The Average Grey Level Intensity method used for features extraction is described in Section 3.4 and the use of GAs to select the best subset of the extracted features is described in Section 3.5. Finally, Section 3.6 discusses the classification which is the last step in any FR system.

3.1 Images Preprocessing

Preparing images before using them in any image processing application is a very important step. Choosing the best technique that suits the set of images used can significantly affect the results achieved. Accordingly, pre-processing the images before applying FR algorithms is considered one of the main steps.

In this research, two different pre-processing steps were used for enhancing the recognition results; one of them is image smoothing and the other is histogram equalization.

3.1.1 Image Smoothing

There are a lot of techniques used for smoothing images; one of the simplest among them is to smooth images using an averaging filter (Zeb et al., 2007). In this operation, each pixel value in the image is replaced with the value of the average intensity of pixels in the neighborhood defined by the average filter. This type of filtering has the advantages of removing noise and reducing the irrelevant details in an image (Gonzalez and Woods, 2008). Smoothing gives a blurring effect as shown in Figure 3.

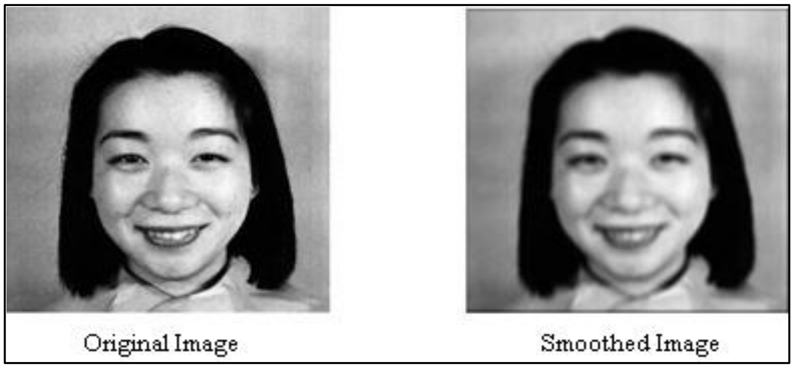


Figure 3: Image smoothing

3.1.2 Histogram Equalization

Histogram equalization is considered one of the most dominant preprocessing methods used especially in the field of FR. The purpose of this method is to enhance image contrast and reduce the effect of variations in facial images due to illumination. Histogram equalization is achieved by mapping the intensity values of image pixels from their original distribution to a new uniform one (Struc et al., 2009).

The histogram of an image represents the relation between the intensity level r_k and its probability of occurrence ($p_r(r_k)$) which is calculated according to equation (1) (Gonzalez and Woods, 2008):

$$P_r(r_k) = \frac{n_k}{MN} \qquad k = 0,1,2, \ldots, L-1 \qquad (1)$$

where n_k is the number of pixels in the image which have intensity r_k, MN is the total number of image pixels, and L is the number of intensity levels in the image.

The histogram equalized image is obtained by mapping each pixel with intensity r_k in the input image into the corresponding pixel with level s_k in the output image as illustrated in equation (2):

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} p_r\left(r_j\right) \qquad k = 0,1,2,\dots,L-1 \tag{2}$$

Figure 4 shows an image before and after histogram equalization and Figure 5 illustrates the histogram of the original image against the histogram after equalization.

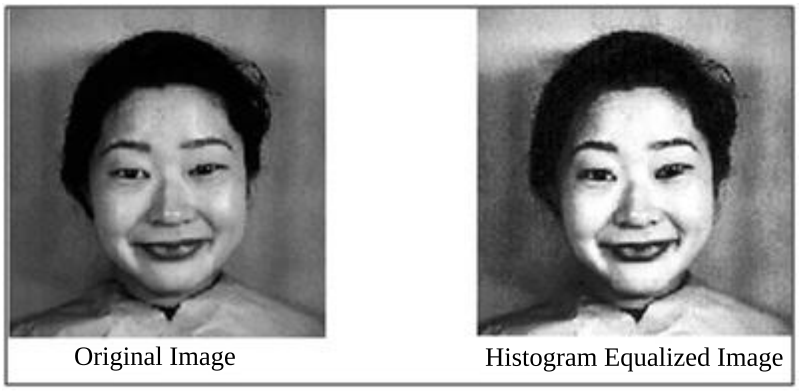


Figure 4: Histogram equalization

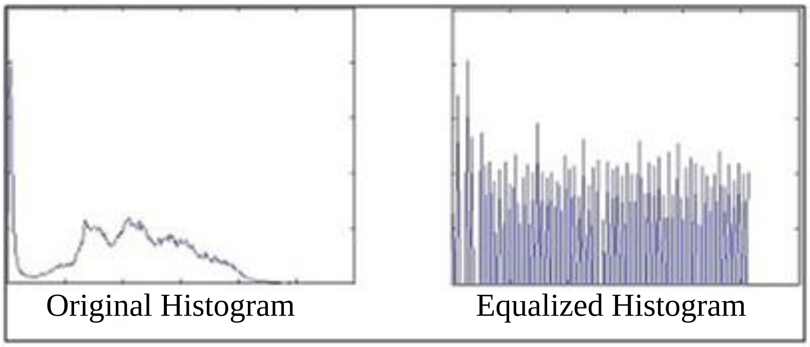


Figure 5: Histogram before and after equalization

3.2 Eyes Region Extraction

This section describes the steps used to extract the two eyes images from the whole face image.

3.2.1 Peak and Valley Maps

In order to study the performance of FR based on eyes, there should be an accurate method for detecting them from a facial image. The first step in extracting the eyes can be done using valley and peak maps proposed by ESME et al. (as cited in Douglas, et al., 2003). The purpose of this method is to select dark regions in an image such as the iris using the valley maps (see Figure 6), as well as selecting the bright regions in an image such as the sclera using the peak maps (see Figure 7). Equations (3) and (4) are used for calculating the valley and peak maps respectively:

$$I_v(x,y) = \frac{u\big(I_w(x,y) - I(x,y)\big) \times |I_w(x,y) - I(x,y)|}{I_w(x,y)} \times 255 \qquad (3)$$

$$I_p(x,y) = \frac{u\big(I(x,y) - I_w(x,y)\big) \times |I_w(x,y) - I(x,y)|}{I_w(x,y)} \times 255 \qquad (4)$$

The valley maps (I_v) aims to find the dark regions in an image by comparing each pixel in image window (I_w) with the average value of that window. Pixels with higher intensity than their window average are assigned 0, while others with lower intensity are assigned a value that is proportional to the difference between the pixel and the window average.

Similarly, peak maps (I_p) finds the bright regions in an image by comparing each pixel value in an image window (I_w) with the average intensity of the window. Pixels with values less than the average of the window are assigned 0, while others with higher intensity are assigned a value that is proportional to the difference between the pixel and the average of the window. The new pixels are normalized to the range 0-255, and u represents the unit step function.

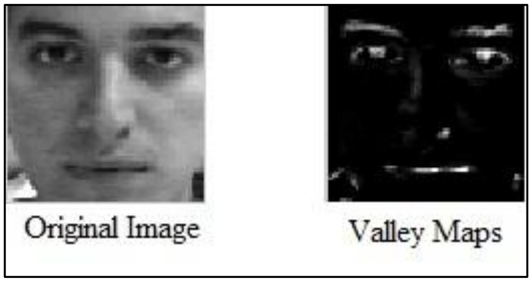


Figure 6: Valley maps

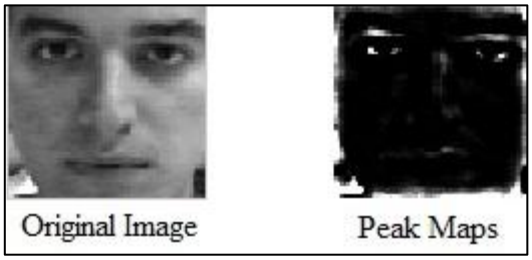


Figure 7: Peak maps

In the datasets used for experiments, all faces appear in almost the same location. So in order to reduce the part of the images being processed to produce peak and valley maps, a fixed window is used where the eyes are expected to appear.

3.2.2 Vertical and Horizontal Projections

Kanade (as cited in Brunelli and Poggio, 1993) successfully used integral projections for human FR. This technique helps in detecting the locations of facial features, and it can be used after applying combined peak and valley maps as in (Douglas et.al, 2003). After calculating the maps, the vertical and horizontal projections of an image *I(x,y)* in a window [x1, x2] [y1, y2], are calculated according to equations (5) and (6):

$$V(x) = \sum_{y=y_1}^{y_2} I(x,y) \tag{5}$$

$$H(y) = \sum_{x=x_1}^{x_2} I(x,y) \tag{6}$$

When projections are calculated, eyes centers can then be estimated by taking the intersection between the two highest peaks in the vertical projection with the highest peak in the horizontal projection.

Figure 8 shows the eyes coordinates detection process using combined peak and valley maps with integral projections on an image from one of the datasets used in the evaluation. In Figure 9 the eyes coordinates of an image from another dataset are detected using only valley maps which were found to be more suitable (during experiments) than the combined valley and peak maps on images from this dataset.

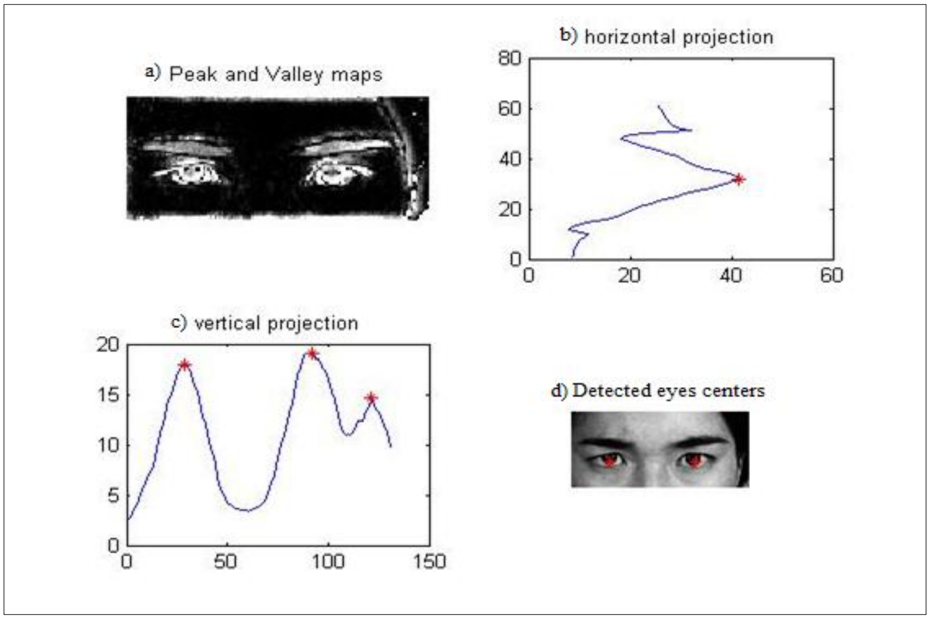


Figure 8: Eye detection using peak and valley maps

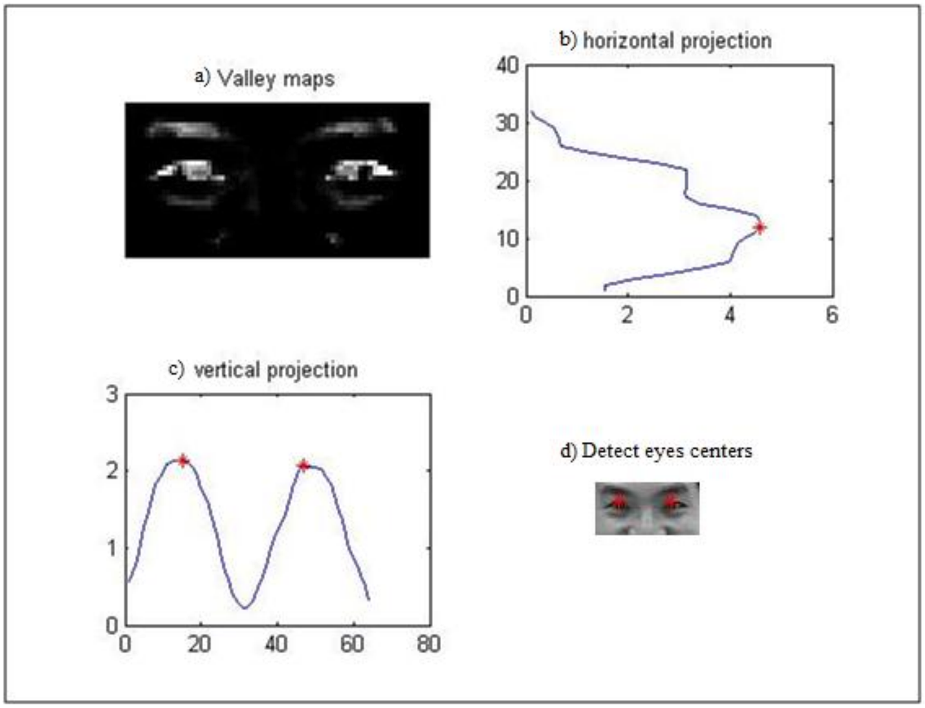


Figure 9: Eye detection using valley maps

3.2.3 Distance Threshold Eyes Extraction

The previous steps are mainly used to estimate the coordinates of eyes centers in facial images. The next step would be to get two separate images for left and right eyes; Distance Threshold method can be used for this purpose (Fan and Verma, 2009).

The Distance Threshold method extracts a facial region by defining thresholds in the horizontal and vertical directions which specify the region size. Knowing the center coordinates of a region along with these thresholds makes locating and extracting local facial regions an easy task. Figures (10 and 11) show the extracted eyes images for two different subjects from different datasets.

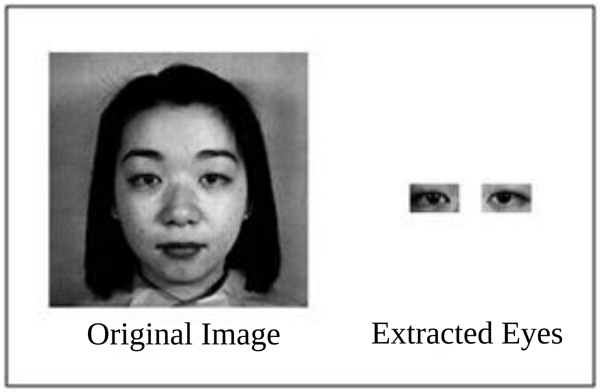


Figure 10: Extracted eyes using distance threshold – JAFFE database

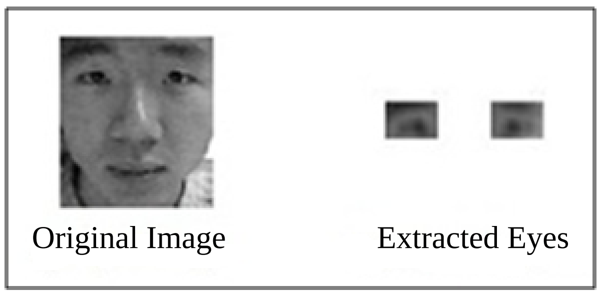


Figure 11: Extracted eyes using distance threshold – AMP database

3.3 Discrete Wavelet Transform

Wavelets are mathematical functions that are used to split data into different frequency components and then study each component with a different scale or resolution. The main advantage of wavelets over other transforms such as conventional Fourier is that they can analyze signals with discontinuities and sharp spikes. Processing data in multi-resolutions provides the ability to explore overall as well as small features of the signal (Graps, 1995).

Decomposing signals and analyzing them in multi-resolutions introduced wavelets as dominant tools in a wide variety of image processing applications. They are used in Image

Compression, Texture Analysis, Noise/Trend Reduction, Feature Extraction, Medical Image Analysis, Image Enhancement and Face recognition.

Wavelet Transforms have many types; one of the very famous types is the Two Dimensional Discrete Wavelet Transform (DWT). Using DWT, an image can be decomposed into multiple sub-images. The result of this decomposition is a matrix of coefficients which can be used to construct four sub images; one approximation image and three details images by applying low-pass and high-pass filtering. Similarly, further multi-level decomposition can be applied to get coefficients in next levels (Seyedzade et al., 2010).

Figure 12 shows a two level decomposed image using Symlet 7 which is one of the wavelet transforms families. By applying successive lowpass and highpass filtering on an image, the 2-D DWT is obtained. As mentioned previously, the DWT yields four sub-bands which are LL, LH, HL and HH. These subbands correspond respectively to the approximate, horizontal, vertical and diagonal image features (Kinage and Bhirud, 2009). A one dimensional Continuous Wavelet Transform is defined by equation (7):

$$\mathrm{CWT}(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t)\psi_{s,\tau}(t) \qquad (7)$$

$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \left(\frac{t-\tau}{s}\, dt\right)$ is a basis function and is called the mother wavelet, s and τ are scaling and shift parameters.

The DWT is the sampled version of CWT and is defined in its two dimensional form by equation (8):

$$DWT(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} f(x)\ \psi\left(\frac{x}{2} - k\right) dx \tag{8}$$

j is the power of binary scaling and k is the filter constant.

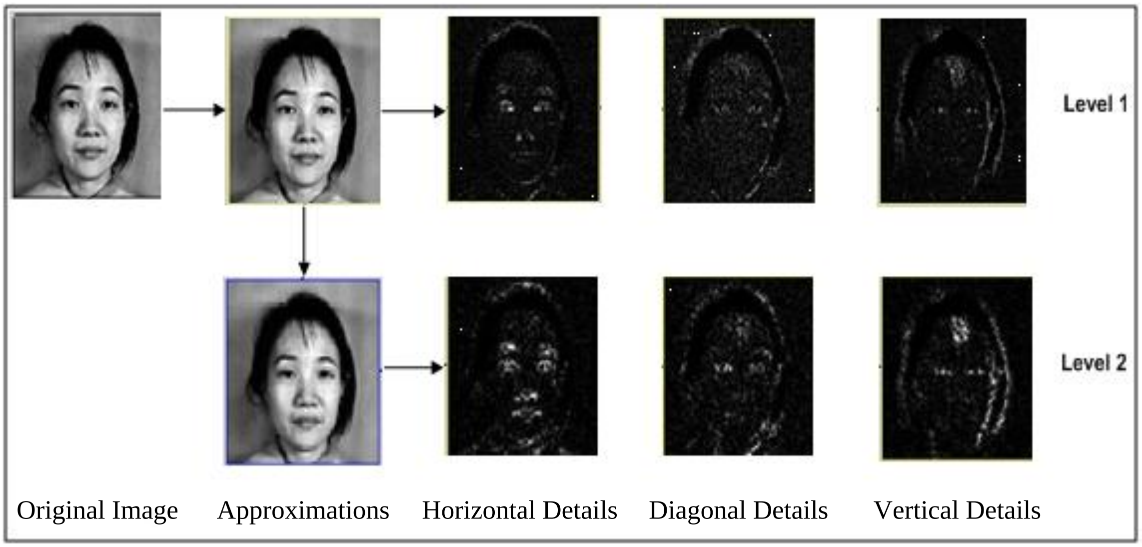


Figure 12: 2-level Wavelet decomposition using 7th order Symlet

It is always the subband LL (the approximation component) that is chosen for further decomposition into more levels because it has high energy. This component of the decomposition contains the most discriminating power among all other components and is the most informative part that represents a basic figure of the original image (Jadhav and Holambe, 2009).

For the previous reason, we chose to use the LL component of the DWT decomposed images in the proposed FR algorithm. Before applying the Average Intensity feature extraction method, the LL subband in level 1 or level 2 (depending on the experienced dataset) are obtained, and then the features are extracted from these approximations.

3.4 Average Intensity for Facial Features Extraction

Selecting discriminating features from facial images is one of the most important factors that affect the accuracy of any feature-based FR algorithm. In this research a simple yet powerful method is used for extracting facial features which depends on the average grey level value features of image pixels (Fan and Verma, 2009). However; instead of applying the method directly on the face or eyes images, it is applied on the approximation image obtained from the first or second level DWT decomposition; in this way we exploit the DWT to achieve a high recognition rate using the Average Intensity method.

In this technique, each image is equally divided into small rectangles; the average intensity value of these rectangles is calculated according to equation (9):

$$av_i = \frac{\sum p(x,y)}{w \times h \times v} \tag{9}$$

av_i is the average intensity value of rectangle i, $p(x,y)$ is the intensity value of pixel p in rectangle i, w and h are respectively the width and height of rectangle i and finally v is the highest intensity value of the examined images.

After calculating the average intensities of the small rectangles from left to right and top to bottom, the feature vector of an image is formed by row concatenation of all these average values.

Since we are evaluating the FR technique on both the whole face as well as on the eyes regions, the Average Intensity method is applied on two types of images (after getting the DWT approximation image from both types): first, the whole face image is divided into small rectangle blocks (see Figure 13) where the average intensity of each block is calculated. The feature vector of the image is formed using the whole rectangles average intensities after concatenating them as one row. The second type of images is the eyes images extracted as described in Section (3.2). The left and right eyes images are separately fed into the Average Intensity extraction algorithm (see Figure 14) and one row feature vector is formed for each of them. After that, the final feature vector is obtained by concatenating both vectors of right eye then left eye.

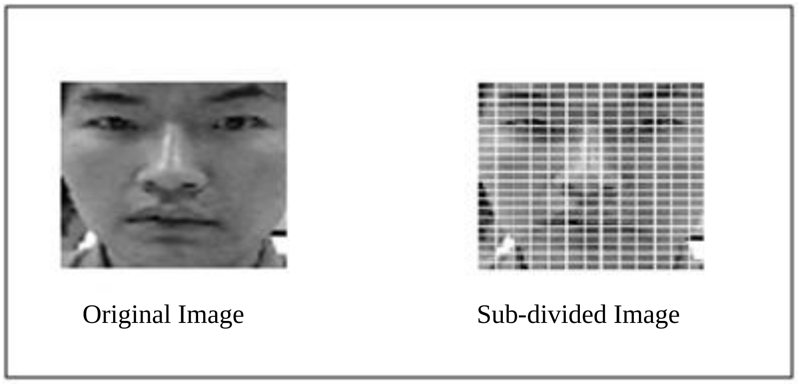


Figure 13: The face image before and after division

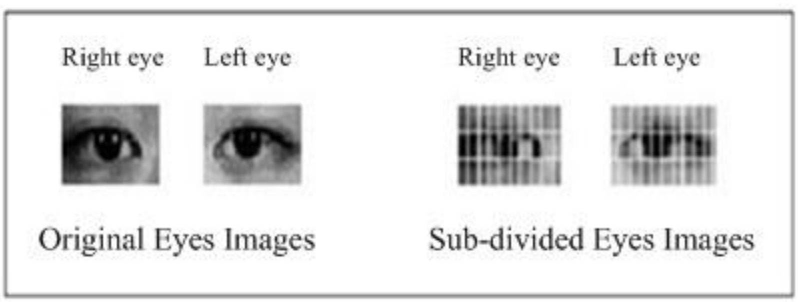


Figure 14: Eyes images before and after division

3.5 Genetic Algorithms for Selecting the Best Features

GAs were developed as a result of applying the principles of evolutionary biology in computer science. They are heuristic methods which are based on the mechanics of biological evolution such as natural selection, recombination (crossover), mutation and inheritance. Their basic idea is "survival of the fittest" (Ozkan, 2006).

GAs are well known for their efficiency as search algorithms. Their characteristics make them very powerful in finding the optimal set of solutions to complicated search problems. Their distinguishing features from classical search algorithms can be summarized as follows (Yen and Nithianandan, 2002):

1- They use parameters encoding rather than working on the parameters themselves.
2- GAs start searching from multiple candidate solutions instead of only on solution.
3- GAs do not use derivative or other auxiliary information, alternatively they use objective function information.
4- Instead of a single solution, GAs generate a population of possible solutions.

To apply GA on a specific problem, the problem must be represented as a list of parameters called chromosomes or genomes. Simple strings of data and instructions are used to represent each chromosome which can either be generated randomly or heuristically to form the initial pool of possible solutions called first generation pool (Ozkan, 2006).

In each generation, each of the individuals is evaluated using a fitness function that returns a value representing the goodness or fitness of the individual. In the next step, any or all of the genetic operators (selection, crossover or mutation) are used to generate a second generation pool. Based on the fitness of the initial generation, a pair of individuals which have better fitness than others are selected to survive. After selection, the crossover operation can be performed on the two selected chromosomes to generate new child chromosomes which are added to the second generation pool. Finally, mutation might take place with a probability that is nearly .01 or less by randomly altering some bits in the chromosome structure (Ozkan, 2006). Figure 15 shows the flow chart of the GA.

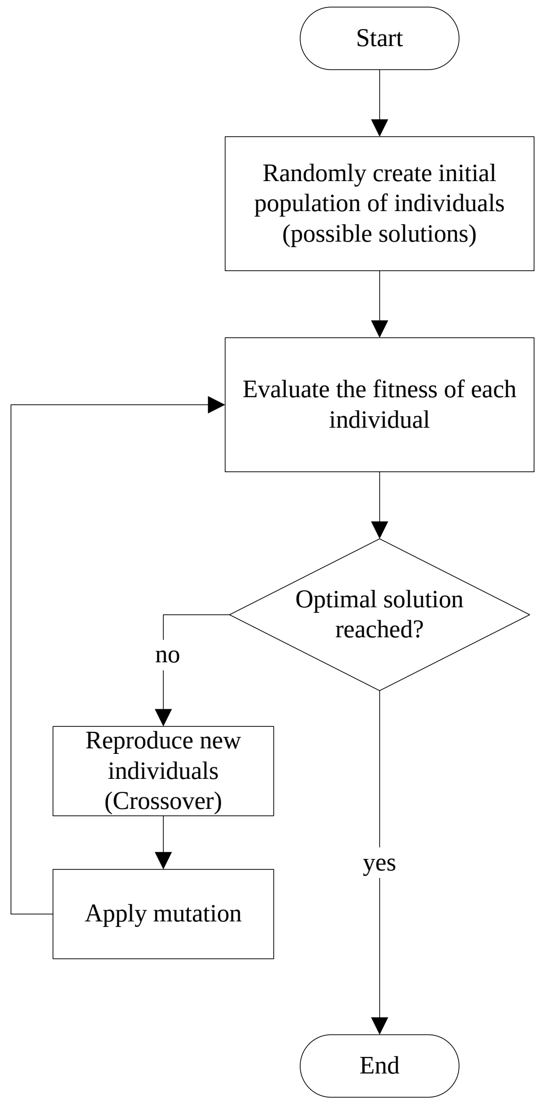


Figure 15: GA flow chart

In any FR system, getting the most discriminating features of a human face is a vital process. Not all features extracted from a human face can contribute positively in the recognition results, in fact, some features might lead to a poor classification rate. One of the interesting solutions for this problem is to use GAs to select the most effective features for a better classification rates.

As described in Section 3.4, the Average Intensity method is used to extract facial features from either a full human face or only the two eyes images. After getting the Average Intensity features, we compare the results of applying classification directly on the whole set of features with the results of running the GA to find the best subset of features combination. GAs proved to reduce the number of features needed for recognition in both cases of using the eyes only and whole face images. This reduction in the number of features gives even a better recognition rate than using the whole set of features which emphasizes the fact that some features might degrade the performance of FR techniques.

To use GA for selecting the best subset of average intensity features (Fan and Verma, 2009), the chromosome can be represented as a string of bits, where a 1 in the string means the feature in this position will be selected for classification and the 0 means it will not.

Every generation, the set of possible solutions (individuals) are evaluated by the fitness function. In this research, the fitness value of an individual represents the recognition rate achieved using the features in the positions of the 1's in that individual. The fittest individuals in each generation are the ones which resulted in the highest recognition rate.

Finally, the best features selected for the recognition process are those in the positions of 1's in the individual that achieved the highest classification rate among all generations.

To clearly illustrate how the GA can be utilized for features selection, the following example is provided:

Example:

Suppose that after reconstructing the approximation of the Wavelet decomposed image and then applying the Average Intensity, the feature vector looks like this:

F_v = {0.548, 0.258, 0.365, 0.785, 0.457, 0.554, 0.145, 0.877}

Now after running GA to select the best combination of the features, suppose that the vector selected by the GA that gave the best fitness (recognition rate) is:

G_v = {0, 1, 1, 0, 1, 0, 0, 1}

Multiplying F_v by G_v produces the final vector that will be used in the classification as illustrated in Figure 16:

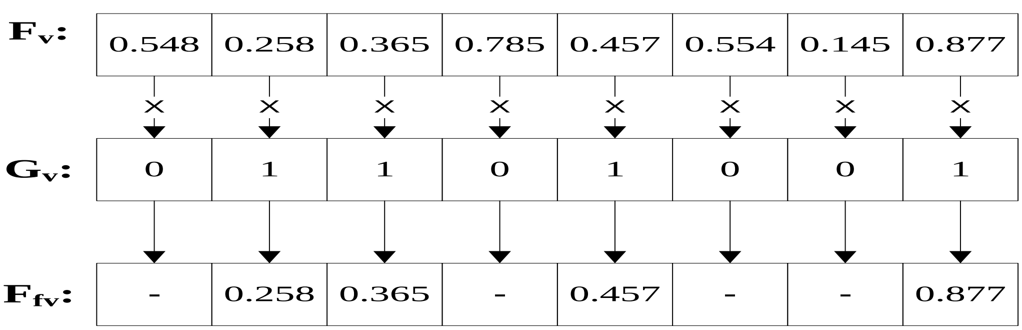


Figure 16: Reducing the number of features

The final feature vector used for classification contains only the features in the positions of 1's which are:

F_{fv} = {0.258, 0.365, 0.457, 0.877}

3.6 Euclidean Distance Classification

After getting the final feature vectors whether using the whole set or a subset of features, or whether they were extracted from the whole face or only from the eyes, we need to calculate the distance between the vector extracted from a test image and each of the vectors extracted from the training dataset images. There are lots of distance functions that can be used for this purpose; a commonly used one is the Euclidean distance function (Wilson and Martinez, 1997). The Euclidean distance between two vectors can be defined using equation (10):

$$E(x,y) = \sqrt{\sum_{m=1}^{n}(x_m - y_m)^2} \qquad (10)$$

where x and y are the two vectors that are subject to the similarity comparison and n is the total number of attributes (features) of each input vector.

After calculating the Euclidean distance between the test and each of the training vectors, the corresponding images of the training vectors with minimum distances between them and the test vector are selected as the recognized images.

4. Experiments and Results

In this chapter the datasets used in the evaluation are described followed by a detailed explanation of the experiments and results obtained from each of them separately. Finally, the whole results are analyzed and discussed.

4.1 Databases Used for Evaluation

In this research two different facial databases were used in the experiments. As we are studying the robustness of depending on human eyes in the recognition process, we chose to work on databases where human faces images have facial expressions variations. The following two sub sections describe these databases and provide sample images.

4.1.1 JAFFE Database

The first database used in the experiments is the Japanese Female Facial Expressions (JAFFE) database (Lyons et al., 1999). The database contains images of 10 Japanese females with 6 facial expressions and one neutral expression. In this research a subset of 40 images was chosen to run part of the experiments; one image for each of the 10 subjects (persons) was chosen for testing and another three images were chosen for training. Figure 17 shows a sample of images in the database. The images are of size 256 × 256 pixels in a Tagged Image File Format (.tiff).

Images in this database were preprocessed using histogram equalization. This step has a powerful effect on the performance of the evaluated FR technique.

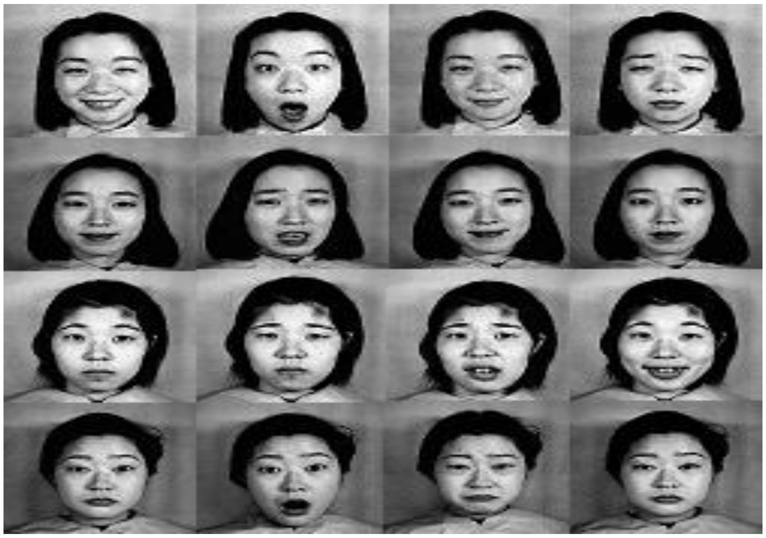


Figure 17: Sample images from JAFFE database

4.1.2 AMP Database

The other database used in the experiments is the facial expressions database from the Advanced Multimedia Processing (AMP) Lab at the Electrical and Computer Engineering Department of Cornell University (http://amp.ece.cmu.edu/projects/FaceAuthentication/download.htm).

Each subject in the database has images with different facial expressions. All images in this database are of size 64 × 64 pixels in a bitmap format (.bmp). Two subsets were chosen for the experiments from the AMP database. The first subset contains 12 subjects each of which having 8 images of various expressions; one image was randomly chosen for testing and the other 7 were used for training. Accordingly, the first subset contains 96 images; 12 testing and 84 training images.

The second subset also contains 12 subjects; each of them has 10 images. These 10 images were divided into 6 testing and only 4 training resulting in a total of 120 images; 72 for testing and 48 only for training.

All experiments using AMP database were conducted on both subsets. Figure 18 shows a sample of the images used from this database.

Images from AMP database were preprocessed using an average smoothing filter before applying the FR technique. During experiments on this dataset, smoothing was found to be more suitable than histogram equalization; and that is why it was chosen as a preprocessing step on images from this database.

Figure 18: Sample images from the AMP lab facial expressions database

4.2 General Experiments Description

In this research, multiple experiments were conducted on each of the three datasets used for evaluation. These experiments are intended to compare the results of applying the proposed

FR technique on the whole face against the results of applying it only on the two eyes images. Furthermore, the experiments also compare between using the whole set of extracted features in the classification step, against running GA first to select only a subset of them for classification. The implementation and testing of the FR algorithm proposed for the evaluation is done using MATLAB (MATHWORK, 2007) on a computer running Windows 7 Home Premium Operating System, with Intel® Core(TM) i3 CPU @ 2.13 GHz and 4 Gigabytes of RAM.

In each one of the experiments, the recognition rate is computed as the percentage of correctly identified images out of the whole of images in the training set as illustrated in equation (11):

$$\text{Recognition Rate} = \frac{\text{Number of correctly classified images}}{\text{Number of images in the training database}} \tag{11}$$

4.3 Experiments on JAFFE Dataset

This section describes the experiments done using the dataset from JAFFE database. The details of each experiment are discussed and the results obtained are presented.

4.3.1 Eyes Regions Extraction

As described in Section 3.2, valley and peak maps were used before applying vertical and horizontal projections to estimate the coordinates of eyes centers. After estimating these coordinates, the distance threshold method was used to get the two eyes images.

The best distance thresholds that gave the exact eye region in horizontal and vertical directions were found to be 40 and 24 respectively (figured by experiments) for each of the two eyes.

4.3.2 Discrete Wavelet Decomposition

Many experiments were conducted to find the best DWT family among (Haar, Daubechies, Coiflet and Symlet) as well as to find the best decomposition level that best suits the dataset experienced. Based on these experiments Daubechies (db4) DWT was chosen to decompose images into two levels. This choice gave the best recognition rate on this dataset.

After applying 2-level DWT, the approximation sub-image from the second level was reconstructed to resume further processing by the FR algorithm.

4.3.3 Average Intensity Features Selection

In the features extraction step, the approximation images resulting from DWT decomposition were divided into small blocks, after trying different sizes of the rectangles; the best results were achieved when using 10 × 8 rectangle size for the whole face image, and 10 × 4 rectangle size for eyes images. It was noted that using a smaller rectangle size for the whole face does not enhance the performance and only results in more features.

The original images are of size 256 × 256, dividing the width by 8 and the height by 10 gives a total of 832 blocks. The average intensity of each block is calculated, and the final feature vector of the whole face image is of size 832.

When using only the eyes, each eye image is of size 40 × 24. Similarly as in the whole face image, dividing the width by 4 and the height by 10 gives a total of 30 blocks. The average intensity for each of the blocks is calculated and the feature vector of each eye image contains 30 features. When the vectors of both eyes images are concatenated, the final feature vector of the eyes has a size of 60 features.

4.3.4 Genetic Algorithm Settings

Table 3 shows the settings of the GA used for features selection in both experiments on the whole face and on the eyes only.

Table 3: Genetic algorithm settings for JAFFE dataset experiments

Image parts	Chromosome length	Population size	Number of generations	Mutation probability	Crossover probability
Eyes	60	60	25	0.002	0.9
Whole face image	832	60	25	0.002	0.9

4.3.5 Results

Table 4 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. The two classification rates are achieved using the whole face image.

Table 4: Number of features vs. recognition rate achieved using the whole face image – JAFFE database experiments

Method	Number of features selected out of 832	Recognition rate
Average Intensity with GA	67	100%
Average Intensity without GA	832	87%

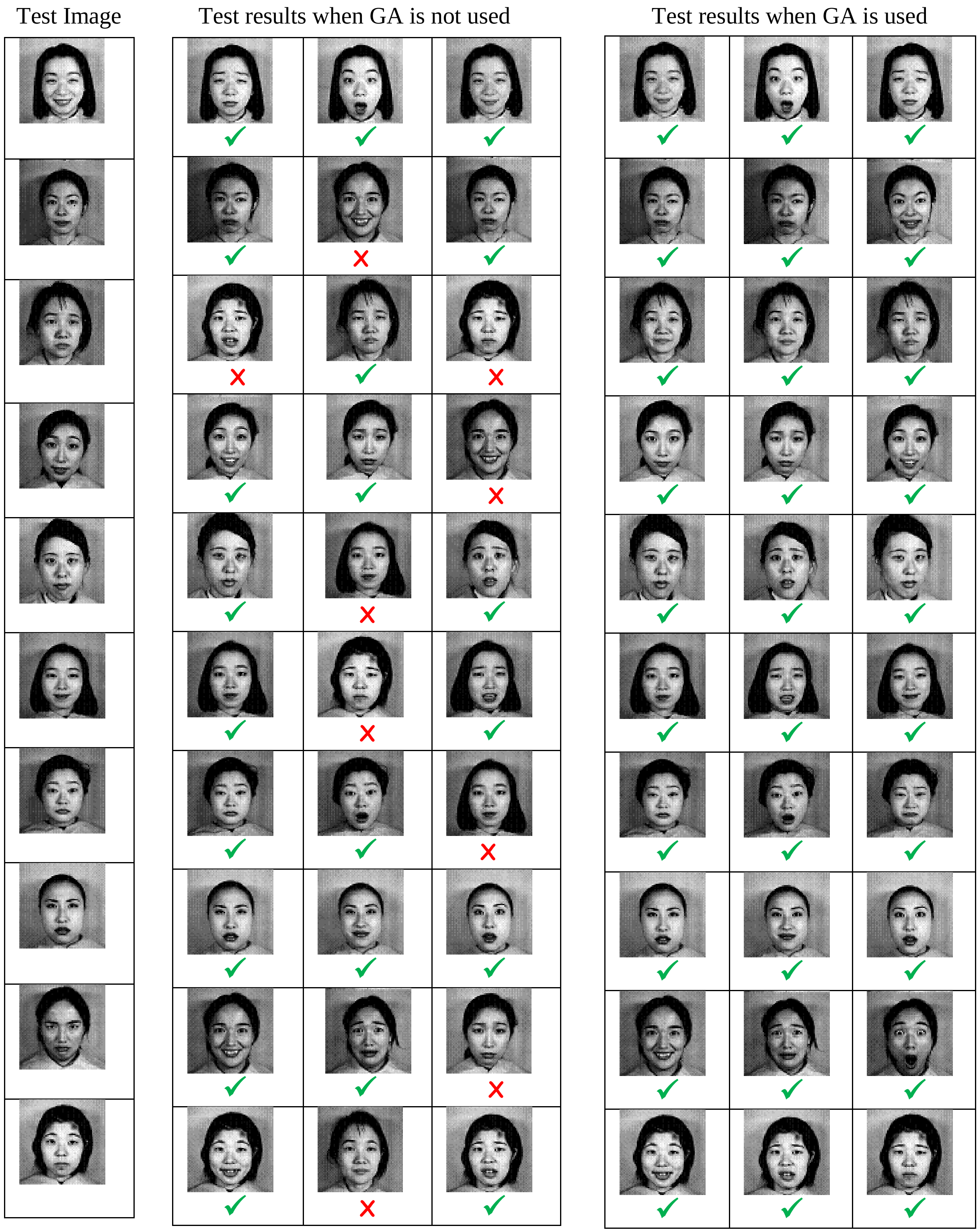
Table 5 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. This time the algorithm is applied only on the eyes images rather than on the whole face.

Table 5: Number of features vs. recognition rate achieved using the eyes images – JAFFE database experiments

Method	Number of features used out of 60	Recognition rate
Average Intensity with GA	18	100%
Average Intensity without GA	60	70%

Since our main concern is to show the contribution of the eyes regions in the recognition rate, we listed the recognition results obtained using only the eyes in Figure 19. The 10 test images used are shown in the first column and next to each one there are two groups of images; the first group shows the most three similar images retrieved when all the eyes features are used for classification, the second group shows the most three similar images retrieved by the system when trained using GA to select a subset of features.

Figure 19: Results of applying FR on eyes – JAFFE



4.4 Experiments on AMP Database – Part One

This section describes the experiments done using the first dataset from AMP facial expressions database. The details of each experiment are discussed and the results obtained are presented.

4.4.1 Eyes Regions Extraction

In this dataset only valley maps were used before applying vertical and horizontal projections to estimate the coordinates of eyes centers. Similarly as in the previous dataset, distance threshold method was used after estimating the coordinates to get the two eyes images.

The best distance thresholds that gave the exact eye region in horizontal and vertical directions were found to be 26 and 18 respectively (figured by experiments) for each of the two eyes.

4.4.2 Discrete Wavelet Decomposition

Many experiments were conducted to find the best DWT family among (Haar, Daubechies, Coiflet and Symlet) as well as to find the best decomposition level. Based on these experiments Daubechies (db4) DWT was chosen to decompose images into one level. This choice gave the best recognition rate.

After decomposing images into level one, the approximation sub-image was reconstructed to resume further processing by the FR algorithm.

4.4.3 Average Intensity Features Selection

In the features extraction step, the approximation images resulting from DWT decomposition were divided into small blocks, after trying different sizes of the rectangles; the best results were achieved when using 5 × 3 rectangle size for the whole face image as well as for the eyes images. This smaller rectangle size compared to the rectangles size in JAFFE dataset images is due to the bigger size of images in JAFFE dataset.

The original images are of size 64 × 64, dividing the width by 3 and height by 5 gives a total of 286 blocks. The average intensity of each block is calculated, and the final feature vector of the whole face image is of size 286.

When using only the eyes, each eye image is of size 26 × 18. In the same manner as in the whole face images, dividing the width by 3 and the height by 5 gives a total of 36 blocks. The average intensity for each of the blocks is calculated and the feature vector of each eye image contains 36 features. When the vectors of both eyes images are concatenated, the final feature vector of the eyes has a size of 72 features.

4.4.4 Genetic Algorithm Settings

Table 6 shows the settings of the GA used for features selection in both experiments on the whole face and on the eyes only.

Table 6: Genetic algorithm settings for AMP – part1 dataset experiments

Image parts	Chromosome length	Population size	Number of generations	Mutation probability	Crossover probability
Eyes	72	60	60	0.002	0.9
Whole face image	286	60	60	0.002	0.9

4.4.5 Results

Table 7 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. The two classification rates are obtained using the whole face.

Due to the large number of training images (seven) for each subject in this dataset, it is noted that the recognition rate achieved was 100% whether GA is used or not. However; the use of GA dramatically reduced the number of features required.

Table 7: Number of features vs. recognition rate achieved using the whole face image – AMP (part1) database experiments

Method	**Number of features used out of 286**	**Recognition rate**
Average Intensity with GA	29	100%
Average Intensity without GA	286	100%

Table 8 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. The two classification rates are obtained using only the eyes.

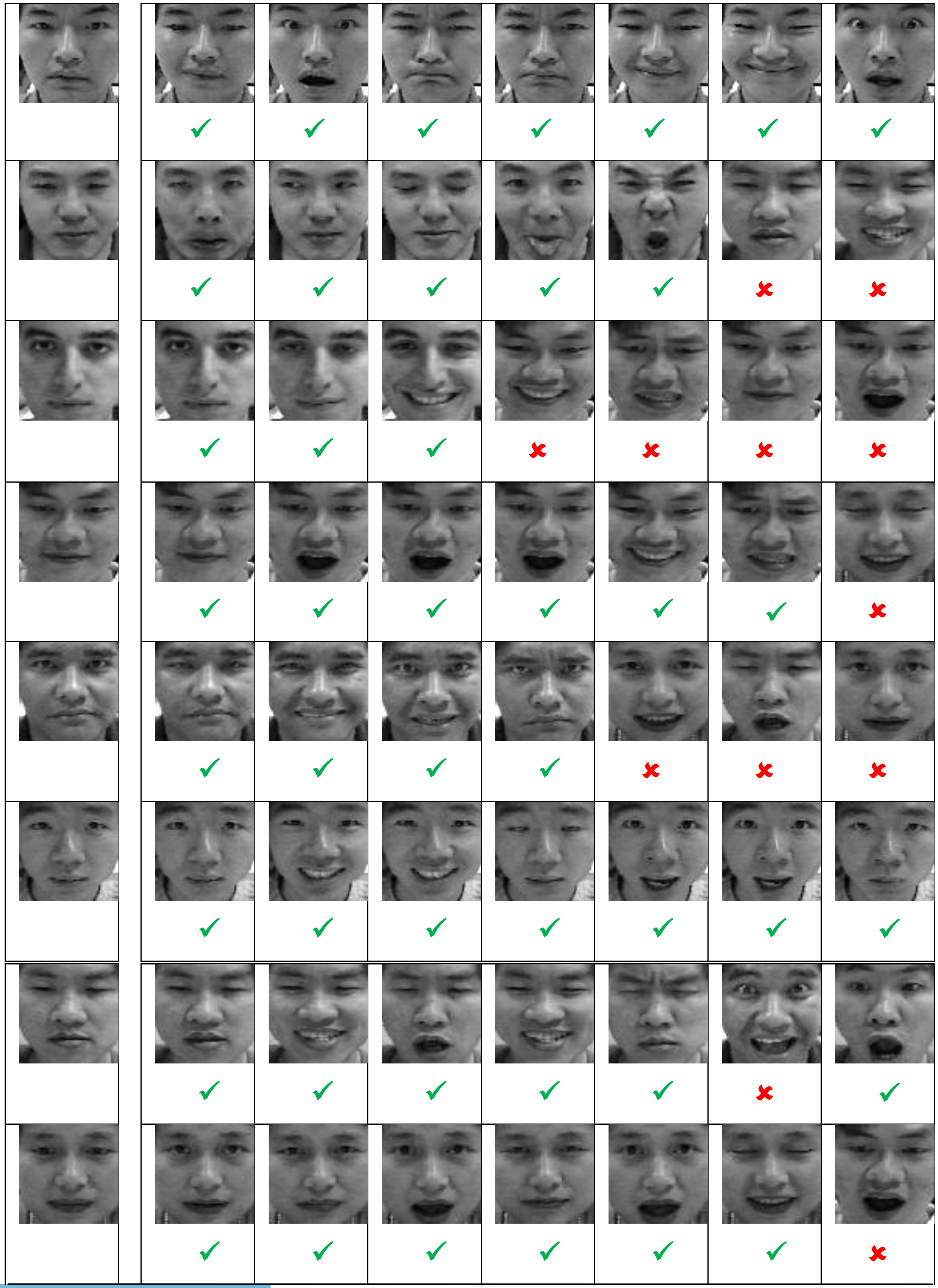
Table 8: Number of features vs. recognition rate achieved using the eyes images – AMP (part1) database experiments

Method	Number of features used out of 72	Recognition rate
Average Intensity with GA	16	98%
Average Intensity without GA	72	86%

Figures 20 and 21 also show the results obtained when applying FR on the eyes images. Results in Figure 20 are based on using the whole feature vector extracted by the Average Intensity method, while Figure 21 shows the results achieved when only a subset of features was selected using GA.

In each figure, the 12 test images are placed in the first column representing the 12 subjects in the dataset. Next to each of the test images the tables show the 7 most similar images retrieved by applying the FR algorithm on the eyes.

Figure 20: Results of applying eye FR without GA



Results of applying eye FR without GA (Cont.)

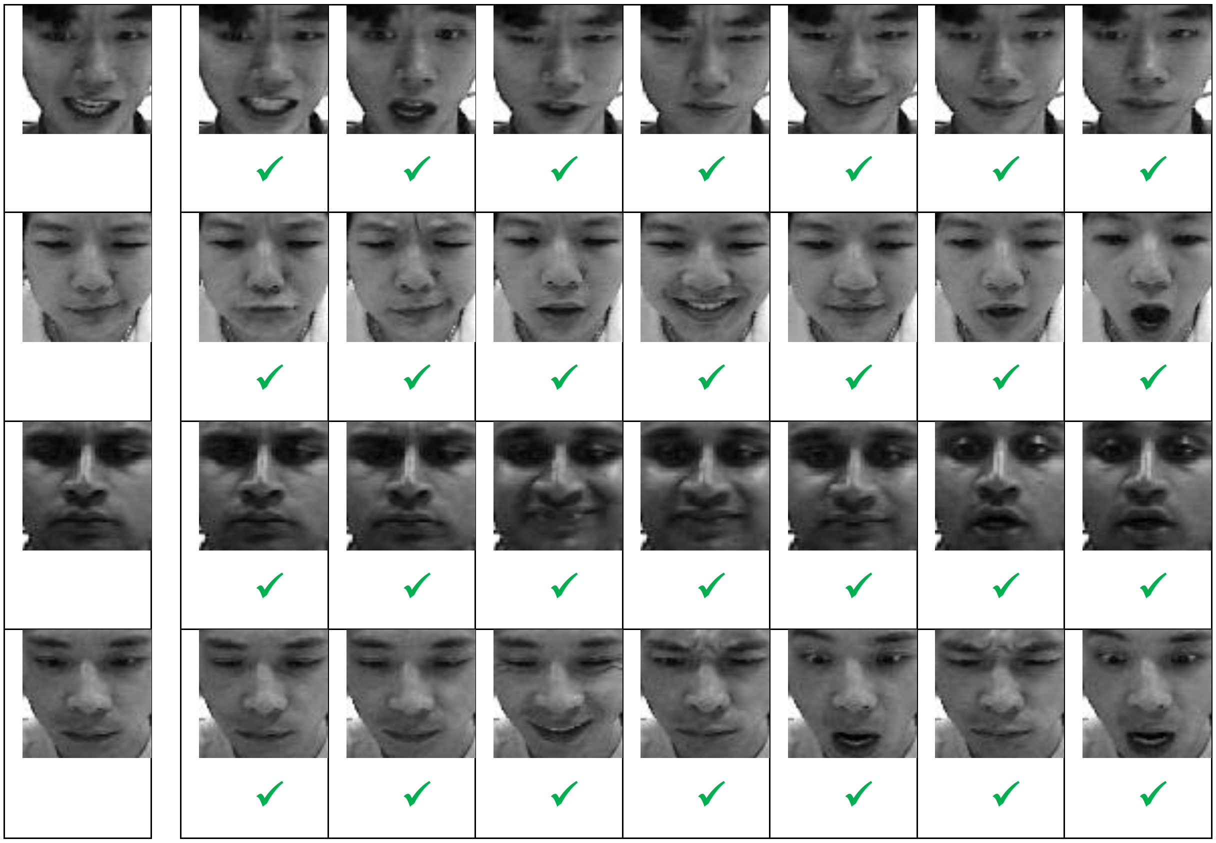
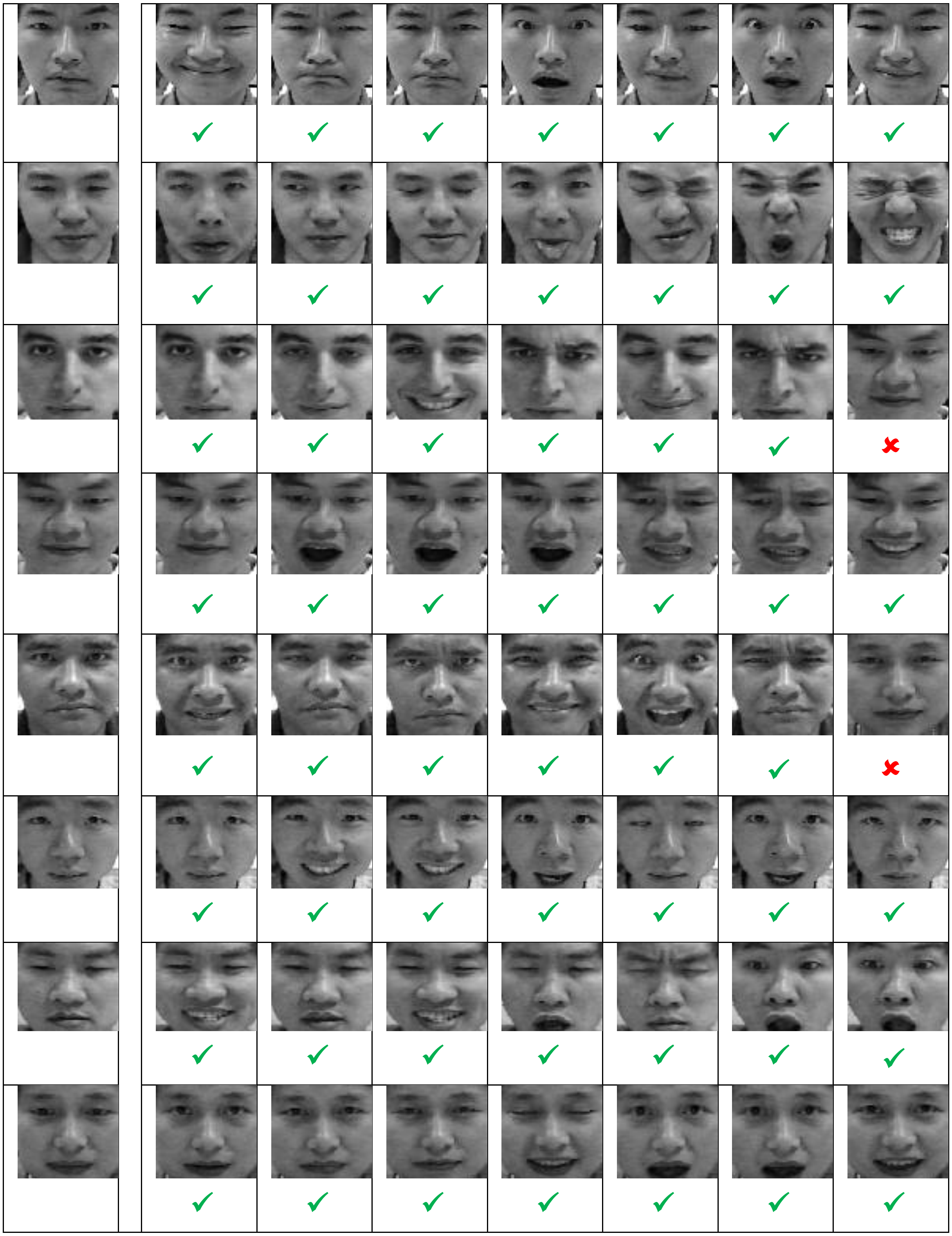
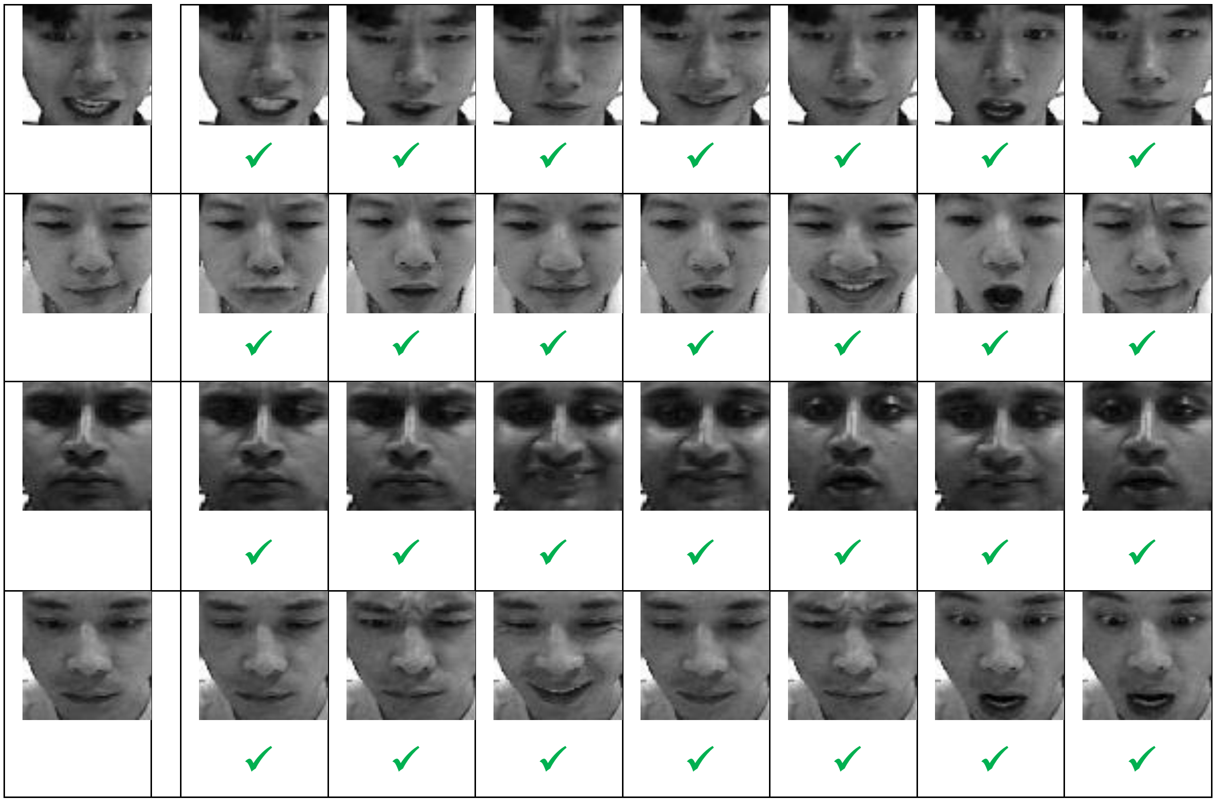


Figure 21: Results of applying eye FR using GA



Results of applying eye FR using GA (Cont.)



4.5 Experiments on AMP Database – Part Two

This section describes the experiments done using the second dataset from AMP facial expressions database. The details of each experiment are discussed and the results obtained are presented.

4.5.1 Eyes Regions Extraction

As this dataset is also taken from AMP facial expressions database, we also applied vertical and horizontal projections on valley maps only to estimate the center coordinates of both eyes.

Vertical and horizontal distance thresholds are also the same as in AMP dataset - part one. The best thresholds were found to be 26 in the horizontal direction and 18 in the vertical, for each of the two eyes.

4.5.2 Discrete Wavelet Decomposition

Many experiments were conducted to find the best DWT family among (Haar, Daubechies, Coiflet and Symlet) as well as to find the best decomposition level. On this dataset Symlet (Sym7) DWT was better than others and thus was chosen to decompose images into one level.

After decomposing images into one level, the approximation sub-image was reconstructed and selected to resume further processing by the FR algorithm.

4.5.3 Average Intensity Feature Selection

In the features extraction step, the images in this dataset were divided into small blocks, after trying different sizes of the rectangles (the same as in part one); the best results were achieved when using 5 × 3 rectangle size for the whole face image as well as for the eyes images.

The original images are of size 64 × 64, dividing the width by 3 and the height by 5 gives a total of 286 blocks. The average intensity of each block is calculated, and the final feature vector of the whole face image is of size 286.

When using only the eyes, each eye image is of size 26 × 18. In the same manner as in the whole face images, dividing the width by 3 and the height by 5 gives a total of 36 blocks. The average intensity for each of the blocks is calculated and the feature vector of each eye image is 36. When the vectors of both eyes images are concatenated, the final feature vector of the eyes has a size of 72 features.

4.5.4 Genetic Algorithm Settings

Table 9 shows the settings of the GA used for features selection in both experiments on the whole face and on the eyes only.

Table 9: Genetic algorithm settings for AMP – part2 dataset experiments

Image parts	Chromosome length	Population size	Number of generations	Mutation probability	Crossover probability
Eyes	72	60	60	0.002	0.9
Whole face image	286	60	60	0.002	0.9

4.5.5 Results

Table 10 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. The two classification rates are obtained using the whole face.

Table 10: Number of features vs. recognition rate achieved using the whole face image – AMP (part2) database experiments

Method	Number of features used out of 286	Recognition rate
Average Intensity with GA	119	100%
Average Intensity without GA	286	97%

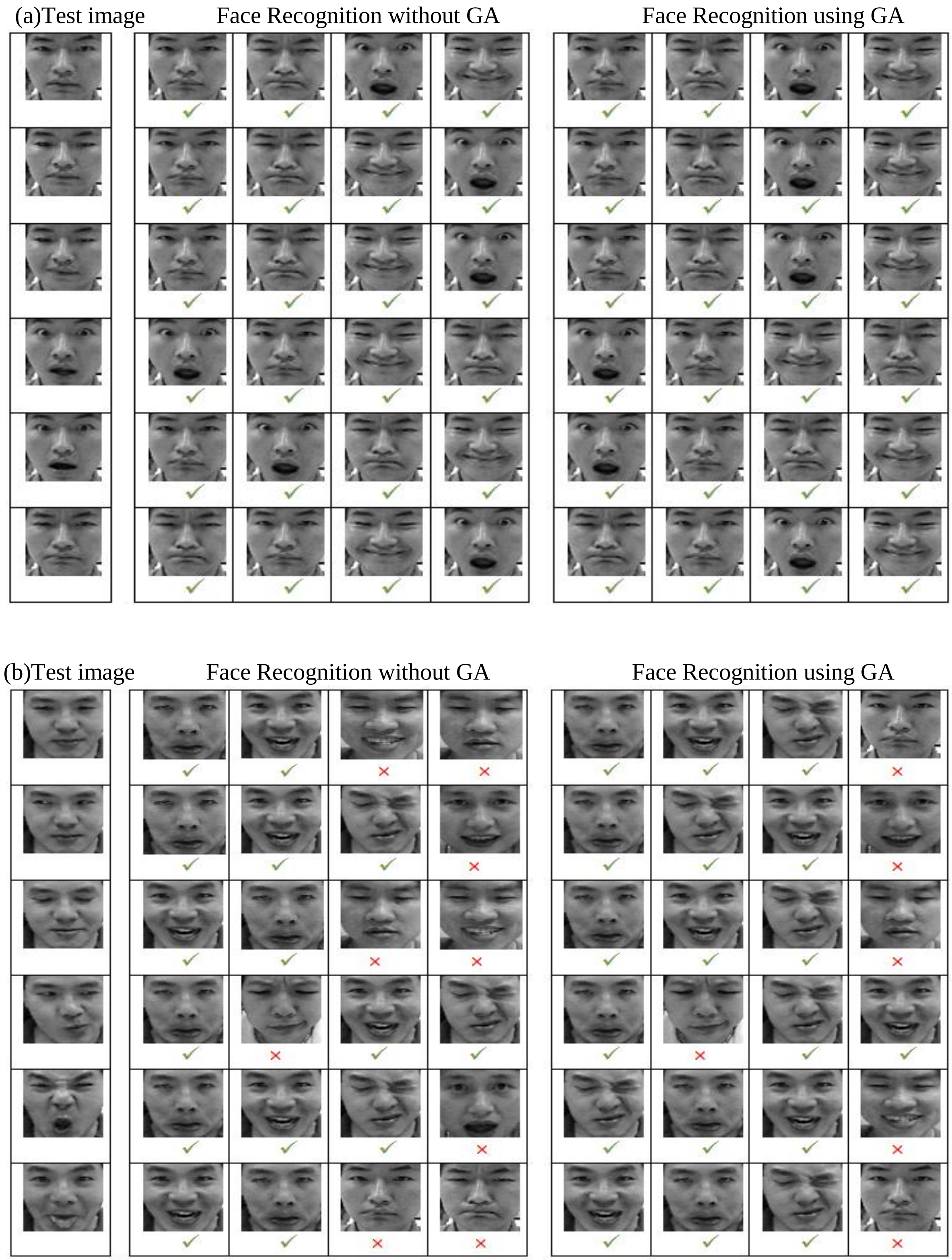
Table 11 shows the classification rate obtained when using the whole features in the feature vector versus the classification rate obtained when GA is used to select only a subset of features. The two classification rates are obtained using only the eyes.

Table 11: Number of features vs. recognition rate achieved using the eyes images – AMP (part2) database experiments

Method	Number of features used out of 72	Recognition rate
Average Intensity with GA	21	94%
Average Intensity without GA	72	81%

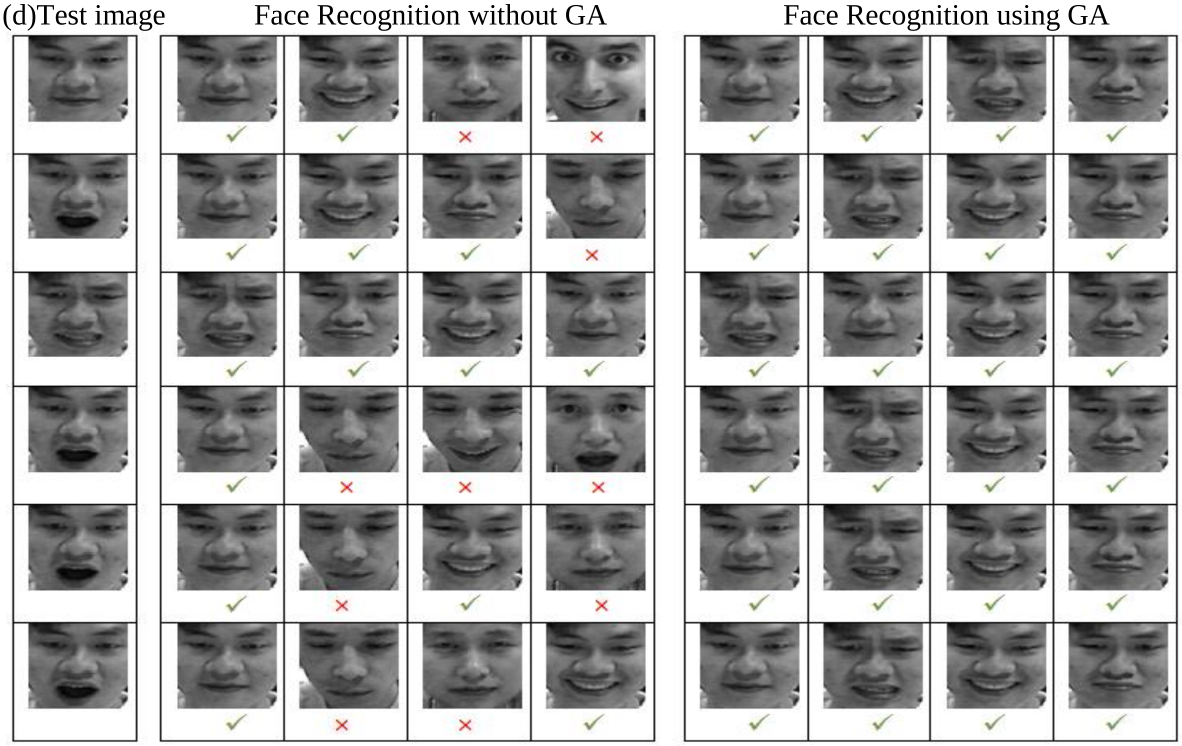
Figure 22 (from a-l) also shows the results obtained when applying FR on the eyes images. The images in the first column represent the 72 images used in the test set (6 test images for each of the 12 subjects). Next to each one of the test images there are two groups; the first group shows the four most similar images retrieved when all the features are used for classification, the second group shows the four most similar images retrieved by the system when trained using GA to select a subset of features.

Figure 22: Results of applying FR on eyes – AMP (part2)

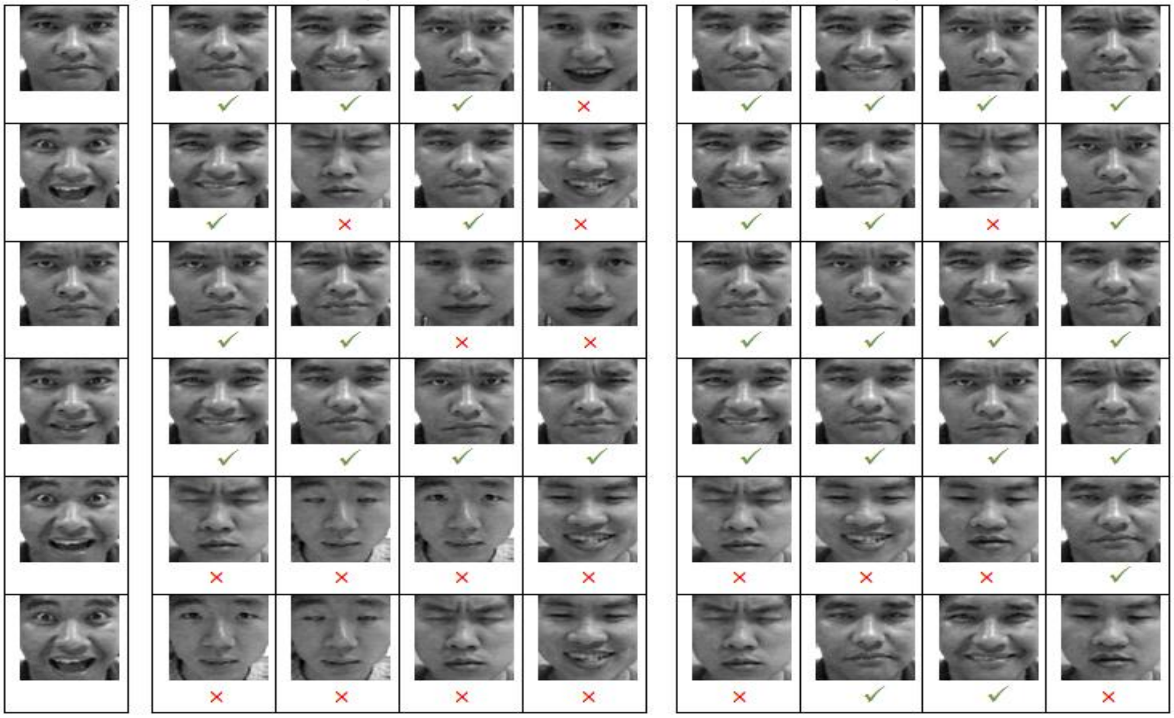


(c)Test image Face Recognition without GA Face Recognition using GA

(d)Test image Face Recognition without GA Face Recognition using GA



(e)Test image Face Recognition without GA Face Recognition using GA



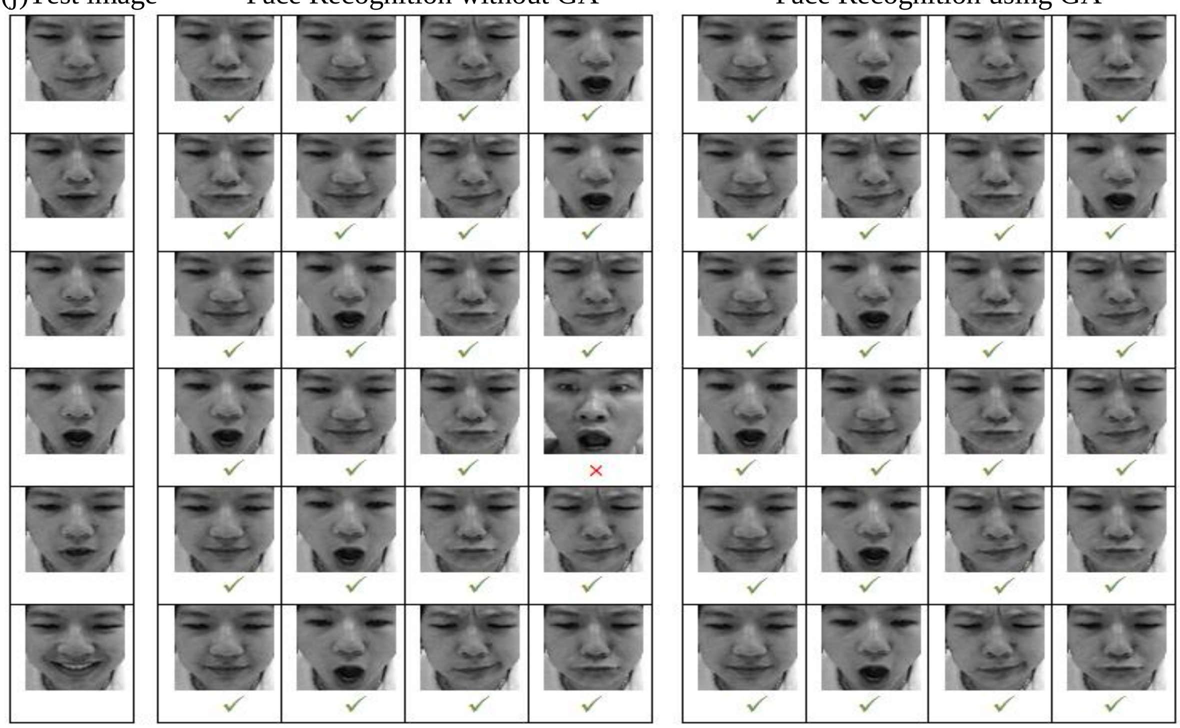
(f)Test image Face Recognition without GA Face Recognition using GA

(g)Test image Face Recognition without GA Face Recognition using GA

(h)Test image Face Recognition without GA Face Recognition using GA

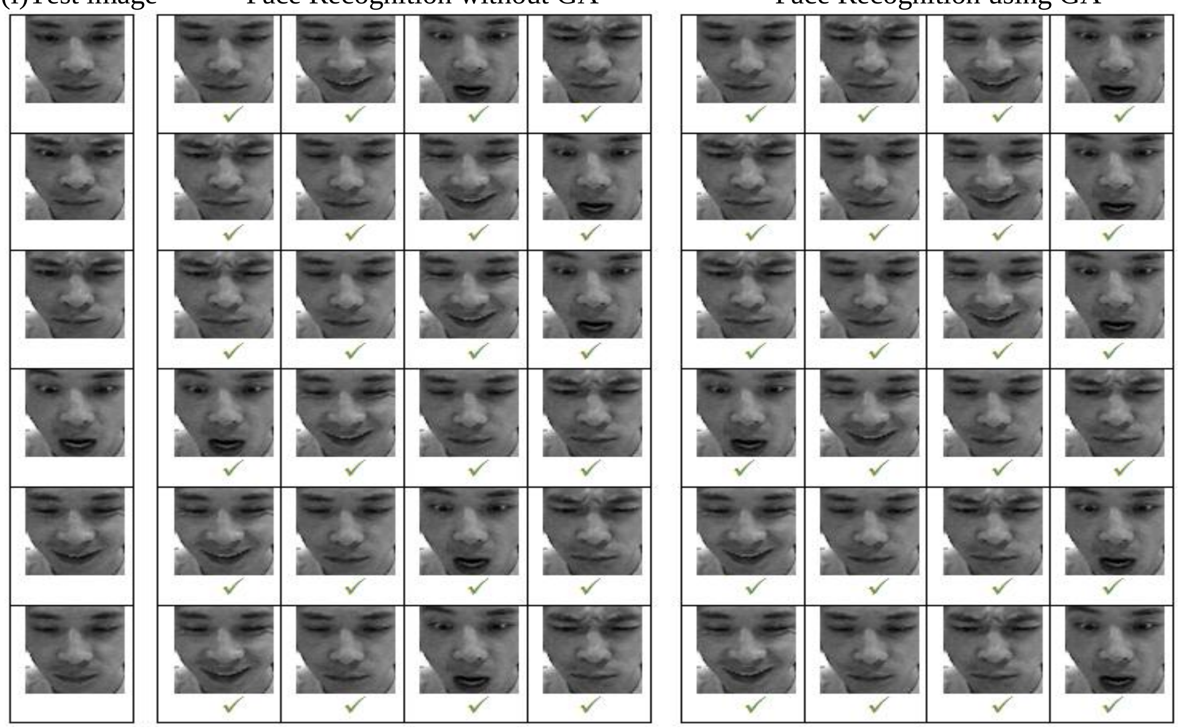
(i)Test image Face Recognition without GA Face Recognition using GA

(j)Test image Face Recognition without GA Face Recognition using GA



(k)Test image Face Recognition without GA Face Recognition using GA

(l)Test image Face Recognition without GA Face Recognition using GA



4.6 Analysis and Discussion

In this section the results of applying GA to reduce the number of features in the three tested datasets are gathered and discussed. Similarly, the effect of using only the eyes for FR is emphasized by listing the recognition rate of the three tested datasets compared to the reduced number of features and time percentage.

4.6.1 Selecting a Subset of Features

As clearly obvious from the results, not all facial features have a positive effect on the classification rate. This was shown in the results of using GA to select only part of the features. In all experiments whether the whole face was involved in the recognition or only the eyes, selecting part of the facial features outperformed the use of the whole feature set.

In the first dataset, the classification rate of the whole face was increased from 87% to 100% when the number of features was reduced to 68 from 832 using GA. Similarly, the classification rate using the eyes was increased from 70% to 100% when the features were reduced from 60 to 18 using GA.

In the second dataset, using the whole face gave a recognition rate of 100% when all the 286 features were used. The same rate was achieved when the features were reduced to 29 using GA. When only the eyes were used for recognition, reducing the features from 72 to 16 increased the classification rate from 86% to 98%.

Similarly in the last dataset, the classification rate using the whole face was increased from 97% to 100% when selecting only 119 features instead of 286. The same effect is clear using only the eyes, where the classification rate was increased from 81% to 94% when only 21 features were selected instead of 72.

Based on the above mentioned results, one can observe that there is a noticeable increase in the classification rate when only a subset of facial features is used. This leads to the conclusion that some facial features are useless in the recognition process and can significantly degrade its performance.

4.6.2 Face Recognition Based on the Eyes

In light of the conclusion drawn in the previous Section (4.6.1), that not all facial features are helpful to use in the recognition process, we chose to test the performance of the proposed FR technique on both eyes only to test their contribution in the recognition rate. After running the proposed algorithm on three different datasets where only the eyes were selected from the facial images, an excellent classification rates (up to 100%) was achieved compared to the small portion of the face taken into consideration.

Experiments on the first dataset show that a classification rate of 100% was achieved using human eyes only. Although the same rate was obtained using the whole face, 67 features were needed from the whole face whereas only 18 features of the eyes were sufficient to give the 100% rate.

In the second dataset where there are various facial expressions for each subject, a classification rate of 98% was achieved using only the eyes. The 100% rate achieved using the whole face required 29 features while only 16 features were needed to get the 98% rate of the eyes.

Finally, in the last dataset where only four training images for each subject exist, the classification rate achieved using the eyes alone reached 94%. Using the whole face also gave a 100% classification rate exploiting 119 features from the whole feature set, while only 21 features were used in case of the eyes.

It is also important to note that in the second dataset where 98% classification rate was achieved, 10 of the 12 subjects were 100% recognized only using the eyes. Additionally, in the last dataset where the best rate achieved was 94%, 9 subjects of the 12 were 100% recognized depending only on the eyes.

From the previous discussion, we conclude that human eyes have a significant contribution in the FR process; using only human eyes achieved a very good recognition rate despite the significant variations in the human faces due to facial expressions. The achieved recognition rate reached up to 100% and was never less than 94% on the experienced databases. The eyes form a relatively small part of the face that is nearly 30%, and using them to achieve a good classification rate can be of a great benefit with regards to time and memory consumption, as proved by the number of features selected from the eyes to get such a good recognition results. Table 12 provides the percentage of reduced time when only the eyes were used instead of the whole face in both testing and features extraction from training images.

Table 12: Percentage of reduced time when the eyes are used instead of the whole face

Dataset	Percentage of reduced testing time	Percentage of reduced time in features extraction from training images
JAFFE dataset	73%	81%
AMP dataset – part one	40%	58%
AMP dataset – part two	31%	56%

It is important to mention that the minimum recognition rate achieved when the proposed method is applied on the eyes - which is 94% - can be compared to results reported by many other techniques that exploited the whole face in the recognition process. For example, Gudur and Asari (2006) used Gabor Wavelets with PCA on the whole face and the recognition rate reported was 90% in the best case on AR database. Similarly, Wavelet Transforms were combined with PCA on the whole face to achieve a recognition rate that reached 92% on ORL database (Wei et al., 2009).

Also, Kyperountas et al., (2008) proposed a FR technique exploiting the whole face. The technique achieved a 94.73% recognition rate when 4 training images were used for each subject (from ORL database), which is the same number of training images that gave 94% on the technique proposed in this research exploiting only the eyes. When they used 7 training images per subject, the recognition rate achieved was 98.5% while the proposed technique gave a 98% using only the eyes when 7 images were used for training per each subject.

5. Conclusion and Future Work

Face Recognition is one of the biometric methods used for human identification based on physiological characteristics. It can be distinguished from other techniques by its non-intrusive nature. FR can achieve high accuracy despite its simple mechanism and low cost compared to other biometric techniques such as iris and retina scan.

A general FR algorithm must pass through three major steps. When an unknown image needs to be recognized, the first step is to detect the human face in the image. Face representation step comes next to extract the discriminating features of the face. Finally, a decision is made based on the matching between the features extracted from the provided image and the features of the images stored in the database from which we want to recognize the face.

Features Extraction step is very important to the FR process. Many methods have been proposed for extracting discriminating features out of the human face. Some of these techniques use the whole face as input while others only use parts of the face which are expected to contain the most useful features.

In this research it was shown that applying the FR algorithm using the whole features extracted from the face image clearly reduces the accuracy of the FR system which indicates that some information in the face might be redundant and invaluable. This was shown in the comparison between the results obtained from the proposed FR algorithm using the whole features extracted from the image and the results obtained when GA is used to select the best subset of features.

As a conclusion from the previous comparison, it was expected that some parts of the face might be sufficient to achieve a very good recognition rate without having to exploit the whole face. The proposed FR algorithm which combines Wavelet Transforms as a tool for analyzing data in multi-resolutions with the simple Average Intensity feature extraction method that provides a high recognition rate, this algorithm was tested one time on the whole face and another time on two images representing both eyes. Unsurprisingly, the eyes provided a high recognition rate compared with the small number of features needed for getting such good results.

The experiments were held on three datasets from two different databases (JAFFE and AMP). These datasets were chosen to contain large variations in human faces due to facial expressions. The eyes which form about only 30% of the face provided a very good recognition rate when used by the proposed FR algorithm. The recognition rate achieved ranged from 94% and up to 100% despite the existence of various facial expressions variations in the tested images.

As a conclusion that the eyes have a major role in discriminating human faces even with the existence of various facial expressions, it is suggested as a future work to test their effect on identifying humans while they age. A good recognition rate is expected to be achieved when the FR technique evaluated in this research is applied on a database where human variations are due to aging rather than facial expressions.

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تقييم خوارزميات التعرف الأوتوماتيكي على الأشخاص من خلال ملامح الوجه

إعداد
مريم "محمد سليمان بدوي" توحيد الشريف

المشرف
الدكتور عزام سليط

ملخــــــــص

لاقت طرق تمييز الأشخاص أوتوماتيكيا اعتمادا على خصائصهم الفيزيائية إهتماما كبيرا في الآونة الأخيرة. هذه التقنيات المسماة بالمقاييس الحيوية فاقت الطرق التقليدية لتمييز الأشخاص و المعتمدة على التوقيع الشخصي أو الكلمات السرية والتي لا تخلو من احتمالية ضياعها أو نسيانها أو تقليدها من الآخرين.
اشتهر استخدام المقاييس الحيوية مثل بصمة القزحية أو مسح الشبكية أو كف اليد في تطبيقات التعرف الأوتوماتيكي على الأشخاص. إلا أن التمييز عن طريق الوجه يتميز عن هذه الطرق بكونه غير تدخلي ولا يتطلب تعاون الشخص المراد تمييزه. كما أنه يتميز بإعطاء نتائج تمييز دقيقة مع كونه بسيط وتكلفة بناؤه قليلة نسبة إلى باقي الطرق المشابهة.
أهم خطوات خوارزميات التعرف على الوجه هي استخراج المعلومات المهمة التي تميز وجه شخص عن شخص آخر. هنالك الكثير من الطرق المختلفة المتبعة لاستخراج هذه المعلومات؛ بعض هذه الطرق يعتمد على الوجه بالكامل وبعضها الآخر يعتمد على أجزاء من الوجه لتقليل الوقت وسعة التخزين اللازمة لاتخاذ القرار.
من جهة أخرى ليس بالضرورة أن تكون جميع المعلومات المستخرجة من صورة وجه الإنسان ذات أهمية في عملية التمييز. على الكس تماما، بعض المعلومات المكررة والتي ليست لها تأثير في تمييز شخص عن آخر قد تؤثر سلبا على فعالية نظام تمييز الوجه. للتأكيد على هذه الفكرة، تهدف هذه الدراسة إلى المقارنة بين استخدام جميع المعلومات المستخرجة من صور الأشخاص وبين توظيف الخوارزميات الجينية في اختيار جزء قليل من هذه المعلومات في عملية التمييز. نتائج هذه الدراسة توضح كيف أثر استخدام جميع المعلومات المستخرجة من الصور بشكل سلبي على فعالية نظام التعرف على الأشخاص من خلال ملامح الوجه.
في ضوء النتيجة السابقة وما أكدته من أن ليس كل معلومة تستخرج من الوجه تؤثر إيجابا على نتائج نظام تمييز الوجوه، تم اقتراح وتقييم خوارزمية تعرف على الوجوه بناء على اختيار جزء الوجه الذي يحتوي على العينين لدراسة تأثير العينين في عملية التمييز. اختيار العينين يرجع إلى أهميتها كجزء مميز لشخص عن آخر و كونها أقل تأثرا بتغير تعابير الوجه للشخص نفسه. تبين من التجارب التي أجريت على نوعين من قواعد البيانات الصورية المحتوية على صور لأشخاص تختلف تعابير

وجوههم إلى حد كبير، أن العينين التي تكون ما يقارب 30% فقط من الوجه بالكامل بإمكانها أن تميز بين الأشخاص بنسبة لا تقل عن 94% بل و تصل إلى 100% بناء على الصور المستخدمة في قواعد البيانات المعتمدة في هذه الدراسة.