A HYBRID GENETIC-FUZZY MODEL FOR CLASSIFICATION OF FACIAL EXPRESSIONS

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MODEL HIBRID GENETIK-KABUR UNTUK PENGELASAN EKSPRESI MUKA

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DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

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ABSTRACT

In recent years, computer technology has led to remarkable increase in use of classification for intelligent systems. Classification of facial expressions opens a new direction to increase the interaction between computers and human. The major issue which divides the facial expressions from the other classification domains is natural based behavior of human as the objects to express the emotions which should be recognized with the classifier model. Existing research recognize the emotions using a range of classification techniques. However, low accuracy rate, large training set, large extracted features or priority for sequence images are the main drawbacks of those works. One of the recent techniques to address the facial expressions problem is Fuzzy Rule Based System (FRBS) which is used as a successful method to model and solve the natural based problems. However, FRBS is poor to adapt the existing knowledge with the diverse conditions. Therefore, the knowledge base which is created for the FRBS by experts such as the Fuzzy membership parameters is not optimum to use in the facial expressions classification model. Furthermore, selecting a proper type of Fuzzy membership functions such as triangular, trapezoidal and bell shaped or combination of them is a boring and uncertain work. With regarding to such problems, this research is an attempt to develop the classification model with small size of extracted features, robustness and optimum performance. The hybrid Genetic-Fuzzy rule based model as the proposed classification not only drives the simplicity of Fuzzy logic on a complicate domain but also optimizes the performance of Fuzzy classification while the limited raw input data as the features are used. In order to improve the Fuzzy knowledge base, membership parameters are tuned in a learning process while the constant rules are defined based on the psychological studies and statistical analysis of emotional states. In this model, the proposed Genetic Algorithm simulates and improves the honey bees offspring generation process called Bee Royalty Offspring Algorithm (BROA) to improve the training process of classic Genetic Algorithms. Therefore, Fuzzy membership parameters are tuned faster also present higher accuracy rate in the classification model. As a result, the main contributions of this research are using less extracted points from the static facial images compared with the existing works. This help to reduce the computation process in the classification, presenting a novel hybrid Genetic-Fuzzy model for the expressions recognition problem. Modification of the Genetic Algorithm to improve its training process and presenting higher accuracy rate than the Fuzzy rule based models and the corresponding existing classification techniques. Furthermore, the accuracy, reliability and validity of the proposed model have been measured and evaluated with several experiments. The outcomes have been compared with the result of previous techniques under the comparison criteria which influence the accuracy rate of classification. The comparison results illustrate that the Genetic-Fuzzy classification model improves considerably the accuracy rate and performance of FRBS while the BROA modify the training process of Genetic Algorithms. Moreover, the results showed that the proposed model is reliable, valid and robustness in the small size of facial feature points, using static images and the database which included non-controlled emotional subjects.

ABSTRAK

Kebelakangan ini teknologi komputer telah membawa peningkatan yang sangat baik dalam penggunaan pengelasan bagi sistem pintar. Pengelasan ekspresi muka membuka hala tuju baru untuk meningkatkan interaksi antara komputer dan manusia. Isu utama yang membahagikan ekspresi muka daripada domain pengelasan yang lain adalah tingkah laku semulajadi yang berasaskan manusia sebagai objek untuk meluahkan emosi yang harus diiktiraf dengan model pengelas. Penyelidikan yang sedia ada mengecam emosi dengan menggunakan pelbagai teknik pengelasan. Walau bagaimanapun, kadar ketepatan yang rendah, set latihan yang besar, bilangan ciri-ciri ekstrak yang banyak atau kerumitan dari segi proses pengiraan merupakan kelemahan utama teknik tersebut. Salah satu teknik terkini untuk menangani masalah ekspresi muka ialah Sistem Kabur Berasaskan Peraturan (FRBS) yang digunakan sebagai satu kaedah yang berjaya untuk memodel dan menyelesaikan masalah berasaskan semula jadi. Walau bagaimanapun, FRBS mempunyai kelemahan untuk disesuaikan dengan pengetahuan sedia ada dengan syarat-syarat yang pelbagai. Sebaliknya, pangkalan pengetahuan yang dicipta untuk FRBS oleh pakar seperti parameter keanggotaan kabur tidak optimum untuk digunakan dalam model pengelasan ekspresi muka. Tambahan pula, untuk memilih fungsi keanggotaan kabur yang sesuai dari segitiga, trapezoid dan bentuk loceng atau gabungan antaranya merupakan satu kerja membosankan dan tidak menentu. Lanjutan daripada masalah yang telah dibincangkan, kajian ini akan membangunkan model pengelasan yang mudah, mempunyai saiz ekstrak fitur yang kecil, keteguhan dan berprestasi optimum. Model hibrid genetik-kabur berasaskan peraturan (HGFM) digunakan sebagai pengelasan bukan sahaja untuk memudahkan domain yang rumit ini tetapi ianya juga dapat mengoptimumkan prestasi bagi input data yang terhad. Untuk meningkatkan pangkalan pengetahuan kabur, parameter keanggotaan diubahsuai di dalam proses pembelajaran manakala peraturan malar telah diwujudkan berdasarkan kajian psikologi dan analisis statistik keadaan emosi. Dalam model ini, algoritma Genetik akan menyerupai lebah madu bagi proses mengawan yang dikenali sebagai Algoritma Anak Anak Permaisuri Lebah (BROA) untuk meningkatkan proses latihan bagi algoritma Genetik klasik. Oleh itu parameter keanggotaan kabur akan disetalakan lebih cepat dengan kadar ketepatan yang lebih tinggi dalam model pengelasan. Sumbangan utama penyelidikan ini ianya dapat menggunakan bilangan titik ekstrak yang sedikit dari imej muka statik jika dibandingkan dengan kajian yang tersedia ada bagi mengurangkan proses pengiraan dalam pengelasan, menghasilkan hibrid model genetik-kabur untuk masalah pengecaman ekspresi, pengubahsuaian algoritma Genetik bagi meningkatkan proses latihan dan membentangkan kadar ketepatan lebih tinggi daripada model kabur berasaskan peraturan dan teknik pengelasan yang ada. Ketepatan, kebolehpercayaan dan kesahihan model yang dicadangkan telah diukur dan dinilai dengan beberapa eksperimen. Hasil kajian telah dibandingkan dengan hasil teknik terdahulu di bawah kriteria perbandingan yang mempengaruhi kadar ketepatan pengelasan. Keputusan yang diperolehi mendapati model pengelasan genetik-kabur dapat meningkatkan kadar ketepatan dan prestasi FRBS manakala BROA mengubah suai proses latihan algoritma genetik. Perbandingan keputusan juga menunjukkan HGFM dapat meningkatkan keteguhan pengelasan dengan saiz titik muka yang sedikit menggunakan imej statik dan pangkalan data bagi emosi subjek yang tidak terkawal.

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LIST OF ABBREVIATIONS

Abbreviation	**Full Expressions**
AAMs	Active Appearance Models
Acc.Rate	Accuracy Rate
AHP	Analytical Hierarchy Process
ANFIS	Adaptive Neuro Fuzzy Inference System
AUs	Action Units
BA	Bee Algorithm
BP	Base Parameter
BROA	Bee Royalty Offspring Algorithm
CBR	Case Based Reasoning
FACS	Facial Action Coding System
FAPs	Facial Animation Parameters
FCM	Fuzzy C-Means
FDP	Fuzzy Discriminate Projection
FIS	Fuzzy Inference System
FPA	Feature Points in the Anger state
FPH	Feature Points in the Happiness state
FPN	Feature Points in Neutral state
FPSa	Feature Points in the Sadness state

FPSu	Feature Points in the Surprise state
FRBS	Fuzzy Rule Based System
GAs	Genetic Algorithms
GA-type-I	Genetic Algorithm-type I
GA-type-II	Genetic Algorithm-type II
HCI	Human Computer Interaction
HMMs	Hidden Markov Models
k-NN	*k*-Nearest Neighbor
LBP	Local Binary Patterns
MOM	Mean value of Maximum
NN	Neural Network
PCA	Principal Component Analysis
Pm	Probability of mutation
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
SVM	Support Vector Machine

CHAPTER I

INTRODUCTION

1.1 INTRODUCTION

In recent years rapid development of human dependence to computer devices for increasing the efficiency and performance in the real life activities is undeniable. Therefore, the interaction between human and computer devices is growing in the various aspects from entertainment electronic devices and home appliance to medicine, business, management, industry, spacecraft and so on. Classification is a method by which the capability of computer to overcome to the human requirements can be enhanced. Classification of objects is an inference task which is used by human mind to analyze the problems. Consequently, a computer device can be intelligent when simulate the mind mechanism to solve the problems.

Emotion recognition improves considerably the interaction between human and computers (Ren 2008). According to Mehrabian & Ferris (1967) in a face to face communication the major factor to transferring the feeling is the facial expression while less portions are allocated to the language and paralanguage factors. This implies the importance of facial expressions to express the emotions in the communication. Therefore, one of the main research interests in the Human Computer Interaction (HCI) is facial expressions recognition (Karray et al 2008). Generally, a facial expressions recognition system includes two main subsystems called feature extraction and classification. Since the main challenges of facial expressions are related to the analysis of facial features therefore, classification of expressions based on the extracted features is the main purpose of this research. The facial expressions analysis deal with some challenges which increase the importance of research on the classification models for facial expressions recognition systems.

A reliable expressions classification technique needs to be robustness adequately with the various appearances of emotional images as well as with limited raw data as the input features. Moreover, a classifier should able to analyze the static images as well as sequence images. Furthermore, its validity should not rely on training with the huge number of training data.

In this chapter, the problem statement of this research, research questions and research objectives are described. Moreover, this chapter consists of an overview of the methodology of research and the research scope. In addition, the research contributions and the structure of thesis are explained at the final sections.

1.2 FACIAL EXPRESSIONS CLASSIFICATION: DEFINITION

The first known study related to analysis of facial expressions recognition was developed by Ekman & Friesen (1978). According to Ekman & Friesen (1978), there are some basic facial expressions which are universal for all people in the world with different ages, cultures and sex. These facial expressions are appeared in the states of Happiness, Anger, Sadness, Surprise, Fear and Disgust. Facial expressions are responses to the stimulants which are created in the human brain (Tie 2011). These responses appear on the face with the facial muscles contraction. Therefore, with regarding to the difference in facial appearances due to the different emotions, a classifier analyzes the changes of facial appearance to classify the facial expressions to the basic emotions. In order to expressions classification a set of facial features are selected as the proper references of facial appearance to show the facial deformations in the emotional states. The selected features should have small bias for an emotion while large bias between the different expressions (Tie 2011). Therefore, a classifier with analysis of extracted features classifies the similar expressions as a similar emotion. In the rest of this thesis, a classification model is considered to develop the current facial expressions classification models with specific criteria in the challenges conditions.

1.3 DESCRIBING THE PROBLEM DOMAIN

Recently, the visual based emotions recognition has been one of the serious researches in the HCI systems (Karray et al 2008). Variation in facial appearance in the emotional states due to different in age, sex, culture and biological background of people as well as variety of facial features make the facial expressions classification more complicate in comparison with other classification domains. As an example we can consider a facial expression in the strong laugh compared with a facial expression in a smile state. In this example both states show the happiness emotion but with bias in face appearance. Therefore, the classification technique should be robust sufficiently to recognize the facial emotions in the variable conditions.

Feature extraction is an important parameter for facial expressions classification. Generally, there are two feature types for facial expressions recognition includes geometric features which is based on the facial extracted points and appearance features which deals with the skin texture of whole the face or some area of face (Paknikar 2008). Geometric features impose less computational process than the appearance features as deal with some specific points on the face image rather than the texture information of the face. However, increasing the number of feature points for the purpose of higher accuracy in classification arise the computational costs both in feature extraction and classification. On the other hand, the classification performance with Geometric features is considerably lower than appearance features (Zhang et al 1998; Youssif & Asker 2011). The difficulty of classification with Geometric features is due to using limited facial data in comparison with appearance type. Therefore, lower performance with Geometric features is still a challenge for classification of emotions. Furthermore, analysis of 2D images or static images, with regarding to elimination of some parts of face, is more difficult than 3D images for expressions classification. As a result, static images in comparison with sequence images present less information into the classification model, which raise the challenges of the expressions recognition.

Rule based classification techniques are the simple approaches to facial expressions recognition (Paknikar 2008) while utilizes the human expert knowledge. In recent years, Fuzzy Rule Based System (FRBS) has been used in several studies as a more proper method than the rule based approaches for classification of facial expressions (Esau et al 2007; Chatterjee & Shi 2010; SeyedArabi et al 2004). FRBS based on the expert knowledge as well as Fuzzy logic create an appropriate classification model to cover most of the expressions recognition requirements. However, the FRBS performance is closely related to its knowledge base. The Knowledge base of FRBS includes two rules base and data base components (Ishibuchi 2009). The rule base involves the Fuzzy rules while data base consists of membership functions. Usually, these two components are set based on the human expert knowledge. However, in the complicate problems such as facial expressions classification the knowledge base is not accurate sufficiently to cover the emotions recognition necessities since the estimation of the proper membership functions is a difficult work. Therefore, the main objective of this research is to present a modified Fuzzy model to provide the mentioned classification requirements.

1.4 PROBLEM STATEMENT

In this section, the challenges of a classification model for facial expressions recognition are described.

a) Facial features extraction

Feature extraction as the initial step of a classification system has an important role in the accuracy of facial expressions recognition. Therefore, higher success rate for facial expressions classification is expectable if a proper set of features are extracted. On the other hand, as the analysis of extracted features is a complicate work, particularly from the facial images, the complexity of classification model is completely depending on its feature parameters. According to Ratliff (2010) Geometric based method decreases the complexity of classification model in terms of computation expense in comparison with appearance method. Geometric method measure the movement of feature parameters extracted from facial feature points from neutral to emotional state. However, number of feature points and the extracted feature parameters from those points influence the classification model in terms of performance and complexity. According to studies by Zhang et al (1998), SeyedArabi et al (2004), Zhan et al (2007), Khanum et al (2009) and Youssif & Asker (2011), the extracted features included 34, 20, 21, 21 and 19 points. However, finding the smallest number of feature points and the best feature parameters extracted from those points while keep the classification performance in a proper level is still a challenge which has been addressed in this research.

b) Classification of facial expressions

According to Mehrabian & Ferris (1967) facial expressions are the major factor to show the emotions. Therefore, we can recognize the emotions if facial expressions are classified into different classes. However, facial expressions are in a variety of appearances to represent an emotion due to different in sex, age, cultures and so on in people. Therefore, facial expressions classification model should be robust sufficiently to recognize the emotion in the ambiguous conditions. Fuzzy Rule based System (FRBS) is used as a popular method to solve the nonlinear complex problems which are faced with uncertain and ambiguous conditions such as facial expressions classification (SeyedArabi et al 2004, Khanum et al 2009, Chatterjee & Shi 2010). However, a Fuzzy rule based classification has some limitations for facial expressions recognition which are listed as follows:

a. Lack of optimized functions

As membership functions are a main part of Fuzzy knowledge base, determination of proper type of membership function with the optimum parameters is a boring and difficult work and usually involves the bias in the values precision while those are obtained from human expert knowledge particularly in the complicate domains.

In order to set the membership function parameters in the traditional approaches, the experts usually use the statistical methods to increase the accuracy of parameters. However, the statistical approaches such as maximum, minimum, mean and standard deviation which are commonly used to estimate the membership function parameters have considerably errors in the complicate problems. The errors may occur due to outliers data which caused the deviation from the real values particularly where the distance of outliers data is far to the normal distribution of data.

b. Lack of learning process

Adaptive learning process to increase the model flexibility to fit with the diverse conditions is not available in the FRBS due to rigidity of the FRBS configuration (Fernandez et al 2011).

These limitations of Fuzzy rule based classification technique influence the performance of facial expressions recognition, so that the Fuzzy classifier cannot use the inherent merits, appropriately for facial expressions classification. As a result, a way to resolve the Fuzzy requirements is needed while general challenging parameters such as static images, low level features and uncontrolled database are used.

To overcome the limitations of FRBS, Genetic Algorithms as a learning method are used to fill in the gaps in various studies (Bonissone et al 1996, Alcala et al 2005, Alcala et al 2009, Alcala et al 2011, Ishibuchi et al 1999, Schaefer 2011). However, Genetic Algorithms training process for optimizing of some complex problems with many parameters need to improvement process (Ishibuchi & Yamamoto 2004). Some important of Genetic Algorithms gaps in the learning process are as follows:

a) Progressive decline in the training process
b) Local optima problem
c) Deviation in obtained solutions in the different run of algorithm

As a Genetic Algorithm performance is completely depending on its operators including Crossover, Mutation and Selection, therefore improvement of those operators modify its learning process. As a result, in this study a modified Genetic

Algorithm was proposed to fill in the Genetic Algorithms gaps as well as to tune the Fuzzy knowledge base in a learning process for facial expressions classification.

1.5 PROPOSED SOLUTIONS

With regarding to the classification requirements the prerequisite steps for facial expressions classification and FRBS characteristics are considered in this section to present a scheme to overcome the lacks.

1.5.1 Features Extraction

Feature extraction is the process of indicating the relevant properties of patterns that determine certain characteristics of objects. Facial features extraction is related to representation of face features including shape, color and texture which are the main face components to recognize the facial expressions. As mentioned in Section 1.3, the Geometric features type which includes the extraction of feature points is more simple in terms of computational cost for the analysis and classification of facial images than the Appearance type if a limited number of feature points are selected and extracted in the recognition process (SeyedArabi 2007). Therefore, detection of proper size of feature points is the aim of feature extraction component to make suitable feature vectors which are determined based on the displacement of feature points from neutral to emotional images for feed in the classification model. As a result in this research a Geometric type with small size of points has been chosen for facial features extraction from static images.

1.5.2 FRBS Inherent Advantages as a Classifier

In general, FRBS uses from some benefits which make it a proper technique for the classification of emotions. The most important of those traits are listed as follow:

a. **Simplicity:**

FRBS formulate a simple model to draws the outputs from inputs space based on the knowledge base which imposes low computation cost to solve the nonlinear problems in comparison with other methods (Li 2006).

b. Most probable estimation:

FRBS estimates the most probable classification for nonlinear problems with uncertainty outputs. In the facial expressions classification, an expression can be classified into the various classes with different probability. Therefore, the expression belongs to a class of emotion with most probable estimated value (Wu et al 2005).

c. Linguistic perceptible:

The rules in FRBS are created based on the perceptible linguistic variables to formulate the expert knowledge into the model. Linguistic terms decrease the complexity of the Fuzzy systems which is derived from the ability of perception of rules and Fuzzy sets (Ishibuchi & Yamamoto 2004).

1.5.3 Learning Algorithm

With regarding to capabilities of the FRBS to use in the classification problem, to fill the FRBS lacks, a Genetic Algorithm is proposed to combine with FRBS for facial expressions recognition. The Genetic Algorithms are the evolutionary learning process, which are applied to complex optimization problems to find the optimum results (Ishibuchi & Nojima 2009). There are several studies (Bonissone et al 1996), (Hoffmann 2001), (Alcala et al 2005), (Ishibuchi & Yamamoto 2005), (Alcala et al 2009), in which the Genetic Algorithms were used to optimize the FRBS performance with generating the optimum Fuzzy rules or tuning the membership functions in the classification and control problems. Therefore, two parameters of Fuzzy rules and membership functions with the purpose of generating the optimum number of rules and membership parameters improvement, respectively, are determined in the learning process of Genetic Algorithms.

The learning process increases the complexity of FRBS, particularly in the rules creation process (Ishibuchi & Nojima 2009). Therefore, in this research, a Genetic Algorithm is presented only to tune the Fuzzy membership functions while the Fuzzy rules are determined based on the expert knowledge. Moreover, to increase the Genetic Algorithms performance, bees offspring generation behavior is simulated and then this process is improved. Therefore, the training process is performed faster with higher accuracy rate to find the optimum construction of classification model. As a result, the Fuzzy knowledge base is improved while the computational costs are kept under control. The proposed hybrid Genetic-Fuzzy model is a novel scheme to fulfill the requirements of facial expressions recognition. Therefore, in this model, we believe that the proposed Genetic Algorithm compensates the learning needs of FRBS to adapt with diverse conditions of facial expressions images while optimizes the membership functions. Moreover, this is expected that the hybrid Genetic-Fuzzy Rule based System provides an appropriate model to overcome the challenges and problems in related to facial expressions classification.

1.6 RESEARCH SCOPE

As the main focus in this research is on the classification component of the facial expressions recognition system, therefore, for the purpose of feature points extraction a method based on analysis of image color information and morphological operations has been proposed. This method has been developed to extract the feature points from the static images in the non-real time systems. Therefore, it is not a suitable method for real time systems due to computational expensive. In addition, this method is not suitable to detect automatically all facial feature points. Moreover, as the main database used in this research included the color images from the natural actions, the feature points extraction technique was developed based on the analysis of color information. Therefore, it is not able to extract the facial points from the grayscale images.

In general, universal facial expressions presented by Ekman & Friesen (1978) are grouped in two positive and negative expressions (Alves et al 2008). Therefore, different numbers of universal facial expressions including positive (Happiness and Surprise) and negative emotions have been used in the existing research for recognition with classification models. For example in the studies of Cheon & Kim (2009), Saatci & Town (2006) and Besinger et al (2011) three expressions, in the studies of Sreenivasa et al (2011), Esau et al (2007), Cheng et al (2007) and SeyedArabi (2004), four expressions, in Chatterjee & Shi (2010) study, five emotions and in the studies of Youssif & Asker (2011), Shan et al (2009) and Guo & Dyer (2005), six facial expressions were considered in the classification models. In this research, analysis of the facial expressions was accomplished on the four basic emotions comprising two positive (Happiness and Surprise) and two negative (Sadness and Anger) emotions. According to Khanum et al (2009), Sadness and Anger are the most difficult emotions to recognize between all universal expressions while a FRBS is used as the classification technique. Therefore, Sadness and Anger as the negative emotions were chosen in this research to evaluate the improvement of FRBS in the proposed hybrid Genetic-Fuzzy model. However, some complicated facial expressions which human able to recognize them such as stress and pain, are not included in this research.

1.7 RESEARCH OBJECTIVES

This research is an attempt to obtain the following objectives:

1. To propose a Geometric based features extraction method from the static images.
2. To propose a Genetic-Fuzzy Rule based System for development of facial expressions classification.
3. To propose a Bee Royalty Offspring Algorithm (BROA) to modify the Genetic Algorithm training process for the purpose of classification improvement.
4. To design and develop the proposed classification model for facial expressions recognition.

1.8 RESEARCH METHODOLOGY

The research is divided into the three phases while in every which, the steps and activities in order to achieve to the objectives of this research are carried out. These phases and the objectives related to those phases are summarized in Figure 1.1.

Phase1:

The main purpose of this phase is to achieve the following objectives:

1- To identify and investigate the challenges associated with facial expressions classification for the purpose of fulfill the system requirements.
2- To propose the Genetic-Fuzzy model for development of facial expressions classification.
3- To propose a Bee Royalty Offspring Algorithm to modify the Genetic Algorithm training process for the purpose of classification improvement.

Phase2:

The main purpose of this phase is to achieve the following objectives:

1- To design and develop the proposed classification model for facial expressions recognition.

Phase3:

The main purpose of this phase is to achieve the following objective:

1- To test the proposed classification model to achieve the accuracy rate of expressions recognition.
2- To evaluate the proposed classification performance in comparison with existing Fuzzy Rule based Systems.

Figure 1.1 Research Phases and the Objectives Related to Those Phases

1.8.1 Research Method for Phase 1

This phase includes three stages namely; literature review, system declaration, analysis of system requirements and architecture of the proposed model for facial expressions recognition. In this phase the facial expressions recognition system has been identified and its subsystems consisting of face image processing, feature extraction and classification have been described. Moreover, the related works of facial expressions recognition have been reviewed. Furthermore, analysis of system requirement has been carried out to find out the model expectations for classification of facial expressions. Therefore, different facial expressions recognition systems including different facial features extractions, normalizations, classifications and training algorithms have been considered critically for the purpose of finding the appropriate techniques and technologies to use in the model. Next, the selected components have been combined for the purpose of making an integrated model as a base for the next phase.

Overall, the aim of this phase has been achieved based on the review of relevant definitions, theories, existing works, techniques, models and comparisons. As a result, the main research method which has been utilized in this phase is:

Library work

1.8.2 Research Method for Phase 2

In this phase, a prototype has been designed for facial expressions classification and developed according to the proposed structure of phase 1. In this phase, the development of facial features extraction as well as proposed hybrid Genetic-Fuzzy classification model under the Matlab environment have been accomplished. The utilized methodology of research in this phase based on the modeling and development of a prototype is as follows:

Prototyping

1.8.3 Research Method for Phase 3

In this phase, the proposed model has been tested and its reliability and validity evaluated in comparison with several scenarios to consider the classification performance of the proposed model which has been developed in the previous phase. In this phase as the experiment results are evaluated therefore, the research method is as follows:

Experimental research

1.9 CONTRIBUTIONS

The main purpose of this research is based on the endeavors to propose a classification model for facial expressions recognition. Therefore, in this section the results of the proposed model which indicate its contributions of this research are described as follow:

1. **Small size of facial features:**

   This research proposes a small size of feature points which are extracted based on the image color information and morphological operation and produces a simple method for measuring the feature vectors based on the neutral and emotional images from static images.

2. **Hybrid Genetic-Fuzzy model:**

   This research proposes a Fuzzy Rule based System with a simple knowledge base in which the membership parameters are tuned with Genetic Algorithms to improve the performance of the facial expressions classification. In the proposed model, a bell shaped membership function with three variable parameters is proposed to increase the solutions space to find the optimum membership function.

3. **Bee Royalty Offspring Algorithm (BROA):**

   In this research a learning algorithm is proposed which is simulated based on the improvement of honey bees offspring generation process called Bee Royalty Offspring Algorithm (BROA). BROA is proposed to develop the optimization process of classic Genetic Algorithms in the training phase. Moreover, BROA adjusts the bees mating behavior model to achieve to the optimum solutions.

4. **Design and development of the model:**

   This research designs and develops the proposed a hybrid Genetic-Fuzzy model based on the BROA and hybrid Genetic-Fuzzy model based on the classic Genetic Algorithms in comparison with a FRBS for classification of facial expressions.

1.10 THE THESIS OUTLINES

The attempts to present the proposed model for facial expressions recognition are described in six chapters of this thesis. In this section an overview of the chapters of this thesis are organized as follow:

CHAPTER 1: Introduction

Chapter 1 of this thesis introduces the problems, research questions, research objectives, solutions and contributions of this work. Next, the outlines of this thesis are summarized in the Chapter 1.

CHAPTER 2: Literature review

Chapter 2 is to review of definitions, backgrounds and opinions which are related to the facial expressions recognition system. Moreover, the techniques, technologies and the existing models in the state of the art related to the facial expressions classification are reported and considered in this chapter.

CHAPTER 3: Research methodology

In this chapter the process in which this study has been developed including the way of data gathering, analysis of proposed model, training and testing phases, simulation environment and system evaluation has been described.

CHAPTER 4: Development of Genetic-Fuzzy classification model

In this chapter the proposed system architecture is described in details to design and develop for facial expressions classification. Therefore, the proposed methods for development and implementation of each component of the proposed framework and the relation of those modules to each other are explained. As a result, the proposed features extraction method based on the image color analysis, morphological operations and normalization technique are described in this chapter. Moreover, the proposed a hybrid Genetic-Fuzzy classification model for recognition of facial expressions is depicted.

CHAPTER 5: Experiment and results

In this chapter the implementation results from experiment of the proposed model are illustrated. Moreover, the reliability and validity of the model are tested in Chapter 4 and the results of those are shown in this chapter. Furthermore, this chapter involves the results of the proposed model based on the BROA training algorithm in comparison with the other models based on the Genetic learning Algorithms as well as the results from FRBS without learning process.

CHAPTER 6: Discussion

In this chapter, the experiment results obtained from the proposed model are considered and evaluated in terms of classification performance in comparison with existing works. In this comparison, the parameters which influence the recognition results are discussed to evaluate the classification performance in a fairly condition. Finally, this chapter concludes that the proposed hybrid Genetic-Fuzzy model including BROA learning process increases the accuracy rate of classification in comparison with FRBS while it shows the comparable performance in front of other existing classification techniques.

CHAPTER 7: Conclusion and future works

In this chapter, the conclusions of this research consisting of summary of the accomplished works which described in the last five chapters are explained. Therefore, the results according to the objectives and contributions are concluded in this chapter. The last part of Chapter 6 comprises the research limitations of this work and is finished with recommendations for future works.

1.11 SUMMARY

This chapter includes the introduction of this thesis. In the introduction firstly, the problems and research questions have been described. Next, according to the problem statement, the research objectives, solutions, research methodology, and contributions of this work have been presented, briefly. Finally, the organization of this thesis have been summarized in this chapter to introduce and review shortly the outlines of this thesis which are described the next chapters.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

The importance of classification is known in variety domains of human life. Classification makes a comprehensible structure for objects to set them in the real situation. It separates area of data into different categories according to their characteristics and qualities. So that, each class includes most similar objects against the others (Ross 1997).

Classification methods are in two groups based on the available information of specifications of classes:

a) Unsupervised classification:

Unsupervised classification does not use expert knowledge or in some cases, there is a lack of information regarding to the pattern of classes and their output attributes. In this technique, statistical procedures are used to estimate similarity within the area of data (Guerra et al 2011).

b) Supervised classification:

In comparison with unsupervised classification, in supervised classification sufficient information about the trait of predefined classes and classes label is provided. Also training data in the learning phase fit the model to classify input data to correct known outputs (Guerra et al 2011).

Classification of objects or patterns into several groups is a main purpose in pattern recognition area. There are many applications in which pattern recognition is used as an important part such as machine vision systems, optical character recognition systems, diagnostic decision support systems, human computer interaction systems, speech recognition systems and so on (Theodoridis & Koutroumbas 2006).

Pattern recognition in the domain of facial image is one of the challenging areas. In recent years, many researchers have developed several classification methods to recognize various emotions based on the images of human face. Classification of facial images can be used effectively to interact human and computer systems which have various applications in digital cameras, teleconference, animation design, customer relation management systems and so on.

The well known facial expression recognition system was introduced by Ekman and Friesen (1978). Based on their studies, there are basic facial emotions: happiness, sadness, surprise, anger, fear and disgust. They showed facial emotions cause movement and change in the set of face muscles which are universal and have similar actions for all people in the different nations (Ekman & Freisen, 1978). Therefore, muscles movements can be used as the criterion of measurement for classification of facial expressions. Facial expression recognition systems need to have feature data of images for classification of facial expressions. Therefore, facial feature extraction is the first step that prepares required data as input data for classification of facial expressions. For the purpose of facial expression recognition there are several techniques have been presented both for feature extraction and classification in recent years. In this section some of the most important of current techniques are surveyed with regarding to their advantages and disadvantages.

2.2 FACIAL FEATURES EXTRACTION

2.2.1 Face Detection

Features extraction can be performed on the static or sequences images by using several techniques including the real time/non-real time and automatic/non-automatic techniques. For the purpose of extracting the facial features, face detection is the pre-requisite step to separate the face area from other parts of body such as hair and neck. Several methods have been proposed to face detection. The most commonly used methods are described in the following part.

i. Active Appearance Models (AAMs)

Cootes et al (2001) proposed Active Appearance Models (AAMs) to represent the human face. The method match a face shape model and appearance parameters to the unseen face images in a searching process. At the training process, the face model may uses labels marked by points. This technique can be used for both gray and color images with various pose as well as illumination and different expressions (Cootes et al, 2001). In Figure 2.1 and Figure 2.2 facial feature landmarks and progress of fitting the model to face image are shown, respectively (Gao, 2008).

Figure 2.1 A Labelled Image in Training Set
Source (Gao, 2008)

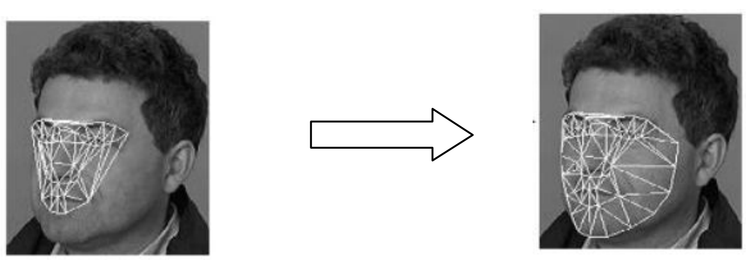

Figure 2.2 Progressive AAMs Fitting
Source (Gao, 2008)

ii. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) uses a set of training images to determine a "face space". For the purpose of face detection in an image, the projection of image selected areas onto the face space is evaluated. Therefore, the region with minimum projection error is accepted as a face position. Menser & Muller (1999) performed PCA onto a set of training face images to calculate a projection matrix that determines a "face space" model. Error criterion in each position of input image by projecting a subspace of image located at that position onto "face space" is calculated. Therefore, face position are the regions with minimum error.

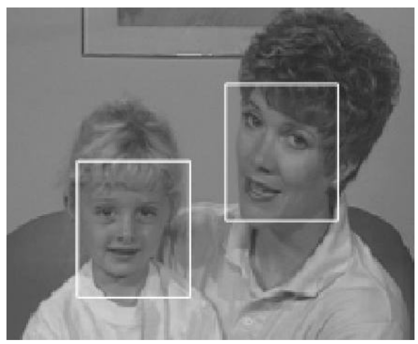

Figure 2.3 Face Detection Using PCA
Source (Menser & Muller 1999)

iii. Neural Network

In the several studies (Rowley et al 1998; Rhee & Lee 2001; Seow et al 2003) Neural Network was proposed to face detection to classify each image to face and non-face regions. In this technique Neural Network is trained with a set of face and non-face training images. Then, it can detect region of face when each region of image evaluate with Neural Networks. Rowley et al (1998) proposed multiple hidden units in the Neural Networks to look for various sub-regions of image to detect main feature face such as eyes, mouth and nose. The output presented the face region.

2.2.2 Facial Features Extraction Techniques

In pattern recognition, feature extraction is the process of indicating the relevant properties of patterns that determine certain characteristics of objects. Facial feature extraction is related to representation of face features including shape, color, texture and components that are important to recognize the facial expression. Geometric features and appearance features are two types of facial features using in the facial expression recognition. Geometric features aim to measure the movement of extracted crucial parts of face such as eyes, eyebrows, mouth and nose landmarks while an emotion is occurred. Another type of features called appearance features, deals with the change of face skin texture in the different emotions (Paknikar 2008). Some of the recent methods for feature extraction are described as follows:

i. Feature Extraction Based on Analysis of Image Data and Its Components

Morphology operators can be used onto dark regions which determine maximum or minimum area on the image, to detect the eyes corners. As the eyes regions include maximum or minimum value of luminance gradient, the information of luminance determines properly the region of eyes. Furthermore, detection of mouth key points needs to information of chrominance and luminance. As the mouth contour includes special colors when the chrominance information is presented, therefore, chrominance data is essential to detect the mouth feature points (Hammal et al 2006).

Ilbeygi & Shah Hoseini (2012) presented an edge detection based method to extract the features from the facial color images. In this method, firstly, the eye maps were detected with chrominance and luminance components from YCBCr format of images. Y component shows the luminance, while Cb and Cr present color information. Then, in order to extract the eye areas a template matching method based on the computing of correlation coefficient in the searching space was used. Finally, the upper and lower positions of eyes were detected using the Canny edge detector and morphological operators to estimate the vertical distance of eyes opening. Moreover, for the purpose of extracting the eyebrows, after estimation of eyebrows areas, the image were converted to the binary format and then a morphology operator used to improve the eyebrows regions. Finally, the centre and the first inner points of eyebrows were extracted as extra facial feature points. In addition, mouth was detected based on the Sobel edge detector from the YCBCr image format to extract the corners also upper and lower of lips.

Sohail & Bhattacharya (2006) presented an anthropometry based technique for facial feature extraction. They used the anthropometry model to detect regions of eyes, eyebrows, nose and mouth. Then, image processing techniques were used to search in the detected regions to extract facial feature points.

Shih & Chuang (2004) extracted the features based on face edge detection process. They used x and y projection to obtain boundary boxes of face features such as eyes, nose and mouth. Also, in order to obtain higher accuracy in the different illumination, Gabor filters are used to detect the eyes location. Then, the positions of other facial features are extracted based on the distances between eyes.

ii. Feature Extraction Based on AAMs

Zhou et al (2011) proposed a hybrid model of Active Appearance Models (AAMs) to extract facial feature points. AAMs (Coots et al 2001) combine the information of Geometric variation as well as texture variation to fit a set of feature points as a face shape with facial images in the diverse expressions. As we explained earlier at the face detection section, to make the statistical model comprising shape and appearance models, a learning process with a set of training images labeled with the feature points is required. Therefore, the face shape model changes to find the close position of points to the features by adapting the texture to the new expression. In general, the AAM shows the proper performance for the features extraction from the objects which are participated in the training phase but also in the different expressions. However, its performance on the new objects shows the bias for the generalization (Bartlett & Whitehill 2011). To improve the AAM results, a classification algorithm was presented in the study of Zhou et al (2011) to classify Gabor features which were extracted from the AAMs initial feature points to find the precise position of facial feature points. Figure 2.4 shows the initial detected feature points and tuned feature points around the eye in the picture (a) and picture (b), respectively.

(a) (b)

Figure 2.4 Modification of Eyes Points Detection, (a) Initial detected feature points with AAM, (b) Modified feature points extraction

iii. Feature Extraction Based on PCA

Principal Component Analysis (PCA) is used to extract the facial features based on the "face space" as it is applied to face detection. In this technique, extracting the facial features needs to train with a set of training data. Training data set led to create independent "feature space" for each relative facial features. Minimizing of projection error of face image regions onto the feature spaces determines the position of features on the face (Pentland et al. 1994).

iv. Feature Extraction Based on LBP

Local Binary Patterns (LBP) method is also used for facial feature extraction with texture consideration in some studies such as Shan et al (2009) and Piatkowska (2010). In this method the face region divides into a grid with small scale pieces as it has been shown in Figure 2.5. Then, the LBP histograms belong to grid cells are extracted as facial features set for a particular emotion (Shan et al. 2009). Figure 2.6 shows the LBP histogram extracted from image grid cells.

(a) (b)

Figure 2.5 A LBP Face Image Segmentation Sample (a) Face image region, (b) Divided face image to small size regions

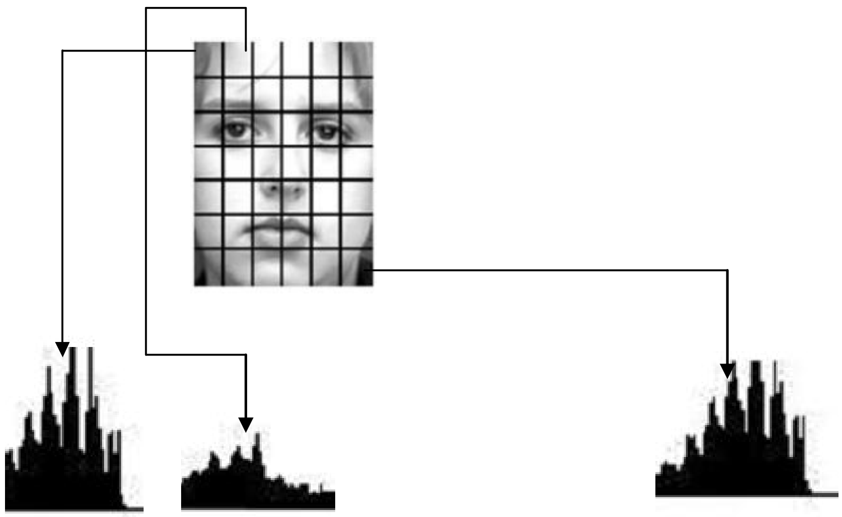

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Figure 2.6 LBP Feature Histograms Extracted From Small Regions

v. Feature Extraction Based on Optical Flow Method

SeyedArabi et al (2007) used optical flow method to extract the facial features from the facial feature points which were manually marked in the first frame. In the proposed method, facial feature points in the next frames were tracked with cross correlation computation method. For the purpose of facial expression classification, facial features were extracted from feature points movements in the first and last frames in the sequence image.

vi. Feature Extraction Based on Gabor Wavelet

Gabor wavelet has been used in the numerous studies for the purpose of facial feature extraction (Guo & Dyer 2005; Hupunt et al 2008; Samad & Swada 2011). Facial expressions recognition using Gabor features shows proper performance in the variable conditions such as illumination of images but need to high computational cost if all Gabor features are used for analysis of images (Samad & Sawada 2011). Gabor filters are utilized as the appearance type of features in which the whole face or some areas of face in the images are extracted as the facial feature vectors. Many researchers have used the Gabor filter bank comprising all filters which need to high computation process. However, in the study of Samad & Swada (2011) Gabor filters with optimum parameters was used in order to decrease the computational cost of features extraction. Experiment results showed that the proposed Gabor filters achieve the proper features for facial expressions analysis. Moreover, for the purpose of simplify the classification process in terms of computation and memory usage, PCA was used to reduce the feature vector dimensions.

As a result, although the Gabor wavelets show the proper performance for facial features extraction but it has the complexity of appearance features type in comparison with Geometric features method (Samad & Swada 2011).

In this research, a Geometric based features extraction method has been proposed based on the analysis of images color information and morphology process. According to the proposed Geometric method, a few number of facial feature points are extracted while the facial feature regions are estimated. Therefore, there is only a limited size of feature references fed into the classifier for the purpose of reducing the complexity of classification model. The proposed Geometric method has been described in details in Chapter 4 of this Thesis.

2.3 FACIAL EXPRESSIONS DATABASES

For the purpose of evaluating the facial expressions models, selecting the suitable database plays the important role to consider the system performance. There are various databases which have been developed with different research studies to use for the facial expressions recognition. However, some of them do not include all the requirements of facial expressions recognition problems to make them suitable as a standard base for testing the models and techniques. Table 2.1 illustrates some of the databases which have been used recently in the more studies as the standard databases. On the other hand, there are numerous facial databases which were created for the purpose of face recognition and usually are not used in the facial expressions recognition problems. FERET (Phillips et al 1998) and AR (Martinez & Benavente 1998) are two examples of face databases which are commonly used for face recognition research.

Table 2.1 Description of Facial Expressions Databases

Database	Cohn-Kanade	MMI	FG-Net	JAFFE	BU-3D
Reference	(Kanade et al 2000)	base (Pantic et al 2005)	(Wallhoff 2006)	(Lyons et al 1998)	(Yin et al 2006)
Subjects	97	52	18	10	100
Nationality	Multiple	Multiple	Europe	Japanese	Multiple
Image Type	Sequence	Static & Sequence	Sequence	Static	Static
Face Pose	Front	Front & Dual View	Front (with natural action)	Front	Front& two views (+45°, -45°)
Color Type	Gray	Color	Color	Gray	Color
Illumination	Still	Still	Still	Still	Still
Resolution	640×490	720×576	320×240	256×256	1040×1329

2.4 FACIAL EXPRESSIONS CLASSIFICATION

Classification of facial expressions is the main part of facial expression recognition systems. Due to complexity of natural characteristics of human facial expressions, classification of emotions need to comprehensive analysis of semantic relations of facial features as a feature set. It means the position and relation of features toward the each others should be considered as a whole form. As the facial features motions in the facial expressions are due to face muscle changes, therefore the parametric set of facial muscles motions have been presented in the form of two standard parameters set known Facial Action Coding System (FACS) and the Facial Animation Parameters (FAPs) which the last are indicated in the MPEG-4 standard.

2.4.1 Facial Action Coding System (FACS)

Facial Action Coding System (FACS) is a known facial expression measurement system which was introduced by Ekman & Friesen (1978) to describe facial behavior according to the face muscles activities. Based on the FACS, Action Units (AUs) are associated with the smallest change of muscles which are appearing with the facial behavior (Cohn et al, 2005). Most of the AUs are related to the movements of eyes, mouth and nose. Therefore, the information of those is popular for facial expression classification systems (SeyedArabi et al, 2007). Facial emotion is specified when a set of AUs appear with together. For example inner brow raiser, outer brow raiser, upper lid raiser, mouth stretch related to the action units number: 1 *and* 2 *and* 5 *and* 26 indicate surprise emotion. Figure 2.7 shows some of the AUs in the facial expressions. Many of research for classification of facial expressions are based on the Ekman et al (1978) studies to categorize the facial expressions to the universal emotions including happiness, sadness, disgust, anger, fear, surprise.

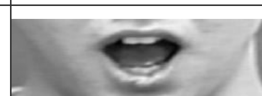
AU - Description	**Sample of images**
AU: 2- Outer brow raise	
AU: 5- Upper eyelid raise	
AU: 27- Mouth stretch	

Figure 2.7 Some AUs Example of Facial Expressions in the FACS

2.4.2 The Facial Animation Parameters (FAPs)

MPEG-4 standard illustrates a facial model in the neutral expression in which 84 feature points are defined on the face (Pereira & Ebrahimi 2002). MPEG-4 standard includes a set of FAPs. The Facial Animation Parameters (FAPs) form a set of facial features actions which indicates the deformations of the facial neutral state to the emotional expressions while each Facial Animation Parameter presents a part of features movement (Lavagetto & Pockaj 1999). For example, in the Surprise state a FAP can be indicated as "raise_l_i_eyebrow and raise_r_i_eyebrow" which can be described as the deformation of inner left eyebrow (i_l_eyebrow) and right eyebrow (i_r_eyebrow). Therefore, according to the AU definition in the FACS which has been explained in the last section of this thesis, there is a close similarity between FAPs in the MPEG-4 standard and AUs in the FACS as the facial actions parameters. Figure 2.8 shows the defined facial feature points in the MPEG-4standard.

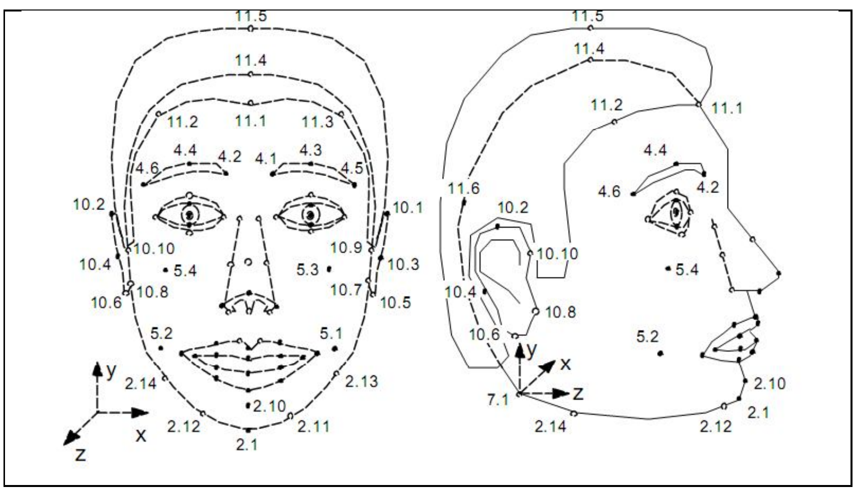


Figure 2.8 Facial Feature Points in the MPEG-4 Standard
Source (Lavagetto & Pockaj 1999)

2.4.3 Classification Techniques

A wide range of classification techniques have been used in the pattern recognition, such as Neural Networks, Radial Basis Function (RBF) Networks, Fuzzy Logic, Bayesian Networks, *k*-nearest neighbor, Support Vector Machine and so on. Those have also been proposed in the facial expressions classification from static and sequence images. In this study, a classification model based on Fuzzy Rule based system combined with a Genetic learning algorithm has been proposed for facial expressions classification. Some of the most popular techniques are summarized and discussed in the following parts.

i. Neural Networks

SeyedArabi et al (2007) proposed a Neural Network classifier model to recognize the facial expressions from the sequence images. They used fourteen manually extracted feature points in the first frame around the eye, eyebrow, nose and mouth. The cross-correlation method was used in this study to track the position of feature points in the next frames which were calculated based on the maximum value of cross-correlation between two frames. Therefore, seven feature vectors based on the feature points displacements from the neutral image (first frame) to emotional image (last frame) were extracted to classify the emotions with Neural Networks. Moreover, to make improvement in the training process Radial Basis Function Neural Network (RBFNN) was proposed in the classification of facial expressions. The proposed model was evaluated into fifty subject images from Cohn-Kanade database. Average accuracy rate for five times running was reported around 91%.

Multilayer Perceptron model of Neural Networks was proposed by Zhang et al (1998) for classification of facial expressions. They selected manually thirty four points onto face images to represent geometric locations of facial feature points. The proposed model of facial expression classifier included multilayer Perceptron with number of hidden units varying from 1 to 20 to reach the best configuration for classification. Experimental results showed the best accuracy rate of 73.3% with using seven hidden units for facial expressions classification. In this study, Japanese female database (JAFFE) was used to evaluate the classification performance of six basic emotions except fear.

Sreenivasa Rao et al (2011) proposed a feed forward Neural Networks model to classification of happy, anger, fear, sad and neutral from sequence images. After extracted the features of eyes and mouth by image processing and morphological operations, the extracted feature vectors were used in three neural networks model in terms of the left eye, right eye and mouth features. As each model in this study represented four facial expressions and neutral, three recognition results were reported with using each vector, therefore, the optimum rate was obtained with respect to the combination of results. Although, the estimation of number of layers and units to make the Neural Networks structure is a time expensive task, the best performance of the proposed Neural Networks model was presented while consisted of five layers with some units for every layer. As a result, the recognition rates of 87% and 81% were reported for training and independent sequence images as testing subjects, respectively.

Appearance features method indicates more information of face images compare with geometric features methods, however, not only the appearance methods need to more complicate computation but also those commonly need to some feature points extracted with geometric feature methods as an initialization step. A combination of Geometric and appearance feature methods was used in the study of Youssif & Asker (2011) to increase the information of facial features. Therefore, it made more accurate classification compared with using geometric methods or appearance methods alone. A total of 19 feature points were extracted from the eyes, nose and mouth regions. Also, a histogram of face edge map as the appearance features from the whole face with 64 feature vectors were used to Radial Basis Function (RBF) Neural Networks classifier. Experiment results showed 93.5% accuracy with using Cohn-kanade images for classification of all basic emotions. The reported accuracy is a considerably rate for using RBF Neural Networks compared with other studies which used the similar classification method. Whereas, the proposed extracted features needs to an expensive time for sequence images.

ii. Rule Based Methods

Hammal et al (2007) proposed a rule based system and compared it with the Bayesian model for classification of facial expressions. Facial feature points around the mouth, eyes and eyebrows were selected to obtain five geometric features from facial movements. Then, the extracted features consist of distances value from feature points were fed to the classifier to categorize four classes including neutral. They evaluated the proposed classifier in the different databases and obtained average accuracy rate of 61.1% for classification of Joy, Surprise, Disgust and Sadness in three classes from Cohn-Kanad and Dailey-Cottrel databases for instance. Furthermore, to improve the classification performance, four expressions were classified into four emotions in which the combinations of expressions were considered as the similar classes such as fear and surprise as one class. This classification model showed the accuracy rate of 99.3%. The last reported rate showed very high accuracy of classification but where the various expressions which have close appearance not only were classified into the different classes but also could be classified into the similar classes.

Hupont et al (2008) used rule-based classifier to facial expressions recognition. In this study, 20 feature points around the mouth, eyes and eyebrows and five distances between them were extracted as facial features for evaluating the model performance in Ekman's all basic expressions. Experiment results showed 71% accuracy rate for using static images of FG-net and MMI databases. Furthermore, for the purpose of accuracy improvement, nose wrinkles and mouth shape information were added to extracted features that increased performance rate to 85% and 91%, respectively. They showed that Geometric features method and rule based technique simplify the classification problem while keep the accuracy rate properly if the face parameters are selected correctly. Figure 2.9 shows five distances between points as the feature vectors that used in the proposed rule-based classifier model.

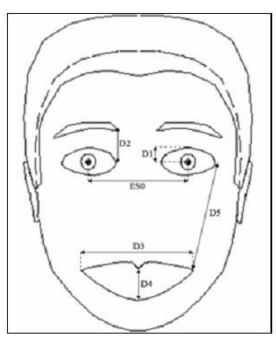


Figure 2.9 Distances Between Points as the Feature Vectors
Source (Hupont et al 2008)

iii. Support Vector Machine (SVM) and Bayes Methods

Samad and Swada (2011) proposed Support Vector Machine for classification of facial expressions recognition where Gabor wavelet with a few parameters was utilized to feature extraction. The proposed model was evaluated on the FG-net (FEED) database and accuracy rate of 81.7% was obtained for classification of basic expressions except disgust emotion. The strength point in the proposed model was simplicity and lower computational cost in feature extraction process than the other studies which used Gabor wavelet as the feature extraction technique.

Shan et al (2009) also examined the SVM method for classification of emotions. In this study, LBP method was used as an appearance method to features extraction. Experiment results on the images of Cohn-Kanade database showed the average of 90% accuracy rate where SVM using LBP method as a features extraction technique for classification of six basic emotions. The results from this study showed that LBP increase the classification performance in comparison with using Gabor wavelet both in time and memory usage.

SVM is also proposed in the work of Piątkowska (2010) with using LBP for features extraction from the image sequences. He evaluated the proposed classification method on the FG-Net and Cohn- Kanade databases for recognition all basic expressions. The recognition rate of 71% with FG-Net database compared with 77% using Cohn-Kanade showed that the FG-Net database includes more complicate expression images than the another one. Whereas, with regarding to the feature extraction method as a robust method and the sequence type of images, it seems that the obtained accuracies are not competitive rates.

Support Vector Machine (SVM), Bayes classifier and Adaboost were examined in study of Guo & Dyer (2005) for facial expressions classification problem. Thirty four points were manually selected in each face image then Gabor filter were used at the selected points to extract the features. 612 extracted feature vectors were used in the SVM classifier model while using 60 and 80 features showed the best accuracy rates of classification in the Bayes and Adaboost methods, respectively. Experiment results showed the best recognition rates of 92.4%, 71% and 71.9% with SVM, Bayes and Adaboost methods for classification of all basic facial expressions with the Japanese Females database, respectively. Based on this study, small size of training samples make bias to estimate the classification of the test data, since the general probability distribution is not covered in the learning process when Bayes and Adaboost are used to classification of facial expressions with few training images. Therefore, according to Guo & Dyer (2005) overfitting problem is a drawback for Bayes method in the low number of training data. On the other hand, SVM showed a considerably difference in the accuracy rate of expressions classification in comparison with Bayes and Adaboost techniques while Gabor wavelets technique as a robust but complicate method were used for the feature extraction.

SVM and Naive Bayes classifier methods were also compared in the study by Hupont et al (2008) in the classification of facial expressions with 14 facial distance parameters including 20 selected feature points. The recognition rate of 70% and 71.5% were reported in the classification of all basic emotions with SVM and Naïve Bayes, respectively. In this study minimum rate belonged to the sadness with the value of 30% and 40% in SVM and Bayes classifier, respectively. Comparison of the reported classification rates in this study with the study of Guo & Dyer (2005) illustrate that SVM is significantly affected with the features type while the Geometric features reduce its performance for classification.

iv. Hidden Markov Models (HMMs)

Hidden Markov Models (HMMs) as popular statistical models are widely used to model time series data and classification problems. Recently, HMMs were used also to classification of facial expressions in the studies of Pardas et al (2002), Cohn et al (2003), Shin and Chun (2008). These studies tried to model the sequence of image states in HMMs to find the highest probability of expressions in new images to fit with trained models.

Pardas et al (2002) obtained a reasonable classification rate for basic emotions from Cohn-kanad sequence images while facial feature points based on the MPEG-4 standard were extracted. They reported 84% accuracy rate for expressions recognition. The proposed model was four states HMMs which was configured after several examinations to find the best HMMs structure for each emotion. Therefore, defining the configuration of the HMMs is a time consuming task for classification of emotions. Moreover, the model is used usually, in the most of research, for classification of facial expressions if a sequence of images is available to make a dynamic process. Therefore, classification of facial expressions from the static images is a challenging mission. Furthermore, based on the Cohn et al (2003) study, falling into the overfitting problem is probable for facial expressions classification with HMMs. Moreover, local optimal results rather than global optimal maybe obtained in the training process for setting HMMs parameters. Whereas, the HMMs has a good potential for classification in varies conditions such as diverse display of a facial expression with different people.

v. k-Nearest Neighbor (k-NN)

k-Nearest Neighbor (k-NN) method showed suitable performance for classification of emotions from sequence images in several studies. Cheon & Kim (2009) proposed k-Nearest Neighbor classifier method to recognize the facial expressions with using Hausdorff distance between face sequence images. The features were extracted based on a modified AAMs method to make robust results in the vary conditions such as pose and illumination for classification of Happy, Anger and Surprise. In this study, different numbers of k were tested to find the best performance of classification as k=3 showed the optimum result of 96.09% accuracy rate for sequence images compared with 92.53% where static images were used. The k-NN can be used for classification of static images indeed, however, to improve the recognition performance the Hausdorff distance was utilized to implement the k-NN classifier on the sequence images. Nevertheless, in this study the numbers of categories were less than other classifier techniques.

Overall, one of the major drawbacks of k-NN in the classification is the computational cost in the large training data with the various features.

vi. Fuzzy Methods

In recent years, Fuzzy logic has been used to model the problems with uncertainty domains for the purpose of making accurate and real results. Classification is one of the ability of Fuzzy models which is applied in various domains (Fernandez et al 2011). As an example, Sharma et al (2011) used a Fuzzy Rule based System for the purpose of satellite image classification. As the border of the objects on satellite images is in ambiguous conditions and in many cases the patterns overlapping is a major problem, Fuzzy rule based model was proposed to classify the objects. They used different types of fuzzy membership functions to divide the patterns on satellite images into different classes. According to this study, a Fuzzy Rule based model shows the accurate classification performance if the proper membership functions are used. As a result, the parameters of Fuzzy knowledge base influence the classification performance. Fuzzy Rule based System was also used in the study by Ishibuchi & Nojima (2005) for classification of Patterns. They used an evolutionary algorithm for optimizing Fuzzy Rule base. Therefore, the proposed classification model showed better performance than a Fuzzy classification model with predefined knowledge base.

Classification of facial expressions is one of the complicated problems that follows the natural rules due to dealing with human activities. Therefore, Fuzzy logic has been used to solve some classification limitations in related to the facial expressions such as ambiguity. As facial features do not belong to only one specific emotion, a set of extracted features may represent different emotions in various classes with different chances. Therefore, ambiguity is an inherent characteristic of facial expressions (Wu et al, 2005).

Xiang et al (2008) proposed a Fuzzy C-Means (FCM) model to classify the facial features which were derived from using Fourier transform. Therefore, FCM classify a set of attributes with different membership values into the several categories. According to this study, FCM showed the robust classification for expressions recognition. They reported 88.8% accuracy rate for basic expressions recognition from sequence images. FCM as a Fuzzy technique benefits of soft classification in which an object is belongs to different classes but with different probability. Therefore, in this method an independent object is classified into a class with minimum dissimilarity with respect to training set. However, according to study of Xiang et al (2008) the variety of subjects in the testing phase was limited to only one subject while all other subjects were used in the training phase. Therefore, the performance of the model was considerably dependent on the training set and it is difficult to consider its generalization with diverse independent subjects.

As facial expressions deal with universal action units for each basic expressions based on the FACS (Ekman & Friesen, 1978), therefore, rule based classifiers were proposed in some studies such as Hammal et al (2007), to model the universal facial behaviors into the rules set to indicate the emotions. Fuzzy Rule Based System (FRBS) is another proposed model which is used to facial expressions to improve the rule based methods with uncertainty estimation for classification. For instance, the Fuzzy model was presented in the study of Tsapatsoulis et al (2000) with the purpose of using expert knowledge in form of rules and based on the MPEG-4 facial definition parameters (Tekalp, 2000). They defined fifteen feature vectors which were computed from the Euclidian distances between feature points in the neutral and emotion expressions to feed the Fuzzy inference system. The recognition rate of 81% was reported to classification of six basic emotions from the static images. In this study, the model performance was evaluated based on the high number of feature vectors while the type of membership function and its parameters as well as rules set were obtained based on the expert knowledge. Although the obtained accuracy rate is not very low with respect to utilized features type, however, the knowledge base is not optimum for using in the different databases, since it needs to reconfiguration to keep its proper accuracy rate.

Further example of FRBS is the proposed model by Esau et al (2007) to classify the emotions. In this study, predefined set of Fuzzy rules and membership functions specified the belonging degree (strong or weak) of facial features vectors to each emotion. The proposed classification model used six angles based on the fourteen feature points to measure the deformation of features from neutral to emotions. The experiment results showed the accuracy rate of 72% for classification of four emotions (happiness, sadness, anger, fear and neutral) from Cohn –Kanade database. In this study, Fuzzy membership functions were estimated based on Mean and Standard deviation of feature vectors values. Therefore, the achieved values for membership functions parameters are not accurate due to weakness of those statistical methods to find the best values. Membership functions which are set with the statistical methods can not cover all input data while diversity of those data is high.

SeyedArabi et al (2004) compared a Fuzzy classification system with different approaches to recognize the facial emotions. They used FRBS with seven feature vectors as a classifier to estimate difference between first frame (neutral expression) and last frame (peak of expressions) of sequence images from Cohn-kanade database. Feature vectors were obtained based on the 21 facial feature points which were selected manually on the first frame and tracked on the last frame. For the purpose of using human knowledge, a table of Fuzzy rules was generated based on the psychological studies on the facial expressions. In this work, the best recognition rate of 89.1% was reported for expressions recognition.

As a hybrid model, we can illustrate Chatterjee & Shi (2010) work. In this study, a FRBS was used for facial expressions recognition while the Fuzzy model was tuned in a learning process. In this study, Adaptive Neuro Fuzzy Inference System (ANFIS) was proposed to tune the Fuzzy rule based model to track properly the given input/output data. The learning process was performed based on the feed forward neural network to generate the Fuzzy rules. They reported 85-95% accuracy rate for classify five facial expressions with five ANFIS model while different LBP model were used to feature extraction of the images from JAFFE database. The achieved results in the testing phase included not only testing but also training data. According to this study, generating the Fuzzy rules in the ANFIS makes the recognition process more automatic also it improves the recognition rate, whereas it decreases the human knowledge intervention in the structure. Therefore, ANFIS benefits the abilities of both Fuzzy techniques and Neural Network. On the other hand, the system is more complicate since neural model needs to more computational process for every ANFIS model compared with the Fuzzy rule based systems to reach the results. Moreover, ANFIS model is limited to characteristics of the Sugeno systems. Furthermore, the variations in the FIS structure are not allowed in the ANFIS as well as the FRBS

(Naseri & Fotohi 2007). For example, the selection of defuzzification functions is limited only to one function in the ANFIS model. In addition, the knowledge base including membership parameters and rules base is set automatically without any influence by expert knowledge which removes, completely the affect of human knowledge to solve the problems. One other drawback of ANFIS is derived from the generation of large number of Fuzzy rules where large number of features is used as the input parameters. The problems with large input features and membership functions increase, dramatically the computation expensive in the ANFIS model (Mejias et al 2007; Golob & Tovornik 2002). Moreover, with increasing the number of features, the number of training set should be raised to map suitably the input data to outputs. As a result, choosing the proper number of input parameters as well as size of training set is essential for model robustness and generalization.

The Case Based Reasoning (CBR) method was combined with the FRBS by Khanum et al (2009) to improve the Fuzzy classification performance in which the accuracy rate of 90.33% was obtained for all basic expressions. In the proposed Fuzzy-CBR method, simplicity of Fuzzy logic as well as intelligent performance of CBR based on analysis of its past knowledge were combined to form a hybrid facial expressions classification. Therefore, CBR as a learning model improved the FRBS performance. However, in this model the membership parameters were set manually which are unsuitable for the different database. Therefore, reset the membership parameters are needed with every database.

As we mentioned before, HMMs is a suitable method to classify the objects in the different domains but HMMs is not enough robust for facial expressions classification in diverse conditions. In the study by Miners & Basir (2005), Fuzzy logic was used in the HMM to improve the recognition process with Fuzzy measures for states and observations. Experiment results showed that Fuzzy HMM compared with classic HMM makes higher recognition rate while takes less training time to classify the expressions. In this model, the core of the classification is based on HMMs while the Fuzzy values improved the analysis of complicate relations between features and expressions for switch from one expression to another in the classic

HMMs. However, this model as a HMMs-based method is more suitable for sequence images than a static image.

According to the existing studies, Fuzzy techniques have good potential to use in classification problems. However, the lack of a proper training algorithm to optimize the Fuzzy construction based on the diverse conditions has reduced its performance in comparison with other techniques such as SVM and Neural Networks. Therefore, the main goal of this research is to fulfill the requirements of FRBS for classification of facial expressions.

2.5 FUZZY LOGIC

Some objects in the real world do not meet all parameters to set in one specific class. For example, classification of some kind of animals such as zebra that is not precisely a horse and also cannot be similar as much as a donkey. Therefore, zebra can be as a member of "horse set" or "donkey set". Fuzzy set was introduced first time by Lotfi Zadeh (1965) to define the membership values of objects in the sets. In a Fuzzy set an object with ambiguous conditions can belong to more than one class with different membership grades.

Fuzzy logic with using Fuzzy sets defines mathematically intermediate values between crisp values such as black and white to apply human thinking way in the computer systems. Therefore, Fuzzy logic can be used to formulate the imprecise problems such as decision making, classification, pattern recognition, control, and etc.

2.5.1 Fuzzy Set

Let assume $A=\{x_1, x_2, x_3 \dots x_n\}$ be a set. $\mu(x_i)$ is the membership grade of x_i in A. Therefore, the Fuzzy set A is indicated as follows (Ross, 1997):

$$A= \{\mu(x_1)/x_1, \mu(x_2)/x_2, \mu(x_3)/x_3 \dots \mu(x_n)/x_n\}, \quad \mu(x_i) \in [0, 1], \quad i=1, 2, 3 \dots n$$

x_i is not belonged to A, If $\mu(x_i) = 0$

x_i is a Fuzzy membership value, if $0 < \mu(x_i) < 1$

x_i is belonged completely to A, If $\mu(x_i) = 1$

2.5.2 Natural Language

In many intelligent systems, human expert knowledge can be used to systems work based on the primary information and make the output more easily and accurately in related to real world problems. Natural language is a communication tool to present the enormous information of human thought. For the purpose of using human knowledge, the Fuzzy sets can be used to present the language variables in form of mathematical functions. For example the Fuzzy set of "young" and its membership function can be shown as follow (Ross, 1997):

$$\text{young} = \int_0^{25} 1/y + \int_{25}^{100} 1/y \left(1 + \left(\frac{y-25}{5}\right)^2\right)^{-1} \tag{2.1}$$

{"∫" is the Fuzzy set symbol and does not shows the Integral operator}

$$\mu\,(\text{young},y) = f(x) = \begin{cases} \left(1 + \left(\frac{y-25}{5}\right)^2\right)^{-1}, & y > 25 \\ 1, & y \leq 25 \end{cases} \tag{2.2}$$

2.5.3 Fuzzy Rule Based System (FRBS)

Fuzzy Rule Based Systems (FRBS) are based on the IF-Then rules which contain linguistic variables to use the human knowledge in the intelligent systems. The Fuzzy rules are implied generally in form of: IF x is *A* Then y is *B* in which *A* is premise and *B* is consequent of the rule. General structure of FRBS is shown in Figure 2.10.

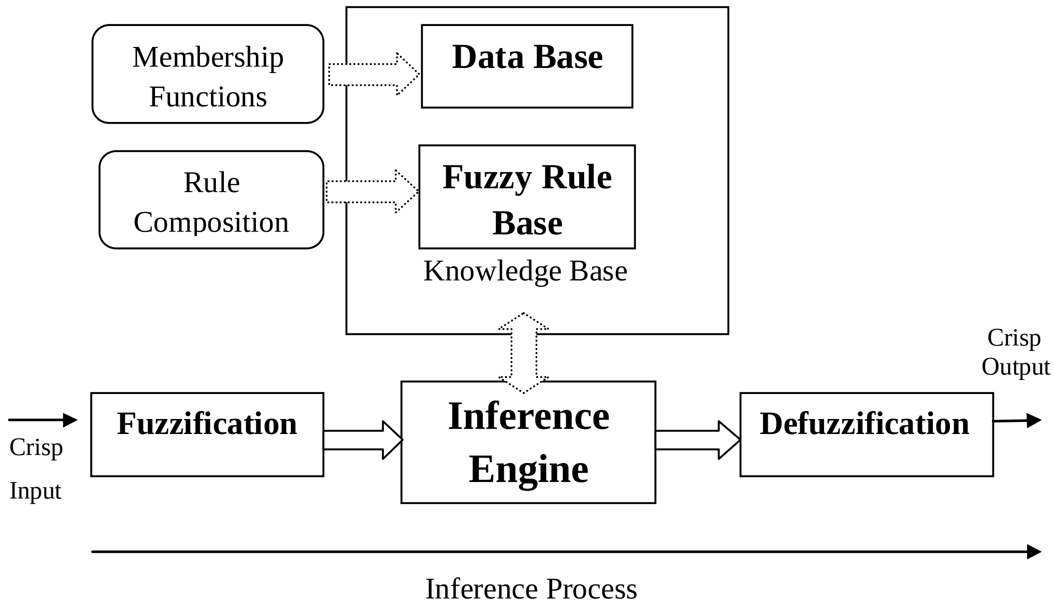


Figure 2.10 Basic Architecture of Fuzzy Rule Based System (FRBS)

Fuzzification is the process of converting the crisp data to a membership value by membership functions.

Inference engine relates the knowledge base to the inputs to predict new conclusions (Abraham, 2005).

Membership function allocates a belonging value of each input and output to the Fuzzy sets (Akerka & Sajja, 2010). There are different representation types of membership functions. The common shapes of membership functions are Triangular, Trapezoidal and Gaussian which are shown in Figure 2.11, 2.12 and 2.12, respectively.

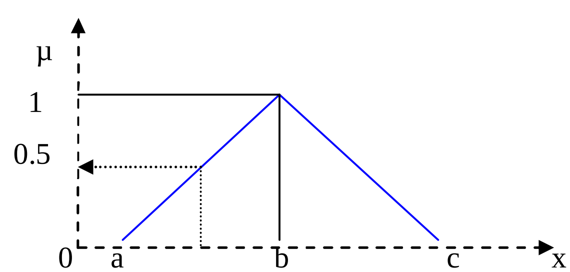


Figure. 2.11. Triangular Fuzzy Membership Function

Triangular function formally indicated by (Siler & Buckley, 2005):

$$\mu\,(x) = \begin{cases} 0 & x \leq a, x > c \\ \frac{(x-a)}{(b-a)} & a < x \leq b \\ \frac{(c-x)}{(c-b)} & b < x \leq c \end{cases} \tag{2.3}$$

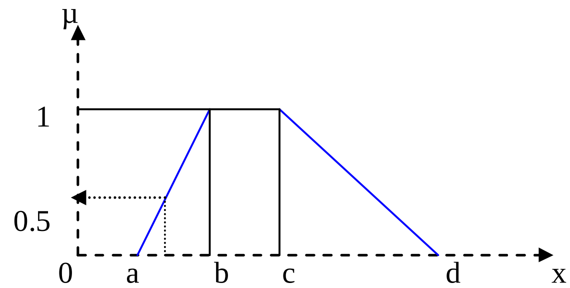


Figure 2.12 Trapezoidal Fuzzy Membership Function

Trapezoidal function described by (Siler & Buckley 2005):

$$\mu\,(x) = \begin{cases} 0 & x < a, x > d \\ \frac{(x-a)}{(b-a)} & a \leq x \leq b \\ 1 & b < x < c \\ \frac{(d-x)}{(d-c)} & c \leq x \leq d \end{cases} \tag{2.4}$$

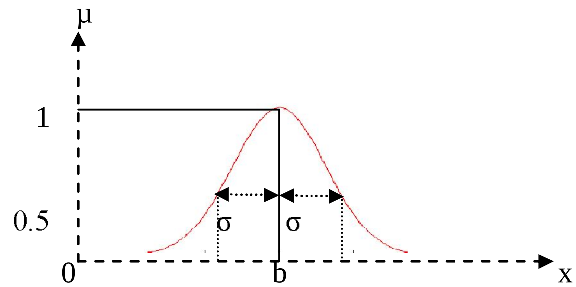


Figure 2.13 Gaussian Membership Function

Gaussian function described by (Lilly 2011):

$$\mu(x) = e^{-\frac{(x-b)^2}{2\sigma}} \tag{2.5}$$

where σ is standard deviation or width of the function and b is centre of the function.

Defuzzification is the process of converting the Fuzzy results to a precise value.

According to the existing research, Fuzzy Rule based Systems as a simple method has the ability to use in the classification models while imprecise input data are fed into the classifier. A FRBS is completely depending on its knowledge base. However, making an optimized knowledge base for complex problems such as facial expressions classification is still a challenge. Genetic Algorithms are used as a popular method for optimizing the complex problems (Holland 1975). Therefore, Genetic Algorithms have been proposed to optimize the Fuzzy classification structure in a training process for facial expressions recognition.

2.6 GENETIC ALGORITHMS

Holland (1975) is well known to introduce and develop Genetic Algorithms to solve the complex problems based on the evolutionary computation. The idea of Genetic Algorithms has been captured from the Charles Darwin's theory of natural selection that creatures follow for survivals. Genetic Algorithms as a popular method of evolutionary computation are used to solve the optimization problems based on the evolutionary process. Therefore, Genetic Algorithms with the search in the solutions space find the best or approximately results in a process of several generations (Sivanandam & Deepa, 2007). Nowadays, numerous applications for Genetic Algorithms are known in the different areas such as engineering, management, medicine, humanity sciences and computer science (Coley, 1999).

2.6.1 Biological Background

The smallest part of every creature is cell inside which exist Genetic information. In fact, Chromosomes are contained all Genetic information. Therefore, every part of each Chromosome is called a Gene which represents individual traits such as hair color or skin color. These characteristics are coded as a set of rules in the Genes as the string of them build a chromosome. Figure 2.14 shows a sample of chromosome structure. Brown eye color is an example of Genetic characteristic of a specific organism. The Genes are shared to an offspring from two organisms when they mate with together. As a result, Recombination occurs when a new offspring is made from the copy of parent's Genes including half from one parent and the rest from another (Sivanandam & Deepa 2007).

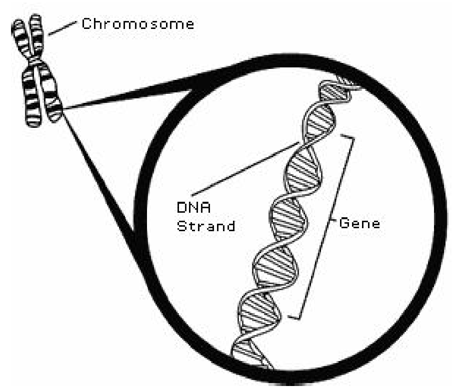


Figure 2.14 Chromosome Structure
Source (Sivanandam & Deepa 2007)

2.6.2 Genetic Algorithms Process

Many computational or optimization problems are not solved simply with using classical mathematical techniques as they need to handle a lot of complex solutions. Therefore, sometimes the results will be local optima rather than global optima (Mitchell, 1998). On the other hand, the traditional methods can be used for just a specific problem and are not enough intelligent to use in every conditions as a whole solution.

Generally, Genetic Algorithms are a computational technique that follows the natural process of Genetics to find the best or approximate solutions among the huge number of solutions (Mitchell, 1998). Overall process of Genetic Algorithm according to the Grefenstette & Baker (1989) model is shown in Figure 2.15.

```
Procedure: Genetic Algorithm
begin    i ← 0
initialize P(i)
evaluate P(i)
   while (termination condition)  do
          recombination P(i) to yield C(i)
          evaluate  C(i)
          select P(i+1) from  P(i) , C(i)
       end
```

Figure 2.15 The Overall Procedure of Genetic Algorithm

Source (Grefenstette & Baker (1989)

The process of Genetic Algorithm is described as follows:

1. **Population:**

   The first step of Genetic Algorithms process is to build an initial set of solutions which is called initial population. Initial population is selected among the others randomly. Each member of population called a chromosome which is used as a solution. Therefore, every population includes a set of chromosomes.

2. **Fitness function**

   In the nature, fitness is the reproducing probability of a creature that, it has for making the offspring in its life (Mitchell, 1998). In the Genetic Algorithms, fitness is a function that indicates the measure of reaching one solution to the optimal solutions. It means a solution with higher fitness value is closer to the optimum solutions and has more chance to generate the new offspring.

3. **Parent Selection**

   Selection is the process of choosing individuals with higher fitness values to generate the new populations. Every two solutions are called parents that crossover and mutation operators are performed on them (Sivanandam & Deepa 2007). Various methods are proposed in Genetic Algorithm for the purpose of the selection operator that the most common are Roulette Wheel, Elitist, Scaling and Tournament (Reeves & Rowe 2002).

4. **Crossover (Recombination)**

New offspring (new solutions) are created from combination of every pair of parent that were selected with the selection operator. Therefore, new offspring contain parent chromosomes characteristics which are generally closer to the optimal solutions. Cross over operator is performed with the probability of *Pc* on the parent chromosomes. If the value of 1 is assigned to *P*c, it means all offspring chromosome are created with crossover operator. There are various methods of crossover operator that single point crossover and two points crossover are more popular among them. Figure 2.16 shows an example of single point crossover:

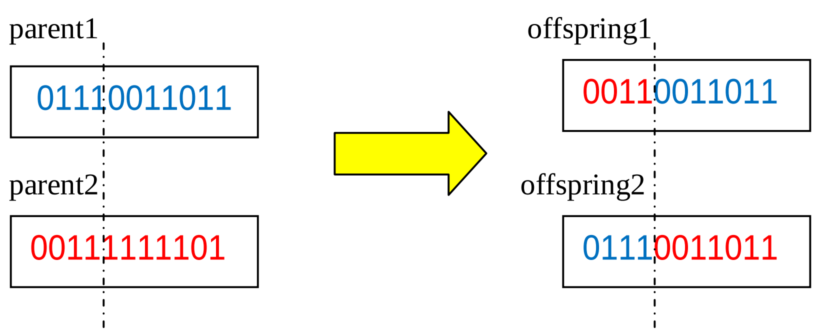


Figure 2.16 Single Point Crossover

5. **Mutation**

Mutation is the probability of diversity that happen in the original chromosomes to avoid of failing to local optima results due to create similar or close chromosomes to each other. Mutation operator is performed with the probability of *Pm* on the chromosomes. One of the popular methods is based on the creating a random number (*Rm*) for each Gene. So that, if the *Rm* is less than the probability number, (*Pm*), then the mutation operator will be performed on that Gene. Figure 2.17 shows a simple example of mutation operation.

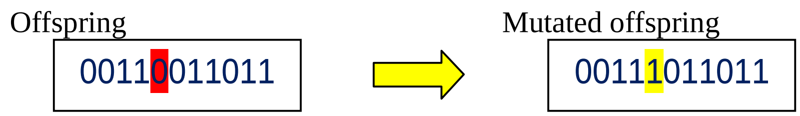


Figure 2.17 An Example of Mutation Operation on the String of Bits

6. New Population Generation

For the purpose of generating the new population, the fitness values of the chromosomes should be evaluated. There are various methods to select the new population. Two examples of common methods are as follow:

a) New population is selected from the new offspring.
b) A part of new population is selected from the new offspring and another part from the other populations in the search space.

7. Termination Condition

The generations are terminated when the conditions are satisfied. The termination can be based on the various conditions such as reaching the optimum results, reaching to the specific number of iteration or having no results improvement in the defined number of iteration.

2.7 GENETIC ALGORITHM APPLICATIONS

Genetic Algorithms are used in many studies as a learning technique to optimize the Fuzzy systems in terms of rules and membership functions. For example in the studies by Karr & Gentry (1993), Bonissone et al (1996), Alcala et al (2005), Alcala et al (2009) Genetic Algorithm were used to select the rules and tune the membership functions in the control problems. The main purpose of using Genetic Algorithms in these studies was improvement of the Fuzzy systems performance and making the parameters adaption in the diverse conditions. Figure 2.18 shows an example of initial and tuned membership functions in a control system. According to Figure 2.18 the initial parameters which were set by the expert knowledge were modified with Genetic Algorithms to reach to the optimum results.

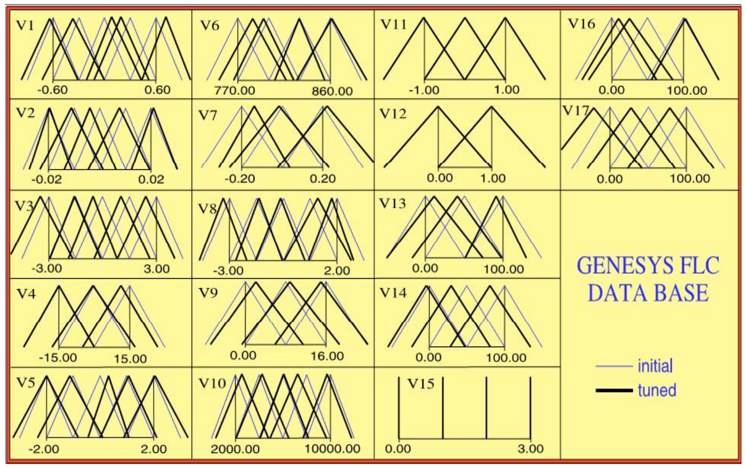


Figure 2.18 An Example of Tuned Fuzzy Membership Function by GA in a Control System, Source (Alcala et al 2009)

Furthermore, Genetic Algorithms were used for the purpose of pattern classification in the study of Ishibuchi et al (1999). They proposed Genetic Algorithm as a learning technique to generate the optimum rules in the Fuzzy rule based system. They showed that Genetic Fuzzy model has the proper performance to pattern classification problems.

Face segmentation is another example in which Genetic Algorithms were used to improve Fuzzy membership functions for human nose and iris localization from the face by Koljonen & Alander (2006). In this study, the Genetic Algorithm performed on the trapezoidal membership function to find the optimum parameters. When the model trained with a Genetic Algorithm, it was tested on the unseen images to approve the performance. Experiment result showed appropriate face segmentation with Fuzzy-Genetic model.

According to existing research Genetic Algorithms as an evolutionary method optimize the problems where a big solution space is available. However, Genetic Algorithms have some limitations in the learning process of complex problems with many parameters, such as computationally expensive and progressive decline in improvement (Adra 2003). Therefore, in recent years to overcome the limitations of Genetic Algorithms, social animal and insects behaviour has been simulated to improve the Genetic Algorithms performance.

2.8 SOCIAL INSECTS BEHAVIOUR MODELLING

In recent years the intelligent behaviours of animals and insects in colony has been studied in various domains for optimization problems. Researchers have found out that modelling of animal and insects behaviours in the group and colony can improves the optimization algorithms in many cases. Ant colony optimization algorithm as a successful meta-heuristic approach was introduced by Dorigo et al (1996) and developed by others. This technique simulates the ant colony seeking behaviours to find the foods for using in the optimization problems. Honey bees behaviour is another popular area which is used for optimization problems. In the past years, honey bees searching method to collect the nectar sources has been simulated in several studies (Drias et al 2005; Nakrani & Tovey 2004) for the purpose of optimization in various domains. Generally, as the base of each type of swarm optimization techniques is similar in the different problems, the difference in problems areas is led to customize the techniques with the domain; and what changes the algorithms performance in the most research is difference in the algorithm parameters.

2.9 SUMMARY AND DISCUSSIONS

Table 2.2 compares the summary of current facial expression classification methods and compares them with the different criterions. Moreover, Table 2.3 illustrates a summary of existing Fuzzy techniques which have been used for facial expressions classification.

Table 2.2 Summary of Existing Techniques for Facial Expressions Classification

Classification technique	**No. of emotion**	**Image type**	**Features extraction**	**No of point**	**Data base**	**Acc. Rate (%)**
Rule based (Hammal et al 2006)	4: 3 classes	Static	Geometric	N/A	Cohn & Daily-Cottrel	61.1
Rule based (Hammal et al 2006)	6: 3 classes	Static	Geometric	N/A	Cohn & Daily-Cottrel	66.33
SVM (Hupont et al 2008)	6	Static	Geometric	20	FG-Net & MMI	70
Rule based (Hupont et al 2008)	6	Static	Geometric	20	FG-Net & MMI	71
Bayes (Guo & Dyer 2005)	6	Static	Gabor Wavelet	34	JAFFE	71
Adaboost (Guo & Dyer 2005)	6	Static	Gabor Wavelet	34	JAFFE	71.9
NN (Zhang et al 1998)	5	Static	Geometric	34	JAFFE	73.3
SVM (Piatkowska 2010)	6	Sequence	LBP	-	Cohn-Kanade	77
SVM (Samad & Swada 2011)	5	Static	Gabor Wavelet	-	FG-net	81.7
NN (Sreenivasa et al 2011)	4	Sequence	Geometric	N/A	Own data set	82
HMMs (Pardas et al 2002)	6	Sequence	Geometric	N/A	Cohn-Kanade	84

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SVM (Shan et al 2009)	6	Sequence	LBP	-	Cohn-Kanade	90
NN(SeyedArabi et al 2007)	6	Sequence	Geometric	14	Cohn-Kanade	91
NN (Zhang et al 1998)	5	Static	Gabor Wavelet	34	JAFFE	92.2
SVM (Guo & Dyer 2005)	6	Static	Gabor Wavelet	34	JAFFE	92.4
k-NN (Cheon & Kim 2009)	3	Static	AAM	N/A	POSTECH: Own data	92.53
NN(Youssif & Asker 2011)	6	Sequence	Geometric& Appearance	19	Cohn-Kanade	93.5
k-NN (Cheon & Kim 2009)	3	Sequence	AAM	N/A	POSTECH: Own data	96

Based on the literature review there are various classifications techniques which are used in the facial expressions domain. In Table 2.2 and 2.3 the popular classifier methods which have been used for facial expressions classification in the recent years are summarized. Each classifier technique has some advantages and disadvantages inherently that make them more appropriate or inappropriate compared with the others to use them in the different domains with various conditions. Some drawbacks that challenge the use of classifiers in the facial expressions are summarized in Table 2.4.

Table 2.3 Comparison of Existing Fuzzy Techniques for Facial Expressions Classification

Classification technique	**No of emotions**	**Image type**	**Features extraction**	**No of points**	**Data base**	**Acc. Rate**
FRBS(Esau et al 2007)	4	Static	Geometric	14	Cohn-Kanade	72
FRBS (Tsapatsoulis et al 2000)	6	Static	Geometric	N/A	Cohn-Kanade	81
FRBS &NN (Chatterjee & Shi 2010)	5	Static	LBP	-	JAFFE	85-95
FCM (Xiang et al 2008)	6	Sequence	Appearance	-	Cohn-Kanade	88
FRBS (SeyedArabi et al 2004)	6	Sequence	Geometric	21	Cohn-Kanade	89.1
CBR & FRBS(Khanum et al 2009)	6	Static	Geometric	22	FG-Net	90.33

Table 2.4 Summary of Popular Classification Techniques Drawbacks

Technique	**Drawback**
HMMs:	a) Configuring the proper structure needs to various experiments. b) It is a robust technique if the sequence of images (not proper for static) is used as input data. c) The overfitting problem is not unpredictable with the small size of training data.

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Rule based Methods:	a) Depending to the prior knowledge, completely. b) Lacking of learning process to adapt with the diverse conditions. c) Generalization ability is low.
Bayesian Classifier:	a) The chance of having an accurate statistical distribution for classes is low with regarding to the database. b) Need to a large training data set.
Fuzzy Methods:	a) Depending completely to prior knowledge of experts. b) Time consuming task for setting the Fuzzy parameters. c) The lack of learning process to tune the models based on the diverse conditions. d) Need to optimize the construction.
Neural Networks:	a) Configuring the optimal structure needs to various experiments. b) Need to large training data to generalize the model (Groth, 2000). c) Numerous attributes increase the over fitting problem (Seetha et al, 2008).
ANFIS:	a) Curse of dimensionality in the large input features and membership functions. b) Need to large training data in the large dimension of input features. c) Removing the affects of expert knowledge in the knowledge base
SVM:	a) High complexity and computation costs for multiclass problems b) Finding its accurate parameters is difficult (Seetha et al 2008)

Beside some weaknesses illustrated in Table 2.4, when we see closely to the Table 2.2 and 2.3 this is found out that various conditions can affect on the accuracy rate of classification methods. Some of the most important are as follow:

1. **Static images versus sequence images:**

   Classification of static images is more difficult than sequence images as the input information of static images to the classification model is too less than the sequence images. Therefore, the accuracy rate of using static images has tangible difference compare with sequence images. But, with regard to simple computation model for classification of static images and existence of many applications that use the static images, the classification of static images is an essential task.

2. **Geometric features versus appearance features:**

   Geometric methods are deal with the position of number of points on the face and analysis their movements when an emotion is occurred. Geometric features impose less computational process than the appearance features as deal with some specific points on the face image rather than whole the face. Moreover, most of the appearance methods need to have feature points as initial step to perform the feature extraction (Shan & Braspenning 2010). Nevertheless, an accurate recognition with geometric features is achieved if more robust classification technique is used. It means that the classification with geometric features is more difficult than classification with appearance type. Therefore, lower accuracy rate of a classification method that uses the geometric features compared with another technique that uses the appearance features is not directly due to low classification performance. To prove this matter, we may refer to the Zhang et al (1998) study. In this study, as it is showed in the Table 2.2, Neural Network classifier with using geometric features showed the accuracy rate of 73.3% while it showed the rate of 92.2% when Gabor wavelet were used.

3. Number of feature points:

There is a direct relation between number of feature points with accuracy rate and computation process. Therefore, using lower number of feature points is an objective for classification systems if the level of accuracy rate is kept up.

4. Database:

With take a look at the Table 2.2 we find that there are different databases which are used to implementation process. Difference between databases is due to number of subjects, variety of subjects and the control conditions that subjects have tested. For example Cohn-Kanade database is one of the full control databases. However, FG-Net database is a non- control database which is more naturally condition. The subjects in the FG-Net database represent the emotions in the semi naturally conditions, therefore the face appearance is more complicate in different emotions than fully control database. Our evidence for this matter is the study of Piatkowska et al (2010) that has been shown in the Table 2.2. They evaluated the proposed classifier on the Cohn-Kanade and FG-net databases and reported the accuracy rate of 77% and 71%, respectively.

2.10 CONCLUSION

There are some important parameters which influence performance of facial expressions classification. Therefore, to evaluate the classifiers, conditions in which implementation is performed such as feature extraction method, database, number of feature points (if exist) and type of images beside the strengths and weaknesses of those classifiers should be considered.

According to the literature, Fuzzy rule based classifier has several factors that makes it as a proper method for facial expressions classification (Khanum et al 2009). Fuzzy rule based classifier consists of expert knowledge that is useful for a classifier with respect to this matter that human as an intelligent individual represent the ways of logic to understand the facial emotions based on the face appearance. Also, Fuzzy methods describe mathematically the uncertainty conditions of facial expressions into the simple model with low recognition complexity compare with some other methods such as SVM and Neural Networks (SeyedArabi, 2004). Therefore, with respect to the Table 2.3 we can see several studies used the Fuzzy methods for the facial expressions problem and obtained the reasonable results particularly where classification of the static images with low training data and Geometric features were followed. However, for the purpose of performance improvement of Fuzzy rule based classification, Genetic based Algorithm was proposed to decreases some limitation of Fuzzy rule based classifier. In various studies (Bonissone et al (1996), Alcala et al (2005), Alcala et al (2009), Alcala et al (2011), (Ishibuchi et al 1999), Schaefer (2011), Genetic Algorithms as a learning algorithm were combined with FRBS to fill in the following requirements of a Fuzzy systems:

a) Making a learning process for Fuzzy model
b) Tuning membership functions or generating the Fuzzy rules, automatically
c) Reaching to optimal performance with construction adjustment of the model
d) Making generalizations in the diverse conditions for the model

On the other hand, Genetic Algorithms show a progressive decline in the learning process for optimizing of some complex problems with many parameters. Therefore, in this thesis a modified Genetic Algorithm has been proposed to improve the Fuzzy Rule based classification for facial expressions recognition from the low level information of images.

CHAPTER III

METHODOLOGY

3.1 INTRODUCTION

The main purpose of this study is development of Fuzzy rule based system for classification of facial expressions from the static images. To obtain the goal, a hybrid Genetic-Fuzzy classifier model was proposed to improve the Fuzzy classification performance. The performance of the model was examined on the facial images obtained from two different databases. FG-net Facial Expressions and Emotions database (Wallhoff, 2006) from the Technical University Munich and Cohn-Kanade database (Kanade et al, 2000). In the present study, a Geometric method was used to extract twelve feature values from the static images of FG-net and Cohn-Kanade databases. Therefore, seven parameters were selected based on the facial feature values as the collected data to feed into the Genetic-Fuzzy model to classify four basic facial expressions. In order to experiment the model performance, Matlab environment was used to evaluate the robustness of the model. The experiment process was carried out in two training and testing phases. When the training process was performed, to evaluate the validity of the model, the trained model was then evaluated with an unseen data set which was not used in the training phase. Therefore, the model was tested based on the all subjects in the data base rotationally with substituting the data from the training part to testing part.

3.2 FACIAL IMAGE DATABASE

In the current research, the images from two FG-net (Wallhoff 2006) and Cohn-Kanade (Kanade et al 2000) databases were used. Therefore, a data set comprising the images from FG-net database and randomly selected images from Cohn-Kanade database was used in the experiment process to evaluate the proposed classification model. Moreover, an extra dataset comprising only images from Cohn-Kanade database was used to evaluate the validity of the model.

3.2.1 FG-Net Database

The FG-net Facial Expressions and Emotions Database (FEED) from Technical University Munich, includes face images taken from 18 male and female different subjects. The subjects showed the basic facial expressions in front of a camera in three times for each expression. The facial images were captured by a Sony XC-999P camera with an 8mm COSMICAR 1:1.4 lens. The subjects expressed the emotions under not controlled conditions which make preferable the FG-net database from the others. For this purpose, the capturing process was carried out, after a brief introduction for subjects, with showing a movie clips or an image to subjects for making the natural conditions in displaying the emotional states. Therefore, emotions were occurred in the real conditions rather than requesting the subjects to show the emotions without any stimulus under the controlled conditions. The capturing process was performed 3 times for every emotion to get at least once in the emotional state. The color sequence images were digitized into the size of 640×480 pixels with the rate of 25 frames per second but then converted to the size of 320×240 and stored in the jpg format. The database also available as MPEG video clips which separable per each emotion. Figure 3.1 and 3.2 show examples of facial images in neutral and emotional states respectively, from FG-net database.

In this study, two static images from each subject in neutral and emotional states were selected. As the emotional states were not appeared in all experiments process by the subjects, therefore from three times attempts of each subject to show the emotional state only one static image in the emotional as well as one static image in neutral state was selected.

Figure 3.1 Examples of Facial Images from FG-Net Database

Figure 3.2 Examples of Facial Expressions in Emotional States from FG-Net Database

3.2.2 Cohn-Kanade Database

Cohn-Kanade database consists of around 486 sequence face images taken from subjects with different age, sex and culture who showed the basic emotions role under the control conditions according to emotions that requested by instructor. This database was obtained from 97 subjects images with the age range of 18 to 30 years old including 65 percent female, 15 percent African-American and 3percent Asian or Latino. A camera which was positioned in front of the subjects captured different emotional states from the facial displays with only front face pose. The sequence images representing an expression are began always from the neutral and ended to one expression with only frontal face pose. The sequence images digitized into 640×490 pixels with gray scale values. These sequence images also were stored frame by frame in the png format in the database. Furthermore, the database included facial feature landmarks which were extracted with AAMs method. Figure 3.3 shows sample of images from Cohn-kanade database.

Figure 3.3 Samples of Cohn-Kanade Images

3.2.3 Training and Testing Data Set

To evaluate the system performance, images from two independent data sets were used in the experiment process. FG-Cohn data set comprising 90 static images from FG-net database and 50 randomly selected images from Cohn-Kanade database were used as the main data set. The static images from FG-net database were selected from every subject in the neutral and four emotional states. Therefore, the images from all subjects in four emotional states were considered in the experiment process. As a result, in this research for every subject one image frame per each emotion was selected while one image frame in the neutral state for each subject were chosen.

Moreover, the static images of 10 subjects from Cohn-Kanade in four emotional and neutral states were considered as the extra images to form the FG-Cohn data set. The second data set including 150 static images selected only from the Cohn-Kanade database. The collected images from the first data set were divided into two parts of training and testing data sets. According to the N. Mamuya (2010) study, to evaluate the classification model, around 20 percent of all data can be used as the testing data set and the rest for using in the training set. The emotional images were classified into four emotional states with the facial expression recognition model with both two data sets while the images of neutral state just was used to estimate the feature movements. Therefore, in the first data set from 112 images as the total emotional data in the states of Surprise, Sadness, Happiness, and Anger, 92 and 20 emotional images were selected for training and testing, respectively. Also, 28 images were used as the neutral state of those subjects with 112 (92+20) emotional images. The description of FG-Cohn data set comprising training and testing data sets is as follows.

$$\text{140 images}\begin{cases} 18\ subjects\ from\ FG-net & \begin{cases} 72(18\times 4) emotional\ states \\ 18(18\times 1) neutral\ state \end{cases} \\ 10\ subjects\ from\ Cohn-Kanade & \begin{cases} 40(10\times 4) emotional\ states \\ 10(10\times 1) neutral\ state \end{cases} \end{cases}$$

$$\text{140 images}\begin{cases} 92\ training\ set: \begin{cases} 52\ (out\ of\ 72)\ images\ from\ FG-net \\ 40\ (out\ of\ 40) images\ from\ cohn-kanade \end{cases} \\ 20\ testing\ data\ set\ from\ FG-net\ database \\ 28\ images\ in\ neutral\ state: \begin{cases} 18\ from\ FG-net \\ 10\ from\ Cohn-Kanade \end{cases} \end{cases}$$

In order to implement extra evaluation on the classification model, second data set was also divided into two training and testing set. In this data set from total 150 images (consisting of 30 subjects), 80 emotional images as a training set and 40 emotional images were selected as a testing set and rest 30 images were used as the neutral state. In the Cohn-Kanade database all 97 subjects have not expressed all four emotional states. Therefore, in the selected data set, the images of 30 subjects comprising 120 emotional and 30 neutral images from total subjects were selected, randomly, while each subject has expressed four emotional states. The description of Cohn-Kanade data set comprising training and testing data sets is as follows.

$$
150 \text{ images} \begin{cases} 80\ training\ set\ includes\ images\ from\ Cohn - Kanade\ database \\ 40\ testing\ set\ includes\ images\ from\ Cohn - Kanade\ database \\ \\ 30\ images\ in\ neutral\ state\ from\ Cohn - Kanade\ database \end{cases}
$$

3.3 EXPERIMENT TOOLS

In this study in order to experiment the model performance, Matlab 7.8.0 (R 2009a) environment has been used. Matlab is known as a technical computing language to implement the algorithms with complicate computation process particularly in matrix operations which make it faster than traditional programming language such as C. Moreover, Matlab is a popular environment to image processing and performing Fuzzy logic and optimization algorithms such as Genetic Algorithms.

For the purpose of experiment the proposed classification model as well as features extraction technique, the Matlab programming codes have been used without using Matlab Toolbox directly. In this operation, first feature extraction process has been implemented to extract the feature points then the classification model has been programmed to experiment the model performance based on the obtained results from the first step.

3.4 RELIABILITY AND VALIDITY OF THE MODEL

To implement the Genetic-Fuzzy model with regarding to the aim of model evaluation with the limited raw data as input feature vectors, at first, 20 unseen images from FG-net database as the testing set were used to consider the model generalization. Whereas, in the training phase 92 static images including 23 subjects from FG-net and Cohn database (called FG-Cohn data set) in the emotional states of Surprise, Sadness, Happiness and Anger, fitted the classifier model as the optimized form. For the purpose of evaluate the model deviations and its reliability, the training process was repeated 10 times and every time the validity of the model was considered with the testing independent data set. Moreover, a part of images which were placed in the training set were replaced into the testing set in a rotation process to cover all images of FG-net database as the testing set. Therefore, the evaluation processes were performed four times, after each time experiment, the testing data as an unseen set interchanged with training data. The testing set only was selected from the images of FG-net database in all four testing groups while the selected images from Cohn-Kanade database which were included in the FG-Cohn data set (the main data set) were used only in the training process.

3.4.1 Validity Evaluation for Classification Performance with Extra Testing Set

For the purpose of more experiment with different images to evaluate the validity of the model, the model was implemented using the images from Cohn-Kanade database. Performance validity was considered with two data sets. First, all 72 emotional images belong to FG-net database selected from FG-Cohn data set formed a training set and all selected images from Cohn-Kanade database including 40 emotional images were used as the testing set. So that, the trained model with images from FG-net database was used to classify the testing set which included only the images from Cohn-Kanade database. As a result, the images in the testing set and training set were selected from two different databases, independently. This process was implemented five times for the purpose of checking the system bias. Second evaluation was experimented with only Cohn-Kanade data set including 120 emotional images with 30 neutral of those subjects. In this phase, when the model was trained with 80 training images, it was tested with the rest 40 emotional images as the testing data set. The images of training and testing were exchanged in the rotation process until all images were used as the testing set. Therefore, the validity of the model was evaluated with the images from Cohn-kanade as the different database in the testing phase. As a result, the model performance was evaluated with the images from Cohn-Kanade database in two phases: first, the model was trained with the images from FG-net database and tested with the Cohn-Kanade and second, the model was trained with the images from Cohn-Kanade database and tested also with it but with different images. The experiments results are described in the Chapter 4 of this thesis in details.

The description of testing set including Cohn-Kanade images for validity evaluation is as follows:

First validity evaluation using FG-Cohn data set:

$$\text{140 images}\begin{cases} 72\ training\ set\ includes\ images\ from\ FG-net\ database \\ 40\ testing\ set\ includes\ images\ from\ Cohn-Kanade\ database \\ 28\ images\ in\ neutral\ state\ \begin{cases} 18\ from\ FG-net \\ 10\ from\ Cohn-Kanade \end{cases} \end{cases}$$

Second validity evaluation with Cohn-Kanade data set:

$$\text{150 images}\begin{cases} 80\ training\ set\ includes\ images\ from\ Cohn-Kanade\ database \\ 40\ testing\ set\ includes\ images\ from\ Cohn-Kanade\ database \\ \\ 30\ images\ in\ neutral\ state\ from\ Cohn-Kanade\ database \end{cases}$$

3.5 FACIAL FEATURES EXTRACTION

As facial data extraction was not the main focus of the current research, therefore, in the proposed model full automatic feature extraction techniques were not applied. But, a Geometric method based on analysis of color information and morphology process was used for the purpose of extracting facial feature points from the colored images from FG-net database. Based on this method twelve points on the face images were detected to analyze the features movements from the neutral to emotional states. Moreover, facial feature points from the images of Cohn-Kanade database were also extracted but manually by computer mouse. Because the proposed automatically feature points extraction was based on the analysis of RGB information which was not proper for gray scale images. Therefore, the extracted feature points made the feature vectors to feed into the classification model. The proposed feature extraction method has been described in Chapter 4 of this Thesis in details.

3.6 FACIAL EXPRESSIONS

In this research, analysis of the facial expressions was accomplished on the four basic emotions comprising two positive (Happiness and Surprise) and two negative (Sadness and Anger) emotions. According to Khanum et al (2009), Sadness and Anger are the most difficult emotions to recognize between all universal expressions while a FRBS is used as the classification technique. Therefore, Sadness and Anger as the negative emotions were chosen in this research to evaluate the improvement of FRBS in the proposed hybrid Genetic-Fuzzy model.

3.7 MODEL EVALUATION WITH DIFFERENT SCENARIOS

In order to evaluate the proposed Genetic-Fuzzy classification model three Genetic based scenarios including Bees Algorithm (BA) Bee Royalty Offspring Algorithm (BROA) and classical Genetic Algorithms (GAs) were developed (See Chapter 4 in details). Modified Genetic Algorithm called Bee Algorithm (BA) was simulated based on the process of bee offspring generation in nature to adjust the Fuzzy Rule based System (FRBS) performance. Therefore, BA training process was implemented to obtain the best accuracy rate of classification. Then, the trained model was experimented in the testing phase. As the natural process of bees behavior has some limitations, this process was also improved. Therefore, an improved Bees based learning algorithm called Bees Royalty Offspring Algorithm (BROA) was combined with FRBS. Then, the learning process by the proposed algorithm (BROA) was implemented on the training and testing sets. On the other hand, the training process was implemented while two classical types of Genetic Algorithms were used as the learning algorithms. Therefore, the achieved results by BROA, BA and GAs were compared in terms of mean and standard deviation. Moreover, T-test statistical approach was used to evaluate the significant difference between those learning algorithms. Furthermore, the proposed hybrid Genetic-Fuzzy model was compared with the FRBS without training process to show the learning algorithm performance in the Fuzzy Rule based classification. The experiment results have been described in Chapter 5 in details.

3.8 SUMMARY

In this chapter the process in which this study has been developed including the way of data gathering, analysis of proposed model, training and testing phases, simulation environment and system evaluation has been described. In this research, a group of static images from FG-net and Cohn Kanade databases were selected to make the training and testing sets. Then, twelve features from each image were extracted as the reference values to feed into the proposed classification model. The proposed classification model is based on a Fuzzy rule based model which is combined with the Genetic based learning algorithm. Therefore, different scenarios of Genetic algorithms and Bee Royalty Offspring Algorithm as a modified Genetic learning process were evaluated in the training and testing phase. The experiment process was simulated in the Matlab 7.8.0 (R 2009a). Reliability and validity of the proposed model were also evaluated with different data sets. Furthermore, T-test statistical approach was used in order to evaluate the significant difference of the proposed model in comparison with other scenarios.

CHAPTER IV

DEVELOPMENT OF GENETIC-FUZZY CLASSIFICATION MODEL

4.1 INTRODUCTION

Development of the proposed Genetic-Fuzzy classification has been described in this chapter. Therefore, facial features extraction as a part of facial expressions classification model has been first demonstrated. For the purpose of facial features extraction a Geometric method was proposed to detect the facial feature points from the static images. According to proposed method, first the facial feature regions were localized from the colored images then, based on those extracted regions the feature points were detected. Therefore, seven facial feature vectors were determined based on the 12 feature points in the feature extraction process. The extracted features fed in the Genetic-Fuzzy model to classify four basic facial expressions. Surprise, Sadness, Happiness and Anger are the most important emotions usable in the real life systems also show both positive and negative appearances. That is why those were selected for the evaluation of the proposed model.

A modified Genetic Algorithm was proposed as a learning method to modify the Fuzzy rule based classifier. Modification process was performed in terms of Fuzzy membership function parameters. Three parameters of bell shape membership function were tuned in the training phase. To make the best performance, the classic Genetic Algorithm was improved and a novel algorithm based on the biological process of bees offspring generation was simulated. The overall system architecture is shown in Figure 4.1.

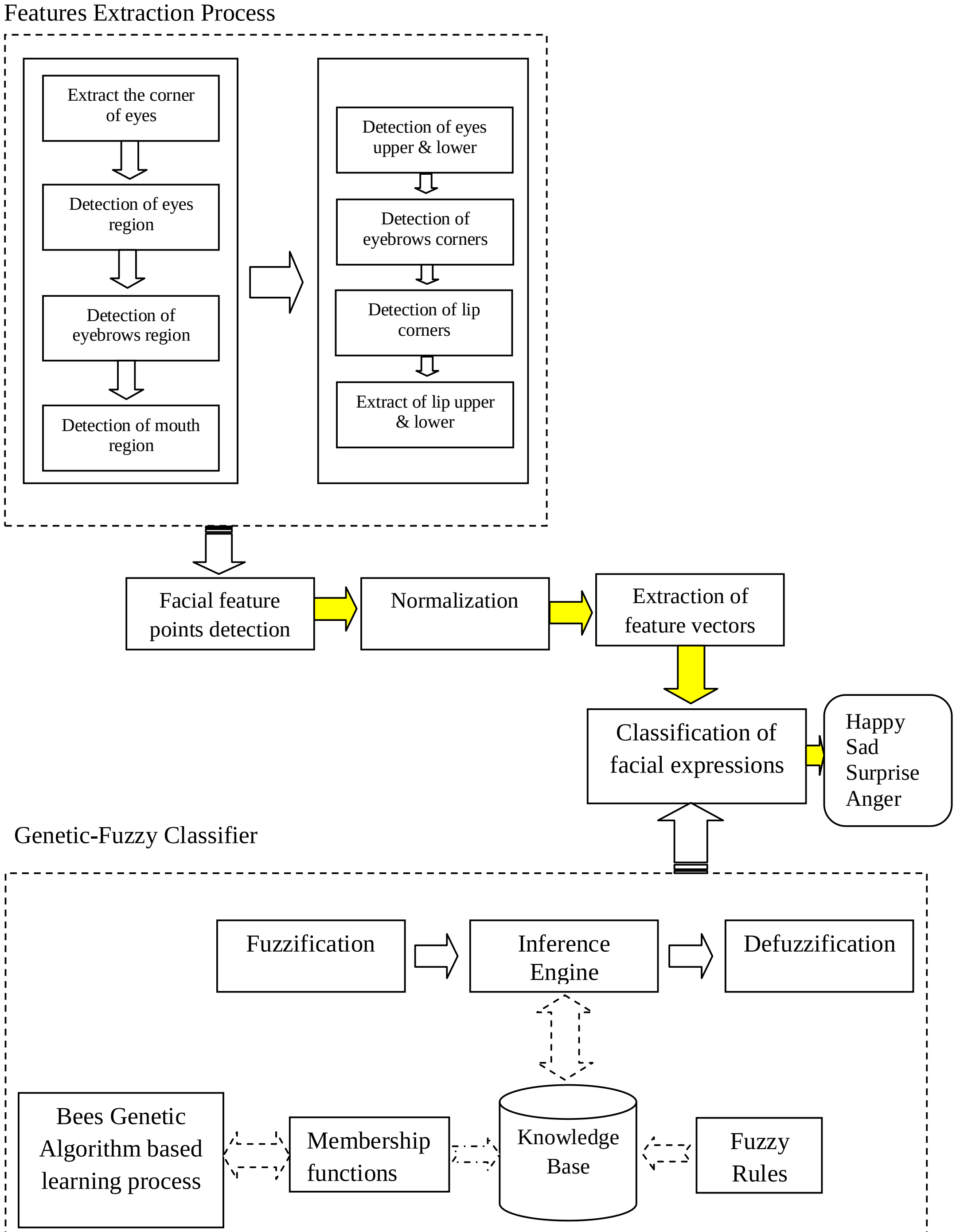


Figure 4.1 Architecture of Proposed Facial Expressions Classification System

4.2 FACIAL FEATURE EXTRACTION

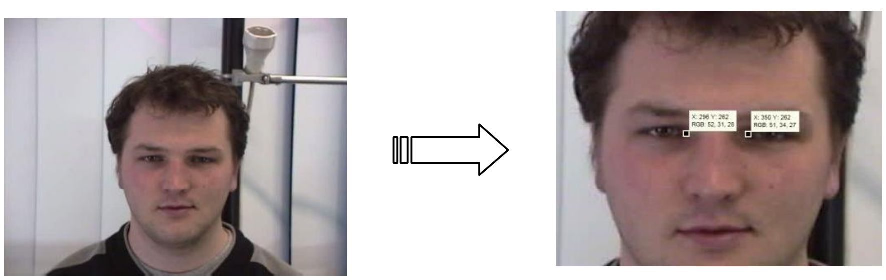
As facial data extraction was not the main focus of the current research, therefore, in the proposed model full automatic feature extraction techniques were not applied. But, a Geometric method based on analysis of color information and morphology process was used for the purpose of extracting facial feature points from the images. Based on this method twelve points on the face images were detected to analyze the features movements from the neutral to emotional states. Image processing techniques and morphology process were operated on the static images which were selected from FG-Net database as the neutral and emotional states. Moreover, in order to evaluate the classification model with extra data set, facial feature points from the images of Cohn-Kanade database (Kanade et al 2000) were also extracted but manually by computer mouse. The Cohn-Kanade database includes not only the images but also a set of facial feature points which were extracted with AAMs method. However, as the feature points extraction with AAMs, as a known feature extraction method, was not as well as manually extraction and indicated considerably errors, therefore the manually extracted points were selected to use in the classification model.

Eyes, eyebrows and mouth are the most effective features on the face for expressing the emotional information (SeyedArabi et al 2007). Therefore, the localization of those was the pre-process step for facial feature points extraction.

Two corners of eyes were marked manually by computer mouse as the base reference of facial features detection. The extraction of eyes corners with distance between them presented a scale to detect the face and location of facial features. Generally, facial features have relatively constant proportion with distance between two eyes (Sohail & Bhattacharya 2006). Therefore, facial features detection was developed with measuring the proportions of the features with regarding to the distance of two eyes as a base parameter.

4.2.1 Feature Points Detection from Eyes Region Localization

Extracting the corners of eyes locates the eyes areas both in horizontal and vertical positions. Therefore, two box areas were approximated around the eyes regions. These boxes included 40 horizontal pixels and around 25 vertical pixels from the inner corner of the eye. The size of horizontal and vertical pixels (40, 25) were approximated based on the trial and error method to achieve the best results for all images. For the purpose of dividing the upper eyelids from the eyebrows in the emotional states, height of the rectangular area around the eyes was estimated a little shorter for the Sadness and Anger facial images and longer for Surprising images. The next step is detection of eye features points. In this research, the dark borders of eyes including eyelash was detected to extract the upper and lower points of eyes. These two points showed the distance of eyes opening or closing. Figure 4.2 shows a sample image with extracted inner corners of eyes and the coordinates of those as the base parameter which have been extracted manually. The base parameter has an important role to find the facial features.



(a) (b)

Figure 4.2 Pre-Processing Operation for Features Localization. (a) static image of subject, (b) manually marked two corners of eyes with coordinate

Figure 4.3 shows the process of feature points extraction from eyes in the images of FG-net database.

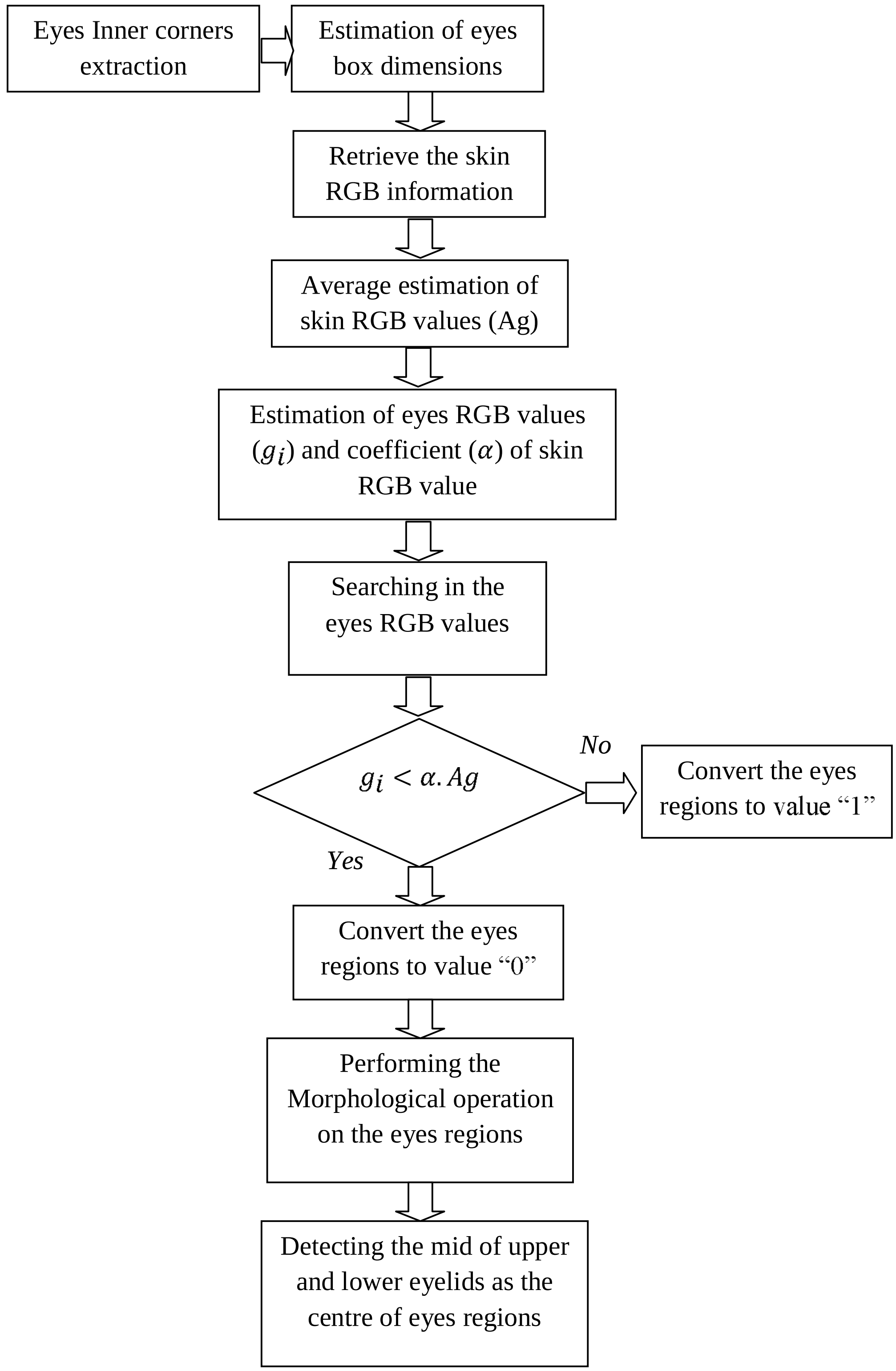


Figure 4.3 The Process of Feature Points Extraction From the Eyes

To detect the dark borders of eyes, RGB information in the images with JPG format were considered. As darker points have lower RGB value, the dark points in the eyes region were detected. Therefore, a range of RGB values was defined to show the eyes borders. The proper range was obtained based on the proportion of face skin RGB values. For this purpose, first an average RGB value from the face skin RGB values was estimated then, a proportion of the skin RGB value was determined as the base of RGB values of darker regions. Then, the pixels with RGB values in the proper range were converted to the binary values to show the extracted regions. Equation 4.1 shows the proposed mathematical function to convert the RGB pixel values to 0 and 1 as the binary values. Figure 4.4 shows RGB color system in a diagram with the elements.

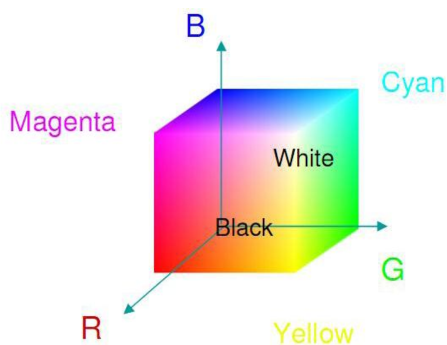


Figure 4.4 RGB Color System With Its Elements

$$\mathrm{Ei} = \begin{cases} 0 & g_i < \alpha . Ag \\ 1 & g_i \geq \alpha . Ag_i \end{cases} \tag{4.1}$$

Where:

- **a.** E_i is a pixel value in the eye region
- **b.** g_i is a pixel value with RGB information in the eye region
- **c.** α is the estimated coefficient (α is around 0.45, 0.75 and 0.56 for eyes, brows and mouth which were estimated based on several experiment results to find the best values)
- **d.** Ag_i is the average of determined RGB values

Morphological processing was operated on the detected eyes regions with using *close* and *open* operators in the Matlab environment to combine *Dilation* and *Erosion* operations. These morphological operators grown the objects thickness with filling the holes then removed the noise objects (Gonzalez et al 2004).

Close and *Open* functions include a structural element called *Strel*. *Strel* function indicates the objects characteristics on which morphological process are operated. *Close*, *Open* and *Strel* functions are as follow:

SE = *Strel* (Shape, Parameters)
IS = *imclose* (IM,SE)
IP = *imopen* (IM,SE)

In the eyes region the *Rectangle* and *Disk* parameters were used in the *Strel* function for close and open operators, respectively. Therefore, first close operators filled the small holes between the pixels then open operator remove the noise objects on the image.

Since the best points for showing the size of eyes opening or closing are determined with the shape of eyelids, therefore, the top and down positions of eyelids shape were analyzed. To find the points of upper and lower levels of eyes, the midpoint of lower and midpoint of upper eyelids, which are estimated in the middle of eyes region, in the vertical position from down to top and top to down were searched in the eyes boxes area. Therefore, the first black pixels in the lower and upper positions of eye regions were detected as the extracted features. Figure 4.5 and 4.6 show the process of eyes feature points extraction.

Figure 4.5 Process of Eyes Search Region Detection

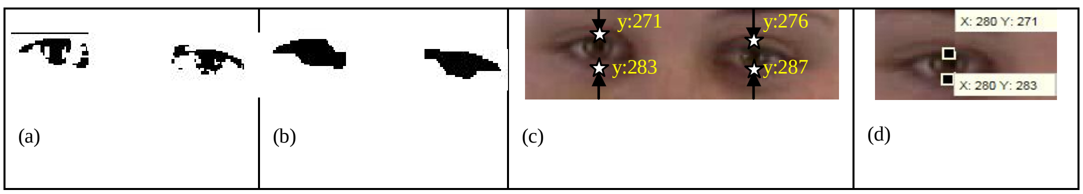


Figure 4.6 Process of Eyes Feature Points Extraction: (a) Eyes dark region detection, (b) Eyes dark region after morphological operation, (c) Extracted midpoints of upper and lower levels of eyes with the coordinates in the proposed method, (d) Extracted midpoints of upper and lower of left eye manually by computer mouse with the coordinates

4.2.2 Feature Points Detection from Eyebrows Region Localization

Eyebrow box areas were approximated when the eyes upper levels detected. As the eyebrows locate in the upper position of eyes region, the above area from the top point of eyes, which were extracted in the previous phase, indicated the eyebrows area. The eyebrow box area is started in the horizontal axes from the midpoint of distance between inner corners of eyes, base parameter, to cover the first inner points of eyebrows. Therefore, with the color information analysis in the eyebrow boxes the dark regions as the eyebrows were extracted. In this process, the values of RGB was estimated in the eyebrows regions based on the coefficient (α=0.75) of average of skin RGB values.

Figure 4.7 shows the process of feature points extraction from the eyebrows areas.

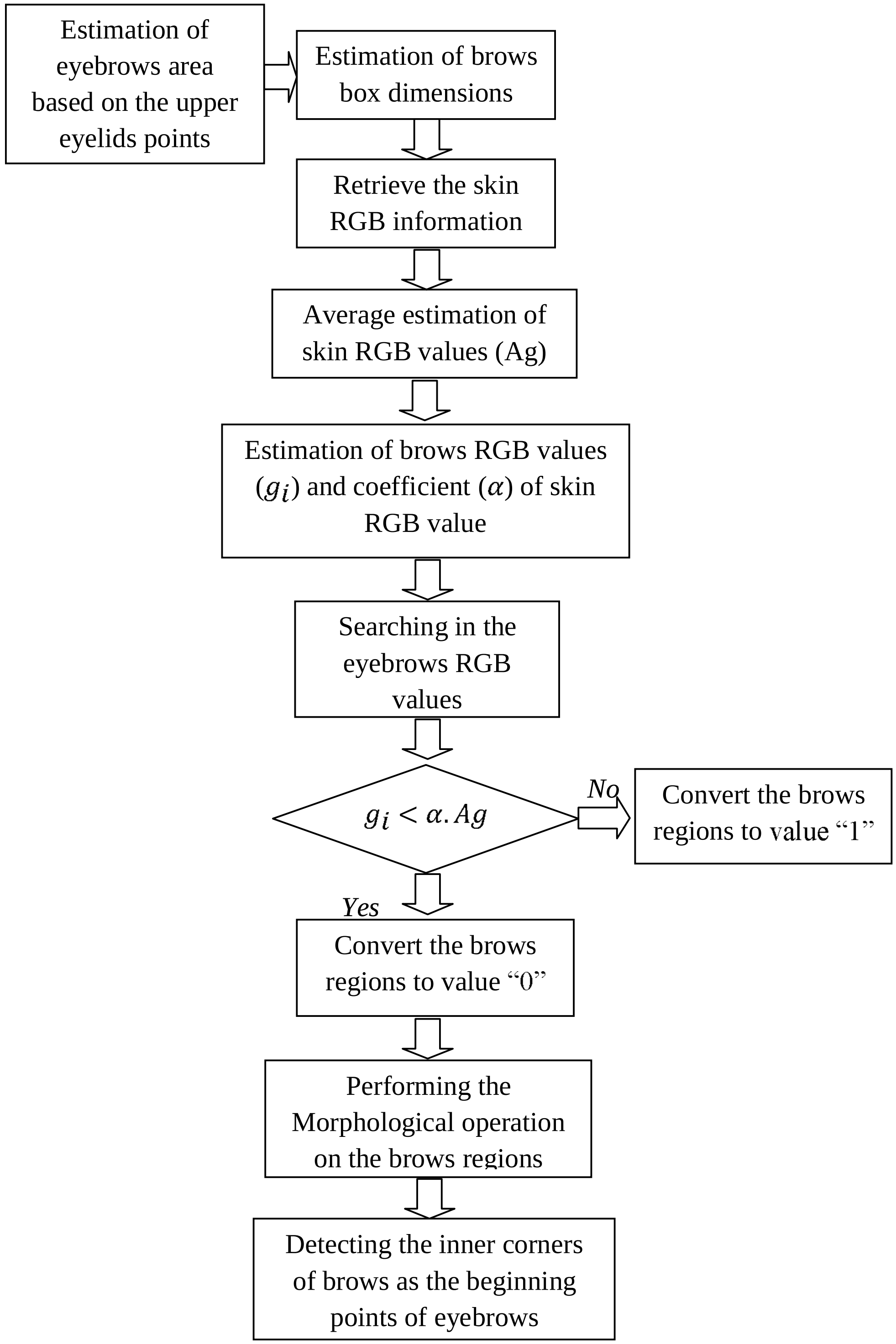


Figure 4.7 The Process Of Feature Points Extraction From the Eyebrows

As a result, with regarding to the dark color of the eyebrows, the eyebrows regions were extracted from the background in the boxes areas.

The morphological operators performed to adjust the eyebrows region. In this process, the *Rectangle* parameter was used in the *Strel* function as the structuring element for close operator to join the separated holes in the eyebrow region. Then, the search process was performed to extract the outer points of eyebrows. Figure 4.8 shows how eyebrows position was approximated based on the upper eyelids. Figure 4.9 shows the process of extracting the eyebrows feature point.

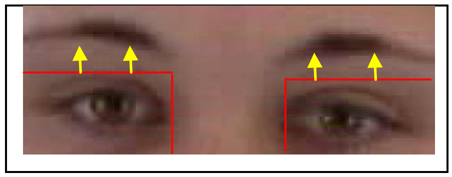


Figure 4.8 Eyebrows Position Estimation

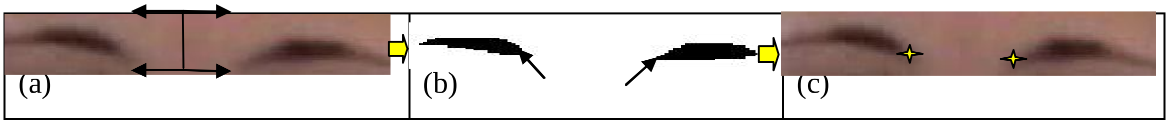


Figure 4.9 The Process of Eyebrows Feature Points Extraction

4.2.3 Feature Points Detection from Mouth Region Localization

Mouth corners detection was performed when the mouth region was estimated. Mouth region was localized based on the position of nose. Therefore, first the location of the nose was approximated, then, the lower area of the nose was detected as the mouth region. Figure 4.10 shows the process of feature points extraction from the mouth.

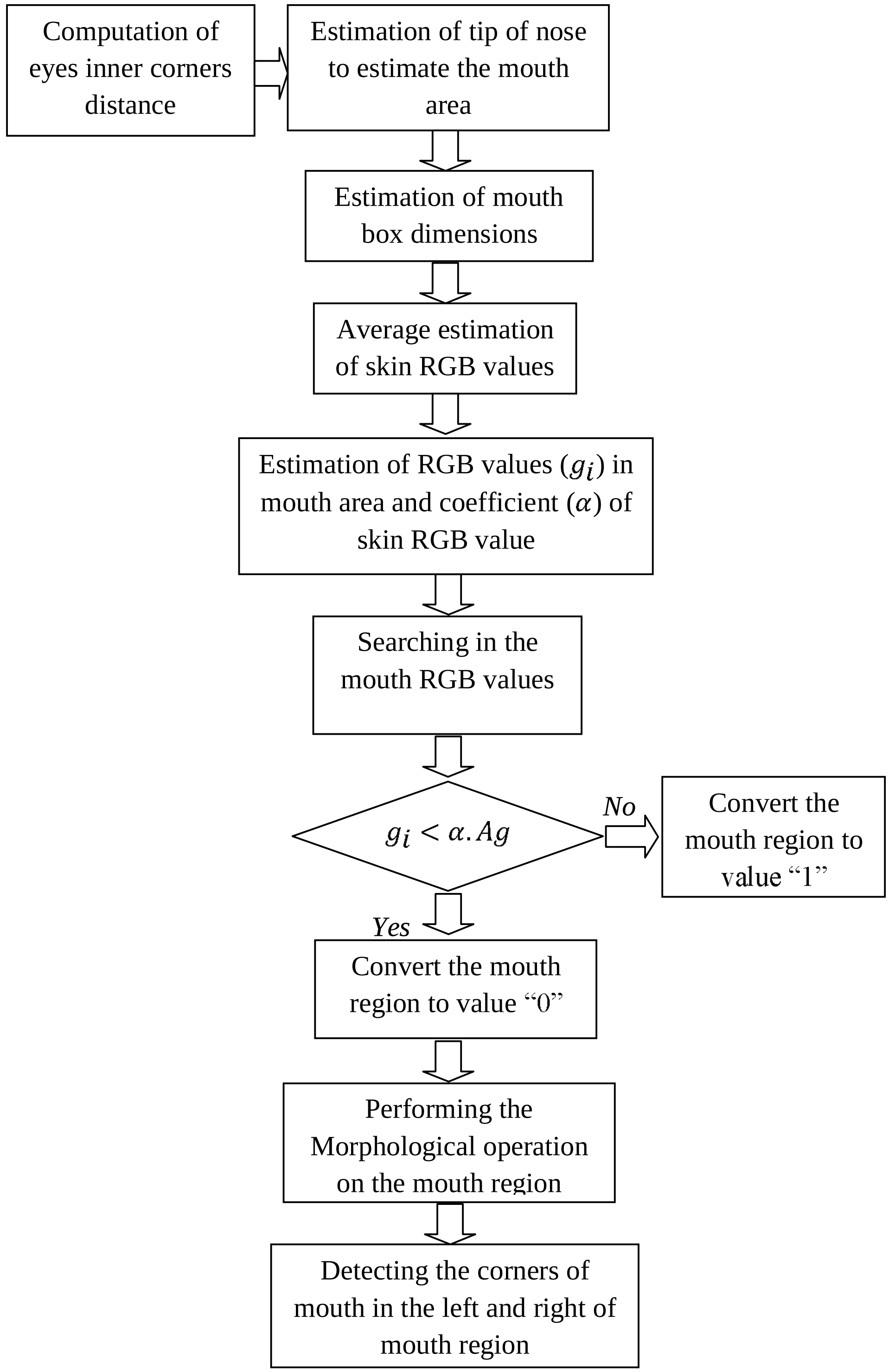


Figure 4.10 The Process of Feature Points Extraction From the Mouth

The distance between two inner corners of eyes, which called base parameter, can be a criterion to find the tip of the nose area. Therefore, the normalized base distance from the mid of two inner corners of eyes to the face down in the vertical position was measured to find the nose area. As a result, the nose area is begun from the end of measured vertical distance which is equal to base parameter.

The lower region of the nose area was considered as the mouth box area. In this area, the position of outer corners of eyes was used to estimate the width of mouth box area.

As the mouth region includes the red dark area in the mouth box, therefore, RGB information can be used to extract the mouth from the left area of the face. Therefore, for the purpose of detecting the corners of the mouth, the extracted mouth region was converted to the binary format.

The morphological operation was performed on the binary shape of the dark regions of the mouth box. In the morphology process, the *Rectangle* parameter was used in the *Strel* function for both close and open operators in the mouth region. Then, two mouth corners were extracted with a search process in the box area.

Figure 4.10 and Figure 4.11 show the process of mouth area estimation and the process of mouth feature points extraction, respectively. In Figure 4.11 (b) and 4.11 (c) we can compare the accuracy of feature points detection in the proposed method with the feature points extraction in using computer mouse manually.

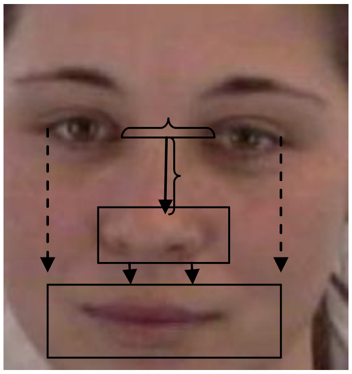


Figure 4.11 The Process of Mouth Area Estimation

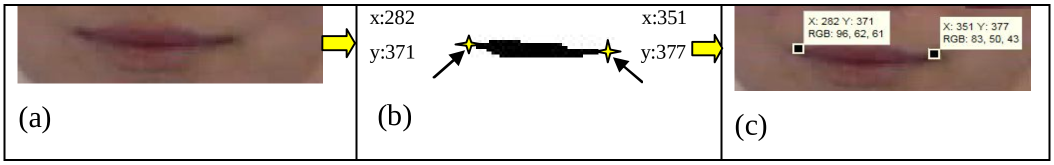


Figure 4.11 The Process of Mouth Corner Points Extraction: (a) detected mouth area, (b) the mouth feature points extraction after morphological operation with the coordinates, (c) the mouth corners detection manually by computer mouse

Two upper and lower points of mouth also were extracted as the mouth features. These points have the vital role in the recognition of emotions. However, the boundary of lip and face skin were not recognizable due to the condition of image illumination and low quality of colors for some objects particularly in the emotional state such as happiness. Therefore, to get higher accuracy in this condition, we preferred to extract the upper and lower feature points manually by computer mouse. Figure 4.12 shows the proposed facial features including lip upper and lower feature points.

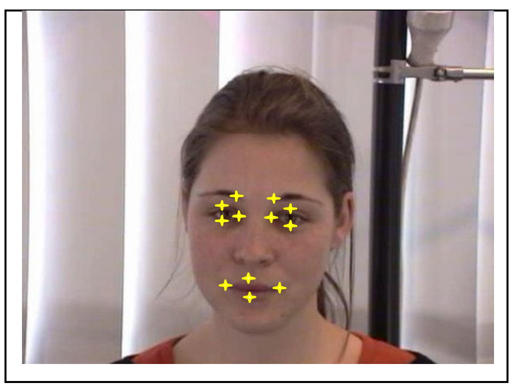


Figure 4.12 Extracted Facial Feature Points

4.3 NORMALIZATION

Normalization was performed on the extracted features against the head motions and distance of objects from the camera. The distance between two inner corners of eyes was measured as a base. The normalization process was performed based on this parameter.

4.3.1 Base Parameter (BP)

The Euclidian distance between eye inner corners was defined as a base parameter (BP) as follow:

$$BP = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \tag{4.2}$$

Where (x_a , y_a) and (x_b , y_b) are the coordinates of eye inner points.

4.3.2 Measuring the Head Rotation Angle

The head motion angle over the horizontal axis was determined using the base parameter (BP) and a point near the tip of nose to measure the face angle in images. The eyes inner corners points and the tip of nose formed a triangular shape in the head rotation position. Figure 4.13 shows the head rotation angle over the horizontal axis.

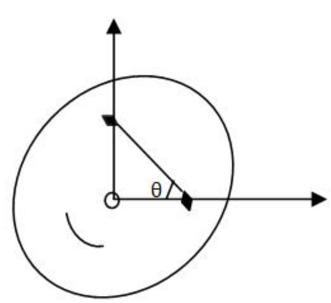


Figure 4.13 Face Rotation Angle over The Horizontal Axis

Therefore, the rotation angle (θ) was measured with using the following mathematical statement:

$$\theta = Arc \tan\left(\frac{y_a - y_b}{x_a - x_b}\right) \tag{4.3}$$

Where, (x_a,y_a) and (x_b,y_b) are the coordinates of inner corners of left and right eyes, respectively.

4.3.3 Coordinate Origin

In order to normalize the coordinate of feature points in the different images with a constant reference, a point around the tip of nose which was located almost in the centre of face, was determined as a new coordinate origin for each image. Then, all feature values in the images were measured based on the coordinate origin (Seyedarabi, 2007). The position of coordinate origin was determined with using the following equations:

$$x_o = \frac{x_a + x_b}{2} \tag{4.4}$$

$$y_o = \frac{y_a + y_b}{2} \tag{4.5}$$

Where (x_o, y_o) is the coordinate of the base parameter (BP) midpoint.

$$\sin\theta = \frac{x_o - xp}{BP} \quad \Longrightarrow \quad x_p = x_o - \sin\theta \,.\, BP \tag{4.6}$$

$$\cos\theta = \frac{y_o - yp}{BP} \quad \Longrightarrow \quad y_p = y_o - \cos\theta \,.\, BP \tag{4.7}$$

Where (x_p, y_p) is the new coordinate origin in the rotation position.

Figure 4.14 shows the head rotation and the coordinate origin position.

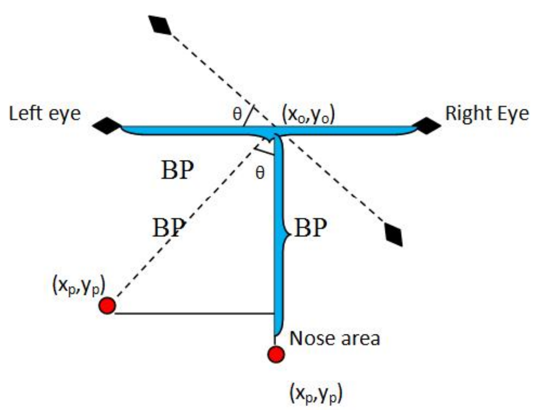


Figure 4.14 Proposed Coordinate Origin With The Coordinate (X_p, Y_p)

Therefore, the new coordinate of facial features were determined based on the new coordinate origin with following equation:

$$\mathrm{X}new = x_c - x_p \tag{4.8}$$

$$\mathrm{Y}new = y_c - y_p \tag{4.9}$$

Where, (x_c, y_c) is the old coordinate of facial features.

4.3.4 Removing the Camera Distance to Objects

Feature points coordinates in the different images were normalized against the different distances to the camera with using Base parameter (BP) as follow:

$$\mathrm{X}_{bp} = \frac{Xnew}{BP} \tag{4.10}$$

$$\mathrm{Y}_{bp} = \frac{Ynew}{BP} \tag{4.11}$$

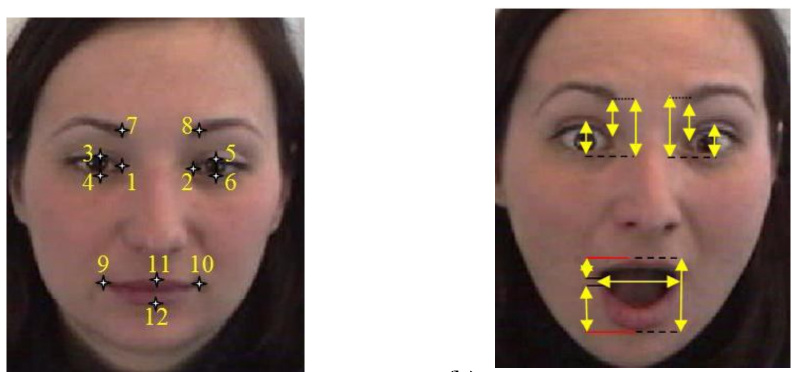
Where $(\mathrm{X}_{bp}, \mathrm{Y}_{bp})$ is the normalized value based on the base parameter (BP).

4.4 FACIAL FEATURE VECTORS

Seven feature parameters were extracted from the feature points in the neutral and emotional images. These feature values showed the feature points geometric movements from the neutral to emotion states. Based on the literature review, various feature parameters were extracted from the feature points in the geometric methods (SeyedArabi et al 2004, Zhan et al 2007, Hupont et al 2008, Youssif & Asker 2011). For most of them the psychological studies in the FACS (Ekman et al, 1978) influenced the features extraction. Therefore, they used psychological knowledge based on the FACS to determine the feature parameters. However, in the current research not only the psychological knowledge but also statistical experiments were conducted to find the best feature vectors. As a result, seven feature parameters were extracted from the extracted feature points. Therefore, in order to find the best feature parameters, for each emotion the change of distance between every two points in the emotional state in comparison with their distance in the neutral state was estimated. As a result, the bias for every point to each other in emotional state in compare to the bias in neutral state was estimated. In this process, Mean, Maximum and Minimum of computed distance parameters for each emotion between all subjects were determined.

Then, with regarding to the achieved distance measures for all subjects, some pairs of feature points which had the biggest movements in emotional state were selected. Furthermore, as the selected parameters should be used in other emotions therefore from the selected parameters those which were similar in most emotions were chosen. The obtained measurements as the feature vectors were used in the classification model to recognize facial expressions.

According to the Figure 4.15 the feature parameters were determined as following equations:



(a) (b)

Figure 4.15 Proposed Facial Extracted Features, (a) Extracted facial feature points, (b) Extracted parameters from the feature points

$$D1 = \frac{(y3-y4)+(y5-y6)}{2} \tag{4.12}$$

$$D2 = \frac{(y7-y1)+(y8-y2)}{2} \tag{4.13}$$

$$D3 = \frac{(y7-y4)+(y8-y6)}{2} \tag{4.14}$$

$$D4 = \frac{(y9-y11)+(y10-y11)}{2} \tag{4.15}$$

$$D5 = \frac{(y12-y9)+(y12-y10)}{2} \tag{4.16}$$

$$D6 = (y12 - y11) \tag{4.17}$$

$$D7 = (x9 - x10) \tag{4.18}$$

In the above parameters (D1…D7) xi and yi are the horizontal and vertical coordinates of feature points, respectively where the tip of nose is the coordinate origin.

In order to compare selected facial parameters in this study with existing research, some of the popular extracted parameters are shown in Table 4.1. These parameters were extracted based on the facial feature labels as are shown in Figure 4.16. According to Table 4.1, four parameters from seven proposed parameters were found in the existing research while three else parameters were proposed based on experiment results in this study. Therefore, according to Equation 4.12 to 4.18, parameters D3, D4 and D5 never used in the existing research. Moreover, the proposed set of feature parameters shows a novel collection of descriptors in comparison with previous studies.

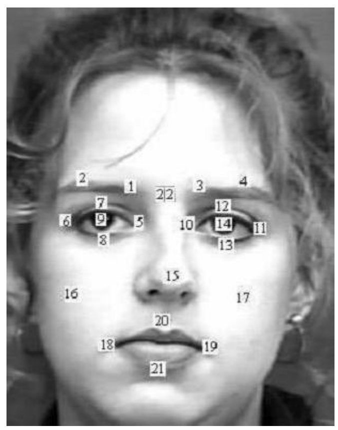


Figure 4.16 A facial image with its labels

In the current research, the measures from D1 to D7 in the neutral image as well as emotional image for each subject were obtained. Then, the proportion of parameters in the emotional state into the neutral state for each subject determined the movement values as the feature vectors for emotions. These feature vectors were fed into the classification model to recognize the facial expressions. If $De1 \dots De7$ and $Dn1 \dots Dn7$ show the extracted features in the emotional and neutral states, respectively, then the feature vectors are shown as follow:

$$f1=\left(\frac{De1}{Dn1}\right),\ f2=\left(\frac{De2}{Dn2}\right),\ f3=\left(\frac{De3}{Dn3}\right),\ f4=\left(\frac{De4}{Dn4}\right),\ f5=\left(\frac{De5}{Dn5}\right),\ f6=\left(\frac{De6}{Dn6}\right),\ f7=\left(\frac{De7}{Dn7}\right) \qquad (4.19)$$

Table 4.1 Extracted Feature Parameters in the Existing Research

Reference	**Extracted Parameters**
SeyedArabi et al (2004):	D1=$\frac{(x11-x10)+(x5-x6)}{2}$, D2=$\frac{(y15-y4)+(y15-y2)}{2}$ D3$\frac{(y15-y3)+(y15-y1)}{2}$ D4=$\frac{(y18-y15)+(y19-y15)}{2}$ D5=$\frac{(y16-y9)+(y17-y14)}{2}$ D6=(y21-y20) D7=(x19-x18)
Hupont et al (2008):	D1=(y1-y5)+(y3-y10) D2=(y7-y8)+(y12-y13) D3=(y6-y18)+(y11-y19) D4=(y20-y21) D5=(x18-x19) D6=(x1-x3)
Song et al (2010):	D1=(y12-y13) D2=(y5-y15) D3=(y15-y20) D4=(x9-x14) D5=(x18-x19)
SeyedArabi et al (2007):	D1=(x5-x6) D2=(y15-y2) D3=(y15-y1) D4=(x18-x19) D5=(y20-y21) D6=$\frac{(y18-y15)+(y19-y15)}{2}$
Khanum et al (2009):	D1=(y2-y7)+(y4-y12) D2=(y9-y14) D3=(y16-y6)+(y17-y11) D4=(y16-y8)+(y17-y13) D5=(y16-y5)+(y17-y10) D6=(y20-y21) D7=(y22-y15) D8=(x18-x19) D9=(x1-x3)

4.5 FACIAL EXPRESSIONS CLASSIFICATION

Classification is the main part of facial expressions system and the challenge matter of recent research in the pattern recognitions. Therefore, the main contribution in the current research addressed the classification performance. In this research, Fuzzy rule based approach was the proposed classification technique while a Genetic based learning algorithm was used in the Fuzzy knowledge base to tune the membership functions for facial expressions recognition. Overall, for the purpose of increasing the accuracy of the model, the process of classification was performed using a modified Genetic Algorithm simulated from honey bees offspring generation process called Bee Royalty Offspring Algorithm (BROA). BROA is as an optimization technique to fit the Fuzzy membership parameters with the problem conditions. Therefore, the BROA learning process optimized the Fuzzy Rule Based System (FRBS) to classify the expressions into four emotions. Figure 4.17 shows the general framework of hybrid classification based on a Genetic-Fuzzy model for facial expressions recognition.

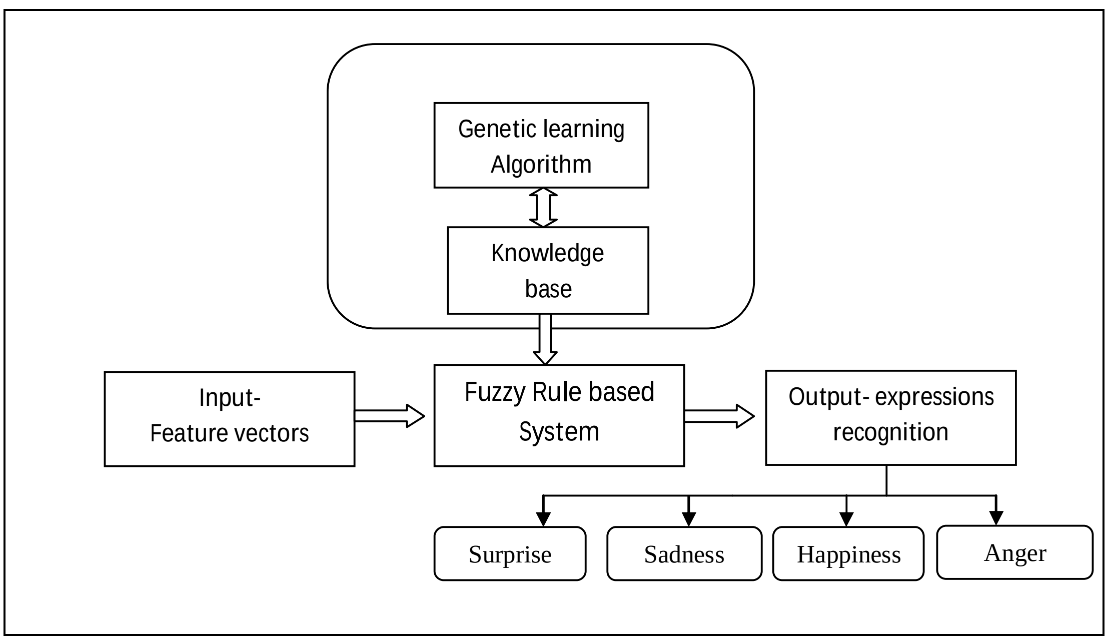


Figure 4.17 General Facial Expressions Classification Framework

4.5.1 Fuzzy Rule Based System (FRBS)

In this research, a novel scheme of Mamdani type FRBS was used for classification of emotions. Generally, a FRBS includes four main components of Fuzzification, Knowledge base, Inference Engine and Defuzzification but in this research it was developed with a modified Genetic Algorithm (BROA) as a learning process.

i. Fuzzification

The process of making Fuzzy values from the crisp values was determined with using bell shaped membership function. Bell shaped membership function is one of the popular functions which is used for modeling of real life problems particularly in the problems that deal with human behaviors. The proposed bell shaped membership function is shown as follows:

$$\mu(x) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad (4.20)$$

Where the parameter b is usually positive which changes the shape of membership function. The parameters c and a are the center and width of the curve, respectively. A range of values was determined for b, c and a parameters with respect to the training data as follow:

> b: For the purpose of changing the shape of membership functions to cover all types of triangular, trapezoidal and general bell shaped membership functions, a range between 0.6 and 3.5 were determined which is optimized in the learning process with BROA. Figure 4.18 shows the bell shaped membership function with different value for b factor.

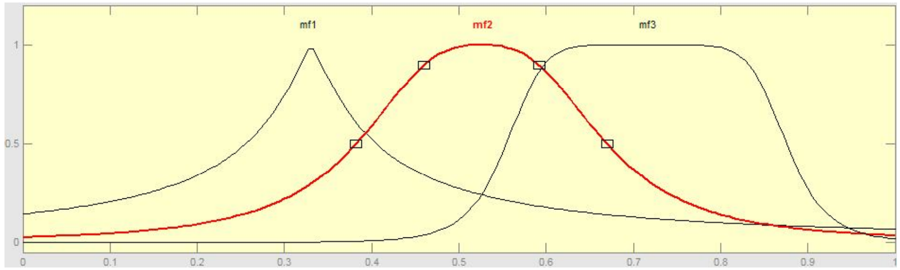


Figure 4.18 Influence of *b* Factor on the Bell Shaped Function: mf1: *b*=0.6, mf2: *b*=1.4, mf3: *b*=3.5

c: The center of curve was determined based on the average (Av) of extracted features (feature vectors) values for each emotion in the training set but with a deviation with respect to the maximum and minimum values of training set to make a range that includes general databases:

$$c = [\text{MinAv MaxAv}] \tag{3.21}$$

a: The width of curve was determined based on the variance (Var) of extracted feature values for each emotion in the training set with a deviation with respect to the maximum and minimum values of training set:

$$a = [\text{MinVar MaxVar}] \tag{3.22}$$

Therefore, the exact values of *c* and *a* in the Genetic learning process were achieved to improve the classification performance according to the data set.

Seven feature vectors used the bell shaped membership function to fuzzification process. In this process, six linguistic terms were used for each input feature vector. As the linguistic sets are fuzzified using membership functions, therefore, six membership functions were determined for each input feature vector. The linguistic terms were defined as follows:

VL: *Very Large*, L: *Large*, M: *Medium*, S: *Small*, VS: *Very Small*, VvS: *Very very Small*

ii. Knowledge Base

The computational procedure of Fuzzy inference system based on the knowledge base to predict the new conclusion is implemented in the Inference Engine. Therefore, knowledge of classification problem with Fuzzy rules were determined in the knowledge base component according to the FACS (Ekman & Friesen 1978) and experiment studies to find the best rules set for classification of emotions. For the purpose of making proper composition of rules, Mean, Maximum and Minimum of every feature vector for each emotional state related to all subjects were computed. Then, the obtained values from each feature vector based on the different emotional states were sorted from very large to very small except for "*f6*" which included *very very small* for all emotional states. In addition, the achieved results were combined with the results from the FACS studies to find the best composition of rules. Table 4.2 shows the created rule base with linguistic terms in the knowledge base.

Table 4.2 Rule Base for FIS Classifier

Emotion	***f1***	***f2***	***f3***	***f4***	***f5***	***f6***	***f7***
Sadness	M	M	VS	L	VS	VS	S
Happiness	S	M	S	S	VL	L	VL
Anger	S	VS	VS	S	VS	VvS	VS
Surprise	VL	VL	VL	VL	VL	VL	VS

In the proposed FRBS seven inputs connected by "and" connective to get a single consequent as emotion. As an example Sadness output is as follows:

If *f1*: Medium and *f2*: Medium and *f3*: Very Small and *f4*: Large and *f5*: Very Small and *f6*: Very Small and *f7*: Small **then** the expression is Sadness.

iii. Defuzzification

The process of converting Fuzzy output values to a crisp value was determined according to the Mean value of Maximum (MOM) defuzzification strategy. This technique consists of the points which have high membership values (Reznik 1997).

Therefore, the validity of the results is more probable compare with the other techniques. In this research, the consequent of defuzzification process is classification of each expression to one of four emotions, while the Fuzzy outputs include four Gaussian membership functions for indicating Sadness, Fear, Anger and Surprise. Figure 4.19 shows the output membership function plots for classification of facial expressions.

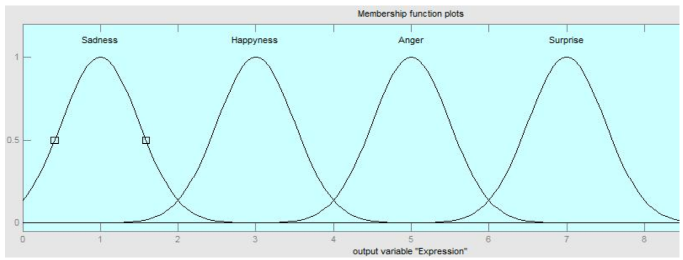


Figure 4.19 Output Membership Function Plots for Classification of Facial Expressions

4.5.2 Modified Genetic Learning Algorithm

For the purpose of improving the Fuzzy rule based classification performance, a Genetic Algorithm as a learning technique was used in the classification model. Genetic Algorithms are popular methods to solve the optimization problems in a learning process. In the proposed algorithm the bees offspring generation process was simulated as a solution for optimization of Fuzzy membership functions. The formulating of this biological process called Bee Royalty Offspring Algorithm (BROA) is described as follows.

Honey bees offspring generation process follows an intelligent structure which leads with the Queen bee in the colony. Queen as the most powerful bee is followed with a group of male bees in the mating flight. The male bees are chosen randomly in the initial mating flight (Initial population) while the mating process is continued with selection of the male bees with higher flight performance (Selection) which can get to the Queen. Generally, between of 7 to 20 male bees succeed to mating with Queen (Crossover). The Queen stores male's sperms to create the offspring. In the next generation an offspring replace with Queen if it is better (fitter) than the Queen, otherwise, it will be one of the population that has the chance of mating with the Queen. Figure 4.20 shows briefly the mating process with the Queen and drones to create new population. One of the main limitations of honey bees behavior is related to number of crossover between each male bee and Queen which is once per each drone. Therefore, the drones which had the transmission chance will be removed forever. Moreover, there is only one Queen in the colony to generate the offspring which limits the diversity of genes. Therefore, in this research, the proposed model overcomes those limitations while the bees colony survival behaviors has been simulated. Furthermore, the main difference of Bee Royalty Offspring Algorithm with classic Genetic Algorithms is in the crossover operation which includes mating two Princess Chromosomes, as the created offspring from the Queen, with a group of drones, independently, rather than crossover with pair of parents. As a result, the main difference in BROA compared with BA and classic Genetic Algorithms is as follows:

BROA includes one Queen Chromosome and two royalty offspring called Princess in each generation. Princess Chromosomes have the major role of crossover with selected chromosomes while those Princesses are created by Queen. However, in BA, the Queen is the main chromosome to create the offspring. Therefore, in BROA the probability of dropping into local optima solutions is lower than BA. Moreover, the diversity of fitter solutions in each generation is higher than BA. Furthermore, the size of offspring population in BROA is bigger than BA due to use of two female chromosomes (Princess) in crossover operation.

BROA and BA have a significant difference in the crossover operation in comparison with classic Genetic Algorithms. Therefore, the offspring are created while the fittest chromosome (chromosomes) as a parent mates with all selected chromosomes.

One of the differences of BROA and BA with natural process of bees behavior to generate the offspring is re-selection chance of drone chromosomes to keep in the new population. This technique keeps a chance for optimum solutions in every iteration to add to the new crossover competition in next generation.

In following parts the process of Bee Royalty Offspring Algorithm performed on the classification problem is described.

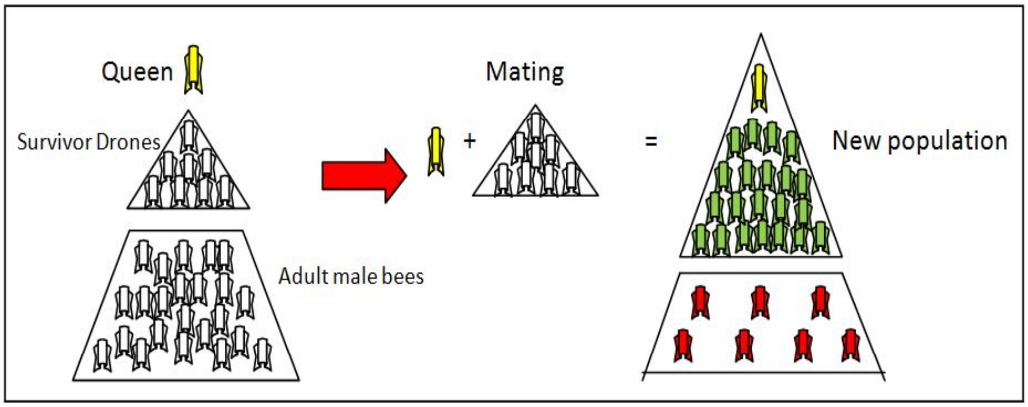


Figure 4.20 Biological Background for Bees Mating Process with Queen

i. Encoding the Chromosomes

Solutions were encoded as the strings of Gens consist of Fuzzy membership function parameters, extracted features and linguistic terms. According to the previous parts of this chapter, three (*b*, *a* and *c*) membership parameters for seven extracted features with six linguistic terms formed the Fuzzy Inference System structure. Therefore, each string of chromosome contains maximum 126 (3*7*6) Genes, $C_i = (G_1, G_2 ... G_n)$, in the form of real values. However, as some feature vectors did not include all types of linguistic terms due to limitation of variety of those vectors in different expressions, therefore, totally, 102 Genes was used in each chromosome.

Figure 4.21 shows a sample of chromosome string comprising of three types of Gene.

a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	....	a_{nm}	b_{nm}	c_{nm}

Figure 4.21 A String of Chromosome with the Genes

ii. Creation of Initial Population

Initial population was created randomly including fifty chromosomes. The membership parameters as the Gene values were determined randomly in the predefined ranges to make the initial results. The results were considered based on the fitness function to measure of reaching to the objective solution. Therefore, fitness values were the criterion for selection. Fitness function was determined based on the following objective function:

$$\text{Min } f(x) = 1 - \sum_{k=1}^{4} \left(\frac{m_k}{n_k}\right)$$

or (4.23)

$$\text{Max } f(x) = \sum_{k=1}^{4} \left(\frac{m_k}{n_k}\right)$$

Where, m_k is the number of corrected classification in the k_{th} emotion while the number of emotions are four. n_k is total number of data in k_{th} class. Therefore, the fittest value is determined according to the following equation:

$$\sum_{k=1}^{4} n_k = \sum_{k=1}^{4} m_k \tag{4.24}$$

iii. Parent Selection

The selection process was performed in two phases, parent selection and selection of new population. In the parent selection step, ten chromosomes were selected as the parents in each iteration based on the Roulette Wheel method. In this popular method, the chance of selecting fitter solutions are higher than the others, therefore, parents with higher fitness values are chosen in the process of selection. Number ten as a suitable number of chromosomes selection was determined after experiments of different values.

In the Roulette Wheel method, the probability of selecting chromosome C_i with fitness value f_i is defined as follow (Talbi 2009):

$$PC_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{4.25}$$

Therefore, selection of a chromosome with higher fitness value is more probable. The process of Roulette Wheel method is start with computation of cumulative fitness values for chromosomes which are arranged as a string. Then, N random numbers in the range of [0 S] per each chromosome are created if S be the maximum value of computed cumulative fitness for N number of selected chromosomes. In the arranged chromosomes from first to last, the chromosome with cumulative fitness value higher than first random number is selected. Therefore, next chromosomes are selected with respect to the next random values. As number of random values (N) is equal to number of chromosomes therefore, N chromosomes are selected (Deb 2001).

iv. Crossover Operation

Crossover is operated with the pair of parent chromosomes. In this research, the parents in the initial generation consisted of ten different chromosomes. Therefore, crossover was operated on each pair of chromosomes to create the offspring. Whereas, in the next generations the elite solution from previous generation called Queen Chromosome as a parent was paired with the first selected solution from Roulette Wheel method in the new population. Therefore, two royalty offspring called Princess were created as the outcomes from Queen crossover. This operation increases the diversity of fitter chromosomes in the population. As a result, further offspring were generated based on the crossover operations with the mutated Princesses and ten selected chromosomes from Roulette Wheel in the current iteration. In Princess Crossover, each Princess chromosome in each generation performed the crossover operation with five selected chromosomes one by one. So that, five crossover operations was performed on each Princess as a parent and each one of the five chromosomes as another parent to create the offspring. As each crossover operation generates two offspring, therefore, ten offspring were created from five mating operation from each Princess. As a result twenty offspring were created from the crossover of two Princesses. As three membership parameters included in the optimization problem, to increase the optimization performance, two point crossover per each *a*, *b* and *c* parameters were performed, independently to transition the Genes. It means a chromosome was crossed from six points with respect to number of parameters which participated in the two point crossover operation. The above mentioned process increases the fitter solutions with two Princess Chromosomes to reach to the optimum results. Figure 4.22 and Figure 4.23 show two point crossover for membership function parameters.

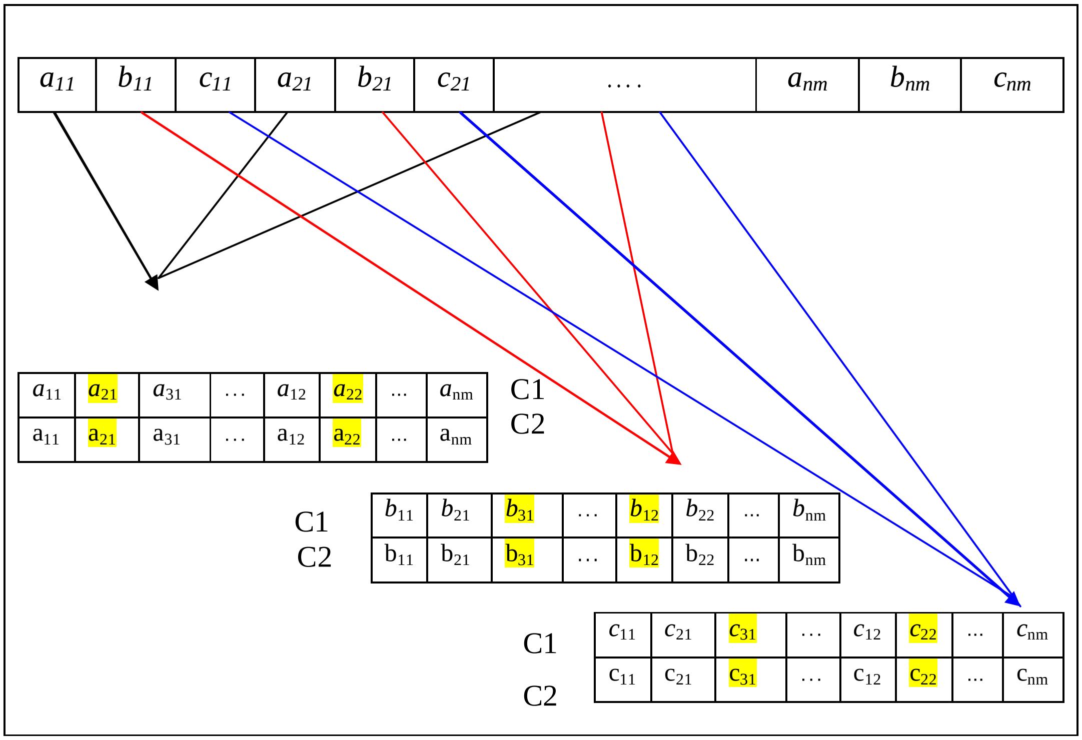


Figure 4.22 The Process of Crossover Operation with the Sample Points per Each Parameter for a pair of chromosomes

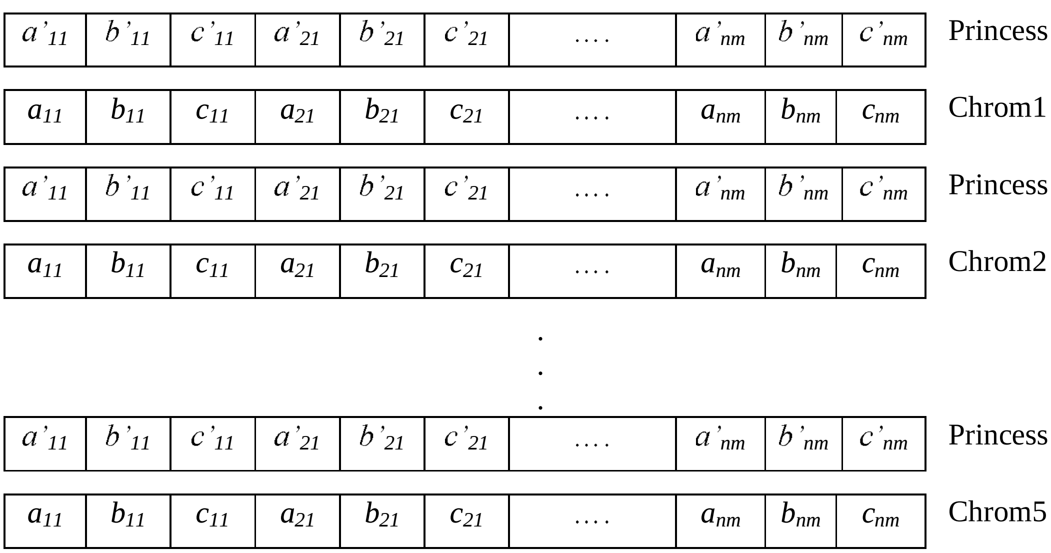


Figure 4.23 The Proposed Recombination of Princess and Selected Chromosomes

v. Mutation Operation

For the purpose of simulate the small changes in the Genetic structure of creatures, mutation operation with the probability (Pm) of 0.1 was performed on the offspring to create some errors on the offspring. This operation increases the diversity of chromosomes to reach the optimum solutions as well as prevent to create the local optima results. To increase the optimization performance, randomly one point mutation per each *a*, *b* and *c* parameters was performed, independently. It means a chromosome was mutated from three points with respect to number of parameters. The probability of mutation (Pm) was obtained with several times experiments of classification model on the training data. For this purpose, various values such as 0.05, 0.1, 0.2 and 0.3 were evaluated on the datasets, then the proper mutation value was selected. The Genes which were randomly chosen based on the mutation operator were replaced with the random values but limited in the predefined parameters ranges. Figure 4.24 shows a sample of mutation operation on the chromosome.

a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	a_{31}	b_{31}	c_{31}	….	a_{nm}	b_{nm}	c_{nm}

C_{nm} :[MinMean$_{nm}$ MaxMean$_{nm}$] $b$nm :[MinVar$_{nm}$ MaxVar$_{nm}$]

Figure 4.24 Randomly Selected Parameters with the Probability (Pm) of 0.1

vi. Selection of New Population

In every generation, ten chromosomes from offspring and exiting population with highest fitness values were selected. The number ten is equal the number of offspring in the initial generation but half the number of the created offspring in the further generations. The Queen as the fittest result was selected from the offspring and the current population. Moreover, nine other fitter results (chromosomes) from the offspring and current population were added to the Queen to make a new population for the next generations. Therefore, new population for next generations included ten chromosomes. In this method, the new Genes were added to the pool of solutions therefore, the probability of creating the fitter solutions was increased.

vii. Termination Conditions

Termination conditions were satisfied based on the number of iterations for generating the results or reaching to the proper solution with optimum fitness value. For the purpose of results optimization from the training data, two termination conditions were determined which included the generation number of 50 times or the fitness value more than 98%. The proper fitness value for termination is obtained while only one classification error in the training data is remained.

Table 4.3 and Figure 4.25 show the overall information of proposed Genetic Algorithm includes Termination Conditions and the process of Bee Royalty Offspring Algorithm (BROA), respectively.

Figure 4.26 shows the proposed Mamdani typed-Fuzzy Inference System (FIS) construction which includes seven inputs and one output extracted from the training process with BROA. According to Figure 4.26 the membership function plots illustrate a snapshot of generated parameters in the tuning process.

Table 4.3 Overall Information of Bee Royalty Offspring Algorithm

Genetic Algorithm Parameters	Information
Initial population	50
Number of parent selection	10
Number of offspring	Initial: 10, Next: 20
Crossover operation	2 points per each parameter
Mutation probability	0.1 per each parameter
Termination condition	Generation numbers, Fitness value
Number of generations for termination	50
Termination with Fitness value	F>98%, Achieve to only 1 failure in classification

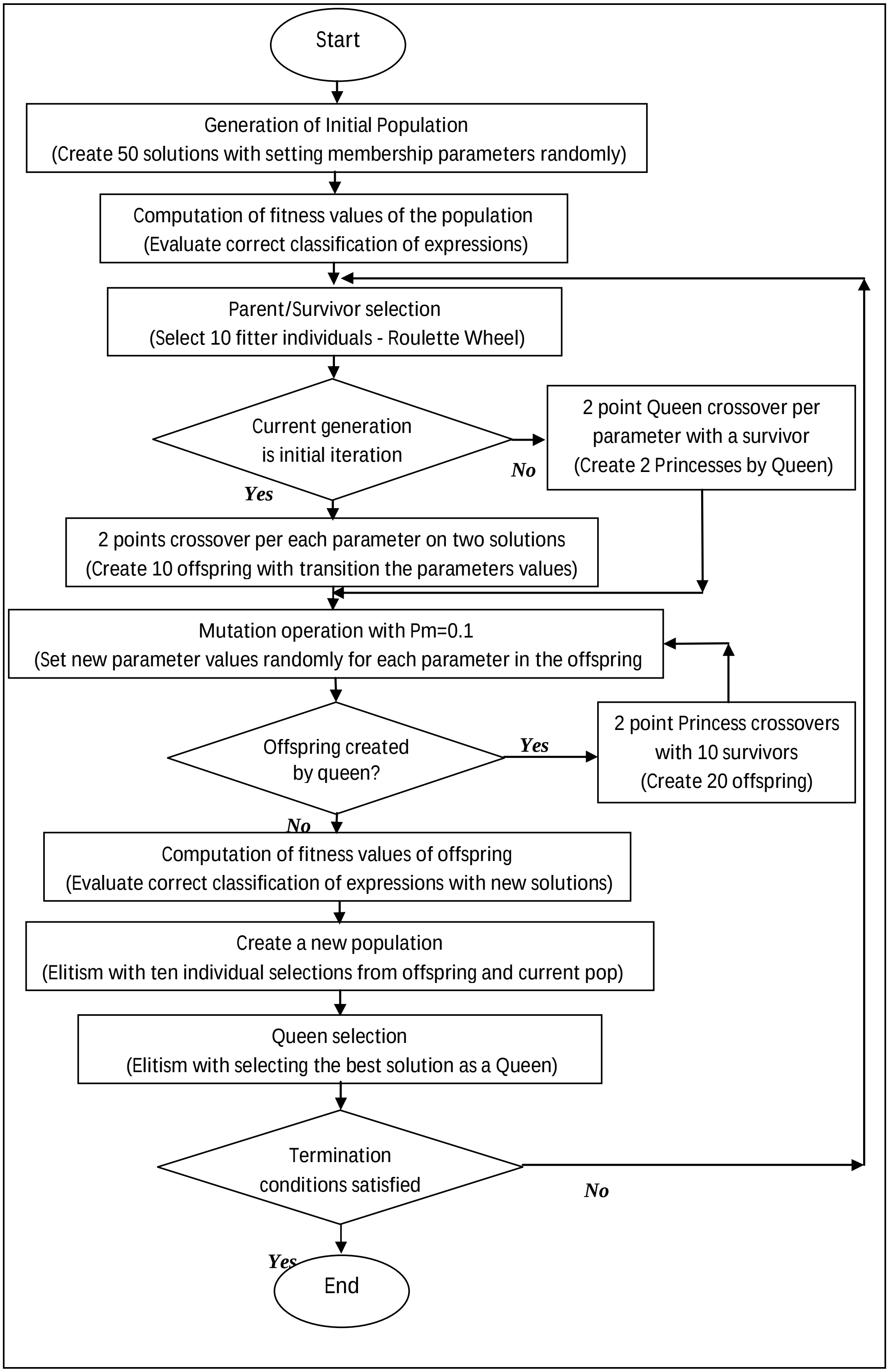


Figure 4.25 The Process of Proposed Genetic Algorithm called BROA

According to Figure 4.25 the proposed BROA includes the following steps:

Initial population:

Create 50 chromosomes as initial solutions with setting membership parameters randomly

Fitness values:

Evaluate the correct classification of expressions

Parent or Survivor selection:

Select 10 fitter solutions using Roulette Wheel method

Crossover:

Combine two solutions from 2 points per each membership functions parameter

Mutation:

Put random values in the crossover solutions

Mutation rate:

Use 10 percent probability for mutation operation

Offspring generation:

Create 20 solutions from muted chromosomes

New population:

Select 10 elitism solutions from achieved offspring and current population

Queen selection:

Select the fittest chromosome among the solutions

Termination condition:

Terminate the generation process if a solution achieved the accuracy of 98 percent (achieved to only one failure of classification)

Or

Terminate the generation process when 50 iterations of generation were carried out

According to Figure 4.26, FIS components are described as follows:

f1:

Measurement of eyes opening in the emotional state

f2*:*

Measurement of eyebrows movement in the emotional state

f**3**:

Measurement of eyebrows movement to eyes opening in the emotional state

f**4**:

Measurement of mouth upper lip movement in the emotional state

***f*5**:

Measurement of mouth lower lip movement in the emotional state

***f*6**:

Measurement of mouth opening in the vertical position in the emotional state

***f*7**:

Measurement of mouth opening in the horizontal position in the emotional state

Fuzzy Inference System:

Mamdani type

Output:

4 expressions including Surprise, Sadness, Happiness and Anger

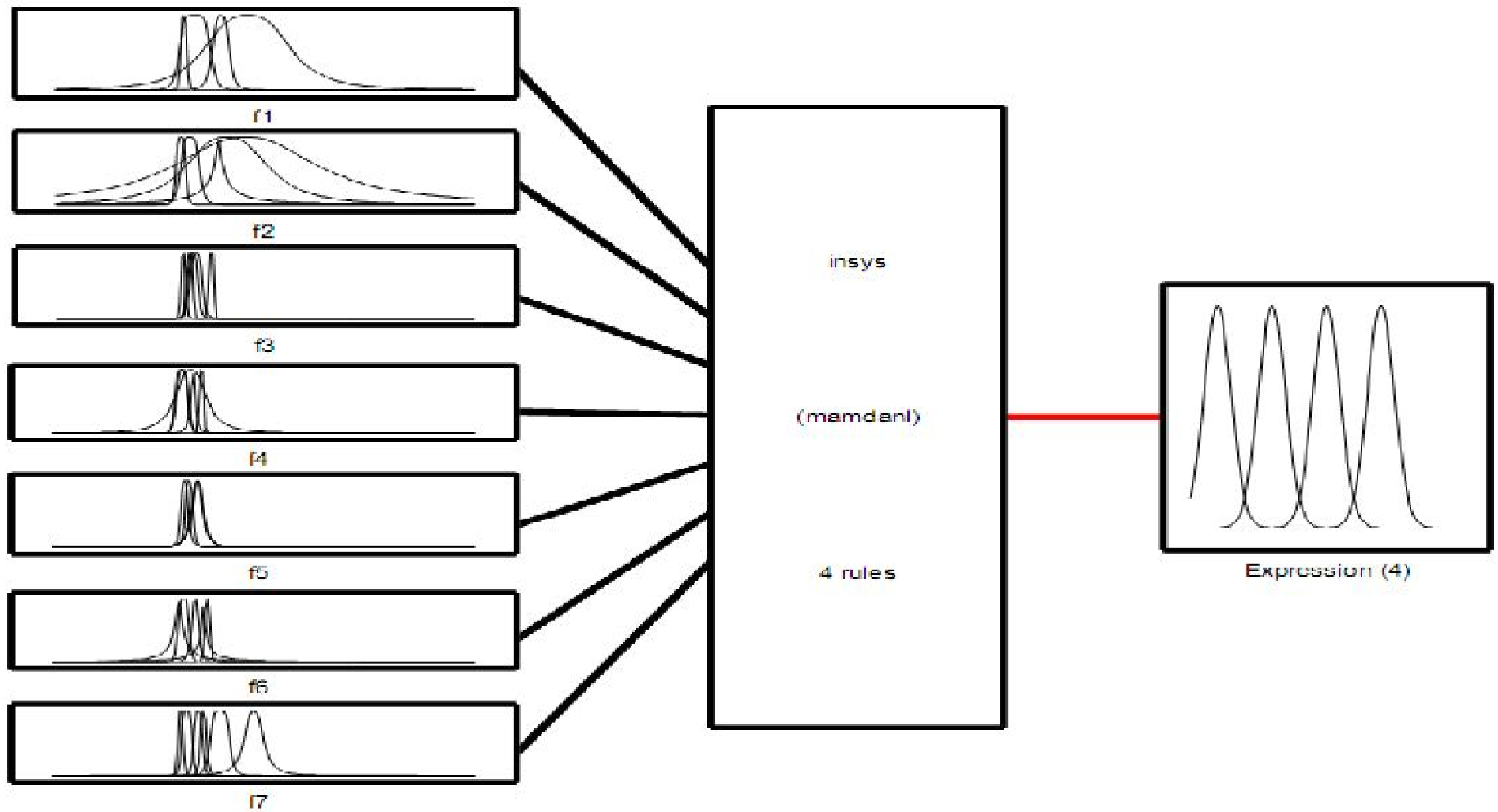


Figure 4.26 A Snapshot of The Proposed FIS Construction: 7 inputs, 1 output and 4 rules

viii. Comparison of Genetic-based Models

In order to comparison of BROA as the proposed training algorithm with some other Genetic Algorithms, three types of Genetic based algorithms have been presented in this research:

The first one is a simulated process from bees behaviour called Bee Algorithm (BA). In this algorithm, Queen is the main chromosome in the crossover operation which is used as a parent to pair with the selected solutions in each generation. In this research, 5 out of 10 selected chromosomes from Roulette Wheel method were paired with the Queen. Therefore, 10 offspring chromosomes were created by Queen and selected chromosomes. The process of BA is shown in Figure 4.27. According to BA, the size of offspring population, which are created by Queen, is less than BROA and dependent on only Queen as a fittest solution from previous population. Generally, the main difference between BA and BROA is related to existence of Princess Chromosomes as the base of crossover operation in BROA while those Princess Chromosomes are not defined in the BA.

Two other types of training algorithms which were used in this research are based on classic Genetic Algorithms. Therefore, the steps such as parent selection, crossover, mutation and new population are close the classic Genetic Algorithms while the parameters are different between these two types.

Table 4.4 shows the overall description of two types of bee algorithms compared with two classic Genetic Algorithms with different parameters used for classification optimization. Generally, according to Table 4.4 as well as Figure 4.25, the proposed BROA in comparison with Genetic Algorithms has major differences in the learning process which are described as follows:

Parent Selection:

According to BROA, there are three types of parent chromosomes including Queen, Princess and survivors. Queen in each generation is the fittest chromosome created from previous generation. Princess is created from Queen crossover operation with a selected chromosome from survivors and survivors are selected from current population. However, in the classic Genetic Algorithms parents are only selected from the current population. Therefore, diversity of Genes in the BROA in the parent selection step is more than Genetic Algorithms.

Two Times Crossover Operation in BROA:

In the proposed BROA, Crossover in each generation was operated in two phases. First, Queen based Crossover and second, Princess based Crossover. In the Queen Crossover operation, the best solution (fittest chromosome) achieved from previous generation plays the role of Queen as a parent to combine with a selected chromosome as another parent. Therefore, two offspring were created from Queen Crossover operation called Princesses. Next, selected chromosomes, from the parent selection step, were divided into two groups while each group was combined with a Princess in the Princess based crossover. Therefore, one of the parents was a Princess Chromosome in each group which was paired with every members of group. However, in the Genetic Algorithms the selected chromosomes from the parent selection step formed the pairs of chromosomes which were different in each crossover operation. As a result, the crossover operation in the BROA followed from an elitism procedure.

Size of Created Offspring:

As the size of selected parents for each generation in the BROA was ten chromosomes in this study, therefore in the BROA two sets including five members were combined with two Princesses. As a result, twenty offspring (ten from each Princess crossover) were achieved from the Princess crossover operation. However, in the Genetic Algorithms in each generation, ten and eight selected chromosomes in the parent selection step as the pair of parents make the Crossover operation in GA-type I and GA-type II, respectively. In this process, the offspring were created from the classic crossover operation. As a result, the size of offspring in Genetic Algorithms was less than BROA.

New Population:

For the purpose of create the new population in the BROA, in each generation elitism process was used to select the chromosomes from muted offspring and current population. In this process, offspring were created based on the Princess crossover while the size of those was twenty which was twice of current population. However, in the Genetic Algorithms the offspring which were used in the selection process including ten and eight chromosomes in GA-type-I and GA-type-II, respectively which were created based on the pair of parents crossover operation. Therefore, the size of survivors for Genetic Algorithms was equal of current population. As a result, the diversity of chromosomes in the BROA was more than Genetic Algorithms for selection process to create the new population.

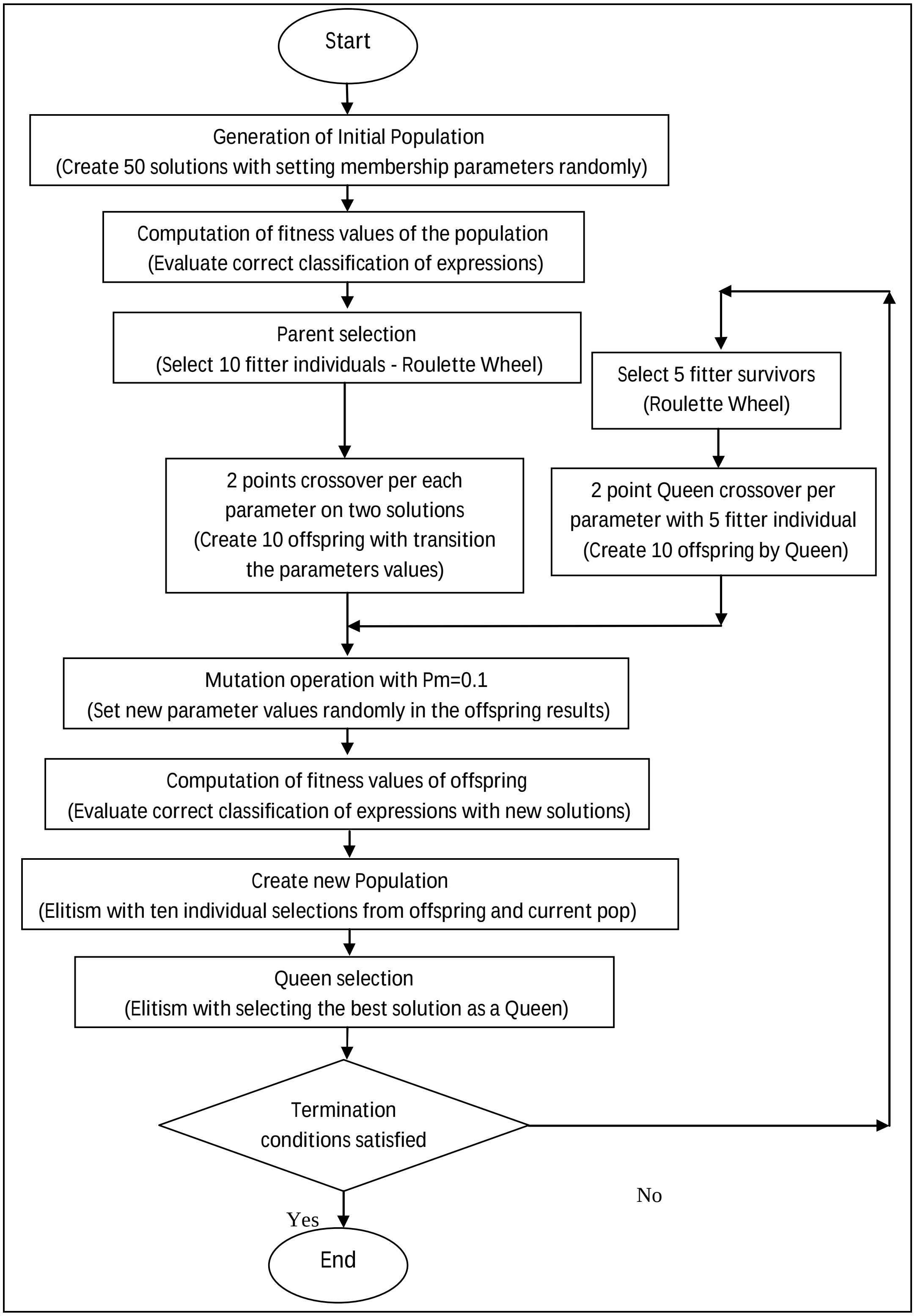


Figure 4.27 The process of Bee Algorithm for Tuning Fuzzy parameters

Table 4.4 Overall Description of Genetic Algorithms

GA Parameters	BROA	BA	Classic GA-type I	Classic GA-type II
Size of primary population	50	50	50	20
Parent selection	Roulette Wheel	Roulette wheel	Roulette wheel	Roulette Wheel
Size of parents	10	10	10	8
Crossover	2 points per each parameter	2 points per each parameter	2 points per each parameter	2 points per each parameter
Crossover chromosomes	Queen/Princess & Survivors	Queen & Survivors	Pair of Parents	Pair of Parents
Mutation	Random per each parameter	Random per each parameter	Random per each parameter	Random per each parameter
Mutation rate	10%	10%	10%	10%
Number of offspring in the first generation	10	10	10	8
No. of offspring in the second and further generations	20	10	10	8
Survivor selection	Elitism based on offspring and primary population	Elitism based on offspring and primary population	Offspring selection	Elitism based on offspring and primary population
Elite solution	Queen/Princess	Queen	-	-
Number of survivors	10	10	10	8
New population	Selected survivors	Selected survivors	Offspring	Selected survivors and new primary generation

4.6 SUMMARY

In this chapter the process of proposed facial expressions model has been described. In this process, at first a geometric method based on the edge detection and morphology process have been developed for the purpose of extracting facial feature points from the images. Then, normalizing process for facial images has been described. Finally, a hybrid classification technique as the main part of current research has been proposed. A novel scheme of Mamdani type Fuzzy rule based system as the core of the emotions classification with using a modified Genetic Algorithm as a learning algorithm has been described. The proposed Genetic Algorithm has been simulated based on an improved model of bees offspring generation behavior to improve the optimization procedure. Also, to evaluate the classification performance, reliability and validity of the model two FG-net and Cohn-Kanade databases have been proposed.

In the next chapter, the results of implementation process are described to show and analysis the system outcomes. Also, the results are compared with the classification results of other models in which classic Genetic Algorithms have been used for facial expressions recognition.

CHAPTER V

EXPERIMENT AND RESULTS

5.1 INTRODUCTION

In the past three chapters of this thesis, the current researches of facial expressions classification models and the challenges of those have been identified. Also, the proposed model based on the Genetic Algorithm and Fuzzy Rule Based System (FRBS) as the solution of those challenges has been described. In this chapter to evaluate the reliability and validity of the system performance, the proposed model has been experimented with the images from FG-net and Cohn-Kanade databases and the results have been analyzed. In order to experiment the model performance, Matlab 7.8.0 (R 2009a) environment has been used. Matlab is known as a technical computing language to implement the algorithms with complicate computation process particularly in matrix operations which make it faster than traditional programming language such as C. Moreover, Matlab is a popular environment to image processing and performing Fuzzy logic and optimization algorithms such as Genetic Algorithms.

For the purpose of experiment the proposed classification model as well as features extraction technique, the Matlab programming codes have been used without using Matlab Toolbox directly. In this operation, first feature extraction process has been implemented to extract the feature points then the classification model has been programmed to experiment the model performance based on the obtained results from the first step.

5.2 FEATURE POINTS DETECTION RESULTS

Feature points extraction is not the main contribution of this thesis but as a preprocessing step for classification has been considered. Therefore, in this section, the results of feature points extraction have been presented and the performance of the facial features detection with the proposed technique has been evaluated. For this purpose 90 static images consisting of the neutral and emotional states have been used from the FG-net database in the experiment process. In the proposed facial features extraction, eight feature points comprising four points related to upper and lower eyelids, two points from eyebrows and two points from lips corners position were detected automatically based on the two inner corners of eyes while two points located in the upper and lower of lips were extracted manually. Therefore, for every expression, 8 facial feature points and for all subjects (18) with all expressions (5 included neutral) 720 feature points were detected. As the coordinate of feature points was needed for using in the classification model, those were determined as the results of performing the proposed feature points extraction technique. Figure 4.1 shows a sample of extracted facial feature points after detection process.

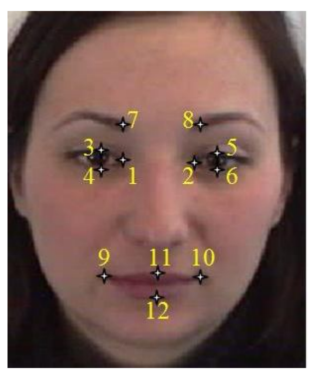


Figure 5.1 A Sample of Extracted Facial Feature Points

The feature points of all subjects were detected independently per each emotion when the data set was separated in terms of different emotions.

To evaluate the accuracy of detection performance, the coordinate of feature points which were detected according to the proposed feature points extraction technique, has been compared with the location of points which were marked manually. According to the Tie (2011) study, if the comparison between marking manually and automatic labeling shows less than 10 percent bias then the automatic detection of facial feature points is successful. Therefore, the following conditions have been determined to identify the acceptable point location:

Detected feature points from the eye region:

$$p_n \textit{ is accepted if } p_n \leq \mathrm{mp}_n \pm 2pix \tag{5.1}$$

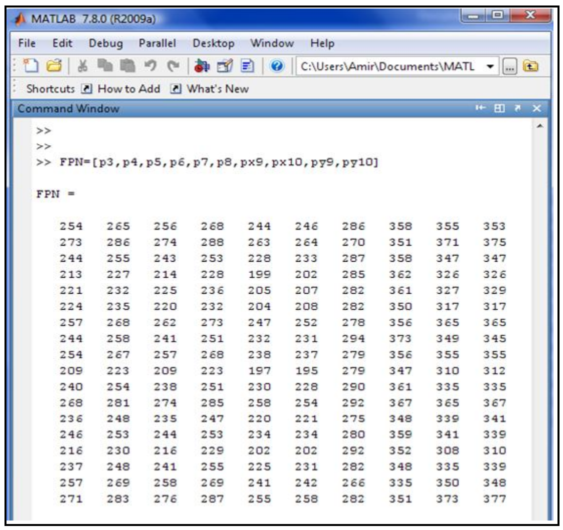
Detected feature points from eyebrows and mouth regions:

$$p_n \textit{ is accepted if } p_n \leq mp_n \pm 3pix \tag{5.2}$$

Where p_n is the coordinate of automatically detected feature point and mp_n is the coordinate of manually extracted feature point. Also, n*pix* indicates the number of pixels which has been identified with number 2 as an acceptable bias for eyes and number 3 for brows and mouth. Therefore, these biases are accepted deviations for features detection which do not influence the accuracy of results.

The final results of implementing the feature points detection technique which have been experimented with all images from FG-net database for Neutral, Sadness, Anger, Surprise and Happiness are shown in following Figures. Furthermore, the correct and false detections for every point are displayed with the mark of (√) and (×), respectively in the following tables. According to Figure 5.1 the feature points are located on the face images based on the identification numbers which are begin from 1 to 12. These numbers were used to define the coordinate of facial feature points. If we assume that (*pxi*,*pyj*) is the coordinate of a feature point, therefore, in the following figures and tables, *py3* ... *py10* are the distance of feature points onto the vertical axes where the first pixel in the top-left position of image was used as the coordinate origin. Also, *px9* and *px10* are the distances of feature points onto the horizontal axes. In addition, with regarding to the Figure 5.1, the feature points *py1*, *py2*, *py11*, *py12* were extracted manually. Note that for all of the feature points only the distances onto the vertical axes are considered except for *(px9,py9)* and *(px10,py10)* which included both horizontal and vertical distances, therefore, for those points just vertical coordinates have been determined which are indicated with *pyj* (*j=1 to 12*).

The coordinates of extracted feature points with implementing the feature points detection technique in the Neutral state (FPN) for all subjects are shown in the Figure 5.2.



254	265	256	268	244	246	286	358	355	353
273	286	274	288	263	264	270	351	371	375
244	255	243	253	228	233	287	358	347	347
213	227	214	228	199	202	285	362	326	326
221	232	225	236	205	207	282	361	327	329
224	235	220	232	204	208	282	350	317	317
257	268	262	273	247	252	278	356	365	365
244	258	241	251	232	231	294	373	349	345
254	267	257	268	238	237	279	356	355	355
209	223	209	223	197	195	279	347	310	312
240	254	238	251	230	228	290	361	335	335
268	281	274	285	258	254	292	367	365	367
236	248	235	247	220	221	275	348	339	341
246	253	244	253	234	234	280	359	341	339
216	230	216	229	202	202	292	352	308	310
237	248	241	255	225	231	282	348	335	339
257	269	258	269	241	242	266	335	350	348
271	283	276	287	255	258	282	351	373	377

FPN: Feature Points in Neutral state, p3 ... p8: *py3* ... *py8*

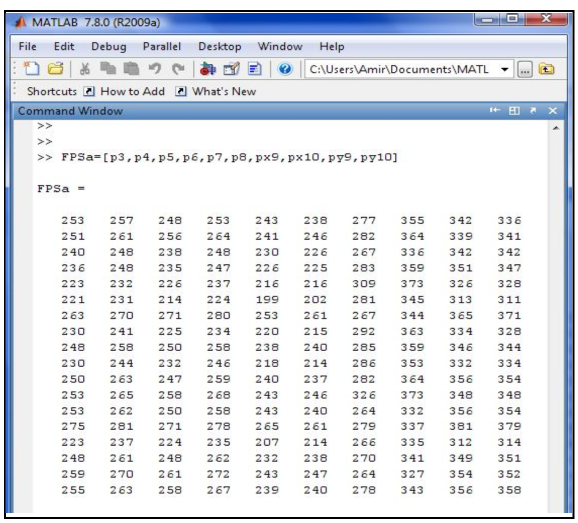
Figure 5.2 The Coordinates of Facial Feature Points in the Neutral State

Table 5.1 shows the results of implementing the feature points extraction technique with number of correct detection and false detection in the neutral state for all subjects.

Table 5.1 Number of Correct and False Detections for FPN

Subjects (Neutral)	Py3	Py4	Py5	Py6	Py7	Py8	Px9	Px10	Py9	Py10	No. of correct detections	No. of errors
Subject1	√	√	√	√	√	√	√	√	√	√	10	0
Subject2	√	√	×	√	√	√	×	√	√	×	7	3
Subject3	√	√	√	√	√	×	√	√	√	√	9	1
Subject4	√	√	√	√	√	√	√	√	√	√	10	0
Subject5	√	√	√	√	√	√	√	√	√	√	10	0
Subject6	√	√	√	√	√	×	√	√	√	√	9	1
Subject7	√	√	√	√	√	√	√	√	√	√	10	0
Subject8	√	√	√	√	√	√	√	√	√	√	10	0
Subject9	√	√	√	√	√	√	√	√	√	√	10	0
Subject10	√	√	√	√	√	√	√	√	√	√	10	0
Subject11	√	√	√	√	√	√	√	√	√	√	10	0
Subject12	√	√	√	√	√	×	√	√	√	√	9	1
Subject13	√	√	√	√	√	√	√	√	√	√	10	0
Subject14	√	√	√	√	√	√	√	√	√	√	10	0
Subject15	√	√	√	√	√	√	√	√	√	√	10	0
Subject16	√	√	√	√	√	√	√	√	√	√	10	0
Subject17	√	√	√	√	√	√	√	√	√	√	10	0
Subject18	√	√	√	√	√	√	√	√	√	√	10	0

The coordinates of Feature Points in the Sadness state (FPSa) for all subjects are shown in the Figure 5.3.




```
>>
>>
>> FPSa=[p3,p4,p5,p6,p7,p8,px9,px10,py9,py10]

FPSa =

   253   257   248   253   243   238   277   355   342   336
   251   261   256   264   241   246   282   364   339   341
   240   248   238   248   230   226   267   336   342   342
   236   248   235   247   226   225   283   359   351   347
   223   232   226   237   216   216   309   373   326   328
   221   231   214   224   199   202   281   345   313   311
   263   270   271   280   253   261   267   344   365   371
   230   241   225   234   220   215   292   363   334   328
   248   258   250   258   238   240   285   359   346   344
   230   244   232   246   218   214   286   353   332   334
   250   263   247   259   240   237   282   364   356   354
   253   265   258   268   243   246   326   373   348   348
   253   262   250   258   243   240   264   332   356   354
   275   281   271   278   265   261   279   337   381   379
   223   237   224   235   207   214   266   335   312   314
   248   261   248   262   232   238   270   341   349   351
   259   270   261   272   243   247   264   327   354   352
   255   263   258   267   239   240   278   343   356   358
```

FPSa: Feature Points in Sadness state, p3 ... p8: *py3* ... *py8*

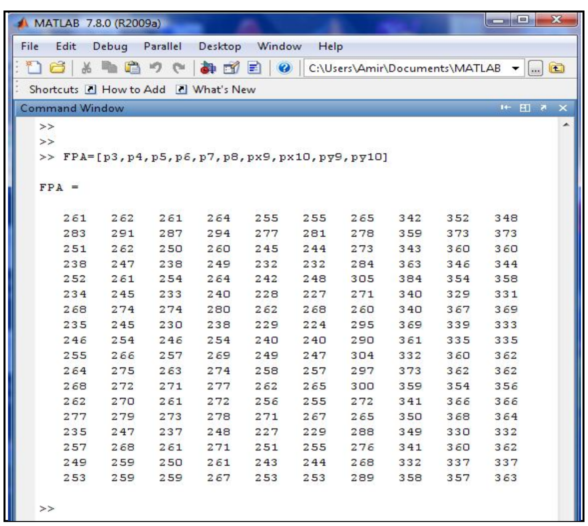
Figure 5.3 The Coordinates of Facial Feature Points in the Sadness State

Table 5.2 shows the results of implementing the feature points extraction technique with number of correct detection and false detection in the sadness state for all subjects.

Table 5.2 Number of Correct and False Detections for FPSa

Subjects (Sadness)	P3	P4	P5	P6	P7	P8	Px9	Px10	Py9	Py10	No. of correct detections	No. of errors
Subject1	√	√	√	√	√	√	√	√	√	√	10	0
Subject2	√	√	√	√	√	√	√	√	√	√	10	0
Subject3	√	√	√	√	×	√	√	√	√	√	9	1
Subject4	√	√	√	√	√	√	√	√	√	√	10	0
Subject5	√	√	√	√	×	×	√	√	√	√	8	2
Subject6	√	√	√	√	√	√	√	√	√	√	10	0
Subject7	√	√	√	√	√	√	√	√	√	√	10	0
Subject8	√	√	√	√	√	√	√	√	√	√	10	0
Subject9	√	√	√	√	√	×	√	√	√	√	9	1
Subject10	√	√	√	√	√	√	√	√	√	√	10	0
Subject11	√	√	√	√	√	√	√	√	√	√	10	0
Subject12	√	√	√	√	√	√	×	√	√	√	9	1
Subject13	√	√	√	√	√	√	√	√	√	√	10	0
Subject14	√	√	√	√	√	√	√	×	√	√	9	1
Subject15	√	√	√	√	√	×	√	√	√	√	9	1
Subject16	√	√	√	√	√	√	√	√	√	√	10	0
Subject17	√	√	√	√	√	√	√	√	√	√	10	0
Subject18	√	√	√	√	√	√	√	√	√	√	10	0

The coordinates of Feature Points in the Anger state (FPA) for all subjects are shown in the Figure 5.4.



FPA: Feature Points in Anger state, P3 ... p8: *py3 ... py8*

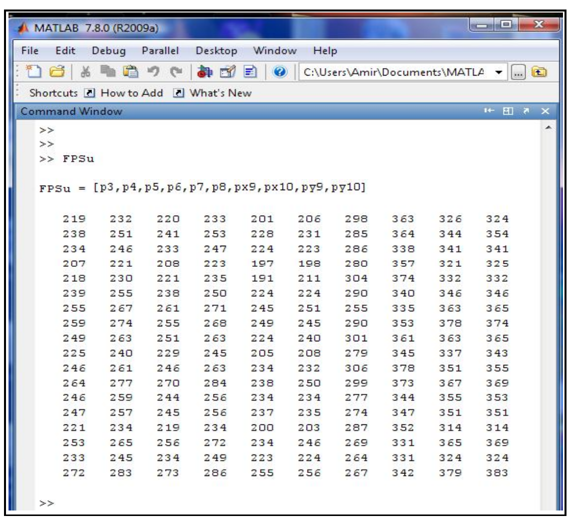
Figure 5.4 The Coordinates of Facial Feature Points in the Anger State

Table 5.3 shows the results of implementing the feature points extraction technique with number of correct detection and false detection in the anger state for all subjects.

Table 5.3 Number of Correct and False Detections for FPA

Subjects (Anger)	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**Px9**	**Px10**	**Py9**	**Py10**	**No. of correct detections**	**No. of errors**
Subject1	√	√	√	√	√	√	√	√	√	√	10	0
Subject2	√	√	√	√	√	√	√	√	√	√	10	0
Subject3	√	√	√	√	√	√	√	√	√	√	10	0
Subject4	√	√	√	√	√	√	√	√	√	√	10	0
Subject5	√	√	√	√	√	√	√	√	√	√	10	0
Subject6	√	√	√	√	√	√	√	√	√	√	10	0
Subject7	√	√	√	√	√	√	√	√	√	√	10	0
Subject8	√	√	√	√	√	√	√	√	√	√	10	0
Subject9	√	√	√	√	×	×	√	√	√	√	8	2
Subject10	√	√	√	√	√	√	√	√	√	√	10	0
Subject11	√	√	√	√	√	√	√	√	√	√	10	0
Subject12	√	√	√	√	√	√	√	√	√	√	10	0
Subject13	√	√	√	√	√	√	√	√	√	√	10	0
Subject14	√	√	√	√	√	√	√	√	√	√	10	0
Subject15	√	√	√	√	√	√	√	√	√	√	10	0
Subject16	√	√	√	√	√	√	√	√	√	√	10	0
Subject17	√	√	√	√	√	√	√	√	√	√	10	0
Subject18	√	√	√	√	×	×	√	√	√	√	8	2

The coordinates of Feature Points in the Surprise state (FPSu) for all subjects are shown in the Figure 5.5.



FPSu: Feature Points in Surprise state, P3 ... p8: *py3* ... *py8*

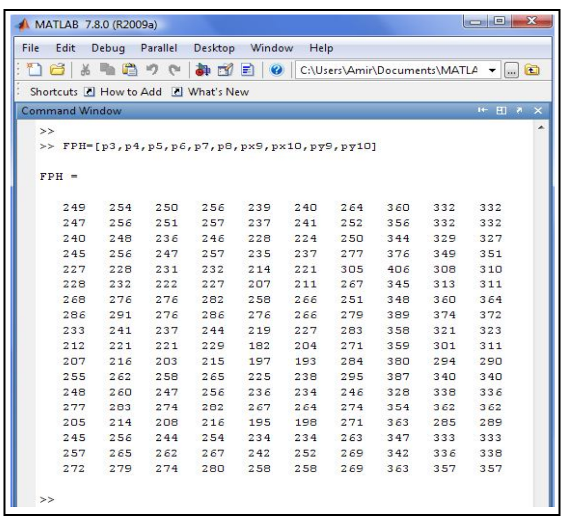
Figure 5.5 The Coordinates of Facial Feature Points In The Surprise State

Table 5.4 shows the results of implementing the feature points extraction technique with number of correct detection and false detection in the surprise state for all subjects.

Table 5.4 Number of Correct and False Detections for FPSu

Subjects (Surprise)	P3	P4	P5	P6	P7	P8	Px9	Px10	Py9	Py10	No. of correct detections	No. of errors
Subject1	√	√	√	√	√	√	√	√	√	√	10	0
Subject2	√	√	√	√	√	√	√	×	√	×	8	2
Subject3	×	√	√	√	√	√	√	√	√	√	9	1
Subject4	√	√	√	√	×	×	√	√	√	√	8	2
Subject5	√	√	√	√	√	×	√	√	√	√	9	1
Subject6	√	√	×	√	√	√	√	√	√	√	9	1
Subject7	√	√	√	√	√	√	√	√	√	√	10	0
Subject8	√	√	√	√	√	√	√	√	√	√	10	0
Subject9	√	√	√	√	√	√	√	√	√	×	9	1
Subject10	√	√	√	√	√	√	√	√	√	√	10	0
Subject11	√	√	√	√	√	√	√	√	√	√	10	0
Subject12	√	√	√	√	√	×	√	√	√	√	9	1
Subject13	√	√	√	√	√	√	√	√	√	√	10	0
Subject14	√	√	√	√	√	√	√	√	√	√	10	0
Subject15	√	√	√	√	√	√	√	√	√	√	10	0
Subject16	√	√	√	√	√	×	√	√	√	√	9	1
Subject17	√	√	√	√	×	×	√	√	√	√	8	2
Subject18	√	√	√	√	√	√	√	√	√	√	10	0

The coordinates of Feature Points in the Happiness state (FPH) for all subjects are shown in the Figure 5.6.




```
>>
>> FPH=[p3,p4,p5,p6,p7,p8,px9,px10,py9,py10]

FPH =

   249   254   250   256   239   240   264   360   332   332
   247   256   251   257   237   241   252   356   332   332
   240   248   236   246   228   224   250   344   329   327
   245   256   247   257   235   237   277   376   349   351
   227   228   231   232   214   221   305   406   308   310
   228   232   222   227   207   211   267   345   313   311
   268   276   276   282   258   266   251   348   360   364
   286   291   276   286   276   266   279   389   374   372
   233   241   237   244   219   227   283   358   321   323
   212   221   221   229   182   204   271   359   301   311
   207   216   203   215   197   193   284   380   294   290
   255   262   258   265   225   238   295   387   340   340
   248   260   247   256   236   234   246   328   338   336
   277   283   274   282   267   264   274   354   362   362
   205   214   208   216   195   198   271   363   285   289
   245   256   244   254   234   234   263   347   333   333
   257   265   262   267   242   252   269   342   336   338
   272   279   274   280   258   258   269   363   357   357

>>
```

FPH: Feature Points in Happiness state, P3 ... p8: *py3* ... *py8*

Figure 5.6 The Coordinates of Facial Feature Points In The Happiness State

Table 5.5 shows the results from implementing the feature points extraction technique with number of correct detection and false detection in the Happiness state for all subjects.

Table 5.5 Number of Correct and False Detections for FPH

Subjects (Happiness)	P3	P4	P5	P6	P7	P8	Px9	Px10	Py9	Py10	No. of correct detections	No. of errors
Subject1	√	√	√	√	√	√	√	√	√	√	10	0
Subject2	√	√	√	√	√	√	×	√	√	√	9	1
Subject3	√	√	√	√	√	√	√	√	√	√	10	0
Subject4	√	√	√	√	√	√	√	√	√	√	10	0
Subject5	√	√	√	√	√	√	√	√	√	√	10	0
Subject6	√	√	√	√	√	√	√	√	√	√	10	0
Subject7	√	√	√	√	√	√	√	√	√	√	10	0
Subject8	√	√	√	√	√	√	√	√	√	√	10	0
Subject9	√	√	√	√	√	√	√	√	√	√	10	0
Subject10	√	√	√	√	×	√	√	√	√	√	9	1
Subject11	√	√	√	√	√	√	√	√	√	√	10	0
Subject12	√	√	√	√	×	×	√	√	√	√	8	2
Subject13	×	√	√	√	√	√	√	√	√	√	9	1
Subject14	√	√	√	√	√	√	×	√	√	√	9	1
Subject15	√	√	√	√	×	×	√	√	√	√	8	2
Subject16	√	√	√	√	√	√	√	√	√	√	10	0
Subject17	√	√	√	√	√	×	×	√	√	√	8	2
Subject18	√	√	√	√	√	√	√	√	√	√	10	0

Table 5.6 and Figure 5.7 show the overall results of experiment process for detection of 10 feature points and the accuracy rate of those based on the images from FG-net database. The experiment result showed the average accuracy rate of 95.67 for detection of facial feature points for all images while the detection process was implemented for every emotional state, independently. According to Table 5.6 the best result for feature points detection is related to the points of py4, py6 and py9 with the detection rate of 100% while the point of py8 as an eyebrow feature point shows the worst rate of features detection.

Table 5.6 The Overall Results of Facial Feature Point Detection

FP	Total images	Correct detection	Errors	Accuracy rate (%)
Py3	90	88	2	97.78
Py4	90	90	0	100
Py5	90	88	2	97.78
Py6	90	90	0	100
Py7	90	81	9	90
Py8	90	74	16	82.22
Px9	90	85	5	94.44
Px10	90	88	2	97.78
Py9	90	90	0	100
Py10	90	87	3	96.67
Total	**900**	**862**	**38**	**95.67**

According to Table 5.6 the parameters are defined as follow:

FP: Facial feature points

Total images: images of four emotional states and neutral (18×5 = 90)

Correct detection: Number of correct detected points

Errors: Number of false detection

Accuracy rate: Percent of correct detections to total detections for every feature point

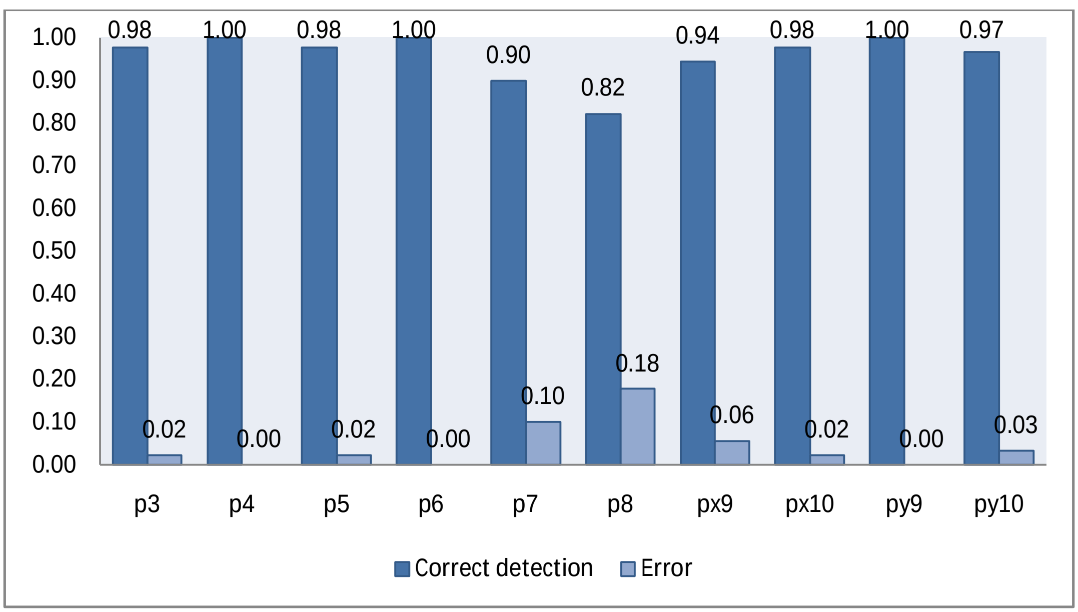


Figure 5.7 Detection Rates of the Facial Feature Points

5.2.1 Extraction of Feature Points from the Gray Scale Images

The images of Cohn-Kanade database as independent subjects were also selected for evaluate the classification model. Therefore, 50 images comprising four emotional state and neutral were selected, equally. The selection process was implemented randomly on the images of Cohn-Kanade database and ten images from every emotion were collected. As the FG-net database was the main source of evaluation process for implementing the proposed classification algorithm, therefore, just number of 50 images from Cohn-Kanade database was chosen which are estimated around 50 percent of images from primary database. Moreover, to evaluate the training and testing process only with Cohn-kanade database without using the FG-net images, one extra data set was created from Cohn-Kanade database which included 150 images from 30 subjects.

In order to extract the feature points in this database manually marking method was proposed, as the automatic technique which was used for the FG-net database was not suitable for the gray scale images. Furthermore, the results of features detection using AAMs method, as a known technique, which was available in the Cohn-Kanade database indicates considerably bias. Therefore twelve points were extracted manually on each facial image from Cohn-Kanade database as an extra database.

5.3 RELIABILITY OF THE CLASSIFICATION MODELS

For the purpose of evaluating the classification model, normalized facial feature points extracted from the feature extraction process fed into the proposed classifier model in form of the feature vectors. Experiment process was implemented based on the 140 images in the FG-Cohn data set included 90 image from the FG-net and 50 images from Cohn-Kanade database in neutral and four emotional states. The evaluation process included two main training and testing phases. In the training phase, the proposed Genetic Algorithm trained the FRBS to optimize the Fuzzy membership parameters in the classification model. Then the tuned Fuzzy rule based system was evaluated to classify the expressions into the four emotions.

For the purpose of evaluate the reliability, the proposed classification model was implemented in several times. Therefore, the training algorithm was ran 10 times using training data set, then, every time the trained model was implemented with the testing data set and the accuracy rate of each time running was reported.

The following charts show the process of Genetic Algorithms learning process with the training data set to improve the Fuzzy membership functions in the 10 times implementation. Furthermore, the experiment process was implemented 4 times to evaluate all data as the testing set with replacing the training data with testing data set in a rotation process. In all experiments the testing set only selected from the FG-net database.

5.3.1 Experiment Results Using BROA Based on the First Training Data Set

With regarding to the following charts, the improvement process for every implementation is begun with a low fitness value and reaches to the optimum value in the final generation. However, as the tuning process was performed based on the Genetic Algorithm which is a random based method, therefore, different improvement processes were obtained in the various runs. In other words, Genetic Algorithm achieves to a solution in every generation that can be different with the solutions in the same generations but in other runs. However, according to Figure 5.8, 5.9, 5.10 and 5.11, the best obtained results from different runs with BROA are same or close to each others in the final generations, while the value of 0.99 was determined as the best fitness value for termination of the training process.

Figure 5.8 shows the tuning process with BROA using the first set of training data (92 images) while the rest part of data set was used as testing set.

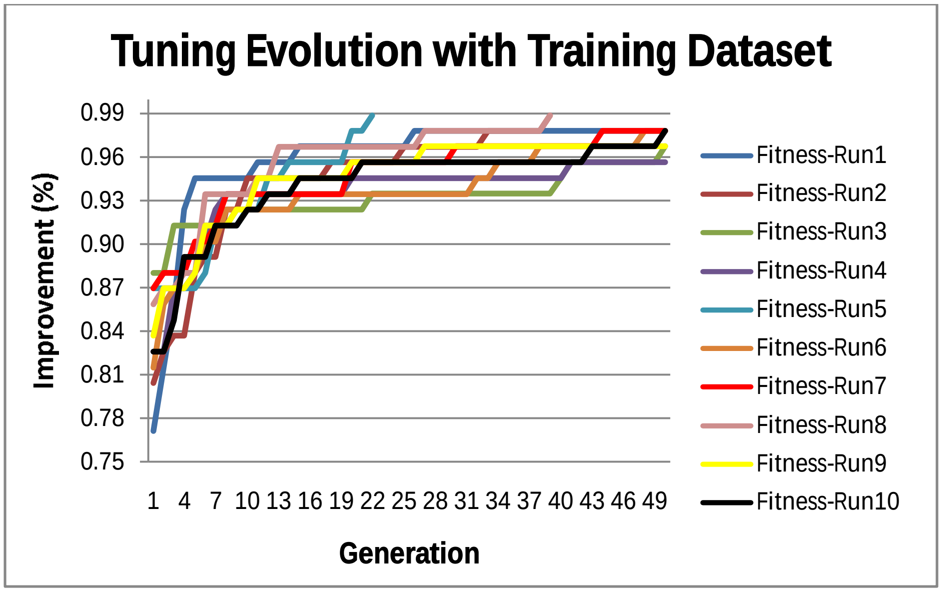


Figure 5.8 Process of Fuzzy Membership Functions Improvement with BROA on the First Training Set

According to Figure 5.8 the best recognition rate was obtained with the fitness value of 0.99 in the improvement process. Moreover, the best fitness value was achieved in three runs while other experiments indicate that the best results are achievable in the rates from 0.96 to 0.98 when the iterations reach to final generation. Therefore, the rate of improvement is proper to find the optimum solutions. Overall, the training algorithm conducted the accuracy improvement in the generation process to obtain the fittest value although lower fitness value was achieved in the first generation of some runs in comparison with the others.

5.3.2 Experiment Results Using BROA Based on the Second Training Data Set

The improvement process with second set of training data is shown in Figure 5.9 while BROA was used as the learning algorithm. According to Figure 5.9 the best accuracy rate of 99% was obtained with the second training set in the final generations while in the run6 and run7 the optimum solution was achieved earlier than reaching to the 30th generation in the improvement process due to creation of proper values in the random process of BROA. Moreover, other experiments indicate the best results in the rates from 96% to 99%. High performance of training algorithm with the second training set shows the classification model has small bias to represent the emotions if the second group replaces with the first training set.

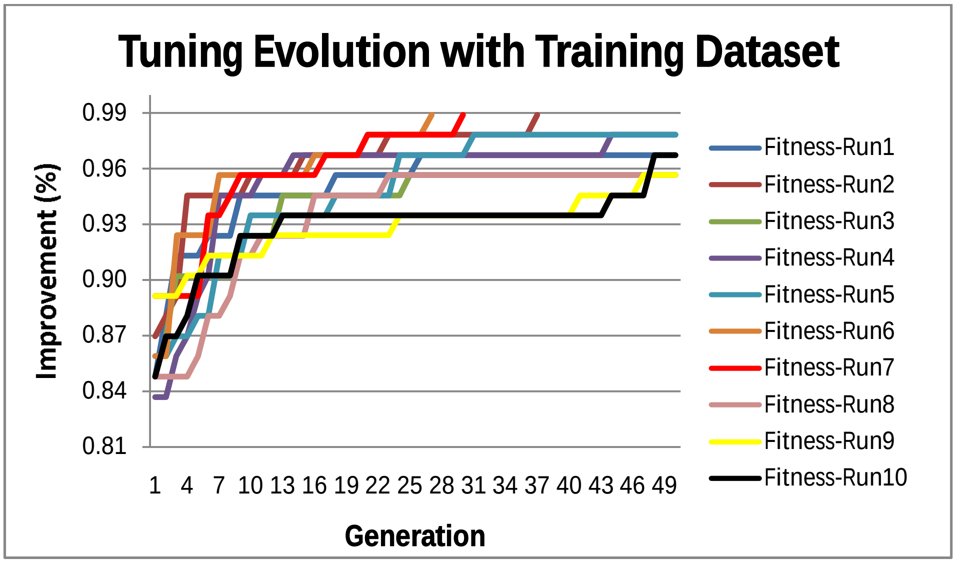


Figure 5.9 Process of Fuzzy Membership Functions Improvement with BROA on the Second Training Set

5.3.3 Experiment Results Using BROA Based on the Third Training Data Set

Figure 5.10 shows the tuning process using BROA with third group of training data (92 images) while 20 images of the data set were used as the testing set. According to Figure 5.10 the best fitness value of 0.99 was obtained in six out of ten experiments that indicate a better rate compared with the experiments of two last training sets which are shown in Figure 5.8 and 5.9. Moreover, the lowest recognition was achieved around the rate of 0.97.

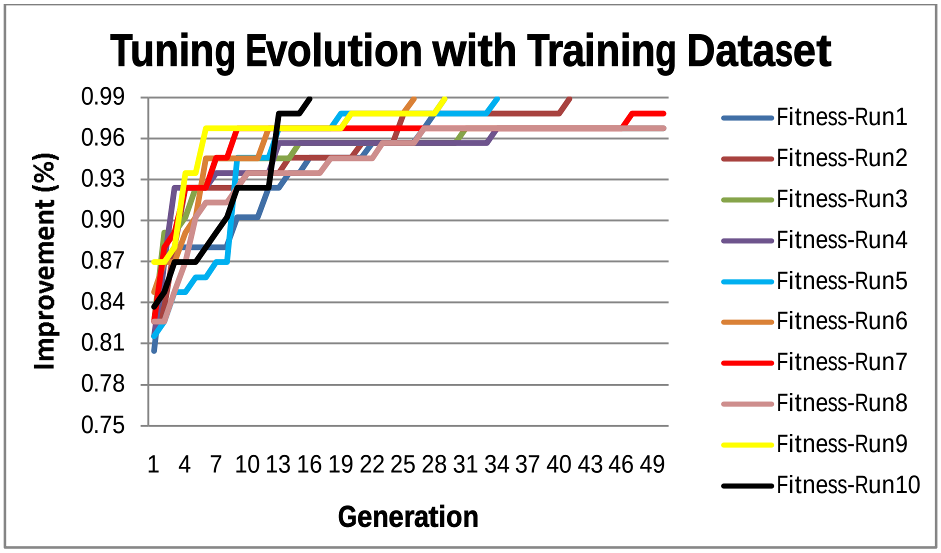


Figure 5.10 Process of Fuzzy Membership Functions Improvement with BROA on the Third Training Set

5.3.4 Experiment Results Using BROA Based on the Fourth Training Data Set

Figure 5.11 shows the process of fitness adjustment with BROA using forth set of training data which was derived from the exchange the testing set with a part of training set in the previous experiment. According to Figure 5.11 the best fitness value of 0.99 was achieved for around 50% of runs while only one experiment has obtained an accuracy rate below than 96%.

Over all, experiment results with the third training set shows higher rate than other training groups. In this training group, the improvement rates reached to the optimum values in the smaller generation which shows the faster adjustment. This bias between rates is due to difference between subjects for express the emotions in the FG-Cohn data set. Therefore, the emotional images belonged to the subjects in the third training set displays more clear emotional states with similar features than the other groups.

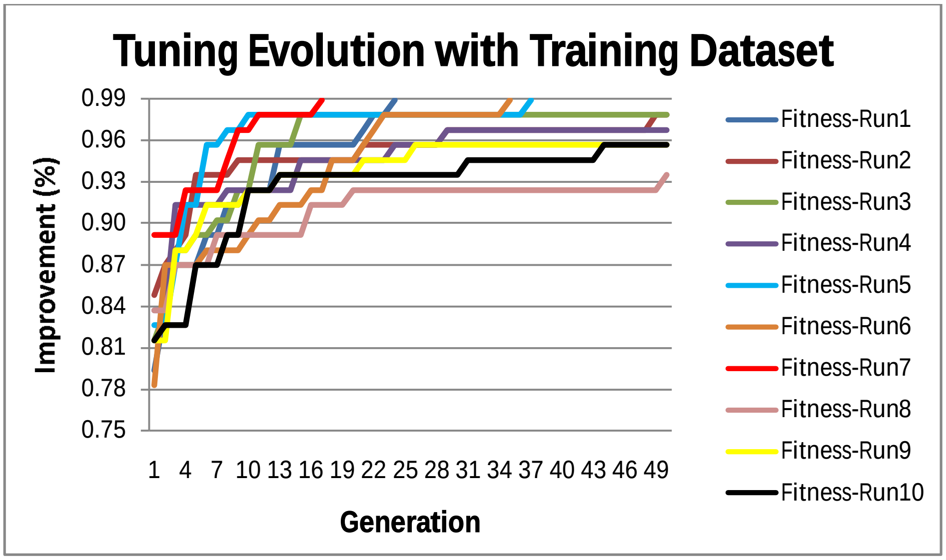


Figure 5.11 Process of Fuzzy Membership Functions Improvement with BROA on the Fourth Training Set

5.3.5 Experiment Results Using BA

Figure 5.12 shows the tuning process of Fuzzy membership parameters using BA for facial expressions recognition in several times implementation. According to Figure 5.12 the BA training model achieved to the fittest value in three runs. However, other experiments show the rates between 94% and 98% as the optimum results. Generally, comparison results in Figure 5.12 with Figure 5.8 as the training process of BROA using first training set shows the higher training results for BROA in which the optimum fitness values are not below than 96%.

Figure 5.13 shows tuning evolution with second training group. According to Figure 5.13 the improvement process to reach to the optimum results is very close in the different runs for the first 30 generations while in the next generations it is almost stable. Training process in the second training group shows only one fittest result from 10 times runs which illustrates the lower rate in comparison with the first training set.

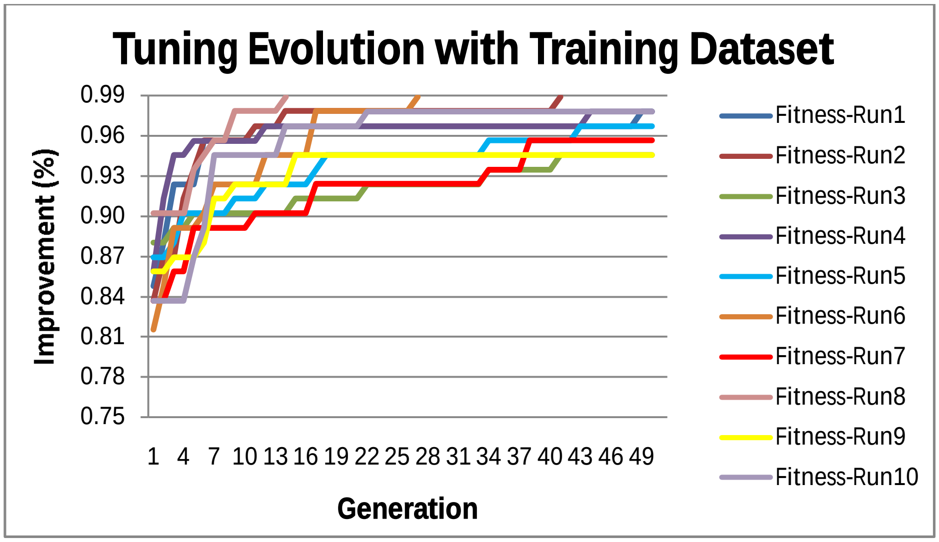


Figure 5.12 Process of Fuzzy Membership Functions Improvement with BA using First Training Set

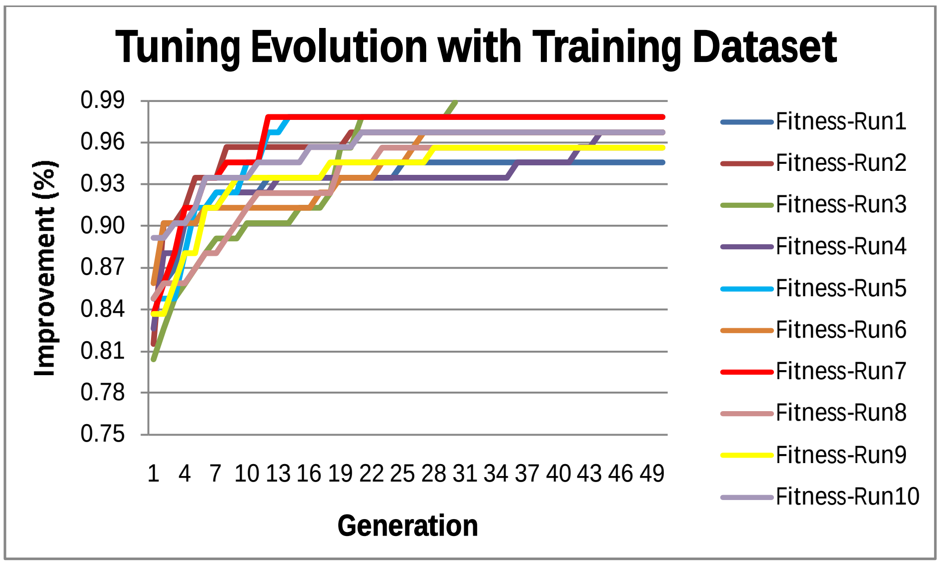


Figure 5.13 The Process of Fuzzy Membership Functions Improvement with BA using Second Training Set

Figure 5.14 illustrates the tuning process using third training set. According to Figure 5.14 the improvement rates from the first to last generations are slower than first and second experiment groups. Moreover, the lowest results are included in this group.

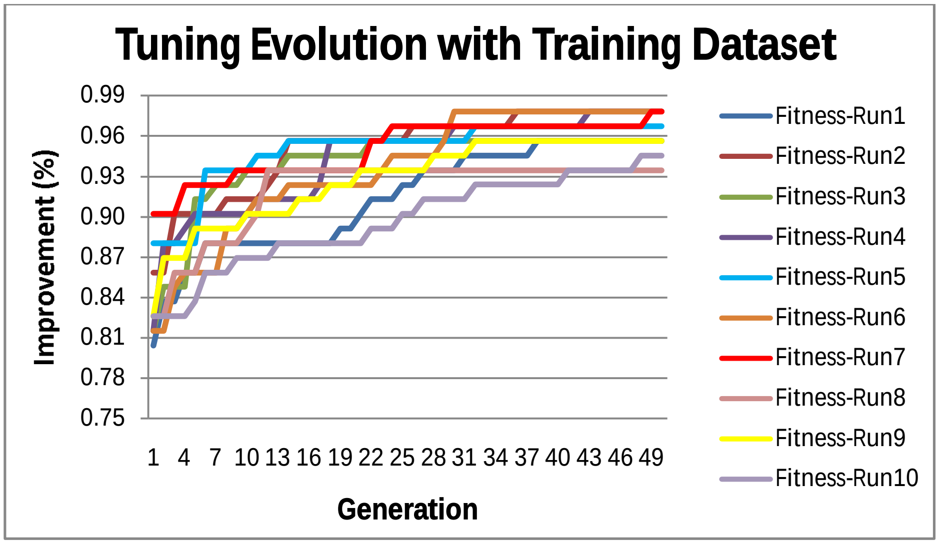


Figure 5.14 Process of Fuzzy Membership Functions Improvement with BA using Third Training Set

Figure 5.15 shows the training process for optimizing the Fuzzy rule based classification model with forth training group. According to Figure 5.15 the classification model achieved to fitter solutions in this group compared with the others. Also, the deviation in the different runs is less than other groups that illustrates higher stability of classification in this training set.

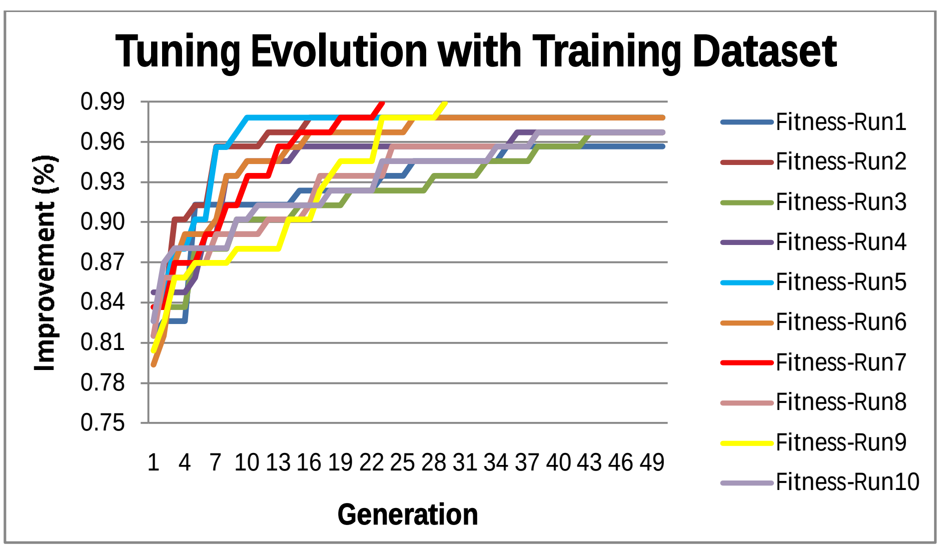


Figure 5.15 Process of Fuzzy Membership Functions Improvement with BA using Fourth Training Set

5.3.6 Classification Performance Using Classic GA-Type I

According to Figures 5.16, 5.17, 5.18 and 5.19 the best fitness value was obtained around the rate of 0.96 while in the most experiments, the best fitness values were achieved in the range of 0.89-0.94 for training with Genetic Algorithm-type I (GA-type-I). Therefore, GA-type I as the best classic GAs shows significant difference in the fitness values in comparison with BROA. Moreover, the rate of improvement per each generation with BROA is higher than classic GAs. As a result, BROA as a modified GA is capable to find the optimum results faster than classic GAs.

Figure 5.16 shows the tuning process using classic Genetic Algorithm with fifty initial population size using the first set of training data (92 images) while the rest part of data set was used as testing set.

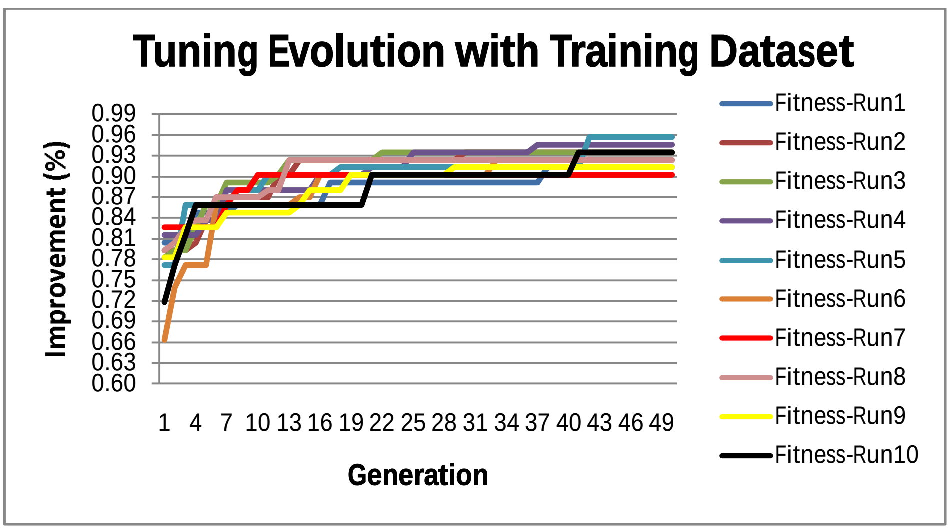


Figure 5.16 Tuning Evolution with Classic GA-Type I on the First Training Set

Figure 5.17 shows the tuning process using classic Genetic Algorithm with fifty initial population size using the second group of training data (92 images) while the rest part of data set was used as testing set.

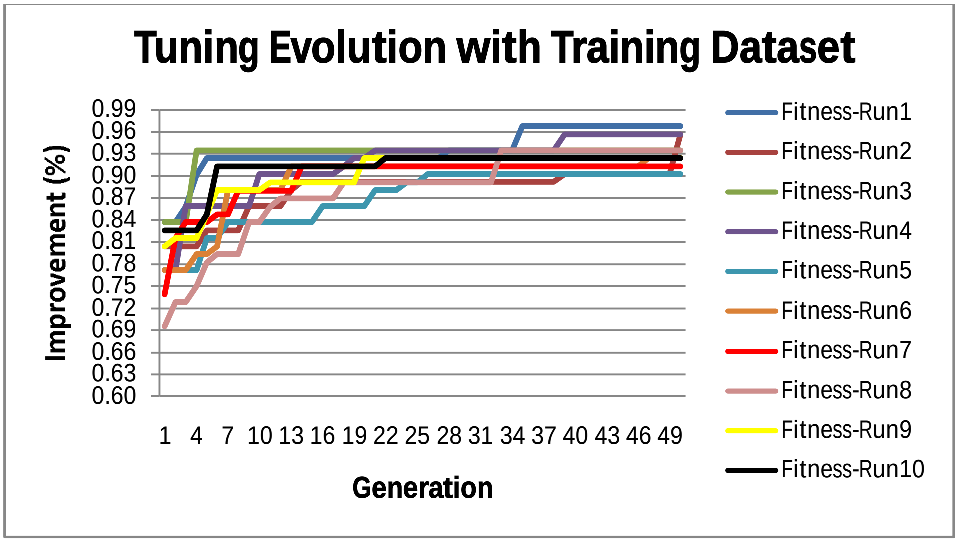


Figure 5.17 Tuning Evolution with Classic GA-Type I on the Second Training Set

Figure 5.18 shows the tuning process using classic Genetic Algorithm with fifty initial population size using the third set of training data (92 images) while the rest part of data set was used as testing set.

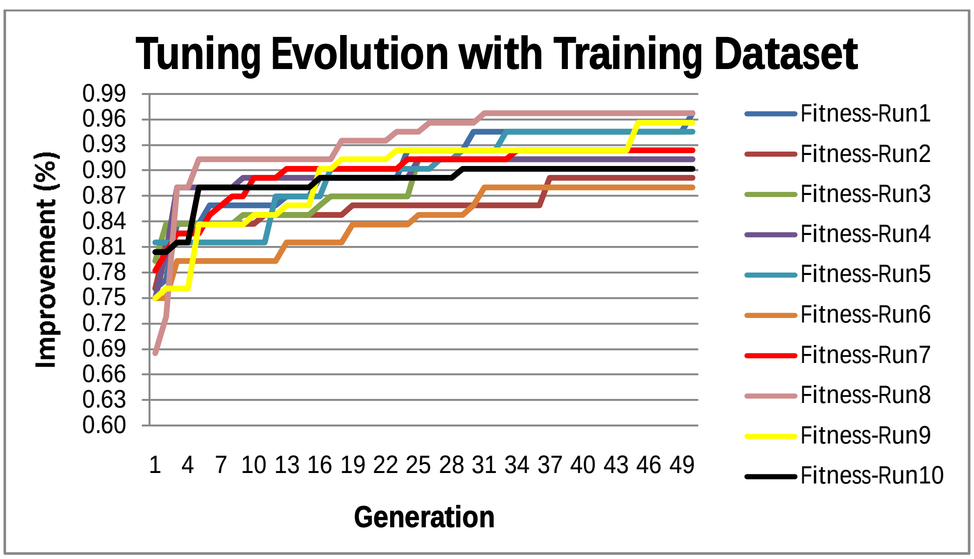


Figure 5.18 Tuning Evolution with Classic GA-Type I on the Third Training Set

Figure 5.19 shows the tuning process using classic Genetic Algorithm with fifty initial population size using the fourth set of training data (92 images) while the rest part of data set was used as testing set.

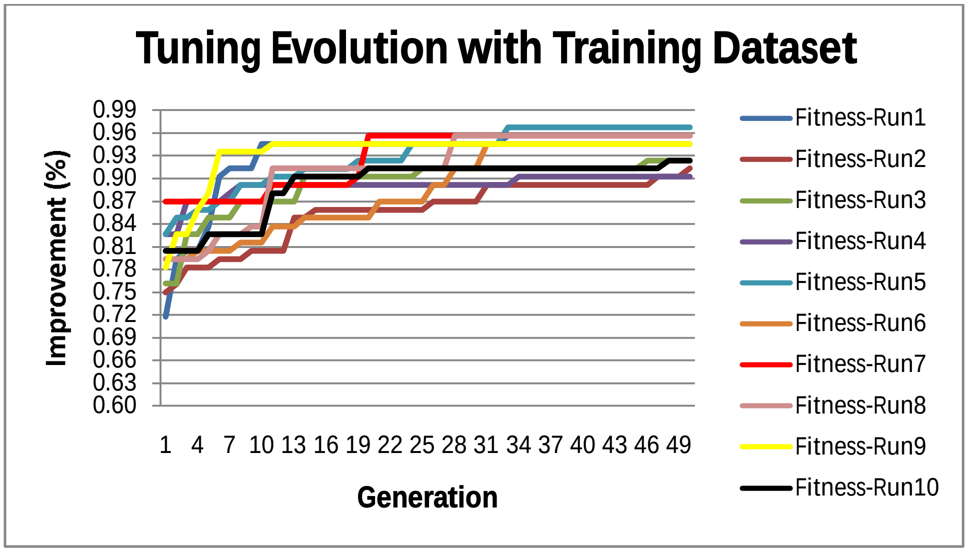


Figure 5.19 Tuning Evolution with Classic GA-Type I on the Fourth Training Set

5.3.7 Classification Performance Using Classic GA-Type II

Figure 5.20, 5.21, 5.22 and 5.23 show the improvement process using Genetic Algorithm-type II. The parameters of GA-type II were indicated in the Table 5.7 for using the first to fourth groups of training data (92 images). According to the Figure 5.20, 5.21, 5.22 and 5.23 the best recognition rate was achieved below than 95% which is lower than the best obtained rate with the classic GA-type I. In the GA-type II, the training process included the initial population size of 20 which was lower than initial population of GA-type I, but it was renewed in every iteration. Therefore, generally, the initial fitness values in GA-type II were obtained lower than the initial values of GA-type I. On the other hand, as GA-type II used new population with every generation, therefore, it made the chance of having better solutions in the further generations. However, this strategy was not capable to compensate the low recognition rates of the GA type II. Moreover, the computation cost in the GA-type II was more expensive than GA-type I, due to evaluating of new populations in terms of fitness values. As a result, GA-type II as a training algorithm not only showed the lower performance than the BROA and BA but also it achieved lower fitness values in comparison with GA-type I.

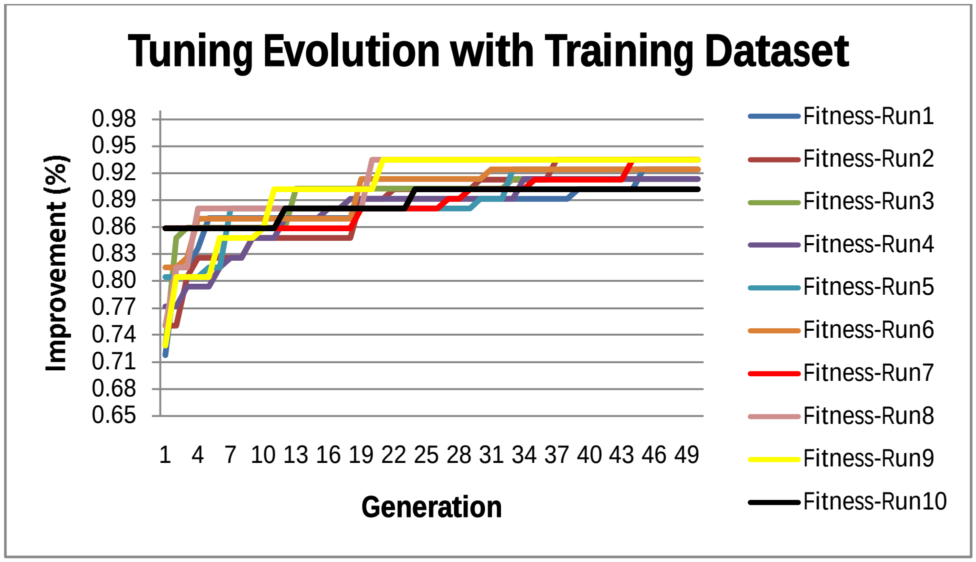


Figure 5.20 Tuning Evolution Using Classic GA-Type II with the First Training Set

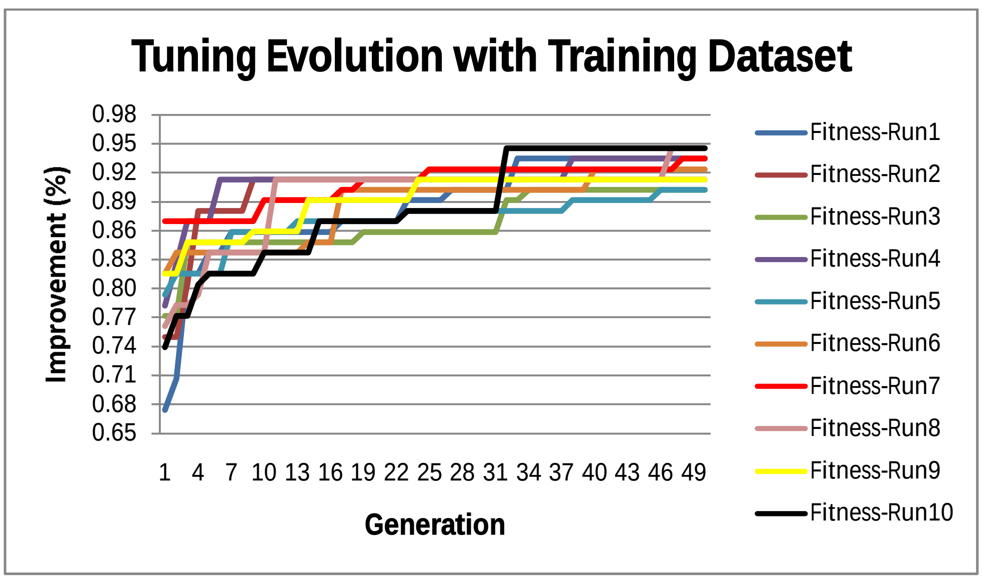


Figure 5.21 Tuning Evolution Using Classic GA-Type II with the Second Training Set

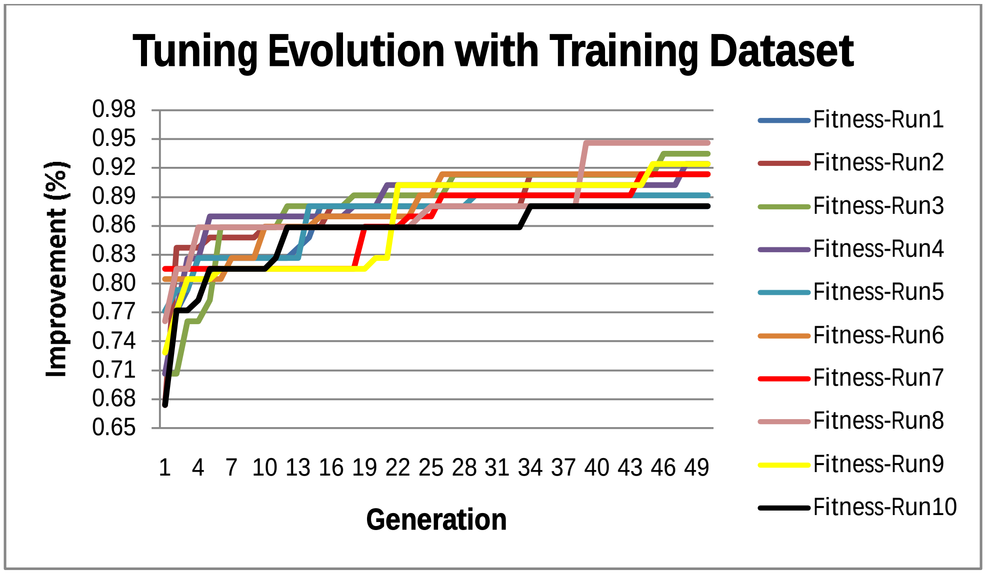


Figure 5.22 Tuning Evolution Using Classic GA-Type II with the Third Training Set

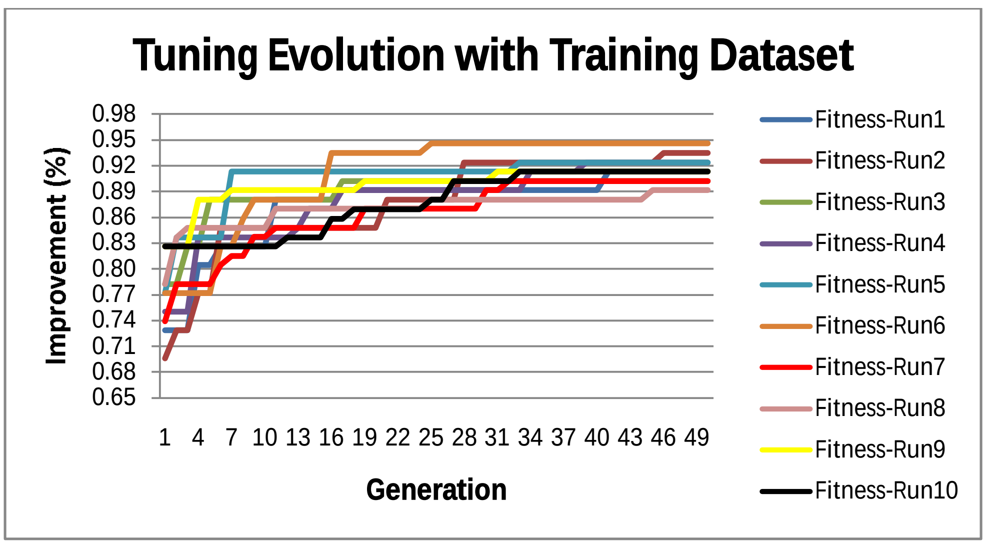


Figure 5.23 Tuning Evolution Using Classic GA-Type II with the Fourth Training Set

5.3.8 Comparison of GAs with BROA for Tuning Process

With regarding to the experiment results, the proposed Genetic Algorithm (BROA) improved significantly the optimization process of classic Genetic Algorithms. Figure

5.24 shows the average of tuning process with BROA in the 10 times running compared with BA and two classic Genetic Algorithms.

According to Figure 5.24 the BROA not only shows the higher accuracy rate for classification in the training process in comparison with BA and classic Genetic Algorithms but also illustrates lower deviation in the several times experiments. Moreover, the tuning process with BROA to reach the optimum results shows the higher slop than classic Genetic Algorithms which means that the BROA is faster than GAs.

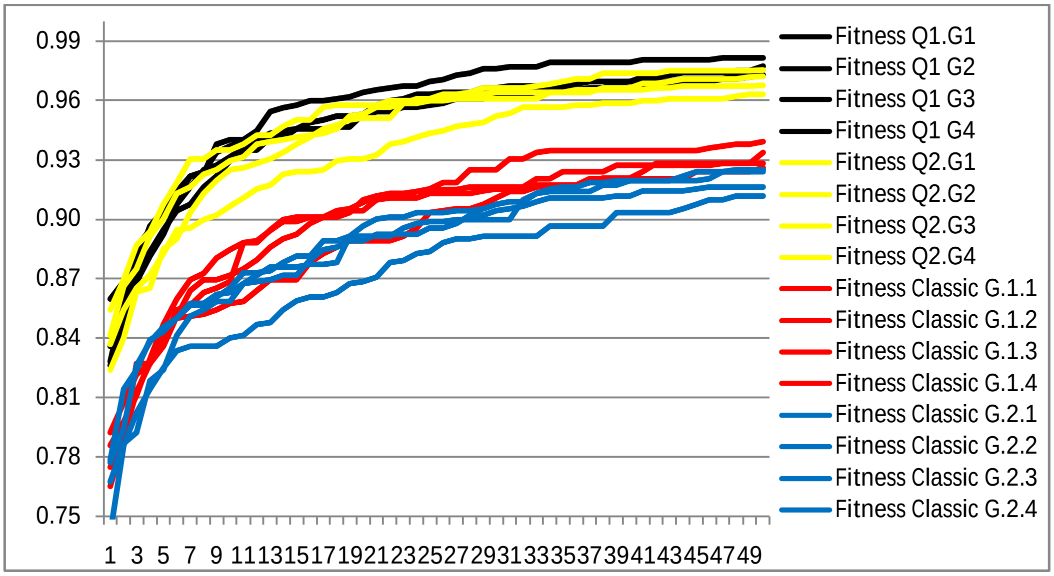


Figure 5.24 Comparison of Tuning with BROA (Q1), BA (Q2) and Genetic Algorithms

Table 5.7 shows the overall outcomes from learning process with BROA in the four training groups. Moreover, the best, average and the worst results as well as the standard deviation (Std) for each training group are shown in the Table 5.7.

According to table 5.7 the average of maximum, mean and minimum of achieved fitness values with regarding to all groups are 99%, 96.8% and 95.5%, respectively.

With regarding to Table 5.7, 5.8, 5.9 and 5.10 the important parameters are described as follow:

Number of implementation: Number of implementing the training algorithm without changing in the training set.

Fitness Max: The maximum of fittest values which obtain in the last generation of training phase for classification from 10 times implementation results.

Fitness Min: The minimum of fittest values which obtain in the last generation of training phase for classification between 10 times implementation results.

Mean: The average of fittest values for classification in the training phase from 10 times implementation results.

Std: Standard deviation value from the accuracy rate of classification in the training phase from 10 times implementation results.

Table 5.7 Overall Experiment Results of Classification in the Training Phase using BROA

Training set	No. of training set	No. of generation	No. of implementation	Fitness Max (%)	Fitness Min (%)	Mean (%)	Std (%)
Training Group 1	92	50	10	99	96	97.2	1
Training Group 2	92	50	10	99	96	97	1
Training Group 3	92	50	10	99	97	97	1
Training Group 4	92	50	10	99	93	96	2
Average	-	-	-	99	95.5	96.8	1.25

Table 5.8 shows the overall information of experiment process using classic Genetic Algorithm (GA-type I) in the training phase with the average accuracy rate of 93.75% for classification of four expressions.

Table 5.8 Overall Experiment Results of Classification in the Training Phase with GA-Type I

Training set	No. of training set	No. of generation	No. of implementation	Fitness Max (%)	Fitness Min (%)	Mean (%)	Std (%)
Training Group 1	92	50	10	96	91	93	1.6
Training Group 2	92	50	10	97	90	93	2
Training Group 3	92	50	10	97	88	93	3
Training Group 4	92	50	10	97	90	94	2
Average	-	-	-	96.75	89.75	93.75	2.15

According to Table 5.8, the averages of maximum and minimum fitness values for all four training groups are 96.75% and 89.75%, respectively, which are lower than training with BROA. However, these results are higher than the results from GA-type II which show the average rates of 93%, 91% and 88% as the maximum, mean and minimum for four testing groups, respectively. The outcomes from GA-type II are shown in the Table 5.10.

In order to evaluate the BROA training performance in comparison with GA-type I, t-test statistical approach was conducted. Table 5.9 shows summary of t-test analysis to compare BROA and GA-type I. T-test analysis results indicated that there is a significant difference among BROA and GA-I while Sig is less than 0.01 (See Table 5.9).

Table 5.9 t-test Analysis Results among BROA and GA-I

Number of group	Mean	Mean Difference	Std. Deviation	t-test	Sig. (2-tailed)
1.BROA	96.8000	3.55000	.54160	9.632	.000
2.GA-I	93.2500				

Table 5.10 Overall Experiment Results of Classification in the Training Phase with GA-Type II

Training set	Number of training set	Number of generation	Number of iteration	Fitness Max (%)	Fitness Min (%)	Mean (%)	Std (%)
Training Group 1	92	50	10	93	90	92	1
Training Group 2	92	50	10	95	90	93	1.6
Training Group 3	92	50	10	93	88	91	2
Training Group 4	92	50	10	95	89	92	1.6
Average	-	-	-	94	89.25	92	1.55

Table 5.11 shows t-test analysis results to compare BROA training performance with GA-type II. T-test analysis, illustrated in Table 5.11, indicated statistically significant difference between BROA and GA-type II performance while *Sig* is less than 0.01.

Table 5.11 t-test Analysis Results among BROA and GA-II

Number of group	Mean	Mean Difference	Std. Deviation	t-test	Sig. (2-tailed)
1: BROA	96.8000	4.80000	0.54160	9.798	0.000
2: GA-II	92.0000				

5.4 CLASSIFICATION RESULTS WITH INDEPENDENT DATA SET

5.4.1 Evaluating the Model Performance with FG-net Database

To evaluate the performance validity of classification, the trained model was examined with the independent data which were not used as the training data set. The evaluation process was implemented with two data sets included FG-Cohn data set and Cohn-Kanade data set, separately. As we mentioned earlier, the FG-Cohn data set includes the images from FG-net database and selected images from Cohn-Kanade database. However, in this data set the testing set involves only the images from FG-net database. Therefore, the images of the Cohn-Kanade were used only as a part of training set. Table 5.12 shows the experiment results in the testing phase using FG-net database while the fitted model from training by BROA was used as the classification model. The testing phase was carried out 4 times with the different testing sets to evaluation process cover all FG-net images in the testing set in a rotation process. According to Table 5.12 the best recognition rate of 100% was achieved for classification of emotions while the lowest accuracy from all runs in four test groups shows the rate of 75% with the proposed model in the testing phase. Moreover, the overall result shows an accuracy rate around 90% from all experiments in four groups. According to Table 5.12 the parameters of experiment results based on the testing data set are described as follow:

Run1 … Run10: Implementing the trained model which was fitted from first to tenth times training process on the testing data set.

Total: Total number of testing data set.

Mean: The average number of correct classification.

Std: Standard deviation of accuracy rate from 10 times running.

Max: The maximum of accuracy rate from 10 times running.

Min: The minimum of accuracy rate from 10 times running.

Table 5.12 Overall Classification Results from Testing Data Set

Implementation	**No. of correct classification. Test group1**	**No. of correct classification. Test group2**	**No. of correct classification. Test group3**	**No. of correct classification. Test group4**
Run1	17	19	17	19
Run2	18	19	16	18
Run3	18	18	15	19
Run4	16	18	18	17
Run5	19	19	18	19
Run6	17	19	17	18
Run7	18	20	15	17
Run8	19	19	19	17
Run9	16	20	17	18
Run10	19	19	19	18
Total	20	20	20	20
Mean	17.7	19	17.1	18
Accuracy rate(%)	89	95	85.5	90
Std (%)	6	3	7	4
Max (%)	95	100	95	95
Min (%)	80	90	75	85

Table 5.13 shows the average of success rates from several times implementing the proposed classification model for each facial expression with the independent testing set while BROA was used as the training algorithm. In this process, all images from FG-net database included in the testing set in four times experiments and the average accuracy rate around 90% for expressions classification was obtained, while the maximum and minimum accuracy rates were belonged to the surprise with the average of 94.5% and happiness with the average of 83%, respectively. According to Table 5.13, as the extracted features from some component of facial image such as eyes and eyebrows in the happiness state are close to surprise, sadness and anger, therefore, with the testing set 3 and 4 the model achieved lower performance to recognize the happiness in comparison with the groups. As a result, the average accuracy rate to recognize the happiness was obtained lower than other emotions. However, this confusion happened only where the images from FG-net database were used as the testing set. Therefore, in the experiments with Cohn-Kanade data set, the model recognized the happiness state with proper accuracy rate. Performance of the model using Cohn-Kanade testing set is illustrated in Table 5.15.

Table 5.13 Facial Expressions Classification Rates with FG-Net Testing Set using BROA

Expression	Average Accuracy rate Test group. 1 (%)	Average Accuracy rate Test group. 2 (%)	Average Accuracy rate Test group. 3 (%)	Average Accuracy rate Test group. 4 (%)	Mean of Accuracy rate (%)
Sadness	78	90	100	96	91
Happiness	100	98	60	74	83
Anger	76	98	98	90	90.5
Surprise	100	94	84	100	94.5
Average	89	95	85.5	90	89.8

Table 5.14 illustrates the recognition results using Genetic-Fuzzy classification model while BA was used as the training algorithm. According to Table 5.14 the best classification rate was achieved for Surprise expression with the accuracy of 93%.

However, the mean of classification for four groups using BA shows the lower rate in comparison with BROA as the training model.

Table 5.14 Facial Expressions Classification Rates with FG-Net Testing Set using BA

Expression	Average Accuracy rate Test group. 1 (%)	Average Accuracy rate Test group. 2 (%)	Average Accuracy rate Test group. 3 (%)	Average Accuracy rate Test group. 4 (%)	Mean of Accuracy rate (%)
Sadness	72	82	84	86	81
Happiness	100	94	60	72	81.5
Anger	86	74	100	86	86.5
Surprise	96	94	88	94	93
Average	88.5	86	83	84.5	85.5

5.4.2 Evaluating the Model Performance with Cohn-Kande Data Set

For the purpose of evaluating the validity of the classification model under diverse condition, the selected images from Cohn-Kanade database were used as the testing set while FG-net database was used as the training set. These training and testing sets formed a set called FG-Cohn set. The model was evaluated with FG-Cohn data set in 10 times implementation of classification. Moreover, the model was evaluated using only Cohn-Kanade data set while both of training and testing set were selected from Cohn-Kanade database. Table 5.15 shows the average of success rate for classification of testing sets in two mentioned cases as the accuracy rate of 93.5% and 92.2% were obtained with respect to training with FG-net database and training with Cohn-Kanade data set. The BROA training algorithm was used in both experiments with different data sets.

Table 5.15 Accuracy Rate of Expressions Classification with Cohn-Kanade Testing Set

Expression	Cohn testing set-Trained with Cohn dataset (%)	Cohn testing set-Trained with FG-net database (%)
Sadness	92	96
Happiness	95.3	96
Anger	86	91
Surprise	95.3	91
Average	92.2	93.5

In the Cohn-kanade data set both training and testing sets were selected from Cohn-kanade database while in the FG-Cohn data set, the training set included FG-net images and testing set was selected from Cohn-Kanade database. The recognition rate of 92.2% and 93.5% were obtained with Cohn-Kanade and FG-Cohn set, respectively. The first testing set included 30 subjects with 120 facial images which were used in four testing groups in four experiments. However the second testing set consisted of 10 subjects with 40 emotional images. In the later data set, the training set included the images from FG-net database. According to Table 5.15 there is around 1% difference in the average accuracy rate between two types of testing sets. The negligible bias was derived from the larger data space of the first testing set compared with the second testing set with regarding to small size of training set.

Figure 5.25 shows the recognition rates in the training and testing phases using FG-Cohn data set. Usually, the accuracy rate of testing phase is less than training phase due to using independent data in the testing set. However, according to Figure 4.25, higher accuracy rates were obtained in some experiments in the testing phase in comparison with training phase. Because, Cohn-Kanade data set includes the facial images of subjects with more clear express of emotions in the controlled conditions which are easier to classify, than the subjects in the FG-net database with uncontrolled conditions.

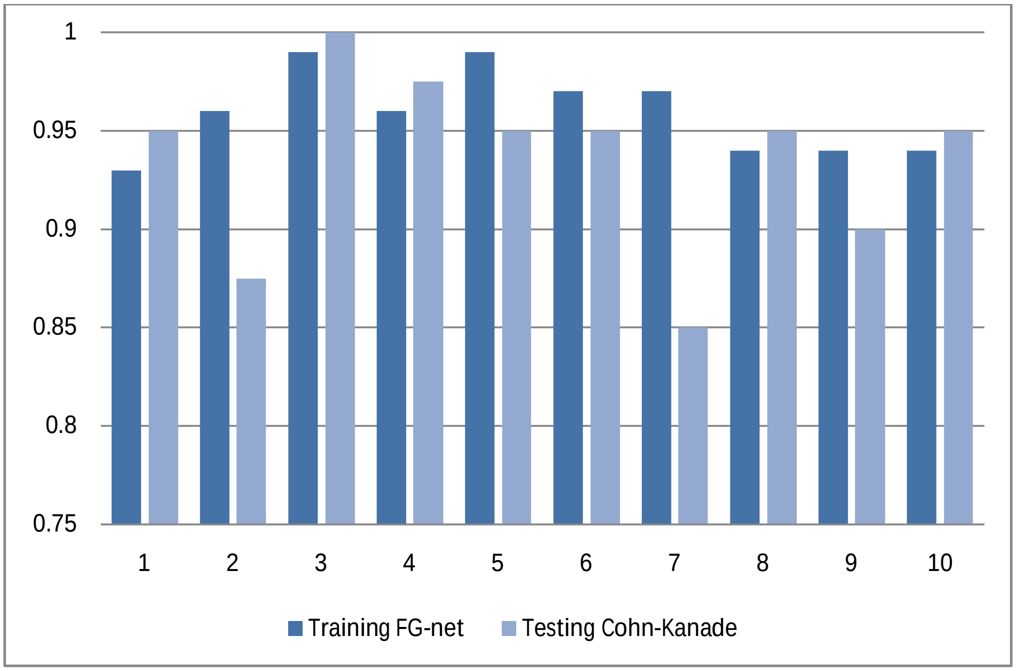


Figure 5.25 Success Rates of Classification with Training FG-Net Data Set Compare with Testing Cohn Data Set

5.5 FRBS WITH PREDEFINED MEMBERSHIP PARAMETERS

In order to compare the results of proposed classification model while Genetic Algorithm was used to train the membership parameters with the classic Fuzzy rule based classification model, the classification problem was solved using only FRBS without training process and the results of both were considered. In this case a rules base similar the Genetic-Fuzzy model was used but the membership parameters were pre-determined based on measuring the Gaussian function parameters using the data set. The tuned Fuzzy membership functions after learning process in comparison with the Fuzzy membership functions without using training algorithm are shown in the Figure 5.27 to Figure 5.33. In the classic FRBS, Gaussian function as a proper membership function in the classification of facial expressions is shown as follows.

$$\mu(x) = e^{-\frac{(x-b)^2}{2\sigma}} \tag{5.1}$$

Where σ is standard deviation or width of the function and b is centre of the function. In order to find the values of σ and b, standard deviation and average of every feature vector from neutral to each emotional state from all subjects were measured, respectively.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(xi - b)^2} \tag{5.2}$$

$$b = \sum_{i=1}^{n} xi \tag{5.3}$$

Where xi is the feature vector (f1 to f7) for each expression and n is number of subjects.

5.6 COMPARISON OF THE PROPOSED MODEL WITH FRBS

The overall information for facial expressions classification using FRBS without training process in comparison with proposed classification model has been summarized in Table 5.16. The experiment results showed the success rate of 70.75% and 74.75% with FG-net data set including 72 emotional images and FG- Cohn data set comprising 112 emotional images, respectively. In comparison, the proposed classification model in the testing phase showed the average of 90% accuracy rate for expressions recognition.

Table 5.16 Comparison of Proposed Model with Fuzzy Rule Based System in Classification Results

Expression	**Fuzzy rule based system- FG-net database (%)**	**Fuzzy rule based system- FG-Cohn dataset (%)**	**Proposed method FG-net testing set- Average rate (%)**
Sadness	39	39	91
Happiness	94	96	83
Anger	56	68	90.5
Surprise	94	96	94.5
Average	70.75	74.75	89.8

Figure 5.26 shows Fuzzy membership functions used for fuzzification of $f1$(the displacement of upper and lower eyelids position from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the p-roposed Genetic Algorithm.

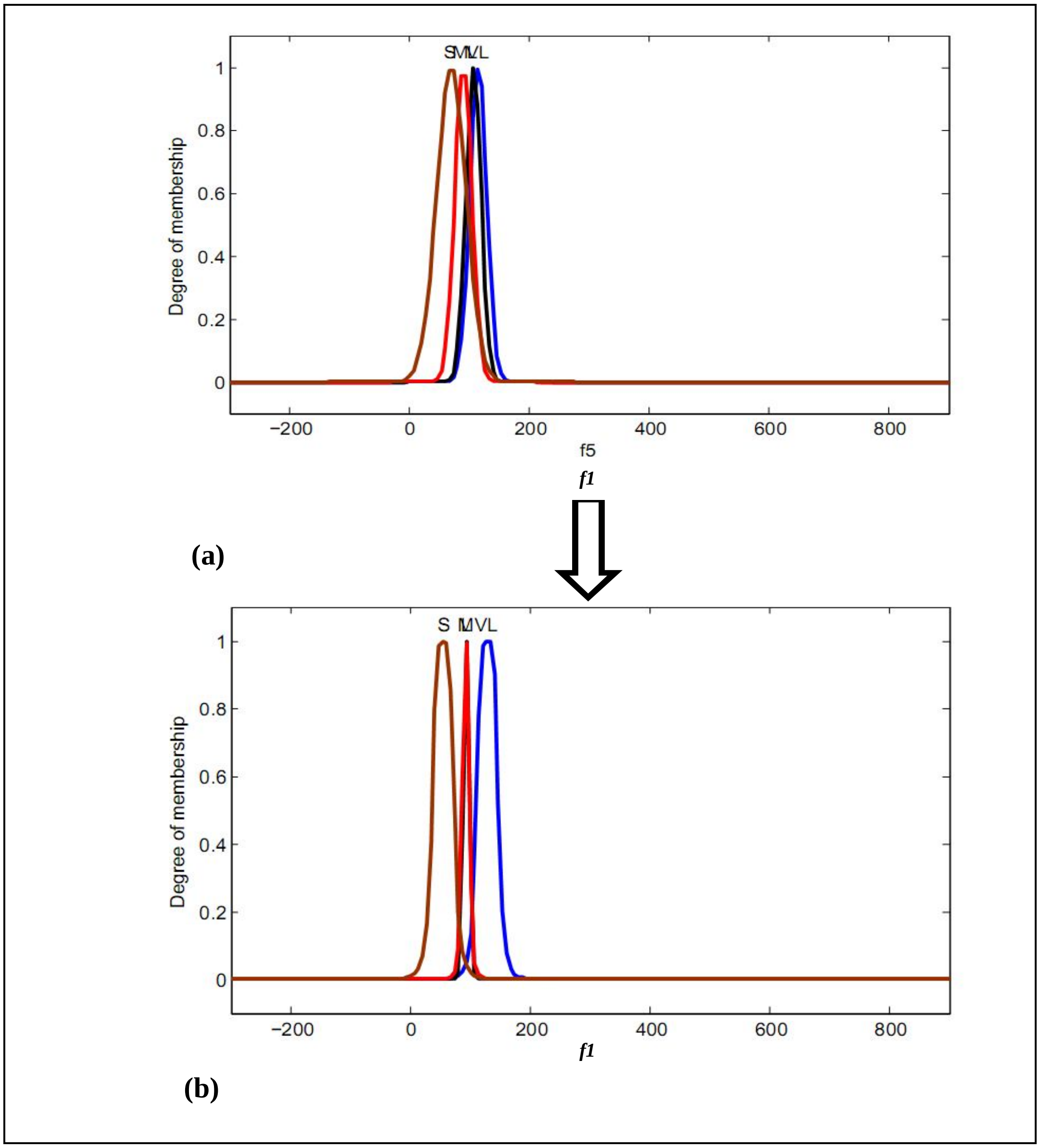


Figure 5.26 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature "f1", (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.27 shows Fuzzy membership functions used for fuzzification of *f*2 (the displacement of eyebrow corners into the eyes inner corners position from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed GA.

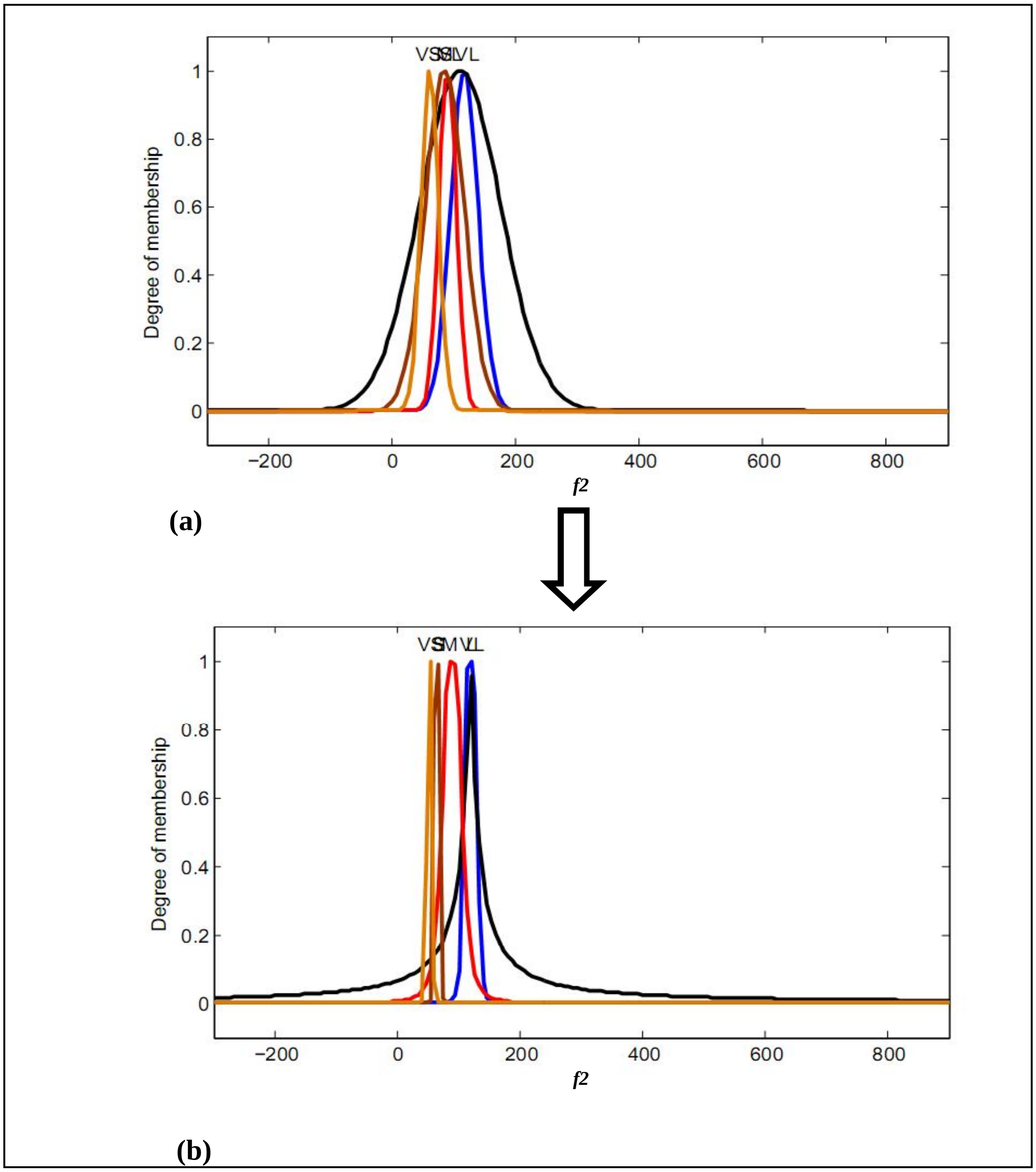


Figure 5.27 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature "f2", (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.28 shows Fuzzy membership functions used for fuzzification of *f*3(the displacement of lower position of eyelids into eyebrows corners from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed GA.

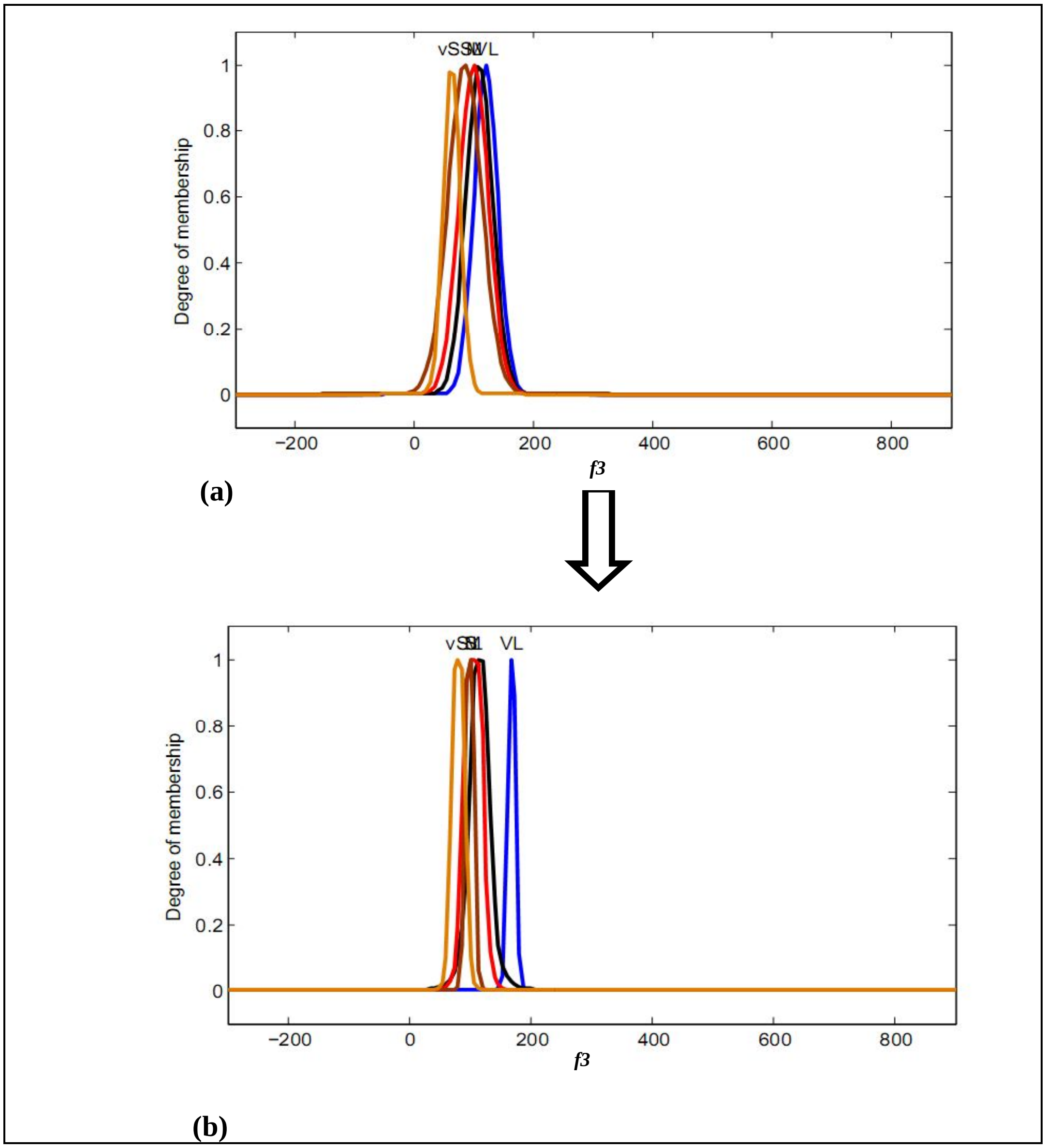


Figure 5.28 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature “f3”, (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.29 shows Fuzzy membership functions used for fuzzification of *f*4 (the displacement of upper lip position into mouth corners from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed Genetic Algorithm.

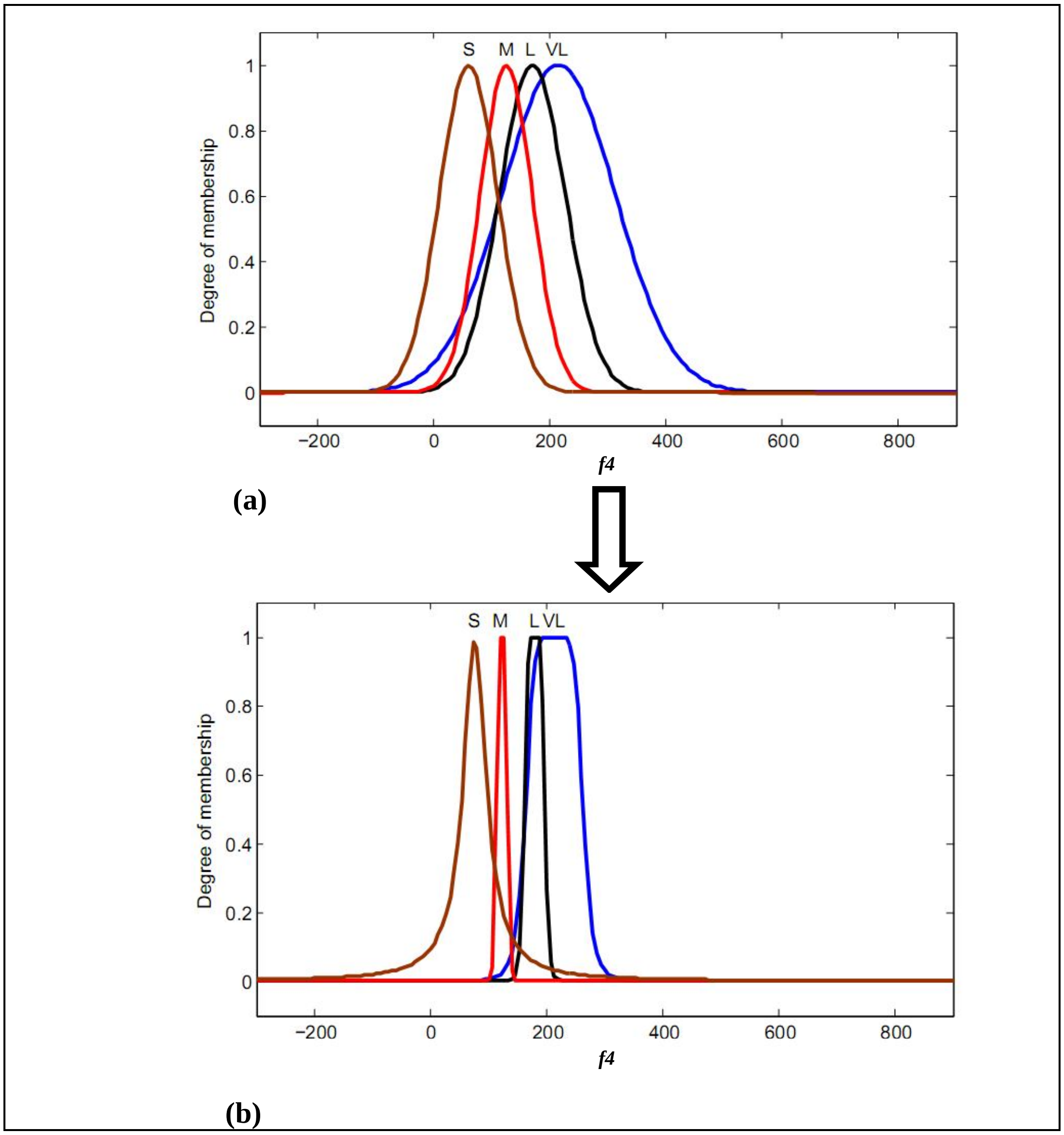


Figure 5.29 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature “f4”, (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.30 shows Fuzzy membership functions used for fuzzification of *f*5 (the displacement of lower lip position into mouth corners from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed Genetic Algorithm.

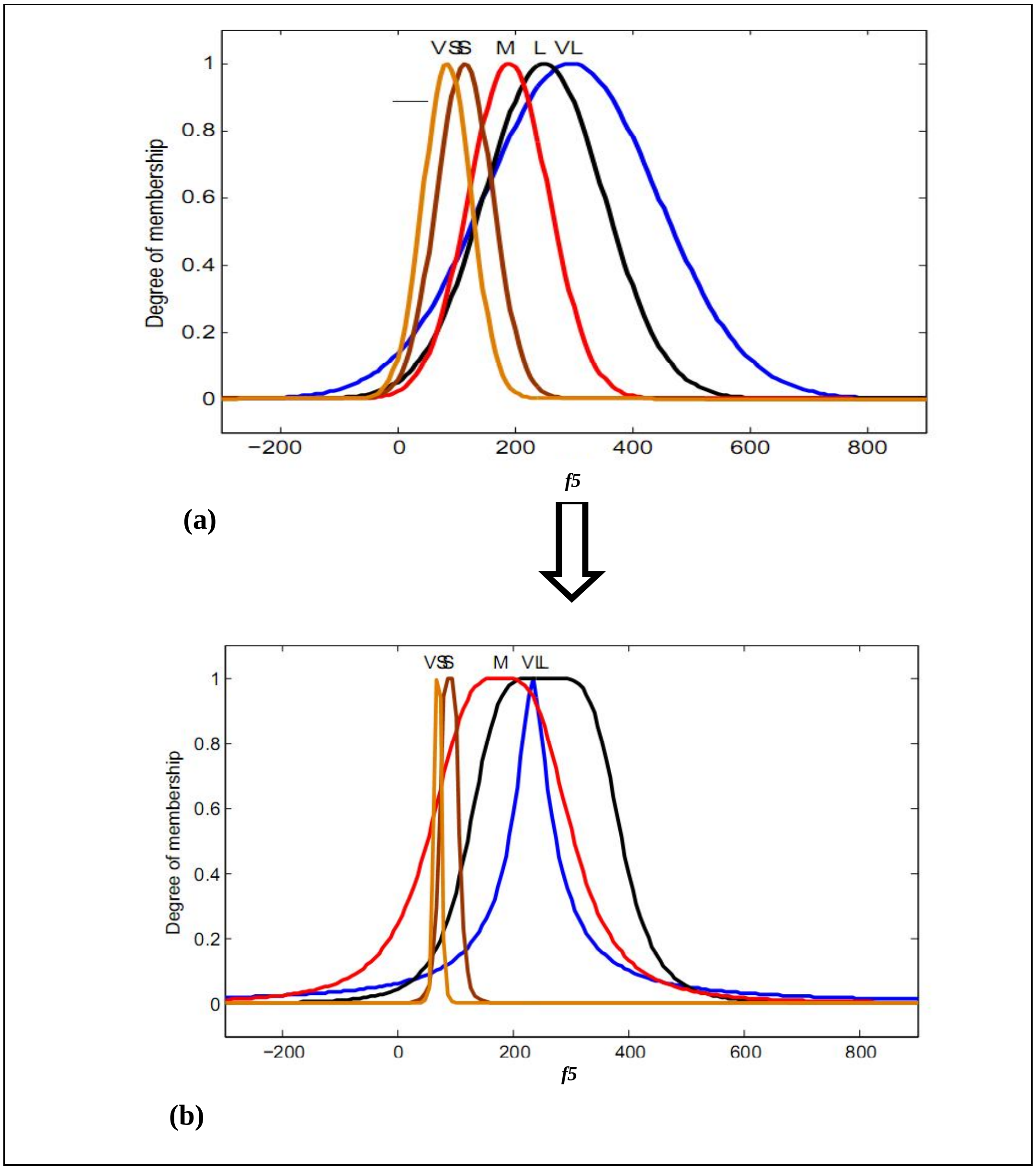


Figure 5.30 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature "f5", (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.31 shows Fuzzy membership functions used for fuzzification of *f*6(the displacement of lower and upper lips positions from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed Genetic Algorithm.

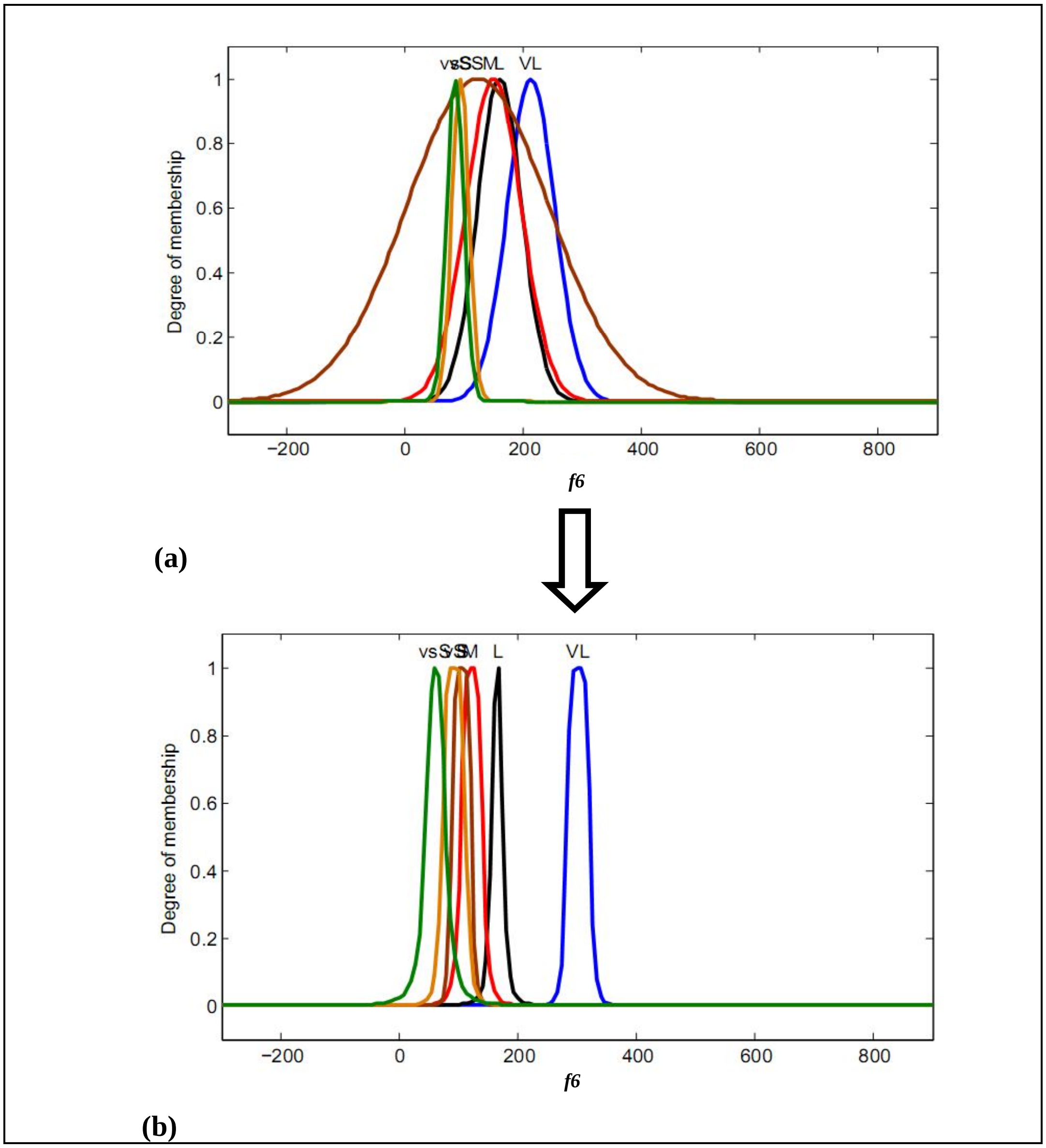


Figure 5.31 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature "f6", (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

Figure 5.32 shows Fuzzy membership functions used for fuzzification of *f*7 (the displacement of mouth corners in the horizontal position from emotional to neutral state) in the classic Fuzzy rule based classification model compared with tuned membership functions based on the training process with the proposed GA.

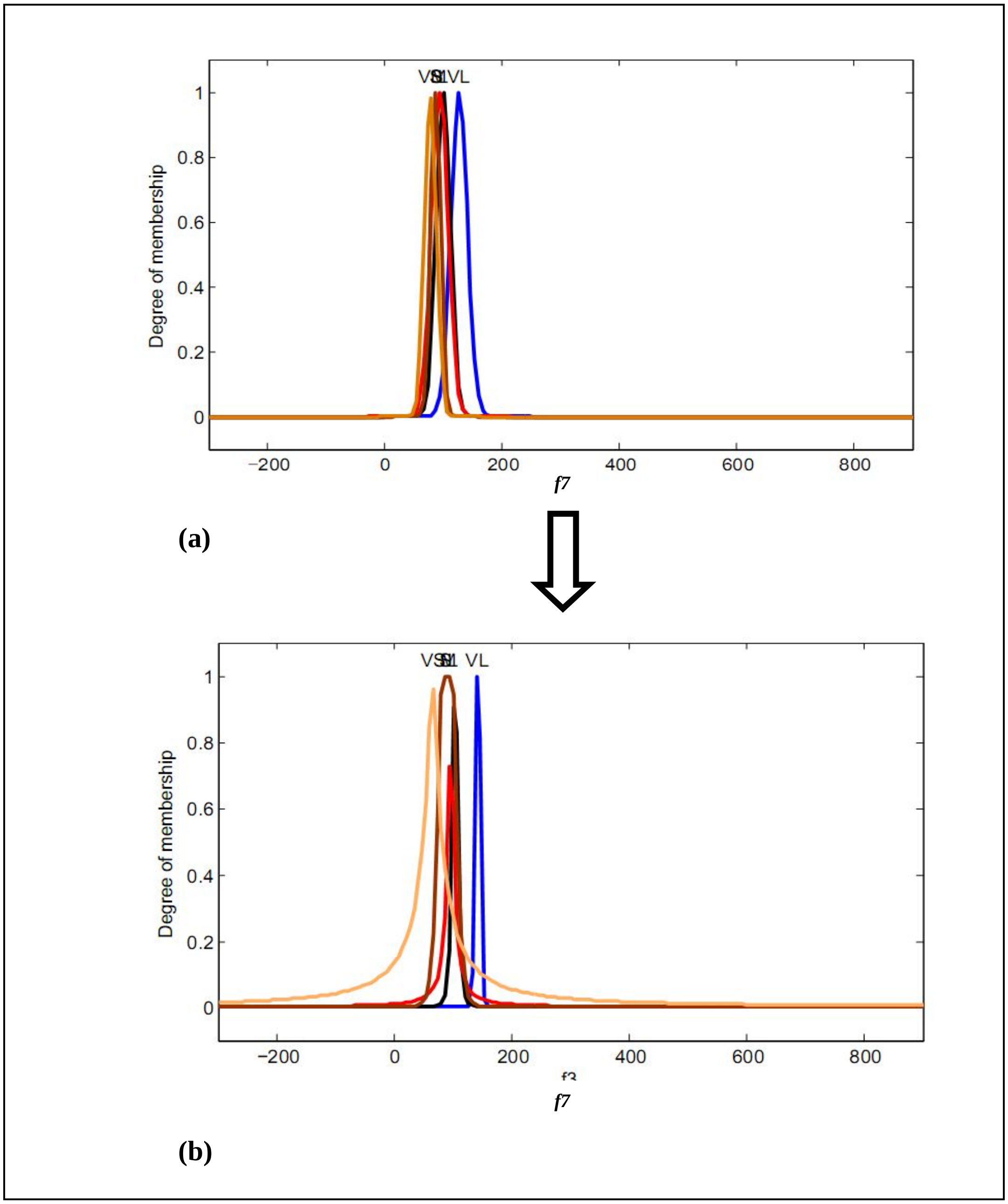


Figure 5.32 Fuzzy Membership Functions Plots Used for Inference Process of Extracted Feature “f7”, (a) Predefined membership functions based on the expert knowledge in the classic Fuzzy rule based system, (b) Membership functions obtained from learning process by BROA

5.7 CONCLUSION

The results of several times experiments, as described in this chapter, showed that the BROA as a modified Genetic Algorithm increases significantly the fitness values of training data set in comparison with other Genetic based algorithms for classification of facial expressions. The average fitness value with four training data set in which each training set was used 10 times in the evaluation process showed 96.8% while the best fitness value for classic Genetic Algorithm reported 93.75% in the training phase. Moreover, the proposed classification model was evaluated with the independent testing data sets which showed accuracy rates around 90% and 93.5% for classification of facial expressions using the images from FG-net and Cohn-kanade data bases, respectively. Therefore, the proposed classification model not only showed the higher accuracy rate in comparison with classic FRBS in which the success rate was reported 74.75% with pre-determined membership parameters, but also proved that the BROA learning process improved the fitness values in comparison with BA and classic Genetic Algorithms for classification problem.

CHAPTER VI

DISCUSSION

6.1 INTRODUCTION

In the past four chapters the current classification techniques for facial expressions recognition as well as proposed classification framework were described in details. Moreover, the results of implementing Genetic-Fuzzy classification model were indicated in comparison with existing classic Fuzzy models while the proposed classifier used BROA as the modified Genetic learning technique. In the present chapter, the obtained experiment results and the main parameters which caused increasing the performance of proposed classification model have been compared with the previous studies. As mentioned earlier in the Chapter 2 there are numerous classification techniques used in the expressions recognition in the recent years. However, the capability of those models under the various parameters such as feature extraction, data set, type of images and so on, for classification is a challenging problem which has been discussed in comparison with proposed model in this section of thesis. As a result, with regarding to small raw data in the training set with limited extracted features and natural emotional images, the experiment outcomes showed that the proposed model improved the classification performance of existing Fuzzy models.

6.2 COMPARISON CRITERIA

There are various criteria that facial expressions classification systems based on which are evaluated and compared. Therefore, in order to compare the classification performance all criteria should be considered, with respect to requirements of facial expressions recognition model. Feature extraction, database, image type, number of feature points (if available) and variety of emotions are the most important parameters which influence the accuracy of classification.

6.2.1 Feature Extraction

Feature extraction as the initial step of a classification system has an important role in the accuracy of facial expressions recognition. Therefore, with increasing the accuracy of feature extraction, the higher success rate of classification is expectable. On the other hand, as the feature extraction is a complicate work, particularly from the facial images, high computing process is required which make it inapplicable in some real time applications (Ilbeygi 2012). Therefore, using a proper feature extraction method not only influences the classification precision rate but also decreases the complexity of the classification in terms of computation process.

Feature extraction based on the geometric method was proposed in this research because the geometric features decreased the computation dimension in the classification process with regarding to representation of some specific components of facial images as the extracted features (Ratliff 2010). Furthermore, 12 feature points which were extracted from the images created the simplest model in contrast with previous studies. The studies of Zhang et al (1998) with 34 points, SeyedArabi et al (2004) with 21 points, Khanum et al (2009) with 21 points, Zhan et al (2007) with 20 points, Hupont et al (2008) with 20 points, Youssif & Asker (2011) with 19 points, Esau et al (2007) with 14 points and SeyedArabi et al (2007) with 14 points, are some examples in which more extracted feature points were used for classification. In addition, in some studies such as Paknikar (2008) more than one method used for the purpose of feature extraction. In the latest research, 16 points with 7 extra parameters as the extracted features were used for facial expressions classification.

Appearance features as another features type were proposed in the recent studies in which the texture information of the face skin was presented to use in the expressions classification. The features extraction methods based on appearance features feed wide information of facial states into the classification system which force computation expense in contrast with geometric features with raw limited data

(Ratliff 2010). Moreover, the complexity of appearance based methods for extracting the features are usually higher than geometric features in terms of computational process and memory usage (Shan et al, 2009). One other drawback derived from need to geometric points as the primary data in the most of the appearance methods, which make them dependent on the feature points for the training set (Samad & Swada 2011).

In this research the proposed geometric features with 12 points as the least numbers of points in comparison with existing models made a proper way to reach to the aim of reducing the classification complexity but with keeping high performance in the expressions recognition. Furthermore, with reducing the detected feature points, the computation process of facial expressions recognition systems is more affordable to use in the real time applications.

Table 6.1 shows some of the results obtained from recent researches with similar conditions in terms of image type. As various parameters influence the accuracy rate of expressions classification, therefore, for the purpose of comparison, the affect of all parameters should be considered in the same time, however, in this section, we ignore from some parameters such as classification technique, number of emotions and database. According to Table 6.1, one of the main reasons of low accuracy rate of classification is derived from the feature extraction based on the geometric features compared with appearance method. As an example, in the study of Zhang et al (1998) using 34 feature points, the affect of two features types were examined in the classification performance. According to their reports, Geometric type of features makes the classification performance so difficult that low accuracy rate of 73.3% was obtained. On the other hand, Gabor Wavelet method as an appearance type increased, considerably the accuracy rate of classification to the 92.2%.

Table 6.1 Comparison of Results from Classification Techniques Based on the Similar Image Type

Reference	**Classification technique**	**Image type**	**Facial Feature representation**	**No of Points**	**Data base**	**Accuracy rate (%)**
Hupont et al (2008)	SVM	**Static**	Geometric	20	FG-net & MMI	70
Hupont et al (2008)	Rule based method	**Static**	Geometric	20	FG-net & MMI	71
Guo & Dyer (2005)	Bayes	**Static**	Gabor Wavelets	34	JAFFE	71
Hupont et al (2008)	Naive Bayes	**Static**	Geometric	20	FG-net & MMI	71.5
Guo & Dyer (2005)	Adaboost	**Static**	Gabor Wavelets	34	JAFFE	71.9
Esau et al (2007)	FRBS	**Static**	Geometric	14	Cohn-Kanade	72
Zhang et al (1998)	NN (Perceptron Model)	**Static**	Geometric	34	JAFFE	73.3
Samad & Swada (2011)	SVM	**Static**	Gabor Wavelets	-	FG-net	81.7
Ratliff (2010)	SVM	**Static**	AAMs	113	FG-net	91.3
Zhang et al (1998)	NN (Perceptron Model)	**Static**	Gabor Wavelets	34	JAFFE	92.2
Guo & Dyer (2005)	SVM	**Static**	Gabor Wavelets	34	JAFFE	92.4
Khanum et al (2009)	CBR & FRBS	**Static**	Geometric	21	FG-net	90.3
This study	**Proposed model**	**static**	**Geometric**	**12**	**FG-net**	**89.8**
This study	**Proposed model**	**static**	**Geometric**	**12**	**Cohn-Kanade**	**93.5**

In summary, with respect to the facial representation method, use of 12 geometric feature points for the proposed classification model in this research is the lowest number of points in comparison with existing research. This proved that the model has precise performance in the classification with average around 90% and 93.5% success rates using FG-net and Cohn-Kanade data set, respectively, while poor numbers of feature points were used in the proposed model. According to Table 6.1, few studies show higher accuracy rate than the accuracy in this research with the FG-net database due to different in database, features type and feature points size in those research.

6.2.2 Database

There are several standard databases which are used in order to facial expressions analysis. However, in the most of the existing research the Japanese Female Facial Expression (JAFFE) database (Lyons et al 1999), Cohn-Kanade database (Kanade et al 2000) or FG-net database (Wallhoff 2006), have been used.

JAFFE database includes 213 gray scale images of six basic expressions and neutral state from 10 Japanese female models. The lack of different nation subjects, few numbers of subjects and controlled emotional images are the main limitations of JAFFE.

Cohn-Kanade database includes 418 sequences gray scale images of six basic expressions from 97 subjects with different skin colors and cultures. The limitation of Controlled emotional images is the main drawback of Cohn-Kanade database.

FG-net database includes around 399 sequences of color images of six basic expressions from 18 male and female subjects. The lack of diverse nationality in the subjects is visible in the FG-net database.

In this research FG-net and Cohn-kanade databases were used to evaluate the classification performance in the experiment process while the main results were obtained using FG-net database. In this database, the images were captured in the almost natural conditions while the subjects responded to the emotional actions under the non-control conditions. As the facial emotional appearance in the non control conditions has the natural bias, the feature movements from neutral to emotional states is less than the controlled conditions in which subjects express the non natural emotions without real stimulus. As a result, the difference between emotional and neutral states with low intensity of feature motions which is derived from natural conditions decreases the classification performance to recognize the class of emotions in front of high motions of features from neutral to emotional states in the controlled conditions. Therefore, it would be difficult for a classification model to recognize the facial expressions from the images of FG-net database in comparison with the other databases (Xiao et al 2011).

As conclusion, in order to compare the success of proposed classification model with existing research two groups of databases are considered, with regarding to the control conditions of the databases. First group is the researches which used the FG-net database while the results of the proposed model showed higher rate than those models, generally, with regarding to all parameters which are influenced the classification performance. The second one is the researches which used other databases such as Cohn-Kanade and JAFFE. To show the effect of database conditions (controlled or non-controlled) on the classification performance some evidences are presented according to the Table 6.2.

According to Table 6.2, the studies of Ratliff (2010) and Obaid et al (2009), also the studies of Zhan et al (2006) and Ramanathan et al (2009), with respect to use the similar parameters in terms of features extraction and classifier, show that the classification performance using Cohn-Kanade and JAFFE databases are not as difficult as using FG-net database. According to Table 6.2, the accuracy rate for using FG-net database shows 83.9% in front of 89% for using Cohn-Kanade database also the accuracy rate of 72% for using FG-net database shows a considerably decrease in comparison with 83% success rate for using JAFFE database. Moreover, in the study of Xiao et al (2011) the classification results for using Cohn-Kanade and FG-net databases reported 88.34% and 67.73%, respectively. This difference in the accuracy rate also is illustrated in the study of Piatkowska (2010) in which the rates of 71% and 77% for using FG-net and Cohn-Kanade were achieved.

Therefore, 8 to 20 percent decrease has occurred obviously for accuracy rate of classification to switch from Cohn-Kanade or JAFFE databases to FG-net database with respect to similarity conditions.

Table 6.2 Comparison of Results From Existing Studies Based on the Different Databases

Reference	**Features extraction**	**Classifier**	**Database**	**Accuracy rate (%)**
Ratliff (2010)	AAMs	Euclidean distance	FG-net	83.9
Obaid et al (2009)	AAMs	Euclidean distance	Cohn-Kanade	89
Zhan et al (2006)	Gabor Wavelet	SVM	FG-net	72
Ramanathan et al (2009)	Gabor Wavelet	SVM	JAFFE	83
Xiao et al (2011)	LBP	k-Nearest Neighbor	FG-net	67.73
Xiao et al (2011)	LBP	k-Nearest Neighbor	Cohn-Kanade	88.34
Piatkowska (2010)	LBP	SVM	FG-net	71
Piatkowska (2010)	LBP	SVM	Cohn-Kanade	77

6.2.3 Image Type

Generally, there are two types of images which are used in the facial expressions databases. Static image as a single image of facial state represents limited raw data from one expression however, in the sequence images a series of images from neutral to emotional state are used into the classification model. With regarding to the images as a data source for classifier, sequence images present more information of facial appearances in contrast with a static image. According to the study of Cheo & Kim (2009) using sequence images increase the accuracy of classification in comparison with static images. They considered the k-NN classifier with sequence images and reported the accuracy rate of 96% while the rate of 92.5% was obtained with static images when all other parameters were similar. Therefore, using sequence images increase the success rate of classification. However, use of sequence images rise the system requirement to complicated process since sequence of images should be considered rather than just a still image. Moreover, in some applications as just static facial images are available, therefore, a sequence images based model is not applicable. Furthermore, low classification performance with static images is still a challenging problem for facial expressions recognition systems. Therefore, in this research, static images were used in the proposed model to evaluate the classification performance.

6.2.4 Variety of Emotions

According to Ekman & Freisen (1978) study, there are six basic expressions which are recognized from the facial states. The variety of expressions which are recognized with the classification model affect the classification performance. Generally, all six basic expressions are divided into two positive (Happiness and Surprise) and negative (Sadness, Fear, Anger and Disgust) emotions (Alves et al 2008). As in the existing studies, different types of basic emotions including two to six expressions were considered with the classification techniques, therefore, in order to comparison the classification methods, a closer look at the type of emotions is required.

In this research, two positive facial expressions of happiness and surprise and two negative facial expressions of sadness and anger were classified with expressions recognition model into four emotions. These expressions are the most applicable emotions in the real application. Therefore, to evaluate the proposed classification performance compared with the other classification techniques in the previous works, the existing of four these emotions should be considered.

6.3 CLASSIFICATION

Several classification techniques in this research were described to solve the emotions recognition problem. Moreover, a Genetic-Fuzzy classifier method proposed to develop the current studies in the specific conditions in which most difficult parameters were set for classification model to consider its performance under those parameters.

The proposed classification model in this research has been founded on the Fuzzy Rule Based System (FRBS). Fuzzy rule based systems have capability of modeling the real problems with ambiguous conditions. Facial expressions recognition is a proper domain to model with FRBS. There are several studies which presented a Fuzzy model to classify the emotions. However, as the Fuzzy model lacks the training process to match properly with diverse conditions, therefore, it was not used as much as other classifiers such as SVM, HMM and k-NN in the classification problem. So, one of the contributions of this research was development of FRBS with training process to optimize the Fuzzy construction under the diverse conditions. For the purpose of indicating the role of training process in the Fuzzy classification performance four scenarios were implemented using Genetic based algorithms in which the BROA as a modified Genetic Algorithm was compared with BA and two classic Genetic Algorithms. According to experiment results described in Chapter 4 of this thesis, BROA and BA show higher accuracy rates in training process than classic Genetic Algorithms. Therefore, two BROA and BA based models have been compared in the testing phase. Table 6.3 illustrates the facial expressions recognition results in testing phase while BROA and BA were used as the training algorithms. According to Table 6.3 the trained model with BROA shows higher classification rates for all classes than the trained model with BA. Therefore, created Princess Chromosomes by Queen Chromosome in the training process of BROA for the purpose of offspring generation configures the facial expressions classification model more accurate and robust in comparison with other scenarios. Moreover, Table 6.4 shows the results from BROA training process compared with classic Genetic Algorithms.

Table 6.3 Comparison of Accuracy Rates in the Testing Phase between Bee Trained Models

Expression	Accuracy rate: BROA (%)	Accuracy rate: BA (%)
Sadness	91	81
Happiness	83	81.5
Anger	90.5	86.5
Surprise	94.5	93
Mean	89.8	85.5

According to Table 6.4 the proposed training algorithm (BROA) obtained the higher fitness rate with 96.8% accuracy of classification and with lower standard deviation compared with two classic type of Genetic Algorithms in which the average of the best results were 93.75% and 92% while the higher standard deviations of those indicate the higher bias of the results in comparison with BROA. As described in the Chapter 4 of this thesis, the average of standard deviations was derived from the results of several experiments on the training sets. Therefore, deviation of 1.25% shows more stability of the final results in the training process. It means BROA which was simulated from the honey bees offspring generation process improved the optimizing process of Genetic Algorithms in the tuning of Fuzzy membership parameters.

Table 6.4 Comparison of Tuning Rates in Training Process between BROA and Genetic Algorithms

Training algorithm	Mean: Fittest rate (%)	Mean: Std (%)
BROA	96. 8	1.25
Classic GA: Type 1	93.75	2.15
Classic GA: Type 2	92	1.55

6.3.1 Evaluate the Model Performance Based on Variety of Emotions

Table 6.5 shows the classification performance of existing research with respect to the emotions of Sadness, Happiness, Anger and Surprise in comparison with the proposed model.

According to Table 6.5 the proposed model obtained the best recognition rate of Sadness expression compared with other studies. The sadness and anger appearance as negative expressions are usually difficult to recognize for most classifiers, as the face appearance parameters in the sadness state is confused with anger and in some cases with neutral. Therefore, the performance of the classification techniques was not precise for recognition of sadness as well as anger in the previous research. However, the evaluation results of the proposed model presented accurate rate for recognition of sadness and anger. However, happiness in contrast of the others was recognized with less accuracy rate which could be derived from the parameter such as database while using images from Cohn-Kanade in the test set increased the success rate to 96% for happiness recognition.

In this research, the proposed model used the geometric features of the static images from FG-net database for classification of four emotions. However, according to Table 6.5, use of appearance features in the studies such as Saatci & Town (2006), Cheo & Kim (2009), use of sequence images such as the study of Sreenivasa et al (2011), use of different databases such as the study of Cheng et al (2007), or different in variety of emotions such as the study of Cheo & Kim (2009) influenced the classification success rates of those research to obtain the results. Furthermore, as the main purpose of the proposed classification algorithm is achievement of the highest accuracy rate from the whole classes, therefore, the proposed model makes a balance between classes while the optimum accuracy rate of total emotions was obtained. As a result, with regarding to the average accuracy rate around 90% using FG-net testing set and 92.2% and 93.5% using Cohn-Kanade testing set for recognition of all four emotions, the proposed model showed the best accuracy rates in both data sets in comparison with the existing research except with the study of Cheo & Kim (2009) in which sadness emotion was not included in the classification performance. Therefore, SVM and *k*-NN as the classifiers of those studies achieved higher success rates without considering the sadness expression. In addition, other parameters such as, utilized data set and features type are different with what used in the proposed Genetic-Fuzzy model. As we explained earlier in the present chapter, changing in the parameters of the proposed model such as FG-net database, Geometric features type and static images can increase the classification rate, but lose other objectives of the model.

Table 6.5 Comparison of Classification Performance in the Existing Researches with The Proposed Model

Classifier	**Rule Based Method**	**Optical Flow based Method**	**HMM**	**SVM (Binary)**	**NN**	**NN (RBF)**	**AHP**	**SVM**	***k*-NN**	**Proposed Model**	**Proposed Model**
Reference	Hammal et al (2007)	Besinger et al (2011)	Shin & Chun (2008)	Saatci & Town (2006)	Sreenivasa et al (2011)	SeyedArabi (2004)	Cheng et al (2007)	Cheo & Kim (2009)	Cheo & Kim (2009)	**This study**	**This study**
No. of Emotions	**3**	**3**	**4**	**3**	**4**	**4**	**4**	**3**	**3**	**4**	**4**
Sadness	49	60	78.22	70.5	82	86	76	-	-	**91**	**96**
Happiness	-	80	77.09	94.4	85	91	94	93.04	96.88	**83**	**96**
Anger	79	50	79.59	77.1	81	81	77	88.5	90.31	**90.5**	**91**
Surprise	-	-	78.70	-	-	91	96	95.79	97.17	**94.5**	**91**
Fear	57	-	-	-	80	-	-	-	-	-	-
Average	61.66	63.33	78.4	80.66	82	87.25	85.2	93.37	96.09	**89.8**	**92.2-93.5**
Features extraction	Geometric	Geometric	Geometric	AAMs	Geometric	Geometric	Geometric	AAMs	AAMs	**Geometric**	**Geometric**
No. of Features	-	18	18	60	-	21	14	-	-	**12**	**12**
Database	Cohn, DailyCottrel	Cohn, JAFFE , own data set	Own data set	IMM, AR, FG-net	Own data set	Cohn-Kanade	JAFFE	Own data set	Own data set	**FG-net**	**Cohn-Kanade**
Image type	Static	Sequence	Sequence	Sequence	Sequence	Sequence	Static	Static	Sequence	**Static**	**Static**

6.3.2 Evaluate the Model Performance Based on Facial Features

As we mentioned earlier, it is difficult to compare directly the recognition rates while different parameters were used in the classification techniques. Table 6.6 illustrates the classification performance of existing research with the similar facial feature representation method in comparison with the proposed classification model.

According to Table 6.6 the proposed classifier achieved higher accuracy rate with Cohn-Kanade data set than the existing techniques. Moreover, with regardless to the negligible higher rate in the studies of Khanum et al (2009) and SeyedArabi et al (2007) which is due to different parameters, the model obtained suitable performance with FG-net database compared with other studies. However, in the proposed model four emotions were used for the purpose of performance evaluation while some of the studies included different number of classes such as 3, 5 or 6 emotions.

6.3.3 Comparison of the Fuzzy Classification Models

Fuzzy logic is a known technique for solving the natural-based problems with uncertain solutions. In the classification domain with overlapped objects, it is difficult to divide each data into the category that belong it more than other classes. In recent years, FRBS has been used in the classification problems such as facial expressions recognition. In addition to inherent superiority to solve the ambiguous problems, human knowledge based decision, simplicity of the model and low computation process are several advantages of FRBS (Khanum et al 2009).

Therefore, with respect to the merits and drawbacks of other classification methods which were described in the Chapter 2 of this thesis and with regarding to the objectives of this research which have been mentioned in the Chapter 1, FRBS was proposed to classify the emotions while its restrictions due to using Genetic Algorithm has been improved. Table 6.7 indicates the Fuzzy classification performance in the existing research compared with the proposed model.

Table 6.6 Comparison of Classification Techniques Based on the Similar Features Extraction Method

Reference	Classification technique	Image type	Features extraction	No. of Points	Data base	Accuracy rate (%)
Besinger et al (2011)	Optical flow based method	Sequence	**Geometric**	18	Cohn, JAFFE , own data set	63.33
Hupont et al (2008)	SVM	Static	**Geometric**	20	FG-net & MMI	70
Hupont et al (2008)	Rule based method	Static	**Geometric**	20	FG-net & MMI	71
Hupont et al (2008)	Naive Bayes	Static	**Geometric**	20	FG-net & MMI	71.5
Esau et al (2007)	FRBS	Static	**Geometric**	14	Cohn-Kanade	72
Zhang et al (1998)	NN	Static	**Geometric**	34	JAFFE	73.3
Shin & Chun (2008)	HMMs	Sequence	**Geometric**	18	Own data set	78.4
Tsapatsoulis et al (2000)	FRBS	Static	**Geometric**	-	Cohn-Kanade	81
Sreenivasa et al (2011)	NN	Sequence	**Geometric**	-	Own data set	82
Pardas et al (2002)	HMMs	Sequence	**Geometric**	-	Cohn-Kanade	84
SeyedArabi et al (2007)	FRBS	Sequence	**Geometric**	21	Cohn-Kanade	89.1
Khanum et al (2009)	CBR & FRBS	Static	**Geometric**	22	FG-net	90.33
SeyedArabi et al (2007)	NN (RBFNN)	Sequence	**Geometric**	14	Cohn-Kanade	91
Seyed Arabi et al (2004)	NN (RBFNN)	Sequence	**Geometric**	21	Cohn-Kanade	91.2
This study	**Proposed model**	**Static**	**Geometric**	**12**	**FG-net**	**89.8**
This study	**Proposed model**	**Static**	**Geometric**	**12**	**Cohn-Kanade**	**92.2-93.5**

Table 6.7 Comparison of Fuzzy Classification Models with the Proposed Genetic-Fuzzy Mode

Reference	Classification technique	Image type	Feature extraction	No. of Points	Data base	Accuracy rate (%)
Esau et al (2007)	FRBS	Static	Geometric	14	Cohn-Kanade	72
Ioannou (2005)	Neuro-FRBS	Sequence	Geometric	18	Own-Data set	78
Tsapatsoulis et al (2000)	FRBS	Static	Geometric	Not-mentioned	Cohn-Kanade	81
Chatterjee & Shi (2010)	Neuro-FRBS	Static	LBP	-	JAFFE	85-95
Xiang et al (2008)	FCM	Sequence	Appearance	-	Cohn-Kanade	88
Seyed Arabi et al (2004)	FRBS	Sequence	Geometric	21	Cohn-Kanade	89.1
Khanum et al (2009)	CBR & FRBS	Static	Geometric	22	FG-net	90.33
Zhi et al (2008)	FDP	Static	Geometric	Not-mentioned	Cohn-Kanade	94.12
This study	**FRBS**	**Static**	**Geometric**	**12**	**FG-net**	**70.75**
This study	**FRBS**	**Static**	**Geometric**	**12**	**FG - Cohn**	**74.75**
This study	**Proposed model**	**Static**	**Geometric**	**12**	**FG-net (trained with FG-Cohn)**	**89.8**
This study	**Proposed model**	**Static**	**Geometric**	**12**	**Cohn-Kanade (Trained with Cohn-Kanade)**	**92.2**
This study	**Proposed model**	**Static**	**Geometric**	**12**	**Cohn-Kanade (trained with FG-net)**	**93.5**

According to Table 6.7, the existing studies obtained the classification results around 72% to 94% with using Fuzzy models. The difference between the accuracy rates is derived not only from classification performance but also from difference in the parameters which were used in the experiments. The study of Esau et al (2007) showed the worst classification rate in the existing research while FRBS as the classification method with 14 geometric points was used in this study. In this study the accuracy rate of 72% was reported for recognition of emotions, however, in the study of SeyedArabi et al (2007) the recognition rate increased to 89.1% with higher number of points extracted from the sequence images.

For the purpose of improving the recognition results, Neural Network was used for creating the Fuzzy rules in the study of Ioannou et al (2005). The proposed Neuro-Fuzzy model showed the accuracy rate of 78% for facial expressions recognition. Chatterjee & Shi (2010) also proposed an Adaptive Neuro Fuzzy Inference System (ANFIS) in order to creating the Fuzzy rules and tuning the membership parameters. These two studies reported lower accuracy rate than the proposed Genetic-Fuzzy model in this research. Moreover, the accuracy rate of the later study was obtained in a range of 85% to 95%, while training samples were used as a part of testing set. Therefore, a large part of samples in the testing set were not independent from training set, because the Neural methods for the purpose of generalization, need to large training samples. On the other hand, Neural Networks increase the complexity of the FRBS in the learning process.

Fuzzy C Means (FCM) method used in the study of Xiang et al (2008) for the classification of emotions. The best recognition rate of 88% was reported with FCM while only one subject was used in the testing set in each experiment process and the rest of images from Cohn-Kanade database were used in the training set. Therefore, the reported recognition rate was obtained in very small testing set compared with the proposed model in this research. It means, the generalization factor in the FCM method is lower than the proposed model. Furthermore, the accuracy rate of Genetic-Fuzzy model is higher than the proposed FCM both in FG-net and Cohn-Kanade data sets while variety of other parameters such as image type, facial features extraction and the variety of emotions were not considered.

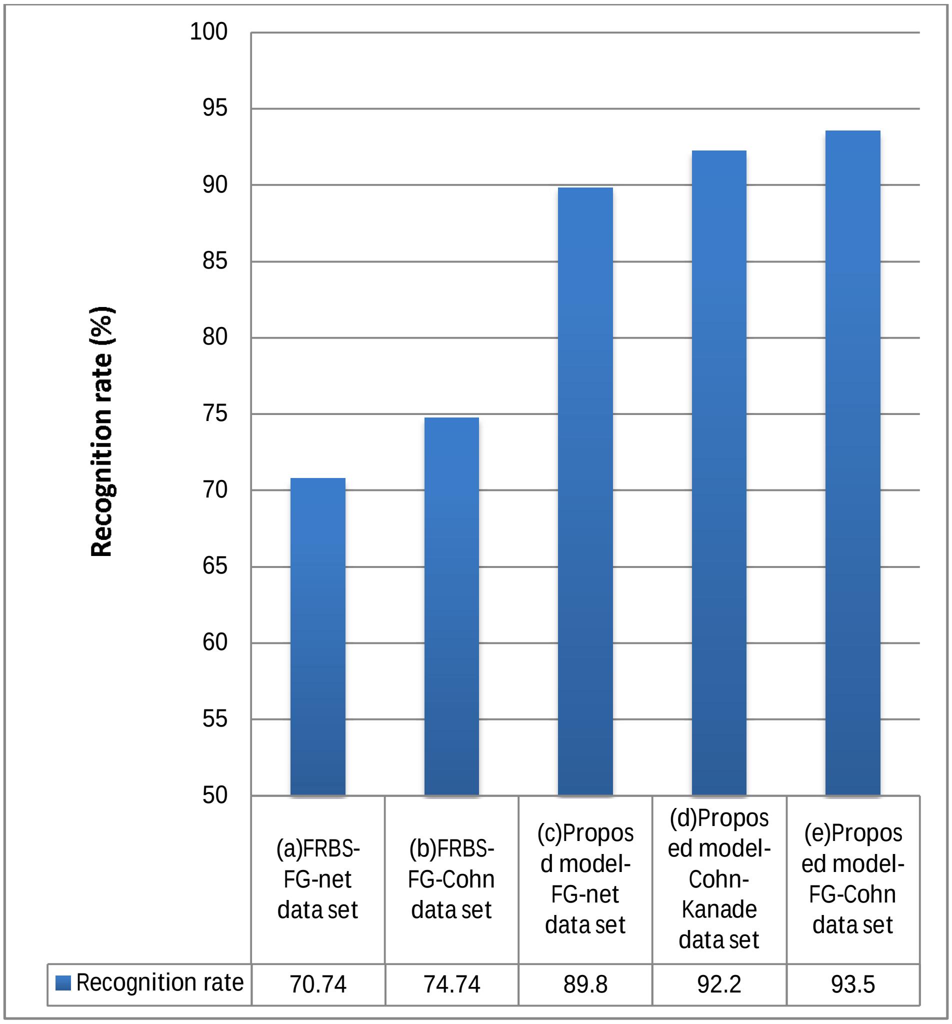
The Case Based Reasoning (CBR) method was used with the FRBS by Khanum et al (2009) to improve the Fuzzy classification performance in which the accuracy rate of 90.33% was obtained for all basic expressions. The reported results are comparable with the proposed Genetic-Fuzzy classifier in the FG-net database. However, in the proposed Fuzzy-CBR method the membership parameters were set manually which are unsuitable for the different database. Therefore, reset the membership parameters are needed with every database, while in the proposed Genetic-Fuzzy model the optimum values for membership functions are obtained independently with human direct intervention. On the other hand, the feature points in the Fuzzy-CBR method are more than the proposed method in this research. Increasing the number of points not only arise the computational requirement for features extraction but also increase the complexity of the classification model.

Fuzzy Discriminate Projection (FDP) proposed in the study of Zhi et al (2008) for classification of emotions while the accuracy rate of 94.12% was obtained. The reported result is the highest rate in comparison with other existing researches which are shown in the Table 6.7, if the difference in the parameters is ignored. However, the success rate was obtained while the subjects of training set were used in the testing set. This experiment process decreases the generalization validity and make it difficult to consider the recognition rates as the validate values. Overall, the proposed FDP technique showed the higher accuracy rate than the proposed Genetic-Fuzzy model in this research while its generalization validity was not properly proved.

As the main purpose of this research is development of FRBS, therefore, Fuzzy rule based classification was used as the extensive experiments to consider its results in comparison with the proposed model. Its results are shown in Table 6.7. According to Table 6.7 the performance of Fuzzy rule based classification has been improved while the proposed Genetic Algorithm called Bee Royalty Offspring Algorithm was used as a training scheme. The experiment result of FRBS for classification indicated the accuracy rate of 70.75% for expressions recognition while the parameters of Gaussian membership function were determined based on the mean and standard deviation values of FG-net data set. Also, the higher accuracy rate of 74.75% was obtained using the FG-Cohn data set included the images from FG-net and Cohn-Kanade. The higher success rate with the FG-Cohn data set is due to the fact that the images from Cohn-Kanade database are clearer than the FG-net database to represent the emotional states. Furthermore, the proposed Genetic-Fuzzy model increased the recognition rate to the value around 90% and 92.2% also 93.5% while the FG-net and Cohn-Kanade testing sets were used, respectively. These results were achieved from the independent data which were not used in the training sets while the success rate of training set is higher than testing set. Therefore, the proposed model in every experiment is blinded to some objects which are used as the testing set. However, the experiments results for classification with FRBS were achieved while the information of all objects were used to determine the membership parameters such as mean and standard deviation values in the Gaussian membership function. In other words, as the experiments results were achieved with regarding to all data in the Fuzzy rule based classification, thus, the testing set was similar to the training set, indeed. Figure 6.1 indicates the results of Fuzzy rule based classification in comparison with the success rates of trained classification model with the proposed Genetic Algorithm.

Overall, with regarding to the experiment results, the proposed learning algorithm adds the following strengths to the FRBS.

It increases dramatically the accuracy rate of Fuzzy rule based classification.
It adjusts the membership parameters which are set manually.
It makes adaptive model to use in any database.



(a) FRBS-FG-net data set: Fuzzy rule based system using FG-net database,

(b) FRBS-FG&Cohn data set: Fuzzy rule based system using FG-Cohn data set,

(c) Proposed model-FG-net data set: Genetic-Fuzzy model using FG-net database,

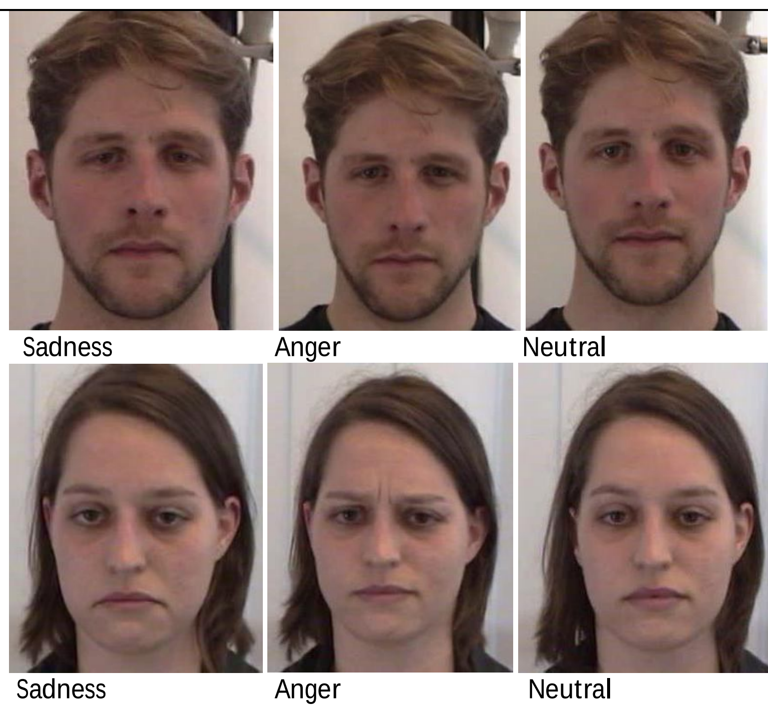
(d) Proposed model-Cohn-Kanade data set: Genetic Fuzzy model using Cohn-Kanade data set,

(e) Proposed model-FG-Cohn data set: Genetic Fuzzy model using FG-Cohn data set

Figure 6.1 Comparison of the Proposed Model Performance with the Fuzzy Rule Based Classification for Facial Expressions Recognition

6.3.4 Robustness of Classification Model

The model performance with diverse images has been evaluated to show the ability of classification in the variable conditions. As the images from FG-net database were captured in the natural conditions, therefore, some images express the ambiguous status of emotions particularly in the sadness and anger expressions. Usually, the classification of these two expressions is more difficult than other emotions in the FG-net database especially where the FRBS is used as the classification model. Table 6.8 illustrates the results from classification using FRBS. According to Table 6.8 the sadness and anger show the worst rates in comparison with other emotions. Furthermore, Figure 6.2 shows some examples from the images of FG-net database in the sadness compared with anger and neutral status. Generally, there are some factors which indicate the sadness status such as, closer eyelids, lower brows and lower position of mouth corners. According to Figure 6.2 the features variations are so slight between neutral, sadness and anger that existing classification models recognize the sadness and anger hardly due to similarity of feature vectors. On the other hand, the experiment results showed the average accuracy rate of 92% for recognition of sadness using the proposed classification model. The achieved rate shows the robustness of the Genetic-Fuzzy classification model in the uncertain conditions.



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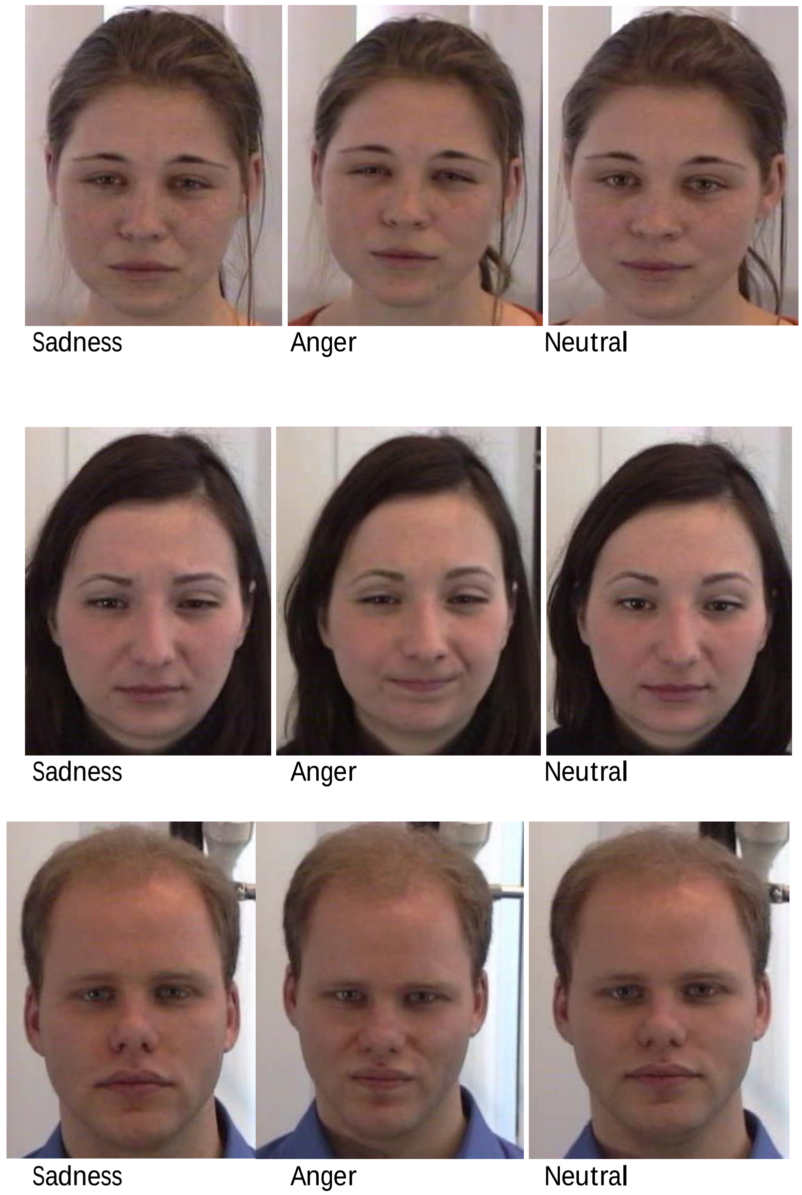

Figure 6.2 Comparison of Neutral and Sadness Expressions in Some Example Images from FG-Net Database

Table 6.8 Comparison of Proposed Model with Fuzzy Rule Based System in Classification Results

Expression	Fuzzy rule based system- FG-net database (%)	Proposed method FG-net testing set- Average rate (%)
Sadness	39	91
Happiness	94	83
Anger	56	90.5
Surprise	94	94.5
Average	70.75	89.8

6.4 SUMMARY

In this chapter, the results of proposed classification model have been compared with the existing research. With a close look to the classification systems, we find that some criteria influence the recognition results. These parameters comprising the features extraction method, number of feature points, database, image type and variety of emotions have been considered to evaluate the classification performance. Therefore, the proposed Genetic-Fuzzy model has been compared with the existing studies with respect to those criteria. With regarding to the features representation method and number of feature points, the proposed model demonstrates less complexity than the existing research. Furthermore, the proposed model was considered with static emotional images with respect to the fact that static images are classified more difficult than the sequence images. The static images were selected from FG-net as a non-control database and Cohn-Kanade data set which includes the images from diverse subjects. As a result, the proposed model showed more accurate performance in comparison with the most existing research to conduct the classification of real images. Moreover, the success rate of the proposed classification model indicated a higher performance in comparison with the existing research while similar variety of emotions included four expressions were used. In addition, comparison of Fuzzy rule based classification with the proposed model proved that the proposed training algorithm has dramatically improved the classification performance, accuracy rate and generalization for facial expressions recognition.

CHAPTER VII

CONCLUSION AND FUTURE WORKS

7.1 SUMMARY AND CONTRIBUTIONS

Classification of expressions from facial images is one of the main interest researches in the pattern recognitions. There is several classification techniques achieved the successful rates for facial expressions recognition while the appearance features, large number of training data, sequence images and/or controlled databases were used in the evaluation processes. Whereas, some parameters such as small size of feature points and static images from the uncontrolled database with diverse subjects are still challenges for classification of facial expressions.

Fuzzy Rule Based System (FRBS) is one of the uncomplicated techniques which are used in the pattern recognition problems. The popularity of the FRBS is derived not only from its simplicity but also from its linguistic perceptible as well as its capability of uncertainty estimations. Therefore, in several studies FRBS used for facial expressions classification problem. However, FRBS performance is closely related to its knowledge base. Therefore, estimation of the optimum knowledge base increases the FRBS performance. As a result, an optimization technique is a requirement task for FRBS as a classifier since estimation of FRBS parameters is a difficult work with human expert knowledge. In this research, a Genetic Algorithm has been proposed for estimating and tuning the Fuzzy membership functions to improve the Fuzzy knowledge base. In general, two factors which were determined in the optimization process included the type of membership function and its parameters. In this research, a bell shape membership function has been proposed that can demonstrates the close shapes to triangular, trapezoidal and bell shape with changing its shape parameter while its other parameters are set with the proper mean and standard deviation values for the classification. Therefore, not only the shape of membership function but also its start point and end point which show the width of the shape as well as the centre point of the shape have been estimated in the learning process. These solutions have been presented in form of a model for facial expressions recognition. The results of this research to express the contributions of this thesis have been explained in the past five chapters. These contributions are summarized as the following list:

1. **Facial Feature Extraction:**

   The extraction of facial features as a prerequisite step for classification of facial expressions has been carried out based on the RGB information and morphological operations for detecting most facial feature points around the eyes, eyebrows and mouth from the images of FG-net database while two eyes inner points was used as the base of face area. The number of selected points was 12 points which are the smallest size of points in comparison with existing research. According to these points, 7 feature vectors were proposed to feed into the facial expressions classification model. As a result, the proposed features extraction presented a simple base in terms of computation cost for classification model. The proposed features extraction method as well as its normalization has been described in Chapter 3 of this thesis in details.

2. **Hybrid Genetic-Fuzzy Model:**

   Genetic learning algorithm is a suitable method to find the optimize solutions in the large solutions space. Therefore, a Genetic Algorithm has been proposed for tuning the Fuzzy membership functions with estimating the proper values of the membership function parameters as the optimized solutions. As a result, in this research a Genetic Algorithm as a learning method has been combined with Fuzzy rule based system to improve the Fuzzy classification performance for the purpose of fulfill the classification requirements. The proposed hybrid Genetic-Fuzzy classifier is a novel model which never been used for facial expressions recognition domain, previously. However, we might find it as a successful method to solve in the different problems such as control and other types of pattern recognition from simple objects. The proposed hybrid Genetic-Fuzzy model has been explained comprehensively in the Chapter 3 of this thesis.

3. Bee Royalty Offspring Algorithm:

Genetic Algorithms in the learning process generate the population of solutions which are used to crossover, mutation and selection operations. This process is repeated in the several iterations to achieve the best result. In this research a new technique has been proposed for crossover and selection process which has been simulated according to the honey bee offspring generation process and modified Queens selection to generate the new populations. Recently, honey bees behaviors have been studied and formulated in some research to use in the optimization problems. However, in this research the proposed algorithm includes the different operations in comparison with other Genetic based algorithms for offspring generation and selection process while it has been customized to use with FRBS for classification of facial expressions. As the main performance of the modified Genetic Algorithm which has been proposed in this research is based on the elite solutions performance in the bees generation process by royalty offspring, therefore, we called this algorithm as the Bee Royalty Offspring Algorithm (BROA). BROA has been presented to improve the Genetic-based algorithms learning process for tuning of the Fuzzy membership functions. The development of the BROA has been described in the Chapter 3 of this thesis, comprehensively.

4. Design and Development of Classification Model:

The proposed hybrid Genetic-Fuzzy model for classification of facial expressions has been designed and developed in this research under the Matlab environment. The implementation process has been developed not only for the proposed model but also for different scenarios of training algorithms as well as traditional FRBS to compare with the proposed hybrid Genetic-Fuzzy model in terms of classification performance. Therefore, we used the Matlab programming codes to experiment the proposed model and illustrate the classification results for the purpose of performance evaluations. The experiment results from the implementation process have been described in Chapter 4 of this thesis.

5. Performance Evaluation of the Proposed Classification Model:

In the past two chapters (Chapters 4 and 5) the proposed classification model was examined and evaluated while the static images from two FG-net and Cohn-Kanade databases were used to train and test the proposed hybrid Genetic-Fuzzy model. Moreover, the achieved results were considered and compared firstly with the other classification techniques with regarding to the important parameters which affect the classification results and next with the FRBS without using the learning algorithm for classification of emotions. According to the experiment results, the classification performance of the proposed model is considerably higher than Fuzzy rule based model in terms of accuracy rate and generalization, which proves that the proposed Genetic Algorithm as a learning process develops the FRBS performance for facial expressions classification. In addition, the training results illustrated that the BROA achieves higher fitness values than the classic Bee Algorithm as well as traditional Genetic Algorithms to adjust the membership functions in this problem. BROA not only shows the higher accuracy rate for classification but also achieves the smallest deviation in comparison with other types of training algorithms. Furthermore, the results from training phase and testing phase show that the proposed learning algorithm copes with the overfitting problem in the classification. These results have been achieved while some facial images are not completely in the front position; therefore, the proposed model is robustness to the limited head pose. Also, the outcomes from the reliability and validity tests indicate that the proposed model is reliable and valid while low values of standard deviation were achieved to classify the facial expressions from the static images.

7.2 LIMITATIONS

This research was developed under the limited conditions which are described as follows:

As the main focus in this research is on the classification component of the facial expressions recognition system, therefore, for the purpose of feature points extraction a simple extraction method based on analysis of image color information and morphological operations has been proposed which is not a proper method for real time systems due to computational expensive. In addition, this method is not suitable to detect automatically all facial feature points. Moreover, the feature points extraction technique is not able to extract the facial points from the grayscale images. Furthermore, analysis of the facial expressions was accomplished on the four basic emotions. However, facial expressions express more emotional states which include other basic emotions such as disgust and combined expressions such as an expression which expresses happy and surprise emotions simultaneously. Moreover, some complicated facial expressions which human able to recognize such as stress and pain, are not included in this research.

7.3 DIRECTION OF THE FUTURE WORK

According to the limitations of this research, in general, there are four issues which can be supposed as the future works for facial expressions recognition:

1. A fully automatic facial features points extraction method with low computational cost, which capable to extract the facial points from all types of images both in color and grayscales images.
2. Development of the model to use in the real time applications.
3. Development of the Genetic learning algorithm based-model to cover the classification of other facial expressions.

4. Development of the BROA based-model to increase the training performance in terms of optimization speed.

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Appendix A

LIST OF PUBLICATIONS

JOURNALS:

Jamshidnezhad, A., Md. J. Nordin. A Heuristic Model for Optimizing the Fuzzy Knowledge Base in a Pattern Recognition system. *Journal of Scientific & Industrial Research* 71(5): 341-348, 2012 [ISI, Impact factor: 0.587]

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