Artificial Neuro-Fuzzy Logic System for Detecting Human Emotions

By

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AUTHORIZATION FORM

إقرار تفويض

أنا أمية منصور مراد أفوض جامعة الشرق الأوسط بتزويد نسخ من رسالتي للمكتبات أو المؤسسات أو الهيئات أو الأفراد عند طلبها.

التوقيع: أمية منصور مراد

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Examination Committee Decision

This is to certify that the thesis entitled "Artificial Neuro-Fuzzy Logic System for Detecting Human Emotions" was successfully defined and approved on Jan/2012.

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DECLARATION

I do hereby declare the present research work has been carried out by me under the supervision of Dr. Mohammad Malkawi, and this work has not been submitted elsewhere for any other degree, fellowship or any other similar title.

Signature:

Date: 16th / Jan /2012

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DEDICATION

(وَإِذْ تَأَذَّنَ رَبُّكُمْ لَئِنْ شَكَرْتُمْ لَأَزِيدَنَّكُمْ)

Almighty Allah says “And remember! Your Lord caused to be declared (publicly): "If ye are grateful, I will add more (favors) unto you”.

So all praise is for Allah, the exalted, for his favors that cannot be counted.

I dedicate this work to my parents, my brothers, my sisters, my beautiful children, my relatives, my friends, and all those who helped, supported, and taught me.

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List of Abbreviations

ANFIS	Adaptive-Network-based Fuzzy Inference Systems
ANN	Artificial Neural Network
ANS	Automatic Nervous System
CI	Computational Intelligence
CTA	Correct Training Array
DBP	Diastolic Blood Pressure
EDA	Electro Dermal Activity
EEG	Electroencephalography
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FT	Finger Temperature
GUI	Graphical User Interface
HDBP	High Diastolic Blood Pressure
HF	High Frequency
HFT	High Finger Temperature
HHR	High Heart Rate
HnSRR	High Nonspecific Skin Conductance Response Rate
HP	High Pre-Ejection Period
HR	Heart Rate
HRos	High Oscillatory Resistance
HRR	High Respiration Rate
HRV	Heart Rate Variability
HSBP	High Systolic Blood Pressure
HSCL	High Skin Conductance Level
HSCR	High Skin Conductance Response
HSV	High Stroke Volume
HVt	High Tidal Volume
ICT	Information and Communication Technology
IO	Input Output
LDBP	Low Diastolic Blood Pressure
LF	Low Frequency
LFT	Low Finger Temperature
LHR	Low Heart Rate
LnSRR	Low Nonspecific Skin Conductance Response Rate
LP	Low Pre-Ejection Period
LRos	Low Oscillatory Resistance
LRR	Low Respiration Rate
LSBP	Low Systolic Blood Pressure
LSCL	Low Skin Conductance Level

LSCR	Low Skin Conductance Response
LSV	Low Stroke Volume
LVt	Low Tidal Volume
mf	Member Function
NDBP	Normal Diastolic Blood Pressure
NFT	Normal Finger Temperature
NHR	Normal Heart Rate
NnSRR	Normal Nonspecific Skin Conductance Response Rate
NP	Normal Pre-Ejection Period
NRos	Normal Oscillatory Resistance
NRR	Normal Respiration Rate
NSBP	Normal Systolic Blood Pressure
NSCL	Normal Skin Conductance Level
NSCR	Normal Skin Conductance Response
nSRR	Nonspecific Skin Conductance Response Rate
NSV	Normal Stroke Volume
NTA	Noisy Training Array
NVt	Normal Tidal Volume
PEP	Pre - Ejection Period
Ros	Oscillatory Resistance
RR	Respiration Rate
SBP	Systolic Blood Pressure
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SNS	Social Network Services
STA	Small Training Array
SV	Stroke Volume
VLF	Very Low Frequency
Vt	Tidal Volume

Abstract

This thesis presents a combined neural fuzzy model for detecting human emotions using physical measurable and physiological human responses. The model has fourteen input variables representing human responses, twenty two types of human emotions represented at the output of the model, and the model has the ability to learn through successive training.

The purpose of this thesis is to build an adaptive neuro-fuzzy system, which can be trained to detect the current human emotions from a set of measured responses such as human body temperature, skin variations, heart beat rates and others. The training will be based on synthetic hypothetical data, although real life data collected by experts in the field is required to train the final model. After training the model with proper data, the emotion of a person can be detected by applying his/her current measurements of the input factors to the model. The model developed in this thesis can be utilized effectively in social networks, health organizations, national security systems, and gaming industries.

The hybrid neuro-fuzzy model developed in this thesis is superior to either the fuzzy logic model or the artificial neural network model when built individually. The hybrid neuro-fuzzy model benefits form the advantages provided by both models and overcome their constraints.

We have developed six models with different types of input/output membership functions and trained by different kinds of input arrays. The models are compared based on their ability to train with lowest error values. Many factors impact the error values such as input/output membership functions, the training data arrays, and the number of epochs required for training.

الخلاصة

يقدم هذا البحث نموذج يجمع المنطق الضبابي مع الخلايا العصبونية لتحديد المشاعر الانسانية باستخدام بعض مقاييس استجابات مادية و فسيولوجية بشرية. يستخدم النموذج أربعة عشرة نوع من المتغيرات التي تمثل رد الفعل البشري, كما يحدد النموذج اثنين و عشرين نوع من المشاعر البشرية, و باستطاعة النموذج التعلم من خلال التدريب.

الهدف من هذا البحث هو بناء نموذج باستخدام الضباب المنطقي و الخلاية العصبونية بحيث يتكيف النموذج مع التمرين لكشف المشاعر الانسانية الحالية باستخدام بعض ردود الفعل الانسانية على سبيل المثال حرارة جسم الانسان و عدد نبضات القلب و قياسات اخرى. وقد استخدمت بيانات حقيقية بالاستعانة بخبراء في هذا المجال لتمرين النموذج. بعد تدريب النموذج يصبح بالامكان تحديد مشاعر الانسان و ذلك بادخال البيانات اللازمة من جسم الانسان في اللحظة الحالية للنموذج. هذا النموذج يمكن استخدامه بشكل فعال في الشبكات الاجتماعية و المراكز الصحية و انظمة الامان الدولية ايضا يمكن استخدامه في اماكن اللعب و التسلية.

ان استعمال هذا النموذج يجمع محاسن انظمة الضباب المنطقي مع انظمة الشبكات العصبونية معا, فضلا عن استخدام كل نظام على حدة.

لقد استخدم نظام MATLAB ANFIS لبناء ستة نماذج مختلفة, و يكمن اختلاف هذه النماذج باختلاف انواع الاقترانات المستخدمة لتمثيل المدخلات و المخرجات الفعلية لهذه النماذج. كما تمت مقارنة النماذج الستة بناءا على مقدرتها على التعلم عن طريق التعلم ثم مقارنة مقادير الخطأ الناتجة من التمرين. و قد تبين من ذلك ان هناك اكثر من عامل يؤثر على قيم الخطأ الناتجة من تمرين النماذج, وعلى سبيل المثال نوع الاقترانات المستخدمة في تمثيل مدخلات و مخرجات النماذج و نوعية البيانات المستخدمة للتمرين و عدد مرات التمرين. لقد حصل النموذج صاحب الاقتران السيني للبيانات المدخلة و الاقتران الخطي للبيانات المخرجة على اقل قيم للخطأ.

Chapter One

Chapter One

1. Introduction

1.1. Overview

In the recent years, ICT (Information and Communication Technology) has been one of the most important research areas in the field of the science and technology. All types of people, young and old, male and female, educated and non-educated use ICT applications for different purposes. In the meantime, researchers are continuously working to improve and introduce new ICT applications. Although the rapid advancement of ICT has created an environment for all types of data transfer including text, images, audio, and video, the transfer of human emotions has not received as much attention despite the importance of this aspect of the human status. That is mainly due to the insufficient research and development in the area of emotions analysis and detection.

The human emotional status is rather intangible “intangible things can't be manufactured in factories but they can be simulated” (Owaied & Abu - Arr’a 2007) [30]. The human emotional status can be correlated to external and internal factors. In this research, we will concentrate on the internal factors, which are manifested in different forms including frequencies generated within the human body. These factors are tangible things, and hence they can be measured and analyzed.

The internal factors come from different parts of the body in several forms such as Electroencephalography (EEG), Heart Rate (HR), Heart Rate Variability(HRV), Pre - Ejection Period (PEP), Stroke Volume (SV), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Skin Conductance Response (SCR), Tidal Volume (Vt), Oscillatory Resistance (Ros), Respiration Rate (RR), Nonspecific Skin Conductance Response Rate (nSRR), Skin Conductance Level (SCL), and Finger Temperature (FT), and others. (Kreibig 2010) [18]

These factors impact the human emotions in different ways for different people, and thus they are not the same for all humans. Every human has his own measurements, which are different at every posture. However, the measurements for each human can be used to predict the emotional status for each individual man or woman. The interesting thing is that these measurements are given in large ranges and often their impacts overlap in an interesting manner. For example, a given measurement of some factors may relate to a person being happy, while the same measurements may reveal a rather careless status for some other person. This kind of behavior lends itself naturally to fuzzy sets and fuzzy logic (Zadah 1965)[52].

In this research, we will use fuzzy operations, such as ‘and’, ‘or’, and ‘not’ operations, (Negnevitsky 2005) [24] to represent the knowledge about each factor; this will enable us to detect the emotion of a person using fuzzy inputs of the various factors. For example, we can use a fuzzy rule as “IF (temperature is high) and (heart rate is high) then (person is excited). Although fuzzy sets and operations are useful for representing the knowledge base, they fail to model the individual behavior of each and every person. In other words, once the rules in our model are defined and fixed they are assumed to model the behavior of all people, which is not possible. A rather cool person may be “excited” while his temperature and heart rate remain normal rather than high. Obviously, a model that is able to adapt to various categories of human responses would be preferred. As such, an adaptive learning mechanism is needed to adjust the model in order to cater for the differences between various humans. This requirement calls for the use of an adaptive learning system such as Artificial Neural Networks (ANN) (Abraham 2005)[2].

ANN can be used for this type of applications because each person has his own values, which relate to his/her emotions. The ANN will give us the opportunity to do back propagation to get the exact emotions related to each person. However, the ANN model does not allow the use of fuzzy sets or rules and calls for the use of exact and crisp values (Negnevitsky 2005)[24]. Consequently, we lose benefit of fuzzy logic representation, which is the more natural way of representing the relation between human emotions and human physical and physiological parameters.

In order to utilize the benefits of both fuzzy logic and artificial neural networks, we will use the hybrid approach, which combines fuzzy logic and artificial neural networks (using backpropagation method)in a single model.

1.2. Problem Definition

Recent development in social networks have allowed for the inclusion of texts, images, videos, animations, and graphics to be communicated across the net and to be shared instantly by the users. One aspect that is lagging behind is the sharing of feelings and emotions across the net. The problem of emotion detection based on the measured physiological changes in the human body has received a significant attention lately (Nie et al. 2011) [25]. However, the instant detection of each human's emotions as an independent being had not been thoroughly studied [25]. The problem is that each person manifests his/her emotions in a manner that is different from others [17]. In social networks, in particular, a person sending a message across the net may experience certain emotional status which need to be transmitted to the other party in the same manner that voice or image are transmitted. To be able to do that it is required to build a system that can detect the current emotional status of a person while conducting a session on the social network. This research will address the problem of identifying and qualifying the emotions of a given person using an adaptive fuzzy logic system, where the factors impacting the emotions are provided in a fuzzy logic manner and the output emotion is evaluated using an Artificial Neural Network (ANN), this is a type of hybrid expert system (Negnevitsky 2005)[24].

1.3. Objectives

The main objective of this thesis is to build a hybrid system (Neuro-Fuzzy), which allows human emotions to be analyzed and detected; such system can be potentially used in Social Network Services (SNS), health systems, security, systems gaming industry and many others. The system relies on obtaining certain measurements from the person using sensors attached to his/her body to the devices used by the individual such as a computer mouse, a keyboard, a webcam, and others. The system will perform some analysis of the measured data, then it will produce the emotion of the person at the moment, and finally the output (emotion) will be detected. In particular, the current research will target the following sub-objectives:

1. Identify and analyze human emotions
2. Find tangible things(factors) which impact human emotions
3. Analyze tangible things(factors)
4. Digitize human emotions factors
5. Get related human emotions
6. Do the frame work for analyzing and detecting human emotions

1.4. Significance of the Problem

The analysis and detection of human emotions using a hybrid system has a direct impact on several fields of the human life. A brief summary of the potential use of the knowledge base system is given below:

1. Health

1. The interaction between a patient and his/her doctor is the first step of the treatment, but in some critical cases, this interaction becomes difficult or maybe it is impossible. (Kreibig 2011) [18]

2. Some of the most difficult illness cases are the cases that the patient cannot explain his/her feelings to the doctor like a coma patient, infant, or autism patient. It is well known that one of the most important things in medical treatment is the patient – doctor conversations or contacts. The system would make a very useful tool in this case, because the doctor can analyze and detect the patient's emotions, even when the patient is unable to correctly define his emotional status.

2. Social

1. In recent years, Social Networks (SNS) have become the most widely spread services in the world that are available for a large population of the people. Although SNS provide many facilities to improve communications between people and exchange information such as texts, videos, images, and audios, they are still unable to transmit human emotions across the net. A person using Facebook ®, Twitter ®, or chat tools would have to explicitly state his/her emotional status to the partner across the net. The system presented in this thesis enables communicating parties to detect the emotional status of their partners in a seamless automatic manner. In essence, a person chatting with a friend on the social networks would be able to tell whether the other partner is sad, angry, embarrassed, afraid or happy without the need for the partner to explain his/her emotional status. This service will add a significant value to the social network services.

3. Security

1. Security systems are widely used for protecting important or critical places. Most of these systems are used to investigate the crimes after their occurrence using photos or video clips obtained from the crime site. Other security systems rely on motion detection and physical presence of potentially dangerous species.
2. The system presented in this thesis can be used to predict a crime before it occurs by detecting a criminal behavior based on the emotional status of the person attempting to commit a crime or breach the security at given facilities. This is based on the psychological status of the criminal before committing a crime. The system allows the security system to detect these emotions before the crime, and thus will enable security system to stop the crime and save lives and assets. For example, at an airport facility, the system can identify individuals with certain emotional postures based on perceived measures of the individual's heart rate, EEG frequencies, body temperatures and other measurable factors.

4. Games Stations and Casinos

1. It is important for casinos and games stations to keep their customers relaxed, satisfied, and happy to enjoy their stay and spend more. This can be done by reducing the problems facing their customers and help them to be in a relaxed mode. The way this is handled now by gaming industry is to mitigate the problem

once it occurs. The manager tries to satisfy the customer to solve the problem and regain the trust of the customer.

2. The(Negnevitsky 2005)[24] system in this thesis can be used at casinos and games stations to help their managers take an action before customers begin to complain and to make them more comfortable. The system can detect the modes of customers based on the various factors studied and analyzed in this thesis.

The rest of this thesis organized as follows. Literature survey is presented in Chapter 2. In Chapter 3, is an explanation of the methodology used in this study; particularly, we will describe the various factors which impact the human emotions. In Chapter 4, the ANFIS model is presented and it is used to build the neuro-fuzzy model. In Chapter 5, we will present and analyze the results obtained by the application of the model. Conclusions and future work are presented in Chapter 6.

Chapter Two

Chapter Two

2. Literature Survey and Related Work

2.1. Overview

The system spans several areas of study including expert systems, fuzzy logic, neural networks, emotion and feeling measurements, and communication systems. Following is a brief literature survey of the areas covered in this thesis.

2.2. Literature Survey Related to Fuzzy Logic(FL)

Lotfi Zadeh (Zadeh 1965)[52] introduced fuzzy logic theory as a tool of building expert systems. Fuzzy logic based expert systems have been used in various areas of technology.

The measurements in our research are rather fuzzy because it is difficult to express them as crisp values for any situation or for any human posture. Every human being has his/her own measurements, but sometimes they have common values. Most of the people know that the normal human body temperature is 37 degrees, but in reality the normal temperature is a range of values rather than a crisp value. As (Sandhar 2005) [34]explained " the human body temperature in health is a range of values (36-37.5C)".

Hellmann (Hellmann2001) [15] noted that the fuzzy operations allow us to get more elements from the set (0,1).

A well-known problem in the medical area is that the characteristics of their results have no crisp values, so black and white, true, and false and zero and one are not good choices to implement the patient's status. Using fuzzy logic in medical area will be a perfect solution for this problem. Fuzzy logic enable expert systems to act like human in decision making problems as (Godil et al. 2011)[13] explained.

Godil (Godil et al. 2011)[13] showed that fuzzy logic has proved its ability to be used in several medical areas such as neuroscience, neurology, neurosurgery, psychiatry and psychology.

Kutuva (Kutuva et al. 2006)[21] developed a cutting machine to be used in surgical operation; the machine use fuzzy logic sets and rules to implement it. Fuzzy logic gives considerable success to be used in medical tools.

Fuzzy logic has been used in critical areas like a laser cutting machine that is used for cutting extra ordinary shapes, corners and slots. The surface roughness is one of the most important factors of evaluating the laser cutting, but it depends on many factors or properties of the material to be cut, the work piece thickness, the focal length, the stand for distance, the gas pressure, the cutting speed, and others. (Sivarao et al. 2009)[39]. These factors are best represented using fuzzy logic sets.

The common characteristic of all of these factors is that all of them have uncertain values, so a fuzzy model is a suitable way to deal with these factors.

Sivarao (Sivarao et al. 2009)[39] develop fuzzy based Graphical User Interface (GUI) for modeling of laser machining conditions . The most significant parameters required for the GUI development were identified. But these parameters have uncertain values, so they can be better defined as fuzzy variables. They used the Mamdani inference model to build their system using MATLAB. The use of GUI at MATLAB gives the researcher the chance to choose the membership function to be used. Also fuzzy model gives the opportunity to predict the output from a given input of the laser cutting machine.

2.3. Literature Survey Related to Artificial Neural Network (ANN)

The human expert systems have special characteristics; there are many probabilities, which could be used for their inputs and their outputs. So they need such a system that is able to accept a huge number of inputs and give a huge number of outputs. Krose (Krose 1996) [20] introduced Artificial Neural Network (ANN) as a concept that consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections.

ANN, a computational model, is used to implement some complex relations between some nodes. These nodes, and their associated activation functions, can receive inputs from other nodes and can do some functions (e.g. adding the weights) for the inputs and give, as an output that may act like an input to another activation function like Gaussian function, sigmoid function, hyperbolic function etc. . Figure (2 – 1) shows an example of ANN.

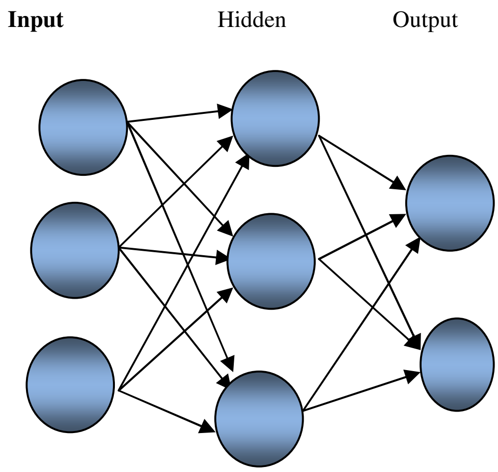


Figure (2-1) An example of ANN

ANN has the adaptability characteristic, which enhances its usability in decision making experts systems by making their decisions closer to the human decisions. (Negnevitsky 2005)[24]

Strano (Strano 2004)[43] introduced a new profiling system that is applicable even to a sole criminal fact, based on a neural network and on data mining, which is able to carry out a more sophisticated linking activity than the one of traditional database mainly to the adaptability property of ANN.

Abdul Hannan (Abdul Hannan, Bahagile & Manza 2010) [1] built an expert system using neural network and back propagation algorithm that helps doctors to diagnosis and inform medical prescriptions to their patients. They collected the disease information and symptoms from patients' histories, while doctors examining patients, and put them in an input vector of the neural network, and then they code it to zeros and ones for simplicity. Using back propagation algorithm the system was not satisfactory as per the result verified by the doctors, but it was a good trial that can be improved to get more performance of the expert system.

2.4. Literature Survey Related to Hybrid systems

Computational Intelligence (CI) became an important area in computer science (Chai et al 2009)[10]. It deals with uncertainty of data and it is more comfortable to be used than regular techniques for implementing databases; that is mainly because of its ability to train and train(Negnevitsky 2005)[24]. Chai mentioned that “Bezdek consider that CI is based on data provided by the operator rather than relying on “knowledge”, which solve problems through establishment of connections by training. CI is data-based intelligence”. (Chai et al 2009)[10].

According to Chai (Chai et al. 2009) [10], the branches of CI are the fuzzy logic as a low level structure of the brain and Neural Network as a high level structure for the brain. Although they are good techniques to be used as knowledge presenters, they have some weakness, so it is better to combine them in one technique like to from a hybrid structure.

Negnevitsky (Negnevitsky 2005) [24] asked an interesting question in his book, which is “how can we combine the German machines with the Italian love?” In our study, we need to combine two kinds of intelligence technologies. The first one is the Fuzzy Logic, which gives us the opportunity to represent the fuzzy data of the factors. The Second one is the Neural Network and its ability of learning from its inputs until it reaches the desired outputs with less tolerance error.

A hybrid system is the one that combines the two technologies Fuzzy Logic and Neural Network. A hybrid system will use the benefits of the two technologies and manipulates their weakness points. A hybrid system has two important characteristics, which make it more suitable to be used in this research. The first one is that it accepts the fuzzy data as its input and the second one is its ability to adapt and learn through training.

2.5. Literature Survey Related to Detecting and Analyzing Human Emotions

Human emotion detection and analysis has been an important field of study for scientists for long time. Scientists have focused on the ability to track the patients' emotions and responses (Silberstein 1990)[41].

Some scientists do their research according to external effects and for commercial objectives. "A method and apparatus for determining the level of attention of a subject to a visual stimulus such as a television commercial displayed on a screen so as to provide objective information designing the advertising presentation" (Silberstein 1990)[41]. Although they got good results using only Electroencephalogram (EEG) measurements, the method can get more specific results, when we use more factors to get the reflection of the television commercial videos displayed on the screen. As a result, if we know the exact emotional reflection of people, we can improve our way of presenting the merchandises.

Timmons and Scanlon (Timmons and Scanlon 2005)[45] introduced a new medical instrument that allows doctors to monitor their patients remotely.

They had used some sensors like insulin sensors, which help the doctors to keep track of their patients. They used the star network topology, because using a star network for medical sensor applications enables an external coordinator to be used with access to rechargeable power supply" (Timmons and Scanlon 2005)[45].

Although the previous research was a good research for monitoring the patients, the blood sugar and blood pressure factors can be used to build a good patients monitoring system.

Ohtaki et al. (Ohtaki, Suzuki & Papatefunou 2009)[28] stated "we focused on development of integrated wearable instrument which is capable of both indoor movements tracking and monitoring of concurrent psycho – physiologically indicated mental activity". In their research, they explained how EDAs (Electro Dermal Activities), heart rate, and vascular change could be acceptable emotional sensors.

EDA can be used to detect the human emotional response by measuring the skin humidity, which reflects the activity of the eccrine sweat glands. Once the human body reflects to some emotions, the sweat glands give their secretions, and the human skin will be wet, so it can conduct electricity, which implies that the human body has an emotional response.

In another study, related to equipments for monitoring the human emotions. Petrushin & Grove explained how "a system and method are provided for detecting emotional state using statistics". In their study, they extracted there parameters from a voice speech then they use an artificial neural network to get the related emotion. They used the artificial neural network as an adaptive classifier which is taught to recognize one emotional state from a finite number of emotional state (Petrushin & Grove 1995) [32].

A more recent study (Affective 2011) [3] introduced a wearable sensor that measures human emotion, where “the new sensor is capable of quantifying human emotions such as fear, excitement, stress, boredom etc”. The devise can be used for autism patients, which allows their doctors to monitor their motion, and temperature, which reflects their emotions.

Santosh and Scott (Santosh & Scott 2009) [35] announced a new project called “auto-sense” aimed at evaluating human’s addiction substances. They defined auto-sense as unobtrusively wearable wireless sensor system for continuous assessment of personal exposures to addictive substances and psychosocial stress as experienced by human participants in their natural environments”. They had connected some sensors to the human body and the others in a mobile phone.

They concluded that physiological stress and response are varied from person to person, and they are varied for the same person with respect to postures and physical activity. This variation implies that these kinds of projects should have the ability of learning to give true results.

Smoking, conversation and interruption also have their effects on the human emotions, this can be seen on the following diagrams (Santosh & Scott 2009)[35]. As shown in Figure(2-2) and Figure (2-3)

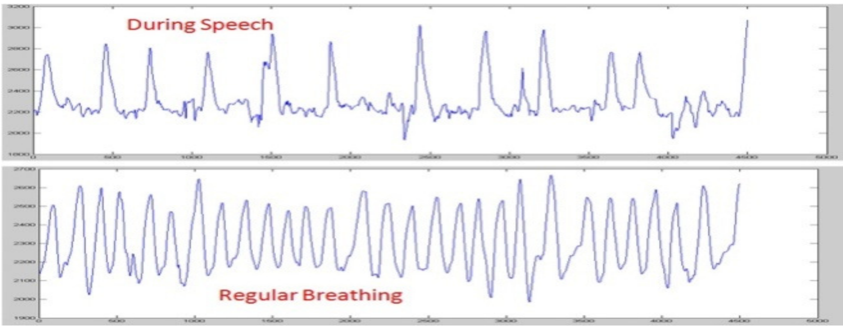


Figure (2-2) The conversation effects the breathing pattern

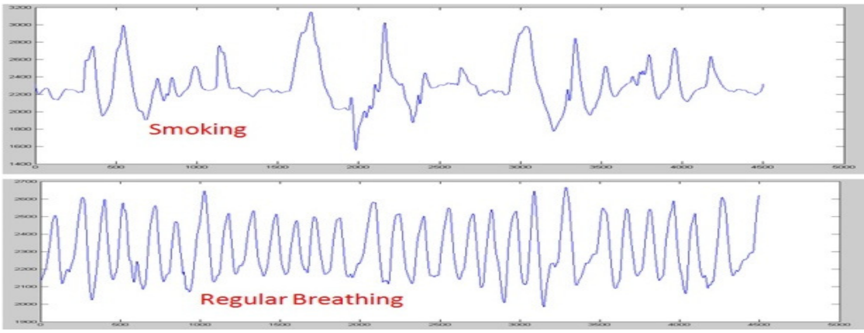


Figure (2-3) Shows the smoking effects the breathing pattern

Philips (Philips and ABN AMRO 2009)[33] announced a new device for a “Rationalizer” which consists of bracelet and an EmoBowl. The bracelet contains the sensors that contact the human body to give the emotional status by playing a lighting pattern on it or on the EmoBowl. This pattern will alert that it is better for him to take a rest or rethink his/her action.

Nie et al. (Nie et al. 2011) [25] have did a study that aims at finding the relationship between the Electroencephalography (EEG) and the human emotion. In their study, it was mentioned that EEG can be used to classify two kinds of emotions: negative and positive. They concluded that brain regions and frequency bands are most relevant to emotion.

(Yuen et al. 2011) [51] believed that the states of the brain changes as feelings change, therefore, EEG is suitable for the task of recording the changes in brain waves, which vary in accordance to feelings or emotions.

They used an EEG (brain Eaves) and EOG (electrodes for the detecting of eye blinks and eye movements. The signals were sampled at the rate of 256Hz.) and then they used a power point slide show to show the subjects some pictures to get the required emotions. A black screen is used to relax and prepare for the next emotion stimuli. The highest percentage was recorded for the sadness and neutral emotions, because they used a neural network to train the data. These emotions (Sadness and Neutral) have more accurate data for them, because a neural network is fully dependent on the input/output data.

Seo et al. (Seo and Lee 2010)[36] found a significant relationship between EEG measures and stress. They noticed that the Alpha activity had been decreased during the stress situation.

Leupoldt (Leupoldt A et al. 2010) [22] mentioned the emotion influence on respiration sensation, skin conductance response and the EEG. After they showed a set of pleasant, neutral and unpleasant pictures to the volunteers, they got interesting results, where the respiration rate, skin conductance response, and EEG measurements increased when volunteers had seen the pleasant and unpleasant pictures more than neutral pictures.

Kreibig (Kreibig 2010)[18] conducted a survey of many researches to find the relationship between Autonomic Nervous System (ANS) and the human emotions. ANS includes the cardiovascular, the electrodermal, and the respiratory responses. This survey shows that the ANS response appears in negative emotions clearer than in positive emotions.

Kreibig (Kreibig 2010) [18] collected his information from many research papers and he had summarized them in a powerful table that shows the impact of every factor and some negative and positive human emotions. This information is summarized in Table (2 – 1) for negative emotions and Table (2 – 2) for positive emotions.

Table 2-1) Overview of ANS* responses for Negative Emotions (Kreibig 2010) [18].

	Anger	Anxiety	Disgust Contamination	Disgust Mutilation	Embarrassment	Fear	Fear Imminent threat	Sadness Crying	Sadness Non-crying	Sadness Anticipatory	Sadness Acute
Cardiovascular											
HR	↑	↑	↑..	↓	↑	↑	↓	↑	↓	↑	↓
HRV	↓	↓	↑	..	(↓)	↓	(..)	..		(↓)	↑..
LF		(↑)				(..)					
LF/HF		(↓)		(↓)							
PWA						(↑)					
TWA	↓			(↑)							
LVET	↓		(↓)	(↓)		(↓)				↓↑	
HI	↑					(↑)					
PEP	↓		(↓)	(↓)	(↓)	↓				↓↑	↑
SV	↓↑	(..)	↓	(..)		↓				↓..	
CO	↓↑	(↑)	(↓)	(↓)	(..)	↑				↑..	
SBP	↑	↑	↑	↑	(↑)	↑				↑	(↓)
DBP	↑	↑	↑	↑	(↑)	↑				↑	↓..
MAP			↑	↑		↑					↓..
TPR	↑		↑	(..)	(↑)	↓				↑	
FPA	↓	↓	↓	↓		↓	(↓)	↓	↓	(↑)	↓
FPTT	↓	(↓)	↓↑	↓↑		↓	(..)			(↓)	↑
EPTT		(↓)	↓↑	↓↑		↓	(↓)				↑
FT	↓	(↓)	↓↑	↓↑		↓		↓	↓	↓↑	↓
HT	↓↑	(↑)	(↓)	(↓)			(↑)				
Electrodermal											
SCR	↑	↑	↑	↑		↑	↑				↓
nSRR	↑	↑	↑	↑		↑		↑	↓	↑	↑..
SCL	↑	↑	↑	↑	(↑)	↑	↓	↑	↓	↑	↓
Respiratory											
RR	↑	↑	↑	↑		↑		↑	↑	↓↑	↓↑
Ti	(↓)	↓	↓	..		↓..					(↓)
Te	(↓)	↓	↑	..		↓					(↓)
Pi	(↓)					(↑)					
Pe											(↓)
Ti/Tlot			(↓)	..		(↑)					
Vt	↓↑	↓	↓	(↓)		↓↑		↓	↑	↓↑	↓
Vi/Ti			(↓)	..							
V(rthyth)			(↑)	..						(↑)	
V(vol)	(↑)	(↑)	(↑)	..		↑					
Sighing		↓↑									
Ros	(↑)	(↑)	(↑)	..							
pCO_2		↓				↓					↑

Note. *Modal responses were defined as the response direction reported by the majority of studies (unweighted), with at least three studies indicating the same response direction. Arrows indicate increased (↑), decreased (↓), or no change in activation from baseline (–), or both increases and decreases between studies (↓↑). Arrows in parentheses indicate tentative response direction, based on fewer than three studies. Abbreviations: pause – respiratory pause time; depth – respiratory depth; exp – respiratory expiration time; insp – respiratory inspiration time; var – respiratory variability. For abbreviations of other physiological measures,

Table (2-2) Overview ANS* Responses for Positive Emotions
(Kreibig 2010) [18].

	Affection	Amusement	Contentmen t	Happiness	Joy	Antic Pleasure Visual	Antic Pleasure Imagery	Pride	Relief	Surprise	Suspense
Cardiovascular											
HR	↓	↓↑	↓	↑	↑	↓	↑	↓↑	↑..	↑	(↓)
HRV		↑	↓↑	↓	(↑)	(↑)		(..)			
LF				..							
LF/HF		(..)									
PWA											
TWA			(↑)								
LVET			(↑)	(..)	(↓)						
HI											
PEP		(↑)		(↑)	↓↑			(..)			
SV				(..)	(↓)						
CO		(↓)		(..)	..			(..)			
SBP		↑..	(↓)	↑	↑						
DBP		↑..	(↓)	↑	..						
MAP		↑..	(↓)	↑							
TPR		(↑)		(↑)	(..)			(..)			
FPA		(↓)	(..)	↑↓					(↑)		
FPTT				↑							
EPTT				↑							
FT		(..		↑		(↑)				↑↓	
HT											
Electrodermal											
SCR		↑	(..)			↑			↓		
nSRR		↑		↑	↑		↑		(↓)		(↑)
SCL	↑)	↑	↓	↑..	..	↑		↑	↓	(↑)	(↑)
Respiratory											
RR		↑	↓↑	↑	(↑)/	(↓)	↑		(↓)	↓..	(↑)
Ti		(↓)	(↑)	↓		(↑)	(↓)		(↑)		
Te			(↑)	↓		(↑)	(↓)		(↑)		(↓)
Pi				(↓)						(↑)	
Pe											(↓)
Ti/Tlot	(↑)	(↓)									(↑)
Vt		↓↑	↓↑	↓↑		(↓)	(↓)		(↑)	↑..	
Vi/Ti				(↑)							(↓)
V(rthyth)	(↑)	(↑)		(..)							(↓)
V(vol)	(↓)	(↑)		(↓)					(↓)		
Sighing									↓↑		
Ros		(↑)	(..)	(↑)		(..)					
pCO_2			↑				(↓)				

Chapter Three

Chapter Three

3. Human Emotions Analysis and Detection

3.1. Overview

The proposed system relies on the ability to correlate human emotions to some perceived measures of human physical and physiological responses to certain emotions. In the chapter we provide an overview of the predictability of human emotions using certain factors, which are known to impact the human emotions. Table (2-1) (in the previous chapter) has an extensive summary of such correlations. In this chapter, we provide a thorough analysis of these correlations.

3.2. Analyzing the Human Emotions

Human emotions are intangible things as has been explained above; however there are several factors which can be used to detect them (Kreibig 2010) [18]. In order to analyze the human emotion we should measure these factors, and use these measurements to detect and evaluate the human emotion at the time of measurement. Because the nature of emotions is rather fuzzy in their description, we will use fuzzy logic system to represent the emotions and the factors affecting them (Sivarao et al. 2009) [39]. Since the expressions of emotions are different for different people and different postures and modes, we will use artificial neural network to allow the system to adapt various individuals and situations (Subasi et al. 2006) [44].

Following is a brief description of the various factors and their potential impact on human emotions. Note that our interest in this study is to develop an automated model, which allow for the identification of the human emotions based on perceived measures of the factors discussed below.

1. Electroencephalography (EEG)

"EEG is a process used for recording of the electrical activity along the scalp, which is produced by the firing of neurons within the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20 – 40 minutes, as recorded from multiple electrodes placed on the scalp. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study". (Niedermeyer & Silva 2004) [26] EEG measurements are given in frequency ranges. Typical measures are the Alpha frequencies (13-15 Hertz per second), Beta frequencies (7.5 – 13.5 Hertz per second), Theta frequencies (2.5 – 8 Hertz per second), and Delta frequencies (less than 4 Hertz per second). EEG is known to have a direct relation to human emotions (Bos 2006) [7].

Alpha frequencies can be seen in all age groups but are most common in adults. Alpha frequencies were shown to manifest with closed eyes and relaxation, but they disappear normally with attention (Blume & Kaibara 1999) [4]

Beta frequencies are observed in all ages, and the presence of drugs, such as barbiturates and benzodiazepines, augment beta frequencies. (Emedicine 2011) [11]

While Theta frequencies can be seen in sleep at any age, Delta frequencies can be seen in deep sleep in adults as well as in infants and in children. (Emedicine 2011) [11]

EEG can be classified into many types Delta, Beta, Alpha, Theta …etc, and the two that are the most important ones are the Alpha and the Beta frequencies. Also (Bos 2006)[7] has found that Alpha waves increased at the positive emotions like the relaxation while Beta frequencies are increased at the negative emotions like stress or anger.

2. Heart Rate (HR)

“Heart rate is defined as the number of heartbeats per unit of time, typically expressed as beats per minute (bpm). Heart rate can vary as the body's need to absorb oxygen and excrete carbon dioxide changes, such as during exercise or sleep” (Emedicinehealth 2012) [12]. For adults a normal HR is 60 to 100 bpm. A rapid heart rate is usually defined as greater than 100 bpm; a slow heart rate; is usually defined as less than 60 bpm(Wikipedia 2011)[48], (Wilmore 2008)

[50]. HR impacts almost all positive and negative emotions as depicted in Table (2 – 1) and Table (2 – 2). For example, “anger” is accompanied with an increased heart rate, while “affection” is accompanied with a decreased heart rate.

3. Heart Rate Variability (HRV)

There are several frequency-domain measures, which pertain to HR variability at certain frequency ranges; and these measures are associated with specific physiological processes (Biocomtech 2011) [6].

HRV has three ranges of frequencies. The high range HF power spectrum is evaluated in the range from 0.15 to 0.4 Hz. The low range LF power spectrum is evaluated in the range from 0.04 to 0.15 Hz. The very low range VLF power spectrum is evaluated in the range from 0.0033 to 0.04 Hz (Biocomtech 2011) [6]. The correlation between HRV and the positive and negative emotions is summarized in Table (2 – 1) and Table (2 – 2). For example, HRV is decreased with “anxiety” and increased with “amusement”.

4. Pre-Ejection Period (PEP)

The Pre-Ejection Period (PEP) is defined as the period between when the ventricular contraction occurs and the semi lunar valves open and blood ejection into the aorta commences (Medical Dictionary 2011) [23]. Its normal range is from 0 ms to 1000 ms (Stevanoviæ et al. 2008) [42]. The impact of PEP on human emotions is outlined in (Kreibig 2010) [18], and summarized in Table (2 – 1) and Table (2 – 2). For example, PEP increases with “acute sadness”, while it experiences an increase or decrease with “joy”.

5. Stroke Volume (SV)

Stroke Volume is defined as the amount of blood pumped by the left ventricle of the heart in one contraction, and its normal range is from 0 ml to 250 ml (Stevanoviæ et al. 2008)[42]. The impact of Stroke Volume on human emotions is mentioned in (Kreibig 2010)[18], and summarized in Table (2 – 1) and Table (2 – 2). SV remains almost invariant for the positive emotions, while it responds activity to negative emotions e.g. it decreased with disgust, fear, and sadness.

6. Blood Pressure (BP)

Blood pressure is defined as the pressure exerted by circulating blood upon the walls of blood vessels, and is one of the principal vital signs. When used without further specification, blood pressure usually refers to the arterial pressure of the systemic circulation. During each heartbeat, BP varies between a maximum (Systolic Blood Pressure SBP) and a minimum (Diastolic Blood Pressure DPB) pressure. The mean BP, due to pumping by the heart and resistance to flow in blood vessels, decreases as the circulating blood moves away from the heart through arteries. Blood pressure drops most rapidly along the small arteries and arterioles, and continues to decrease as the blood moves through the capillaries and back to the heart through veins. Gravity, valves in veins, and pumping from contraction of skeletal muscles, are some other influences on BP at various places in the body. (Wikipedia 2011)[47].

BP can be measured by these two factors SBP and DBP. In our model, we will use both SBP and DBP as a means to detect human emotions. These two factors have different ranges, which will be listed down:

a. Systolic Blood Pressure (SBP)

Low SBP values are taken to be between 105 and 121, normal values are between 117 and 134, and high values are from 120 to 147, and very high values above 140 (Vaughns 2012) [46]. SBP is known to increase with "fear", "anxiety: See Table (2 – 1) and (2 – 2) for complete relationships between SBP and both negative and positive emotions.

b. Diastolic Blood Pressure (DBP)

While DBP minimum values could be between 60 and 75, the average values are between 77 and 87, and the maximum values are from 81 to 91(Vaughns 2012) [46]. DBP increase with "anger", 'anxiety", "disgust" and decreases with "acute sadness" Table (2 – 1 and 2 – 2).

7. Skin Conductance Response (SCR)

"The skin conductance response, also known as the electrodermal response (and in older terminology as "galvanic skin response"), is the phenomenon that the skin momentarily becomes a better conductor of electricity when either external or internal stimuli occur that are physiologically arousing" (Boucsein 1992)[8]. It is normal ranges from 2 to 20 ms. (Cacioppo et al. 1999)[9]. For example description of the relationship between SCR and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

8. Tidal Volume (Vt)

Tidal volume is the lung volume representing the normal volume of air displaced between normal inspiration and expiration when extra effort is not applied. Typical values are around 500ml or 7ml/kg bodyweight (Sherwood 2010) [37]. Its ranges can be classified as the following:

1. At quiet breathing rest 500 ml/breath.
2. At deep, slow breathing 1200 ml/breath.
3. At shallow, rapid breathing 120 ml/breath. (Sherwood 2010) [37]. For complete description of the relationship between Vt and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

9. Oscillatory Resistance (Ros)

Respiratory resistance and elastance are computed from pressure and flow recorded at the airway opening under the assumption that the contribution of the patient's respiratory muscles is nil, so that airway pressure coincides with transpulmonary pressure. Ros values are for children 0.53 and for adults 0.88 (Padiatr K 1983) [31]. For complete description of the relationship between Ros and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

10. Respiration Rate (RR)

Respiration Rate RR is a parameter, which is used in ecological and agronomical modeling. In theoretical production ecology and aquaculture, it typically refers to respiration per unit of time (usually loss of biomass by respiration per unit of weight), also referred to as relative respiration rate. In theoretical production ecology, biomass is expressed as dry weight, in aquaculture as wet fish weight. The respiration rate is dependent of species, type of tissue or organ studied, and temperature. (Haton et al. 2009) [14] Normal respiratory rate for adult is only 12 breaths per minute at rest, while most adults breathe much faster (about 15 – 20 breaths per minute) than their normal respiratory rate. (Normalbreathing 2011) [27]. For complete description of the relationship between RR and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

11. Nonspecific Skin Conductance Response (nSRR)

This factor is used to measure the moisture level of the skin but it appears spontaneously. (ed. Kaluer et al. 2011)[17] “The number of SCRs in absence of identifiable eliciting stimulus, and its typical values are 1 – 3 per min.” (Normalbreathing 2012) [27]. For complete description of the relationship between nSRR and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

12. Skin Conductance Level (SCL)

Skin Conductance is "a method of measuring the electrical conductance of the skin, which varies with its moisture level. This is of interest because the sweat glands are controlled by the sympathetic nervous system, so skin conductance is used as an indication of psychological or physiological arousal. (Osumi & Ohira 2010) [29]

Tonic level of electrical conductivity of skin, and its typical values are 2 – 20 ms. (Emedicinehralth 2012) [12]. For complete description of the relationship between SCL and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

13.Finger Temperature (FT)

In a room of normal temperature, when you are neither deeply relaxed nor stressed, starting hand temperature will be in the mild or high 80's. Finger temperature of 80°F is cool, 75° F is cold and 70° F or below is very cold; 90° F is warm. (Bio Medical 2012) [5]. For complete description of the relationship between FT and the negative and positive emotions, please refer to Table (2 – 1) and Table (2 – 2).

In fact, most of these measurements related to human beings are evaluated in an experimental sense and difficult to be common for all human beings. Each individual has his/her own characteristics that may be different than the characteristics of the ones possessed by others. Medical measurements cannot be analyzed and generalized using crisp data, black and white or (1) and (0) values. It seems to be a pool of values and all values are available for all people in various situations. Fuzzy logic provides a suitable environment to deal with this type of data. In Chapter 4, we will provide logical variables for each of the factors and define the fuzzy ranges for each of the variables.

Using fuzzy logic can help in analyzing these factors by giving each parameter linguistic variables such as (low, normal and high) for each factor. This kind of variable gives a huge range of values to cover all possible real values.

Some fuzzy rules will be created in the rule base system that is usually extracted and developed by experienced people. These rules will be applied to the inputs we have, and the deffuzzifier will convert the fuzzy output into crisp outputs.

The output of the deffuzzifier will be the pool of inputs for an artificial neural network that can take every input and send it to its activation functions to give it a weight and move to other layers and keep training to get the most reliable output and save that path for the next use. This kind of system is called hybrid system, which can be modeled using MATLAB system (Sivarao et al. 2009) [39].

3.3. Detecting Human Emotions

The measurable factors impact the human emotions in different way. Their impact also varies from one person to another. In addition, the amount of information presented by the various factors is enormous, thus drastically increasing the complexity of any model used to correlate the factors to the emotions. In order to simplify the model by reducing the amount of data required to evaluate the model, we make use of Fuzzy Logic, where the input parameters are quantified with linguistic variables such as low, normal, and high which represent a wide range of input values. Rules associated with fuzzy linguistic variables can be extracted by experts.

For example, an expert in the field may write a rule of the following form:

IF (FINGER TEMPERATURE is HIGH) and (DBP IS HIGH) THEN (person IS EXITED).

Rule of this type can be very useful to express the relations between various factors (INPUT) and various emotions (OUTPUT). While this method is simple, straightforward, and efficient, it lacks the adaptability to different conditions and to different categories of people responses to various stimuli. Besides, once the rules are built, the system cannot be trained to different environments. In Chapter 4, we will present a Fuzzy Logic model for the system under consideration.

Artificial neural networks allow the system to be adaptable and to be trained. In our model, a set of training data can be obtained from physical subjects where the emotions of the subjects are mapped against their measured factors. For example, the data will contain records like this. Each filed will have a crisp value (for example, a temperature value would be 37.8; a SBP will be 71; an anger output would be 0.7; relaxed value would be 0.6; and so on). The array of input values will be exactly like Table (3 – 1).

Table (3-1) An example of an input array

	Anger	Fear	Sadness Crying	Affection	Joy	Pride
EEG	10	4	1	12	12	3
HR	84	88	85	32	105	98
HRV	0.0033	0.0073	0.0043	0	0.1064	0.0173
PEP	0	88	0	0	857	392
SV	4	0	0	0	92	0
SBP	120	123	0	0	140	0
DBP	81	84	0	0	87	0
SCR	0.85	0.93	0	0	0	0
Vt	100	680	102	0	0	0
Ros	0.5	0	0	0	0	0
RR	15	19	16	0	15	0
nSRR	2	0	3	0	3	0
SCL	20	24	21	21	0	22
FT	65	69	66	0	0	0
HE	1	6	8	12	16	19

As discussed earlier in Chapter 1, the system can be used for personals conversations across the net or via cell phones. Various factors will be measured for participating individuals. The data taken will be provided as the inputs to the system; the system will analyze the input and apply some fuzzy rules in order to evaluate the emotion of the person at that instant of time. After evaluating the person's emotion anger, anxiety, fright or happiness, the system will detect this emotion for the person using the system.

The emotion prediction and detection system will eventually require the installation of the sensors and measurement devices. These devices can be installed in personal computers, laptops or mobile phones as well as they can be attached to human body parts such as wearable bracelets. In this research, we will focus on the software part of the model, i.e., the architecture of the neural fuzzy network, which receives the input from sensors and measurement devices. The actual implementation of the hardware part will be for future research and development. It is worthwhile mentioning, however, that there exists a wide range of sensors and measurement devices, for all types of measurements such as EEG, pulse rates and others. Some of these sensors have wireless capabilities, i.e., they transmit the measured information over the wireless network (Shnayder et al. 2005) [38]. For example, a sensor can be placed in a ring, which measures the pulse rate and transmits the measured data to the computer being used by the user.

Chapter Four

Chapter Four

4. Neuro-Fuzzy Model for Emotions Detection

4.1. Overview

There are a large number of human emotions experiences by human beings, which are manifested in varying degrees. However, the number of factors, which can be used to describe and detect these emotions, is limited and relatively small. According to (Kreibig 2010) [18] thirteen factors can be used to detect most of the human emotions. The model presented in this study will utilize these factors in a neuro-fuzzy network to detect and describe human emotion at any given time.

In this chapter we will present the structure of the model. It contains a full description of all the input membership functions, and the output, membership functions.

The rules used in our model will also be explained in this chapter. This chapter also includes an example, which is used to explain the main idea of the model.

4.2. Membership Functions of the Input Factors

It has been mentioned above that the factors impacting the human emotions, i.e., the input have rather fuzzy properties. Consequently, we will use linguistic variables to describe and implement these factors rather than crisp values as commonly used. Chapter 3 provided detailed description and definitions of these factors. In this chapter, we will discuss the means of implementing these factors and including them in a fuzzy/neural model. Note that we will only consider those emotions, which are known to be impacted by these factors. We also limit the study to the factors, which can be measured and monitored using sensors, and can be easily attached to human body or to computer IO devices (e.g., keyboard, mouse, camera, microphone, etc.). A summary of the factors and their impact on various emotions is summarized in Tables (2 – 1) and (2 – 2). An example of the input values is shown in Table (3 – 1).

1. Electroencephalography (EEG)

The EEG has four different wave ranges (Delta, Theta, Beta and Alpha), and each one relates to a specific human situation. Four linguistic variables will be used to implement the EEG and we adopt the same names for the linguistic variables, i.e., Delta, Theta, Beta, and Alpha.

The spectrum of the EEG frequencies ranges from 0 to more than 13 Hertz, and is distributed as follows.

The Delta type ranges from zero to 4 Hz and these slow waves appear at deep sleep. Theta type ranges from 2.5 to 8 Hz and these are normal waves and are observed during sleep mode for all ages. Beta type ranges from 7.5 to 13.5 Hz and these waves can be augmented by drugs. Alpha ranges will be from 13 to 15 Hz and these waves appear with closed eyes and relaxation while they disappear with open eyes and stress situation

(Emedicine 2012) [11]. Each of the EEG linguistic variables is represented by a member function (mf) in the ANFIS model (Artificial Neural Fuzzy Inference System), as shown in Figure (4 – 1). The choice of the member function type has a direct impact on the performance of the model. So we will choose several member functions for each linguistic variable and compare the results. Figure (4- 1) shows the input member functions using the Gaussian membership function. More on the input member functions will be provided later in this chapter.

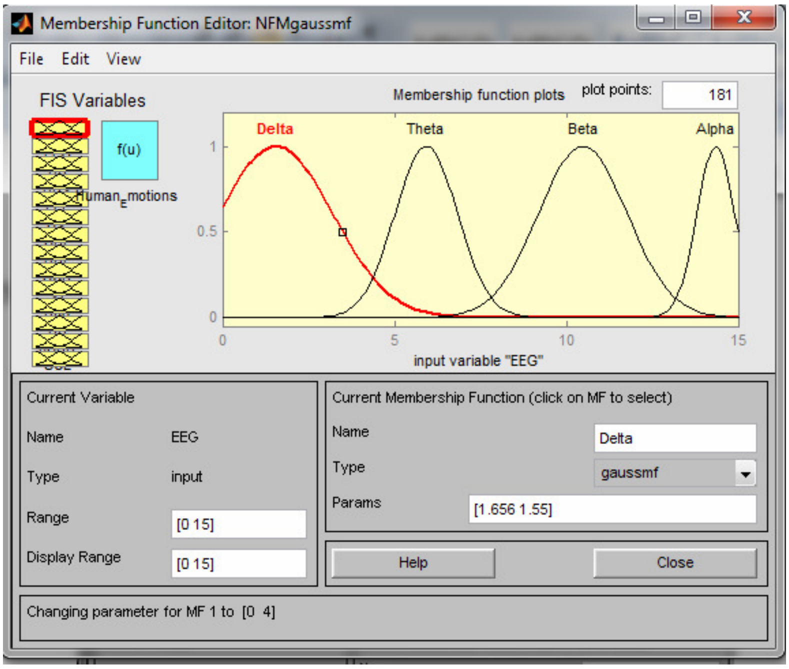


Figure (4-1) Shows the input membership function for EEG

2. Heart Rate (HR)

Measured heart rate ranges from a low 20 beats per minute (bpm) to 120 bpm. Three heart rate ranges are identified, and categorized with fuzzy linguistic variable low (LHR), normal (NHR) and high (HHR). Low HR values range from 20 to 70 bpm; Normal values range from 45 to 100 bpm, and High values range from 84 to 120 bpm. The LHR, NHR, and HHR linguistic variables and their corresponding member functions (Gaussian membership function) in the ANFIS model are shown in Figure (4 – 2).

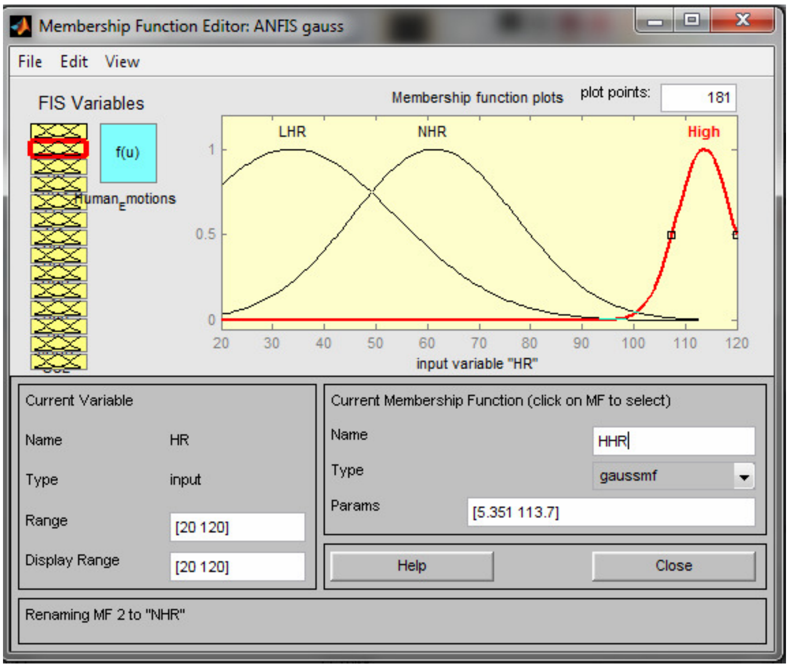


Figure (4-2) Gaussian Input Mmebrship functions of the HR

3. Heart Rate Variability (HRV)

Three linguistic variables are used to implement HRV, namely very low frequency (VLF), low frequency (LF) and high frequency (HF). VLF values range will be from 0.001 to 0.04 Hz, LF values range will be from 0.0033 to 0.043 Hz, and HF values will be from 0.035 to 0.16 Hz. For the impact of HRV on human emotions, please refer to Table (2 – 1, 2 – 2). Figure (4 – 3) shows the HRV input functions (Gaussian membership function).

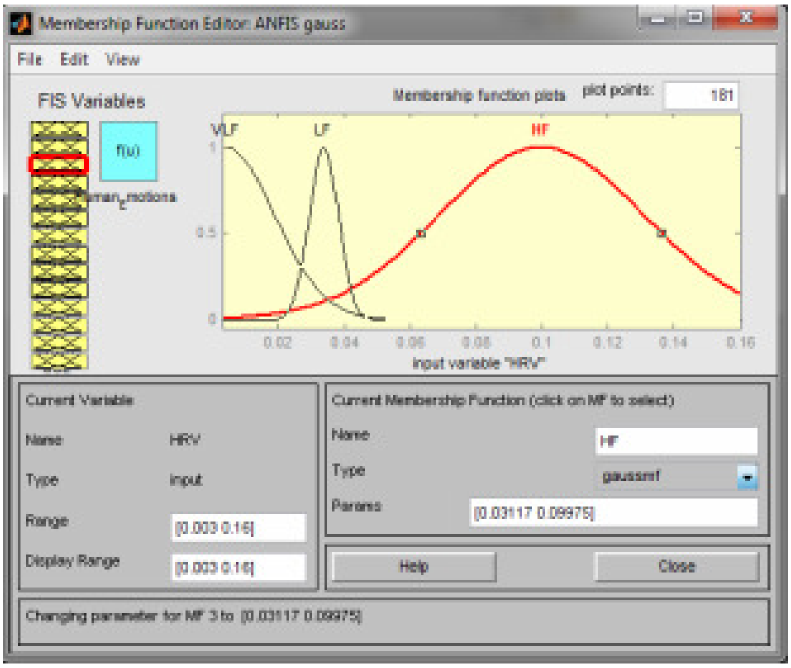


Figure (4-3) Gaussian Input Membership Function of HRV

4. Pre-Ejection Period (PEP)

Three linguistic variables are used to implement PEP, namely low (LP), normal (NP), and high (HP). Low values range will be from 0 to 800 ms, normal values range will be from 0 to 1000 ms and high values range will be from 500 to 1100 ms. For the impact of PEP on human emotions, please refer to Table (2 -1, 2- 2). Figure (4 – 4) Shows the PEP Gaussian input functions.

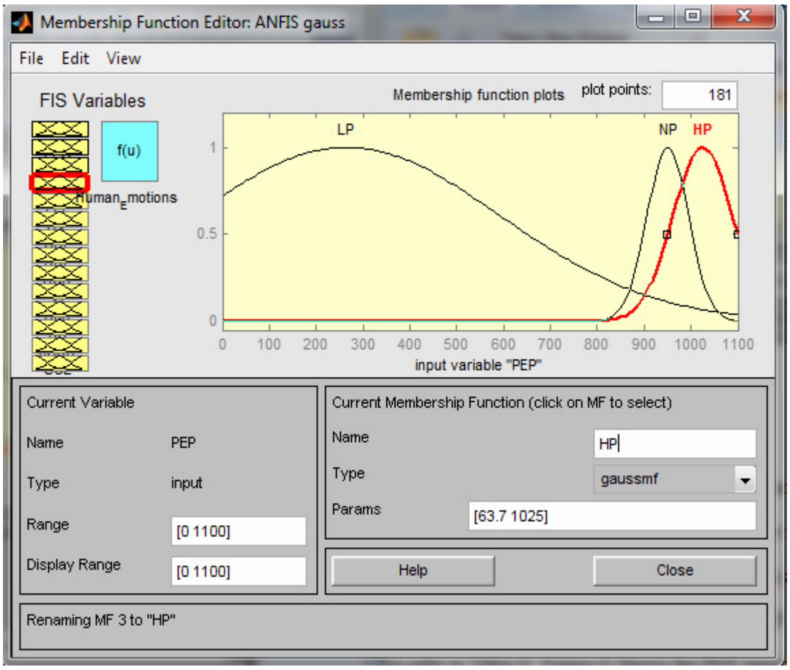


Figure (4-4) Gaussian Input Membership Function of PEP

5. Stroke Volume (SV)

Three linguistic variables are used to implement stroke volume, namely low (LSV), normal (NSV), and high (HSV), see Figure (4 – 5). Low values range will be from 10 to 144 ml, normal values range will be from 10 to 250 ml and High values range will be from 240 to 400 ml. For the impact of SV on human emotions, please refer to Table (2 – 1, 2 – 2). Figure (4 -5) Shows the SV input functions.

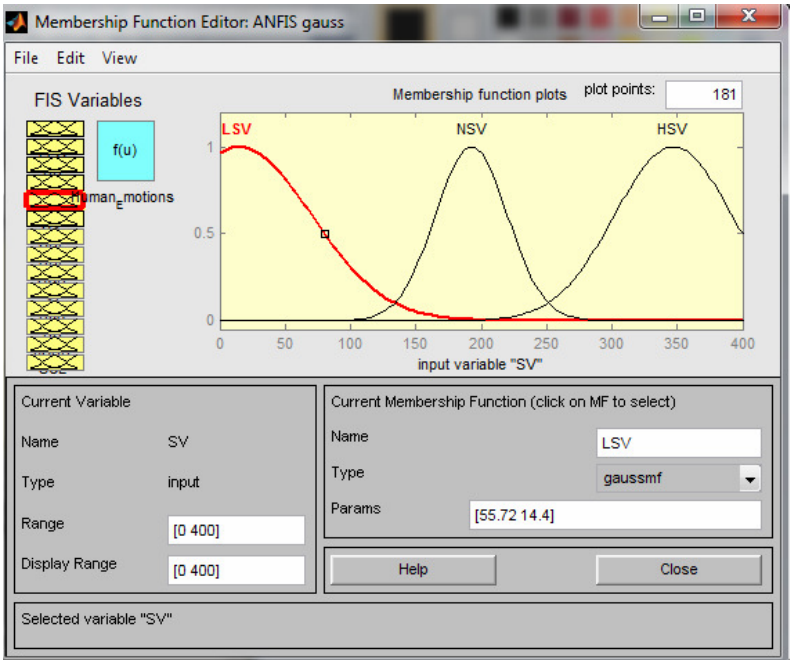


Figure (4-5) Gaussins Input Membership Function of the SV

6. Blood Pressure (BP)

Blood pressure is characterized by systolic (SBP) and diastolic (DBP) blood pressure. We use both measures in this model as factors impacting the human emotions.

1. Systolic Blood Pressure (SBP)

Three linguistic variables are used to implement SBP, namely low (LSBP), normal (NSBP), and high (HSBP). Low values range will be from 100 to 121, normal values range will be from 110 to 134 and high values range will be from 120 to 147. For the impact of SBP on human emotions, please refer to Table (2 – 1, 2 – 2). The member functions Gaussian for LSBP, NSBP, and HSBP are shown in Figure (4 – 6).

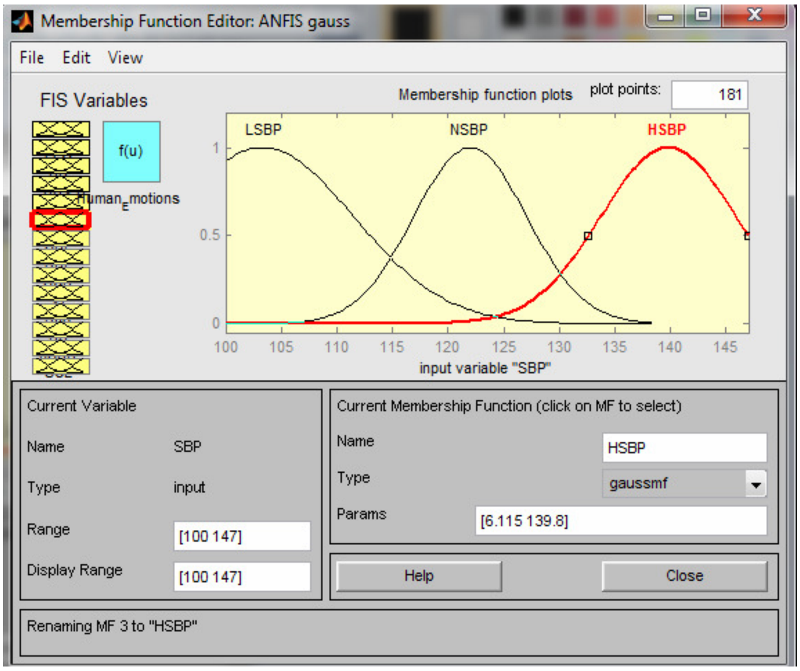


Figure (4-6) Gaussian Input Membership Function of the SBP

2. Diastolic Blood Pressure (DBP)

Three linguistic variables are used to implement DBP namely low (LDBP), normal (NDBP) and high (HDBP). Low values range will be from 60 to 73, normal values range will be from 77 to 87 and high values range will be from 81 to 91. For the impact of DBP on human emotions, please refer to Table (2 – 1, 2 – 2) (Vaughn's 2011)[46] (Kreibig 2010)[18].The Gaussian member functions for LDBP, NDBP, and HDBP are shown in Figure (4 – 7).

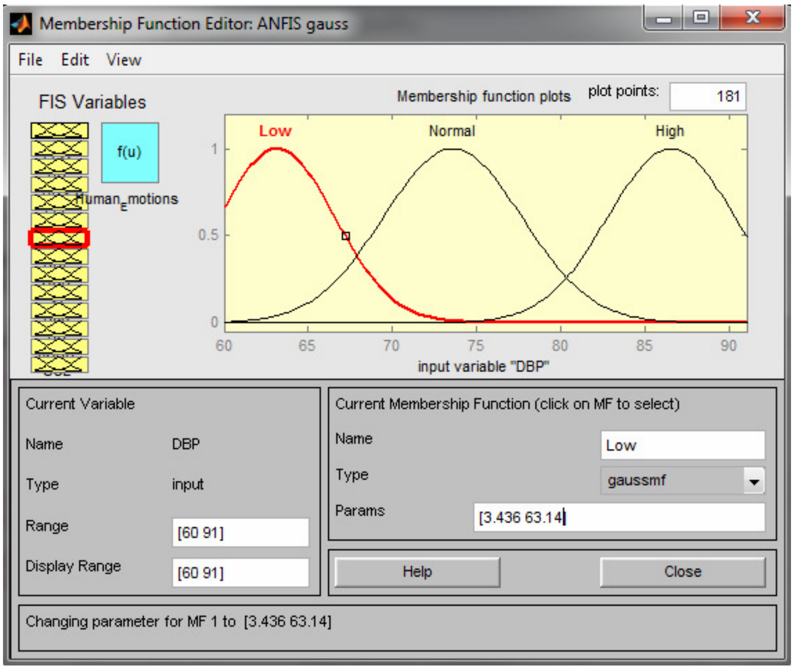


Figure (4-7) Gaussian Input Membership Function of the DBP

7. Skin Conductance Response (SCR)

Three linguistic variables are used to implement SCR namely low (LSCR), normal (NSCR) and high (HSCR). Low values range from 0 to 0.2 ms, normal values range from 0.1 to 1 ms and high values range from 0.85 to 1.5 ms. For the impact of SCR on human emotions, please refer to Table (2 - 1, 2 – 2).The Gaussian member functions for LSCR, NSCR, and HSCR are shown in Figure (4 – 8).

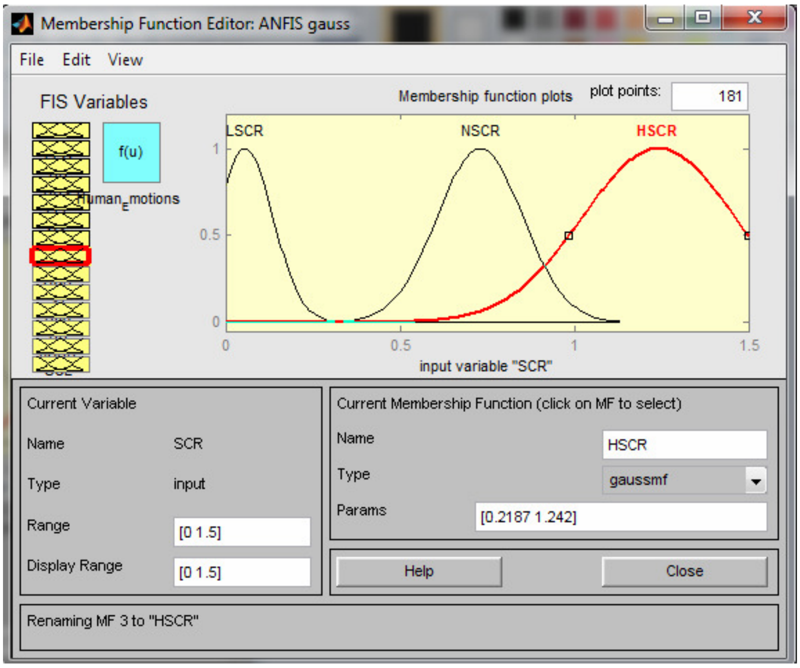


Figure (4-8) Gaussian Input Membership Function of the SCR

8. Tidal Volume (Vt)

Three linguistic variables are used to implement Vt namely rapid breath (RapidL), quiet breath (QuietN) and deep breath (DeepH). RapidL values range from 100 to 150 ml/breath, QuietN values range from 200 to 750 ml/breath and DeepH values range from 600 to 1200 ml/breath. For the impact of Vt on human emotions, please refer to Table (2 – 1, 2 – 2).The member functions for RapidL, QuietN, and DeepH are shown in Figure (4 – 9).

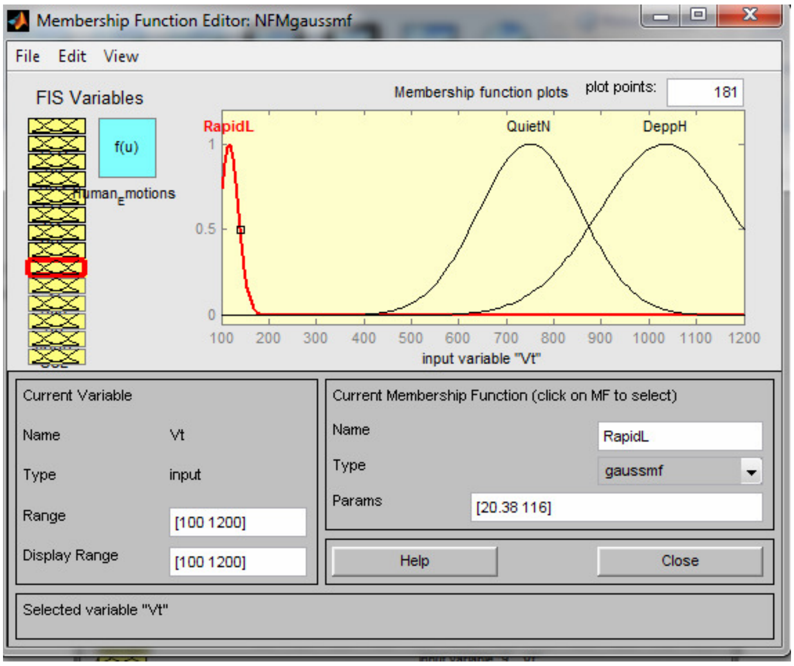


Figure (4-9) Gaussian Input Membership Function of the Vt

9. Oscillatory Resistance (Ros)

Three linguistic variables are used to implement Ros namely low (LRos), normal (NRos) and high (HRos). Low values range from 0 to 0.49, normal values range from 0.4 to 0.88 and high values range from 0.5 to 1. For the impact of Ros on human emotions, please refer to Table (2 – 1, 2 – 2).The Gaussian member functions for LRos, NRos, and HRos are shown in Figure (4 – 10).

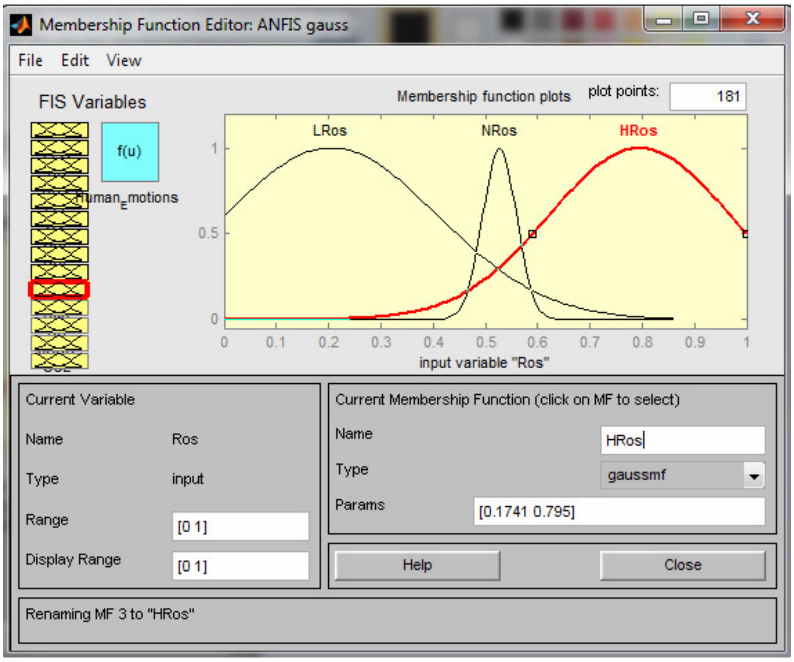


Figure (4-10) Gaussian Input Membership Function of the Ros

10.Respiration Rate (RR)

Three linguistic variables are used to implement RR namely low (LRR), normal (NRR) and high (HRR). Low values range from 5 to 10 breath/min, normal values range from 7 to 23 breath/min and high values range be from 15 to 25 breath/min. For the impact of RR on human emotions, please refer to Table (2 – 1, 2 – 2).The Gaussian member functions for LRR, NRR, and HRR are shown in Figure (4 – 11).

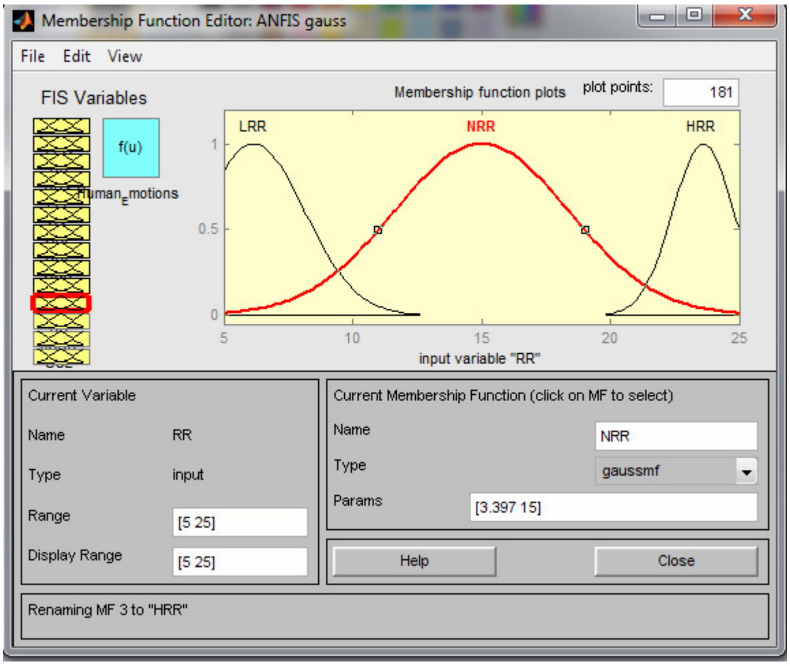


Figure (4-11) Gaussian Input Membership Function of the RR

11.Nonspecific Skin Conductance Response (nSRR)

Three linguistic variables are used to implement nSRR namely low (LnSRR), normal (NnSRR) and high (HnSRR). Low values range from 0 to 2 per min, normal values range from 1 to 3 per min and high values range from 2 to 5 per min. For the impact of nSRR on human emotions, please refer to Table (2 – 1,2 – 2).The Gaussian member functions for LnSRR, NnSRR, and HnSRR are shown in Figure (4 – 12).

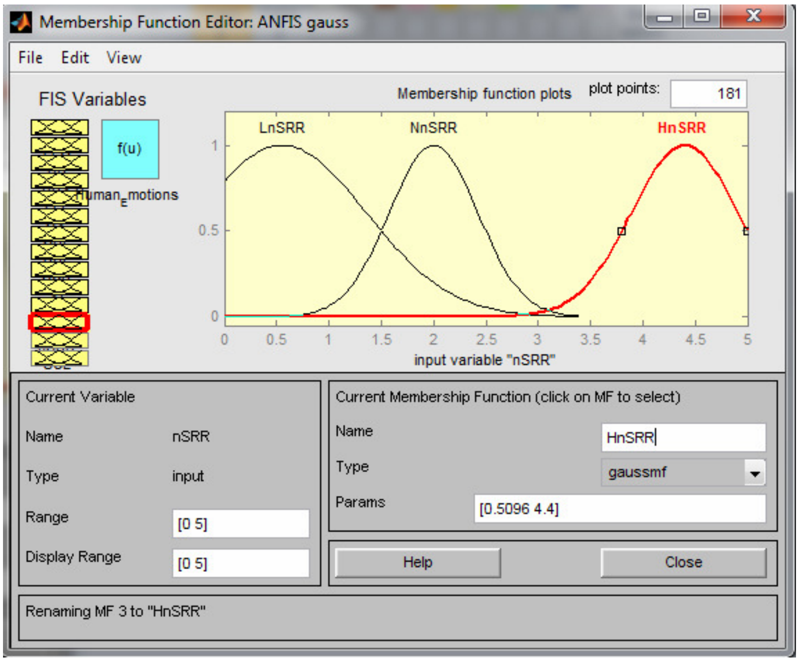


Figure (4-12) Gaussian Input Membership Function of the nSRR

12.Skin Conductance Level (SCL)

Three linguistic variables are used to implement SCL namely low (LSCL), normal (NSCL) and high (HSCL). Low values range from 0 to 2 ms, normal values range from 2 to 25 ms and high values range from 20 to 25 ms. For the impact of SCL on human emotions, please refer to Table (2 – 1, 2 – 2).The member Gaussian functions for LSCL, NSCL, and HSCL are shown in Figure (4 – 13).

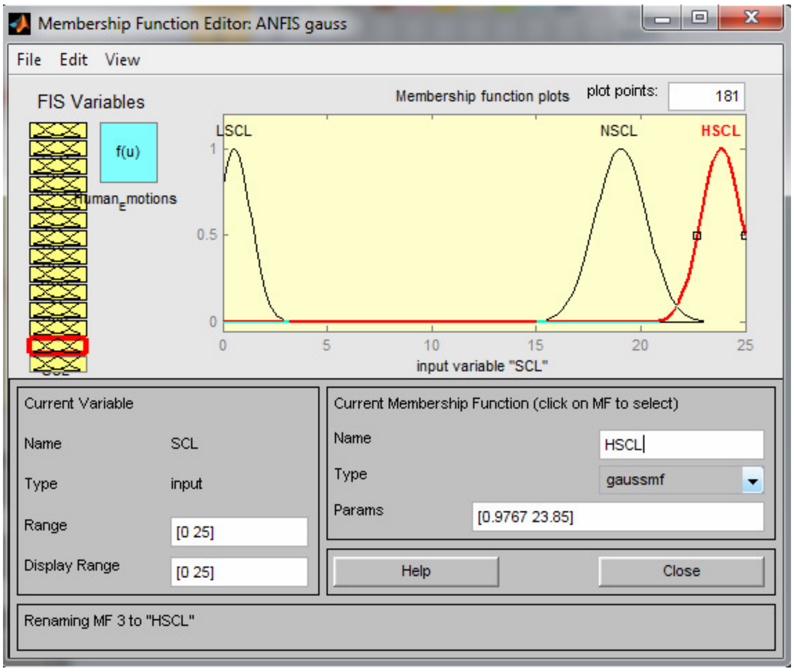


Figure (4-13) Gaussian Input Membership Function of the SCL

13.Finger Temperature (FT)

Three linguistic variables are used to implement FT namely low (LFT), normal (NFT) and high (HFT). Low values range from 65 to 75-° F, normal values range from 75 to 85-° F and high values range from 80 to 90-° F. For the impact of FT on human emotions, please refer to Table (2 – 1, 2 – 2). The Gaussian member functions for LFT, NFT, and HFT are shown in Figure (2 – 14).

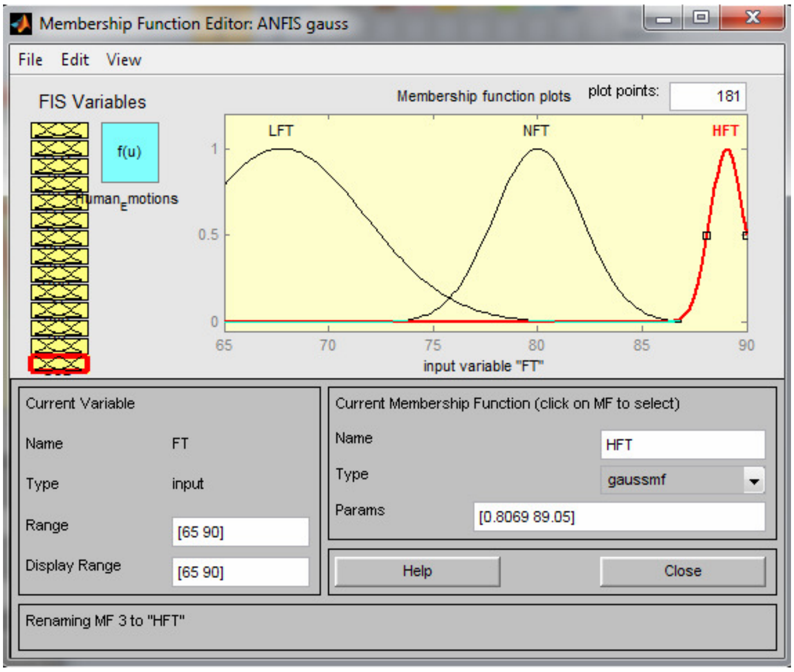


Figure (4-14) Gaussian Input Membership Function of the FT

The following Table (4 – 1) summarizes the input variables and their corresponding fuzzy linguistic variables and ranges

Table (4-1) Linguistic Variables and Ranges

Input Factor	**Input Factor**	**Ling. Var 1**	**Ling. Var 2**	**Ling. Var3**	**Ling. Var 4**
EEG	Delta 0 -4 Hz	Beta 2.5 – 8 Hz	Theta 7.5 – 13.5 Hz	Alpha 13 – 15 Hz	Delta 0 -4 Hz
HR	LHR 20 – 70 bpm	NHR 45 – 100 bpm	HHR 84 – 120 bpm	LHR 20 – 70 bpm	------
HRV	VLF 0.001 - 0.04 Hz	LF 0.0033 - 0.043 Hz	HF 0.035 – 0.16 Hz	VLF 0.001 - 0.04 Hz	------
PEP	LP 0 – 800 ms	NP 0 – 1000 ms	HP 500 – 1100 ms	LP 0 – 800 ms	------
SV	LSV 10 – 144 ml	NSV 10 – 250 ml	HSV 240 – 400 ml	LSV 10 – 144 ml	------
SBP	LSBP 100 – 121	NSBP 110 – 134	HSBP 120 – 147	LSBP 100 – 121	------
DBP	LDBP 60 – 73	NDBP 77 – 87	HDBP 81 – 91	LDBP 60 – 73	------
SCR	LSCR 0 – 0.2 ms	NSCR 0.1 – 1 ms	HSCR 0.85 – 1.5 ms	LSCR 0 – 0.2 ms	------
Vt	RapidL 100 – 150	QuietN 200 – 750 ml/breath	DeepH 600 – 1200	RapidL 100 – 150 ml/breath	------

	ml/breat h		ml/breath		
Ros	LRos 0 – 0.49	NRos 0.4 – 0.88	HRos 0.5 – 1	LRos 0 – 0.49	------
RR	LRR 5 – 10 breath/m in	NRR 7 – 23 breath/min	HRR 15 – 25 breath/min	LRR 5 – 10 breath/min	------
nSRR	LnSRR 0 – 2 per min	NnSRR 1 – 3 per min	HnSRR 2 – 5 per/min	LnSRR 0 – 2 per min	------
SCL	LSCL 0 – 2 ms	NSCL 2 – 25 ms	HSCL 20 – 25ms	LSCL 0 – 2 ms	------
FT	LFT 65 – 75 ° F	NFT 75 – 85 ° F	HFT 80 – 90 ° F	LFT 65 – 75 ° F	------

4.3. **Output Membership Functions**

The output of the model will be the human emotions as shown in Table (4 – 2). In particular, there are twenty-two different emotions impacted by the factors outlined in the previous section. These emotions are anger, anxiety, disgust contamination, disgust mutilation, embarrassment, fear, fear imminent threat, sadness crying, sadness non-crying, sadness anticipatory, sadness acute, affection, amusement, contentment, happiness, joy, antic pleasure visual, antic pleasure imagery, pride, relief, surprised and suspense. Each emotion represents one output function. In the artificial neural fuzzy system the output can be based on one of two models, namely the Mamdani and the Sugeno models (Negnevitsky 2005) [24]. However, the MATLAB ANFIS system supports only the Sugeno model; The Sugeno model allows the output function to be represented as a single point constant or a linear function of the input factors. The Mamdani model allows output to be represented as nonlinear function such as Gaussian, Sigmoid and others. We will use the Sugeno model in this study. This choice does not impact the overall results of the model, since both models equally represent the real system, differing only in the performance of the models; the Mamdani model being the more expensive in terms of time complexity. (Negnevitsky 2006) [24] For Sugeno model, we use both a single point constant and linear outputs models. We will compare the results for both output types in Chapter 5.

Using the Sugeno model, each output is represented by exactly one fuzzy rule. In other words, the system will have exactly N rules, where N is the number of distinct outputs. In the single point constant output model, each output is represented by one contestant value. If the output ranges from 0 to 1, then the constant values can be distributed over the range 0 to 1. The distribution can be uniform across all output emotions, or it can be a non-uniform distribution. In our model, we use constant representation ranging from 1 to 22 as shown in Table (4 – 2). Figure (4 – 15) shows the constant output model.

Table (4-2) Values of output constant membership functions (human Emotions)

Output Function	Constant Value
Anger	1
Anxiety	2
Disgust Contamination	3
Disgust Mutilation	4
Embarrassment	5
Fear	6
Fear Imminent threat	7
Sadness Crying	8
Sadness Noncrying	9
Sadness Anticipatory	10
Sadness Acute	11
Affection	12
Amusement	13
Contentment	14
Happiness	15
Joy	16
Antic Pleasure Visual	17
Antic Pleasure Imagery	18

Pride	19
Relief	20
Surprise	21
Suspense	22

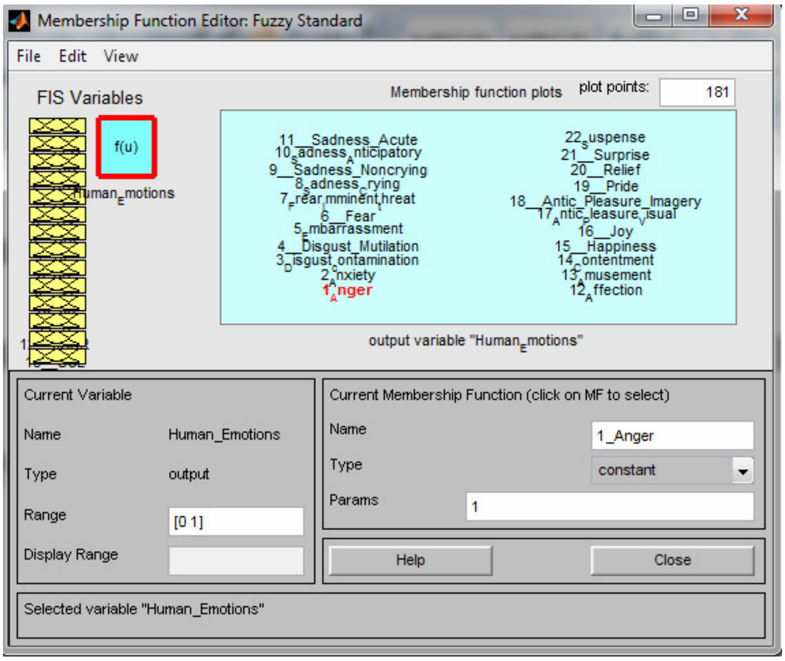


Figure (4-15) Sugeno Constant Membership Functions

The initial choice of the output values does not have an impact on the accuracy of the model, because the training part of model adjusts the final output values based on the training data. In fact, this is exactly why the ANFIS model is used in this study. Particularly, it allows the model and the output functions to be adjusted based on a set of training data. The training data and the training iterations adjust the output values such that they correlate more properly to the input factors. In Chapter 5, we will show how different sets adjust the output values in different ways.

The linear output format allows each output to be represented as a linear function of the input factors. The format of a linear output is as shown in formula (4 - 1)

$$Y = \sum_{i=0}^{n} a_i X_i + z \quad (4\text{-}1)$$

Where a_0, a_1, …. , a_i are constant parameters and X_0, X_1, X_i, are input variables. For constant functions, the values of a_0, a_1, …. , a_i are equal zero so the value of Y = z (constant value). For the linear function model, the values of $a_0, a_1, \ldots, a_i$ can be entered to the linear model at the ANFIS editor, while $X_0, X_1, \ldots X_i$ are the input values related to the desired output value. Every value for output level Y_i from each rule is weighted by the firing strength weight w_i of the rule. For example for an "AND" rule with input X_1 and X_2 the firing strength is shown at formula (4 - 2)

$$\mathbf{Wi} = \cap\left(\mathbf{F1(X1)}, \mathbf{F2(X2)}\right) \quad (4\text{-}2)$$

Where F_1 and F_2 are the membership functions for input 1 and input 2. The final output of the system is the weighted average of all rules output values computed as shown in formula (4 - 3).

Final output $= \dfrac{\sum_{i=0}^{n} \mathbf{X_i W_i}}{\sum_{i=0}^{n} \mathbf{W_i}}$, n= number of inputs.

(4-3)

The easiest way to visualize first order Sugeno systems is to think of each rule as defining the location of a moving singleton. That is the singleton output spikes can move around in a linear fashion in the output space, depending on what the output is.

4.4. Rules

The correlation between the input and the output variables is done through a set of fuzzy rules. Each rule uses AND/OR connectors to connect various input factors with a particular output emotion. Table (4 – 3) shows the relation between the input factors and the various emotions.

Using the information presented in Table (2 – 1, 2 – 2), we build twenty two rules as shown in Table (4 – 3). We use MATLAB GUI interface of the ANFIS model, to edit the rules. For example, rule 1 shows all the input factors, which produce the “anger” emotion. The anger emotion is given the constant output 1. In rule 1, it is shown that the Beta EEG frequencies and the high heart rate values among others produce the anger emotion. The “anxiety’ emotion represented by constant value (2) is produced by rule #2. The EEG impacts these emotions when the EEG frequency is anything but Alpha; and so on.

Table (4-3) Rules for ANFIS Neuro-Fuzzy Model

Rules
1. If (EEG is Beta) and (HR is HHR) and (HRV is LF) and (PEP is LP) and (SV is LSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT) then (Human_Emotions is Anger) (1)
2. If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (SV is NSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT) then (Human_Emotions is Anxiety) (1)
3. If (EEG is not Alpha) and (HR is HHR) and (HRV is HF) and (PEP is LP) and (SV is LSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT) then (Human_Emotions is Disgust_contamination) (1)
4. If (EEG is not Alpha) and (HR is LHR) and (PEP is LP) and (SV is NSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is NRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is HFT) then (Human_Emotions is Disgust_Mutilation) (1)
5. If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (PEP is LP) and (SBP is HSBP) and (DBP is HBP) and (SCL is HSCL) then (Human_Emotions is Embarrassment) (1)

6. If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (PEP is LP) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (RR is HRR) and (SCL is HSCL) and (FT is LFT) then (Human_Emotions is Fear) (1)
7. If (EEG is not Alpha) and (HR is LHR) and (HRV is LF) and (SCR is HSCR) and (SCL is LSCL) then (Human_Emotions is Frear_Imminent_threat) (1)
8. If (EEG is not Alpha) and (HR is HHR) and (HRV is LF) and (Vt is RapidL) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT) then (Human_Emotions is Sadness_Crying) (1)
9. If (EEG is not Alpha) and (HR is LHR) and (HRV is VLF) and (Vt is RapidL) and (RR is HRR) and (nSRR is LnSRR) and (SCL is LSCL) and (FT is LFT) then (Human_Emotions is Sadness_Noncrying) (1)
10. If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (PEP is LP) and (SV is LSV) and (SBP is HSBP) and (DBP is HBP) and (Vt is RapidL) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is HFT) then (Human_Emotions is Sadness_Anticipatory) (1)
11. If (EEG is not Alpha) and (HR is LHR) and (HRV is HF) and (PEP is HP) and (SBP is LSBP) and (DBP is LDBP) and (SCR is LSCR) and (Vt is RapidL) and (RR is HRR) and (nSRR is HnSRR) and (SCL is LSCL) and (FT is LFT) then (Human_Emotions is Sadness_Acute) (1)
12. If (EEG is Alpha) and (HR is LHR) and (PEP is HP) and (SBP is LSBP) and (DBP is LDBP) and (SCL is HSCL) then (Human_Emotions is Affection) (1)
13. If (EEG is not Alpha) and (HR is LHR) and (HRV is HF) and (PEP is HP) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is NFT) then (Human_Emotions is Amusement) (1)
14. If (EEG is not Alpha) and (HR is LHR) and (HRV is HF) and (SBP is LSBP) and (DBP is LDBP) and (SCR is NSCR) and (Vt is DeepH) and (Ros is NRos) and (RR is HRR) and (SCL is LSCL) then (Human_Emotions is Contentment) (1)
15. If (EEG is Alpha) and (HR is HHR) and (HRV is VLF) and (PEP is HP) and (SV is NSV) and (SBP is HSBP) and (DBP is HBP) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is HFT) then (Human_Emotions is Happiness) (1)
16. If (EEG is Alpha) and (HR is HHR) and (HRV is HF) and (PEP is HP) and (SV is LSV) and (SBP is HSBP) and (DBP is NDBP) and (RR is HRR) and (nSRR is HnSRR) and (SCL is NSCL) then (Human_Emotions is Joy) (1)
17. If (EEG is Alpha) and (HR is LHR) and (HRV is HF) and (SCR is HSCR) and (Vt is DeepH) and (Ros is NRos) and (RR is LRR) and (SCL is HSCL) and (FT is HFT) then (Human_Emotions is Antic_Pleasure_Visual) (1)
18. If (EEG is Alpha) and (HR is HHR) and (Vt is RapidL) and (RR is HRR) and (nSRR is HnSRR) then (Human_Emotions is Antic_Pleasure_Imagery) (1)
19. If (EEG is not Alpha) and (HR is HHR) and (HRV is LF) and (PEP is NP) and (SCL is HSCL) then (Human_Emotions is Pride) (1)
20. If (EEG is not Alpha) and (HR is HHR) and (SCR is LSCR) and (Vt is DeepH) and (RR is LRR) and (nSRR is LnSRR) and (SCL is LSCL) then (Human_Emotions is Relief) (1)
21. If (EEG is not Alpha) and (HR is HHR) and (Vt is DeepH) and (RR is LRR) and (SCL is HSCL) and (FT is HFT) then (Human_Emotions is Surprise) (1)

22. If (EEG is not Alpha) and (HR is LHR) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) then (Human_Emotions is Suspense) (1)

4.5. Explaining the Model: An Example

In this section we will demonstrate the idea of the model by showing a complete example with only two factors and each factor has three linguistic variables such as (Low, Normal and High), and two human emotions as output membership functions. We will build three models. The first model is a simple fuzzy logic model, where the system employs only fuzzy logic system to detect human emotions using two input factors. The second model is based on a simple neural network, where we show how the system can be trained to adjust the relations between input factors and output human emotions using a set of training data. The third model is a hybrid combination of both fuzzy logic and neural networks. The hybrid model allows the set of fuzzy rules to be adjusted and the system to be trained.

1. Fuzzy Logic Example

Two input factors are used to illustrate the emotion detection system. In particular, we use the Heart Rate HR and the systolic blood pressure SBP. Each factor is represented by three linguistic variables (low, normal, and high) as shown in Figures (4 – 16), and (4 – 17).

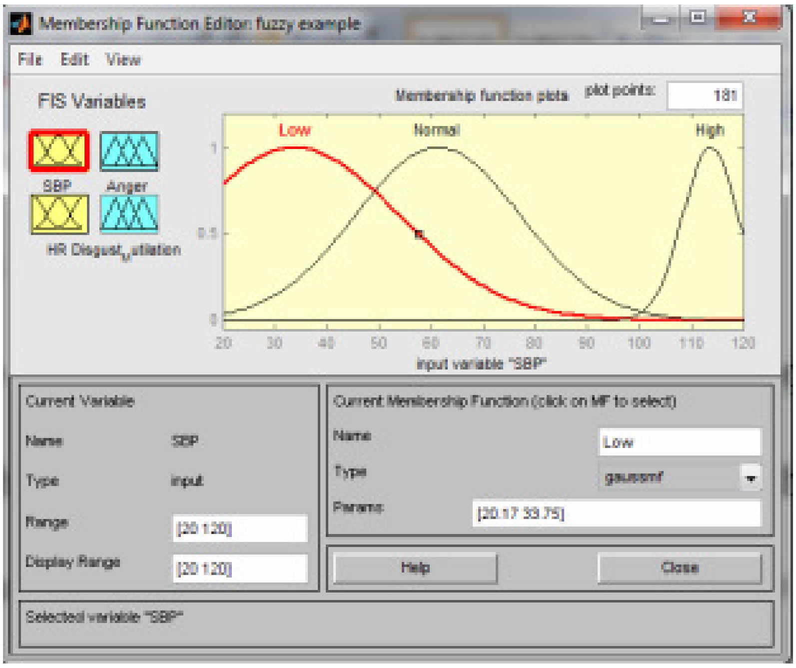


Figure (4-16) Input Membership Functions of SBP in the Fuzzy Model

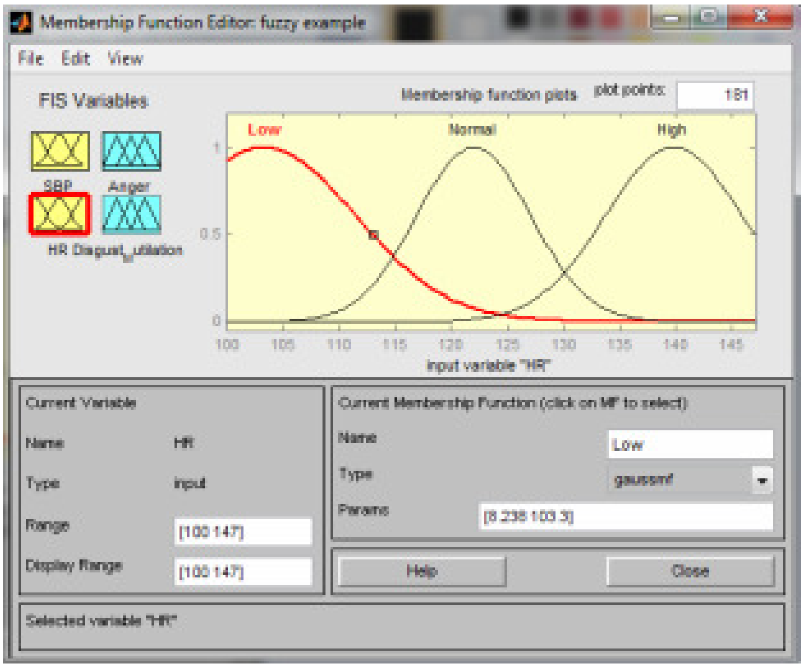


Figure (4-17) Input Membership Functions of the HR for the Fuzzy Model.

The human emotions chosen for this model are “anger” and “disgust mutilation”; also, each output has three linguistic values, as shown in Figure (4 – 18, 4 – 19).

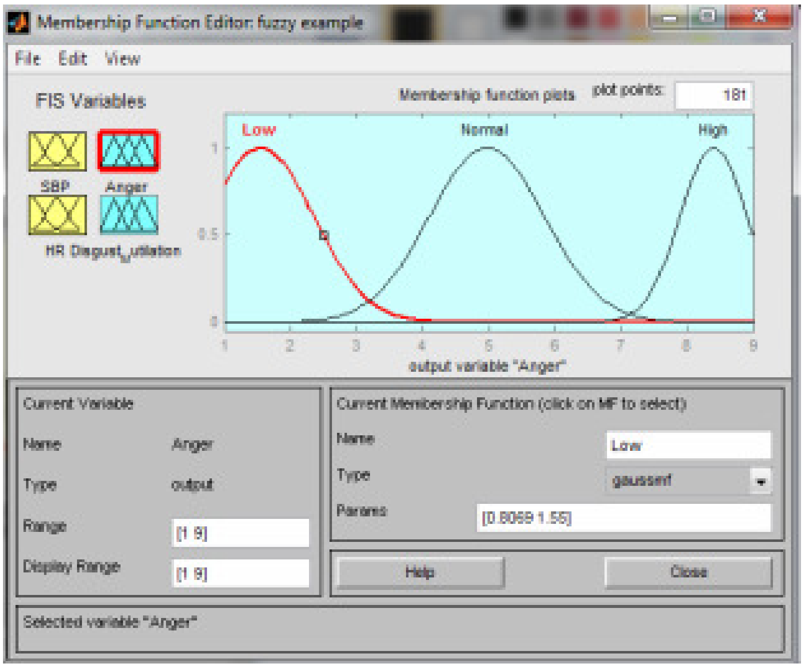


Figure (4-18) Gaussian Output Membership Function of the Anger Emotion

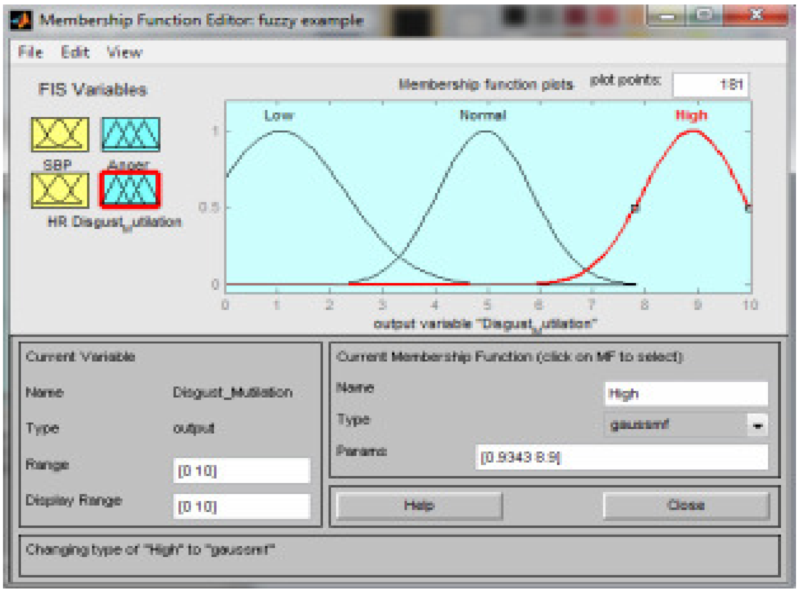


Figure (4-19) Gaussian Output Membership Function of the Disgust Mutilation

This fuzzy logic system has nine rules according to the HR and SBP impacts on anger and Disgust Mutilation emotions. Using Table (2 – 1) and Table (2 – 2), we observe that HR value increased at anger and decreased at Disgust Mutilation. SBP value increased at both of these human emotions.

Using the rule editor provided by the Fuzzy logic toolbox in MATLAB and the information extracted from Table (2 – 1) and Table (2 – 2) we can define the nine rules for the model; see Table (4 – 4). Each rule connects one or two input functions to generate one output. For example, rule #1 states that a low systolic blood pressure together with a low heart rate reveal a normal value of the disgust mutilation emotion.

Table (4-4) Rules for the ANFIS Example Model

Rules
1. If (SBP is Low) and (HR is Low) then (Anger is Low)(Disgust_Mutilation is Normal) (1)
2. If (SBP is Low) and (HR is Normal) then (Anger is Low)(Disgust_Mutilation is Normal) (1)
3. If (SBP is Low) and (HR is High) then (Anger is Normal)(Disgust_Mutilation is Low) (1)
4. If (SBP is Normal) and (HR is Low) then (Anger is Low)(Disgust_Mutilation is Normal) (1)
5. If (SBP is Normal) and (HR is Normal) then (Anger is Normal)(Disgust_Mutilation is Normal) (1)
6. If (SBP is Normal) and (HR is High) then (Anger is High)(Disgust_Mutilation is Low) (1)
7. If (SBP is High) and (HR is Low) then (Anger is Normal)(Disgust_Mutilation is High) (1)
8. If (SBP is High) and (HR is Normal) then (Anger is High)(Disgust_Mutilation is High) (1)
9. If (SBP is High) and (HR is High) then (Anger is High)(Disgust_Mutilation is Low) (1)

The surface tool in fuzzy logic toolbox can be used to plot the relation between the input factors and one of the output factors. Figure (4 – 20) shows the relation between the “anger” emotion and the two input factors, the SBP and HR. the figure shows that high SBP and High HR values result in high “anger” values.

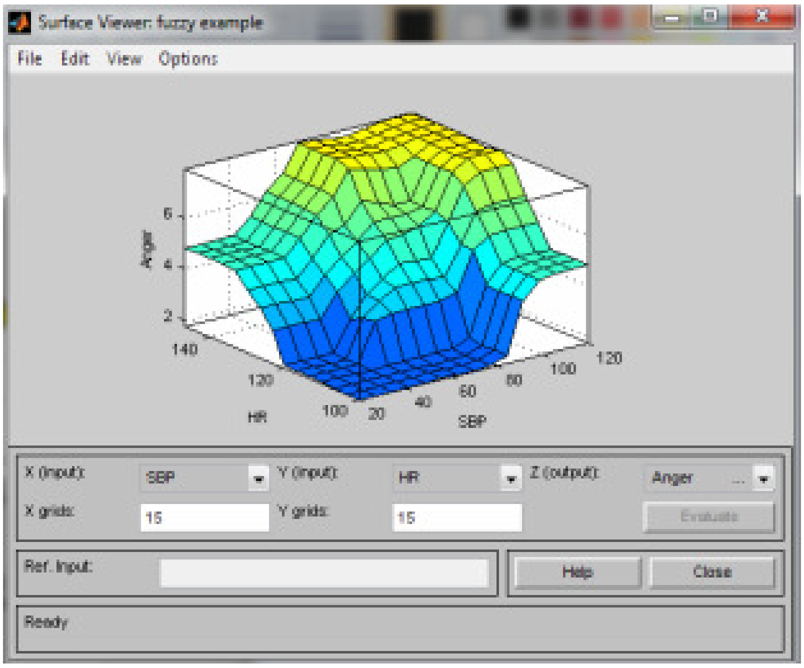


Figure (4-20) Relation between the “Anger” Emotion and HR and SBP

Figure (4 – 21) shows the relation between both input factors and the disgust mutilation emotion.

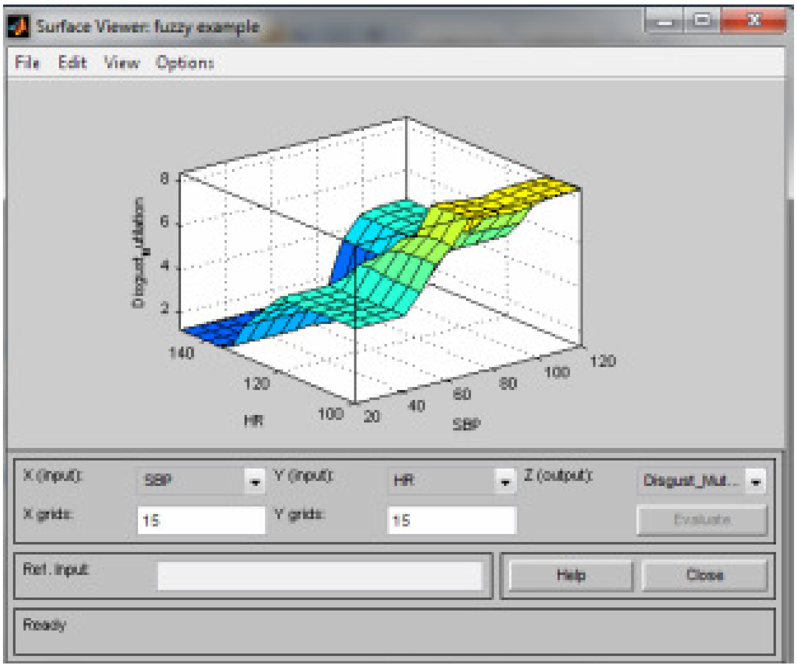


Figure (4-21) Relation the "Disgust Mutilatior" Emotion and HR and SBP

For the complete system with 13 input factors and 22 emotions, the number of rules will be very large. With an average of three linguistic variables per input factors, the number of rules will be on the order of 3^{13}. In addition to the large complexity of the system, this method (fuzzy logic) is not flexible and cannot be trained to adjust the rules based on available data from the field.

In other words, the developed rules by the experts in the field cannot be modified or adjusted in a systematic manner. If the end user is not satisfied with the current rules mix, he/she must reconsider the rule formulation. This is a tedious process and given the large number of rules, it will be prohibitive. Therefore, we will consider the more adaptive method, particularly the artificial neural networks as a means of correlating the input factors to the output human emotions.

2. Neural Network Example

Artificial neural network (ANN) have been developed in the context of expert systems to solve those expert systems, which require training in order to be tuned and adapted to real life data (Kröse & Smagt 1996)[19]. ANN systems accept crisp data as input, rather than fuzzy variables or fuzzy values. Next, we develop an ANN example for the system under consideration, with both HR and SBP input factors and anger and disgust mutilation emotions as output.

A two-layer feed-forward network with 20 sigmoid hidden neurons and linear output neurons, can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.

The network will be trained with Levenberg-Marquardt backpropagation algorithm, unless there is not enough memory, in which case scaled conjugate gradient backpropagation (Kröse & Smagt 1996)[19] will be used.

The example includes two sets of input data, for HR and SPB factors. The first set of data relates to HR and contains data elements starting from the low value of 20 until the highest value of 120 with an increment of 2. The training data for the SBP input ranges from the lowest value 100 had been incremented by 1 to the maximum value of 147. The output set includes six values (1, 2, 3, 4, 5, and 6) which correspond to the emotion “anger” and “disgust mutilation”. The structure of the ANN for the given example is given in Figure (4 – 23). We use the training data sets to train the network. After one epoch of training, the system achieves a regression value of 0.49355, and after five epochs of training, it achieves a regression value of 0.095269. The results of the system training are shown in Figures (4 -23, 4 – 24).

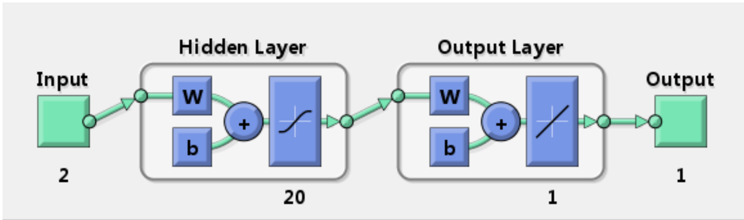


Figure (4-22) The Structure of the ANN of the example model

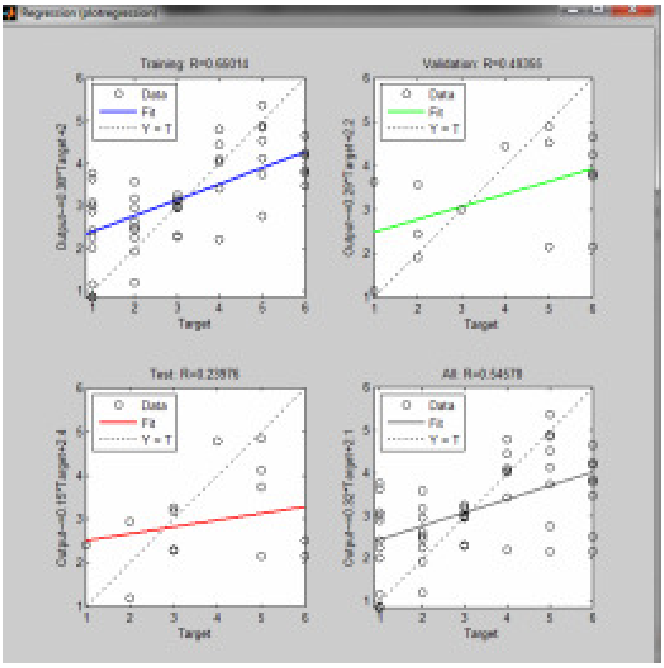


Figure (4-23) Trained data at ANN model After 1 Epoch

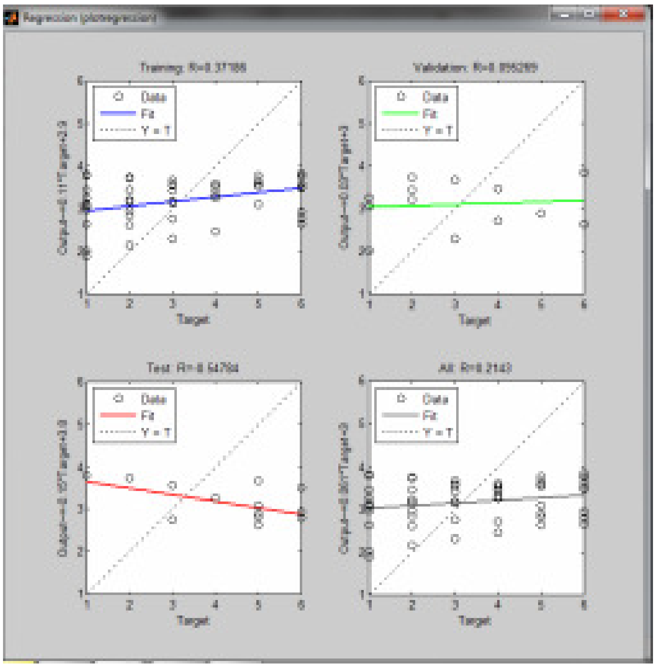


Figure (4-24) Trained data at ANN model After 5 Epoch

Contrary to the fuzzy logic system, the ANN is able to learn and adjust the parameters of the system in response to the training data. However, the Neural Network input should be crisp and does not accept fuzzy data (Negnevitsky 2005)[24]. For a system with 13 factors and large data ranges for each factor, the system needs a very large number of crisp data. In our system, the size of the training data will be prohibitive. Beside, the ANN prevents the user from representing the data in a fuzzy manner, which is more suitable for the system under consideration. As such, we will present the more practical method, which combines both ANN and fuzzy logic.

3. Adaptive Neuro-Fuzzy Inference System (ANFIS) Example

This example was developed using MATLAB ANFIS editor. An ANFIS model allows the user to create fuzzy rules to represent the relation between the input factors and the output emotions (as in the fuzzy logic model) and in the meantime to use crisp data to train the model (as in the ANN model). The ANFIS model thus combines the power of the fuzzy logic representation and the power of ANN training.

There are several variations of the model, which have a direct impact on the outcome, and on the results. Namely the choice of the training data, the choice of the input membership functions, and the choice of output model. In this example, we experiment with three types of input member functions, namely the Gaussian function, the dual Gaussian function, and the Sigmoid function.

The most important measure of the model is the final error value after training the model, which is defined as the difference between the obtained output value and the expected output value; obviously, the smaller the error, the better is the model. It has been noticed that the error value is impacted by many factors. In the final model, which is represented in Chapter 5, we will present six different variations of the model and compare the results based on the obtained error value.

The training data for the model has three columns. The first two columns represent the two input factors (SBP and HR). The third column represents the output as a constant value. The output column is constructed using the Sugeno method, which implies a constant value corresponding to the two input values. The input values should be based on the best judgment of the expert in the field and will be utilized to train the model and adjust the fuzzy rules specified for the model.

As noted earlier, ANFIS editor has some constrains, and the first one is that the input file of Fuzzy Inference System (FIS) should be in Sugeno type not Mamdani type.

The second constrain is that output membership function cannot be duplicated in the set of rules, so the number of the rules will be equal to the number of the output membership functions. For this example, we will do two output membership functions for simplicity. The first one is for the “anger” and the second one is for “disgust mutilation.” Our two rules are

1. If (HR is Low) and (SBP is High) then (Human_Emotions is Disgust_Mutilation)

2. If (HR is High) and (SBP is High) then (Human_Emotions is Anger)

The third constrain for ANFIS editor at that the output membership function should be either constant or linear. We use the value 1 for ‘anger’ and 2 for ‘disgust mutilation’, for both constant and linear functions.

In the final model, we use three training data sets and we use both output functions (constant and linear). However, for the input membership functions, we will use the function, which has the best training results. In this example, we demonstrate the impact of various membership functions and set the model for one of these functions. Figure (4 – 25) shows the structure of a neural/fuzzy system with 2 inputs and 1 output. The model has five layers; following is a description of each layer.

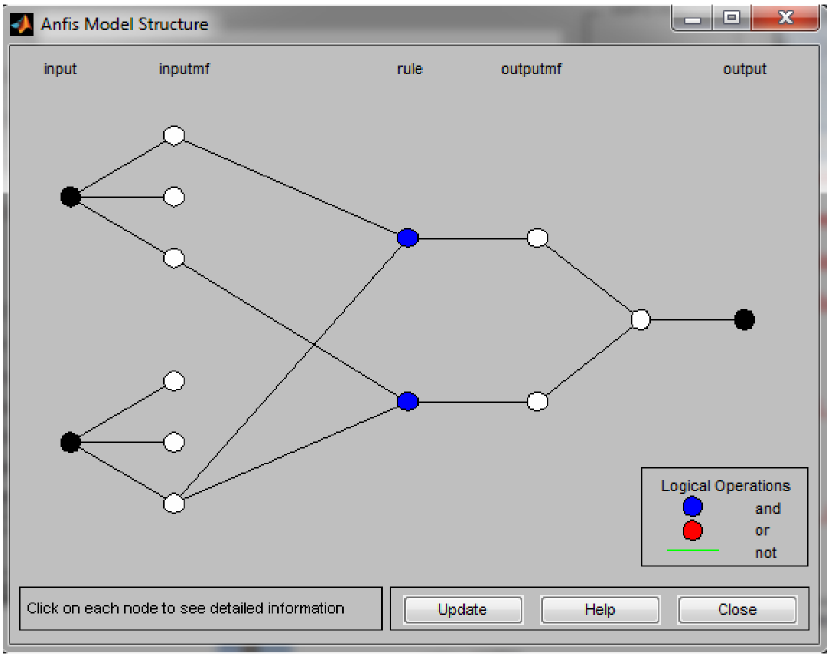


Figure (4-25) Structure of a Neuro-Fuzzy system with 2 Inputs and 1 Output

There are five layers in the ANFIS model structure. The first layer is the input layer which takes the raw crisp data from the user, which is received in the form of input array then sends it as input values to the second layer. (Negnevitsky 2005)[24]

The second layer is the fuzzification layer, which takes the crisp value from the first layer and converts them to the proper fuzzy set according to fuzzy membership functions for the linguistic variables, which will be the input to the third layer. The third layer is the rule layer. At this layer, each rule relates to one output value according to the Sugeno constrains. The rules are executed using the received from the neurons, which is activated by the input membership function.

The fourth layer (normalization) is activated when each neuron receives inputs from all neurons in the rule layer, and calculates the normalized firing strength of a given rule. (Negnevitsky 2005)[24]

The last layer is the defuzzification layer, which calculates the weighted consequent value of a given rule. Finally a single summation neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output. (Negnevitsky 2005)[24]

4.6. ANFIS Input Member Functions

ANFIS editor provides several input membership functions. The Gaussian and Sigmoid functions had been chosen in this model because of their ability to deal with small numbers. On the other hand, the linear functions like trapezoid function could not deal with small numbers. A brief description of the membership functions used in this model is presented below.

Formula (4 - 4) shows the trapezoid function, which has at its denominator (b-a); when a and b hold small numbers the result will be undefined number, and the system may become unstable during training, when the value of (b) approaches the value of (a), i.e., a=b. Hence, the trapezoid function will not be used in this model.

$$f(x,a,b,c,d) = \begin{cases} 0, & x \leq a \\ \dfrac{\mathbf{x}-\mathbf{a}}{\mathbf{b}-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{\mathbf{d}-\mathbf{x}}{\mathbf{d}-a} & \mathbf{c} \leq \mathbf{x} \leq \mathbf{d} \\ 0, & \mathbf{d} \leq \mathbf{x} \end{cases} \qquad (4\text{-}4)$$

The Gaussian function on the other hand formula (4 - 5) allows more realistic representation of the data. The Gaussian function provides a symmetric “bell curve” shape that quickly falls towards plus/minus infinity (Wikipedia 2012) [49]. The parameter (σ) is the position of the center of the peak, (c) is the width of the bell part of the curve, and X is the input vector. Formula (4 - 6) shows the Gaussian membership function provided by MATLAB ANFIS editor.

$$sig(x, \sigma, c) = e^{\frac{-(x-c)2}{2\sigma 2}} \quad (4\text{-}5)$$

(4-6)

ANFIS editor provides another input function, namely the ‘gauss2mf’ function, which is a combination of two Gaussian functions. Gauss2mf needs four parameters as shown at formula (4 - 7).

$$Y = gauss2mf(X, [sig1\ \ c1\ sig2\ \ c2]) \quad 4\text{-}7)$$

Where sig1, and sig2 are given by formula (4 - 5). The parameter c1 and c2 control the width of the two bells.

The third function is ‘psigmf’ which is a product of two sigmoid shaped member functions as shown at formula by (4 - 9). The sigmoid function for the input vector X depends on two parameters (a) and (c) as given in formula (4 - 8). And the membership function psigmf is given in formula (4 - 8) which is a product of two sigmoid formulas, with parameters a1, c1, a2, and c2.

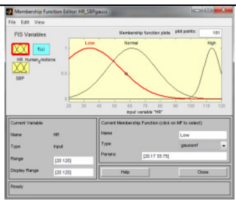
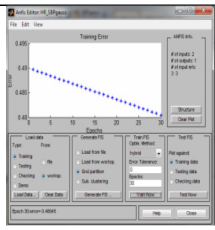
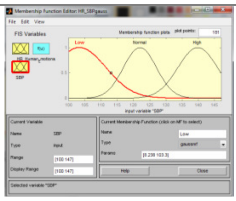
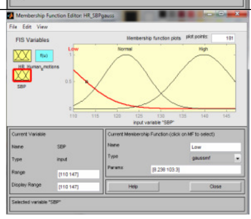
Y= psigmf(X, [a1,c1,a2,c2]) (4 - 8)

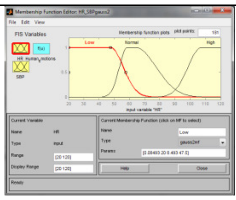
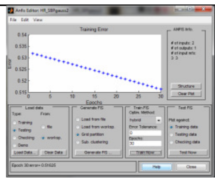
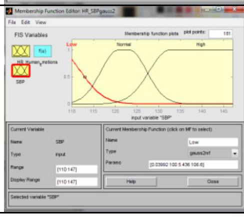
$$F(x, a, c) = \frac{1}{1 + e^{-a(x-c)}} \qquad (4 - 9)$$

The models presented in this study use the gaussmf, the gauss2mf, and the psigmf functions, these functions are built in functions in MATLAB ANFIS editor. The trapezoid function will not be used for the reasons explained above, namely the inability of trapezoid function to deal with small parameters in the denominator of the function (b-a).

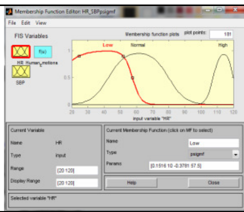
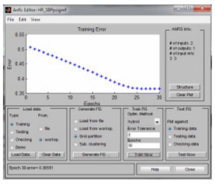
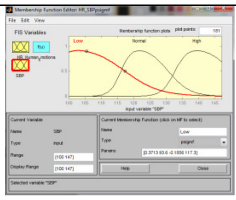
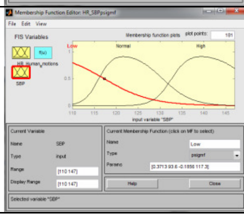
Table (4 – 5) shows the results obtained for the example presented in this section. The results are provided for several training sets, three different input functions, and two output types.

Table (4-5) Results of training the six example models

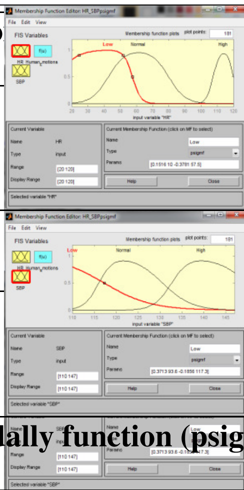
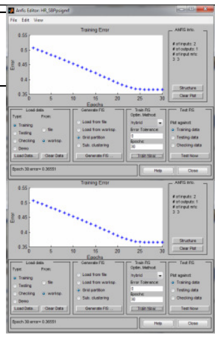
Constant Type				
1. Gaussian curve function (gaussmf)				
Input	**Before Training**	**After Training**	**Error value**	**Output MF value after training**
HR				Output range = [1 3] Anger =0.9308 Disgust Mutilation = 2.06
SBP			Error value is 0.48045	
2. **Gaussian 2 curve function (gauss2mf)**				

HR				Output range = [1 3] Anger =1.257 Disgust Mutilation = 2.155
SBP			Error value is 0.51625	

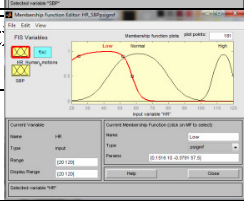
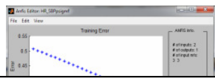
3. **Product of two sigmoidally function (psigmf)**

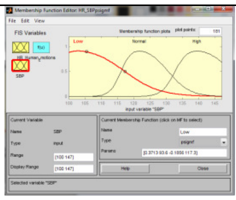
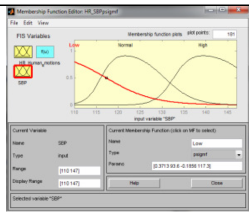
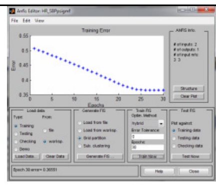
HR				Output range = [1 3] Anger = 0.9796 Disgust Mutilation = 2.201
SBP			Error value is 0.36551	

Linear type

HR **1. Gau**		**io** 		Output range = [1 3] Anger = [-0.021 -0.02204 6.315] Output range = [1 3]
HR				Anger = [0.01238 -0.004538 -1.0341] Disgust Mutilation = [0.01006 -0.02252 4.627]
SBP			Error value is 0.37835	Disgust Mutilation = [-0.005662 -0.02902 6.161]
SBP			Error value is 0.43291	

3. **Product of two sigmoidally function (psigmf)**

HR **2. Gau**		**ct** 		Output range = [1 3] Anger = [0.007555 -0.005618 0.9574] Disgust

SBP				Disgust Mutilation = [0.01058 - 0.0258 5.042]

Error value is 0.21087

4.7. Discussion

We can conclude from the previous sections that fuzzy logic system performs well when it represented the fuzzy data for input and output variables, but it does not have the ability of adapting so it could not be a good choice for our model. Although ANN is an adaptive system, it accepts only crisp data as its input values. Our input variables have a huge number of input range values, so we cannot manage all the combinations of 13 kinds of fuzzy inputs as crisp data to enter it to an ANN system. Thus, a hybrid system that combines the ability of a fuzzy logic to accept fuzzy input and the adapting feature of ANN system will be the perfect system to build our model. In the next Chapter, we will build six different ANFIS models to demonstrate the idea of our model. The models will be differ according input/output membership functions used. The comparison between them will be according to the error values occurred after training.

Chapter Five

Chapter Five

5. Experimental Results and Discussions

5.1. Overview

In this chapter, we will present the complete neuro-fuzzy models with 13 input factors and 22 output emotions. In Our models we will use three input membership functions, namely the gaussmf, the gauss2mf, and the psigmf function. The models will use two variations of the Sugeno output, namely the constant and the linear output functions. We will use three different training sets to test the models. The performance of the models will be measured against the trainability of the models, the training time, and the training error.

5.2. Neuro-fuzzy Models

The fuzzy model for all the input factors and the output emotions is shown in Figure (5 – 1). The models are done using MATLAB ANFIS editor with Sugeno type. ANFIS editor has many options for the input member functions. The Gaussian and the Sigmoid functions are used in this model because of their ability to deal with small numbers, as opposed to trapezoid functions.

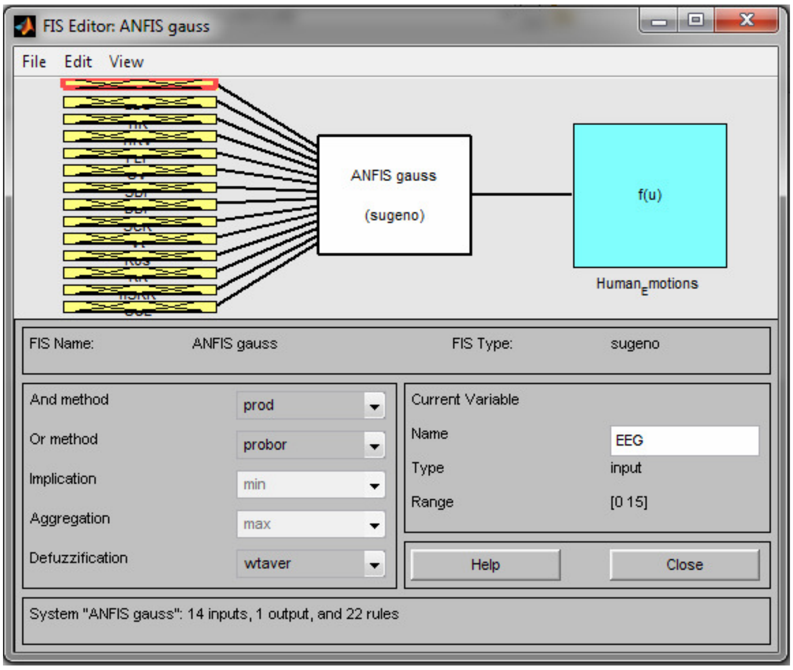


Figure (5-1) Fuzzy model of the 14 input mfs

MATLAB ANFIS editor supports only the Sugeno type, and the Fuzzy Inference System (FIS) supports two types of output functions types, the constant, and the linear function. The rule in Sugeno fuzzy model has the form

If (input 1 = x) and (input 2 = y) then output z = ax +by +c.

For the constant Sugeno model, the output level z is constant c, where a = b = 0. The output level z_i of each rule is weighted by firing strength w_i of the rule.

Six distinct neuro-fuzzy models are used to demonstrate the correlation and delectability of human emotions using the 13 factors presented earlier. The classification of the models are given in Table (5 – 1). Each model is characterized by the type of the input/output membership function and the output type.

Table (5-1) Model Specifications

Model Name	Input member function	Output member function
Gaussian/Constant	gaussmf	Constant
Gaussian/Linear	gaussmf	Linear
Gaussian2/Constant	gauss2mf	Constant
Gaussian2/Linear	gauss2mf	Linear
Psigmf/Constant	psigmf	Constant
Psigmf/Linear	psigmf	Linear

For each of the models shown in Table (5 -1), we build the neuro-fuzzy structure. The structure of the neuro-fuzzy model is shown in Figure (5 – 2). Each model has five distinct layers. The first layer is a crisp input value for each of the input variables. The fuzzification of the input values is performed at layer 2 and presented to the third layer, where the fuzzy rules are processed. The output of the third layer is then applied with a weighted firing strength to the fourth layer, where the output function is evaluated with the Sugeno method (constant or linear) and presented to the final layer (layer 5) as a crisp output. More details on the layered neuro-fuzzy structure can be found in (Negnevitsky 2005) [24]. Note that the general structure of the ANFIS model is the same for all models. The models differ in the specifications of the membership functions and the output specifications. However, the general structure remains the same for all.

Each of the models is characterized by an input membership function (Gaussian, Gaussian2, or Sigmoid) and an output membership function (linear or constant). Initial parameters have to be chosen; for each input membership, function. For example, the model with Gaussian input membership function, is characterized by two parameters σ and c whose initial values must be selected.

The output values are selected in a manner similar to the method described in the previous chapter.

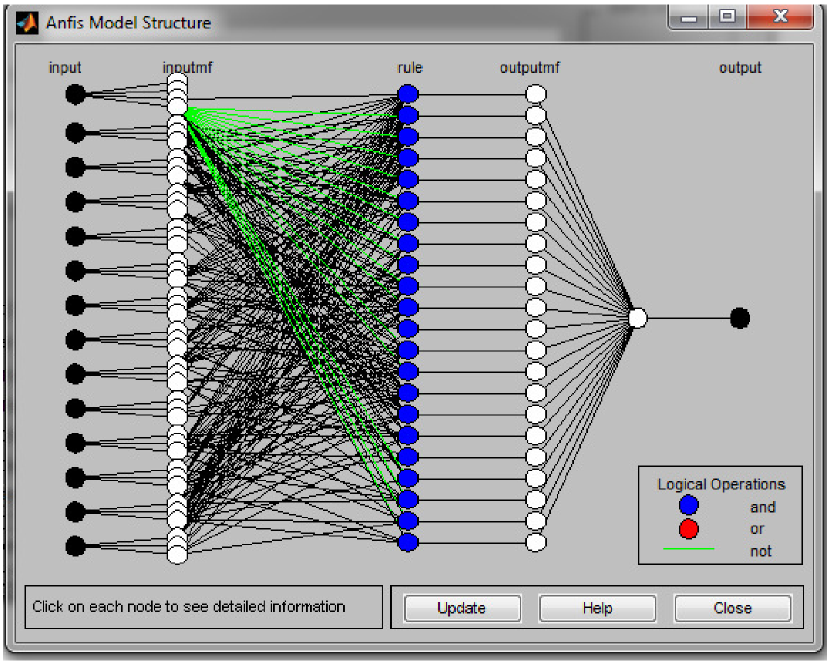


Figure (5-2) Shows the Structure of the neuro/fuzzy model

5.3. Training

As we explained in Chapter 3, our models have the adaptive property through training. The purpose of the training is to adjust the model parameters, particularly the input membership function parameters, and the corresponding output values. For example, for a gaussmf model, the (σ) and (c) parameters are adjusted and tuned to produce the desired output. The adjustment and tuning depend on the accuracy of the training data, as will be shown later.

Training needs two kinds of arrays, the first is the training array and the other one is the testing array. A training array is a two dimensional array [m×n] , where (m) is the number of rows containing input values, and (n) is the number of input factors plus one for the output column.; in our model, n = 15 since there are 14 distinct input variables and one output variable. Each row of the array contains some of the possible values for each input corresponding to the first n-1 columns representing the 14 variables, and the last column holds the desired output values. The testing array holds the data in the same way as the training array, but the data in this array is more accurate than the data of the training array.

It is almost impossible to obtain all the possible combinations for 14 inputs variables and 22 output values. Each input factor has on the average three linguistic variables, thus making the total combinations = 3^{14}, which makes it prohibitive to define a complete training data array. Instead, we will take a snapshot of this huge number of possibilities in three sets of training arrays. The training arrays used in this study are built using the MATLAB help assistant. A sample of training array is shown in Table (5 – 2), where m = 15 and n= 15.

Table (5-2) Sample Training Input Array

	EEG	HR	HRV	PEP	SV	SBP	DBP	SCR	Vt	Ros	RR	nSRR	SCL	FT	HE
1	8	84	0.0033	4	10	120	81	0.85	100	0.5	15	2	20	65	1
2	9	85	0.0043	22	13	121	82	0.87	103	0.52	16	3	21	66	1
3	10	86	0.0053	44	16	122	83	0.89	106	0.54	17	4	22	67	1
4	11	87	0.0063	88	20	123	84	0.91	109	0.56	18	5	23	68	1
5	12	88	0.0073	110	24	124	85	0.93	112	0.58	19	2	24	69	1
6	13	89	0.0083	132	28	125	86	0.95	115	0.6	20	3	25	70	1
7	8	91	0.0103	176	36	127	89	0.99	121	0.64	22	5	21	72	1
8	9	92	0.0113	198	40	128	90	1.01	123	0.66	23	2	22	73	1
9	10	93	0.0123	220	44	129	91	1.03	126	0.68	24	3	23	74	1
10	11	94	0.0133	242	48	130	81	1.05	129	0.7	25	4	24	75	1
11	12	95	0.0143	264	52	131	82	1.07	132	0.72	15	5	25	65	1
12	13	96	0.0153	286	56	132	83	1.09	135	0.74	16	2	20	66	1
13	7	98	0.0173	330	64	134	85	1.13	141	0.76	19	4	22	68	1
14	8	99	0.0183	352	68	135	86	1.15	144	0.78	20	5	23	69	1
15	9	100	0.0139	374	72	136	87	1.17	147	0.8	21	2	24	70	1

For example the first row relates to the “anger” emotion, which follows the definition in the first rule. So the EEG value should be taken from the Beta range (7.5 – 13 Hz) which is 8 in at the example. The value of HR input is 84 bpm which belongs to HHR range (84-120 bpm), the value of HRV is 0.0033 Hz which belongs to the LF range (0.0033- 0.043 Hz), the value of PEP is 4 ms which belongs to the LP range (0 – 800 ms), the value of SV is 10 ml which belongs to LSV (10 – 144), the value of SBP is 120 which belongs to the HSBP range (120 - 147), the value of DPB is 81 which belongs to the HDBP range (81 - 91), the value of SCR is 0.85ms which belongs to HSCR (0.85 – 0.15 ms), the value Vt is 100 ml/breath which belongs to RapidL range (100 - 150 ml/breath), the value of Ros is 0.5 which belongs to HRos range (0.5 - 1), the value of RR is 15 breath/min which belongs to HRR range (15 - 25 breath/min), the value of nSRR 2 per min breath/min which belongs to HnSRR range (2 – 5 per min), the value of SCL is 20 ms which belongs HSCL range (20 – 25 ms), and finally the value of FT is 65 ° F which belongs to LFT range (65 - 75° F). Note that the last value 1 is given in the last column relates to the constant value given to the "anger" emotion.

The training matrix should be done carefully, because the model will use the training array data to adjust the rules based on the values of the training array. In this study, the training array had been constructed according to the rules developed for the models. For example, consider the anger emotion which appears in the first rule in the list of rules shown in Table (4 – 1). Rule 1 (formula [9] below) shows that the heart rate (HR) is high when the emotion is characterized as "anger". So we took the first value from the high range HHR [84 - 120] and then incremented it by one until we reached the last value of the high range, thus taking 37 different values for HR in different rows of the training array. We proceed in a similar fashion for the rest of the records.

The last column holds the output value, which is given by the same rule. When the input values belong to the ranges as shown in formula [9], the output will take the value of "anger" emotion.

If (EEG is Beta) and (HR is High) and (HRV is LF) and (PEP is Low) and (SV is Low) and (SBP is High) and (DBP is High) and (SCR is High) and (Vt is rapid L) and (Ros is High) and (RR is High) and (nSRR is High) and (SCL is High) and (FT is Low) then (Human_Emotions is Anger) [9]

The testing array will have more accurate data, which helps the system to train and fix its data and rules. We use five records for each emotion value. The values of the input variables were chosen carefully. Because of the fuzzy nature of data and the fact that data of different variables may intersect, we will take values, which belong to the non-intersecting region. For example, a record for an anger emotion will contain HR values in the range [100 - 120] rather than [84 - 120] range, since the upper high range [100 - 120] does not intersect the normal range of the HR variable.

Three training arrays were built. The first one NTA (Noisy Training Array) has (814×15) records. The second one CTA (Correct values Training Array) has (814×15) with less noise, and the last one STA (Small Training Array) has (465×15) record. The impact of the training data on the model parameters will be presented later in this chapter.

Noisy data appears when we choose the input values from a range that is the opposite of the range needed. For example, for the anger emotion a good choice of values for HR should be taken from the high range HHR (84 - 120), but a noisy choice will be taken from the low values LHR (20 - 70).

5.4. Results

1. The Impact of Training Array

The main purpose of the training in ANFIS models is to adjust the parameters of input membership functions such that the model becomes closer to reality. We will demonstrate the impact of training as it pertains to the SCR input factor. SCR has three linguistic variables, low, normal, and high. The SCR input functions are shown in Figure (5 – 3). After applying the training set (NTA), we obtain the shapes shown in Figure (5 – 4). The parameters of the Gaussian bell shaped functions had been adjusted after applying the training. Table (5 – 3) show the parameters of the three input functions before and after training. Note that the σ values increased for both the LSCR and NSCR, while σ decreased for the HSCR. The (c) values remained the same for LSCR, decreased for NSCR, and increased for HSCR.

Table (5-3) SCR the Gaussian/Constant Model.

	σ		C	
	Before Training	After Training	Before Training	After Training
LSCR	0.08	0.09	0.06	0.06
NSCR	0.12	0.16	0.73	0.72
HSCR	0.22	0.10	1.24	1.28

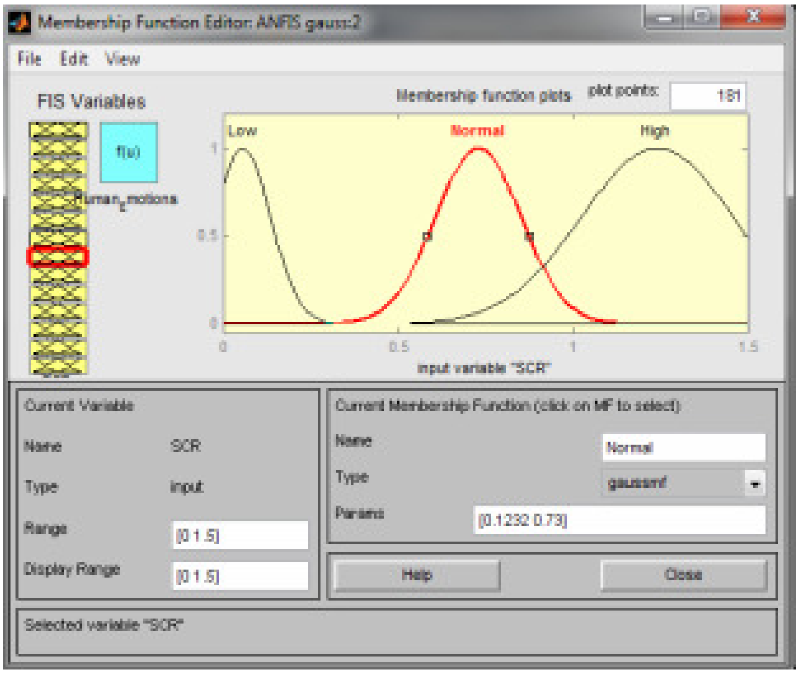


Figure (5-3) Charactersistic for Gaussian/Constant model before training

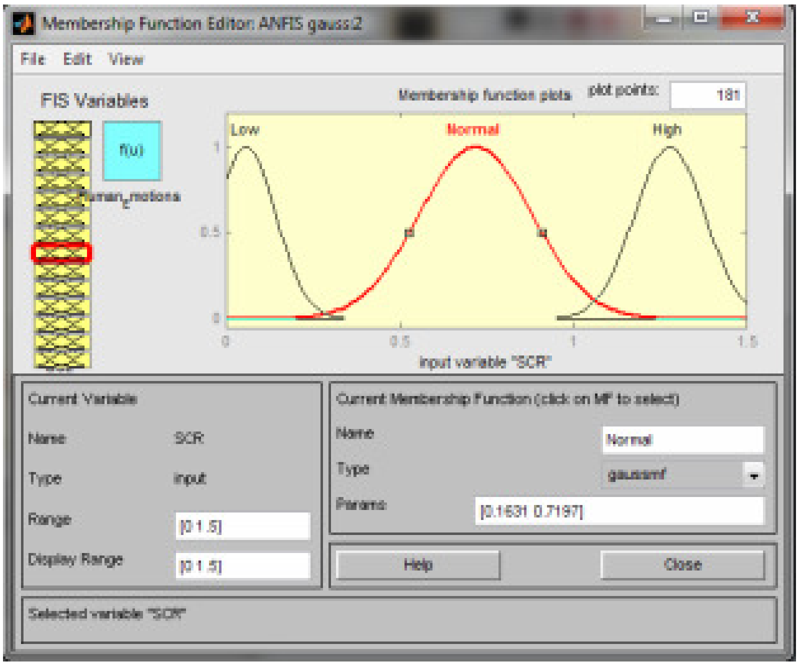


Figure (5-4) SCR Characteristic for Gaussian/Constant model after training

Similar observations are made for the SCR models with the linear output function. The results are shown in Table (5 – 4) and Figure (5 – 5). The adjustments for the linear type are slightly smaller than the ones of the constant output model. The results were obtained with 800 training epochs.

Table (5-4) SCR Gaussian/Linear model Before and After Training

	σ		C	
	Before Training	After Training	Before Training	After Training
LSCR	0.08	0.08	0.06	0.05
NSCR	0.12	0.12	0.73	0.73
HSCR	0.22	1.21	0.24	1.24

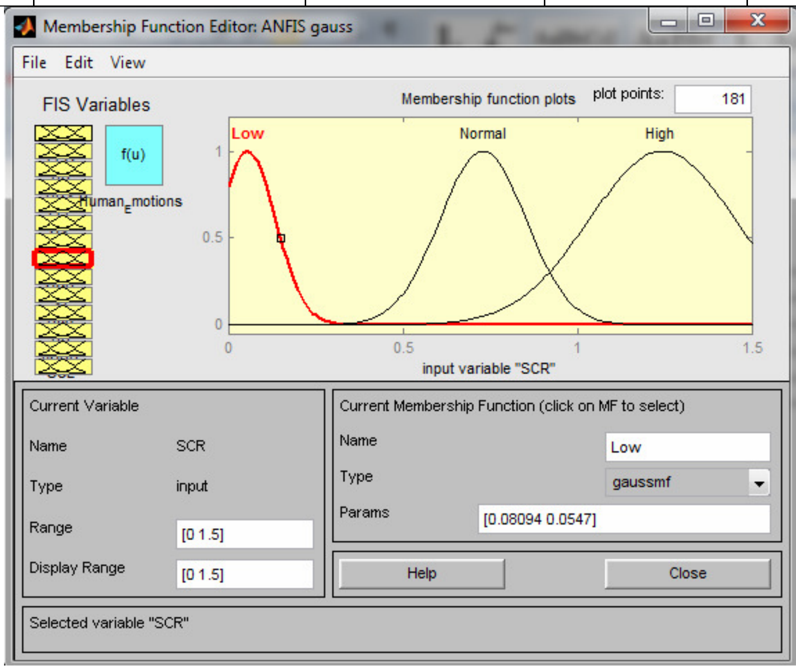


Figure (5-5) SCR the Gaussian/Linear model after Training

The results for the Gaussian2/Constant model are shown in Figure (5 – 7) (before training) and Figure (5 – 8) (after training) summarized in Table (5 – 5). Note that the Gaussian2 function has four parameters σ_1, C_1, σ_2, C2. Recall the Gaussian2 function is a product of two Gaussian functions. After going through the training, several parameters changed their values. For example σ_1

changed from 0.05 to 0.08 for the high SCR variables. The value of C1 changed from 0.99 to 1.01 for the HSCR variable. The impact of training in other factors will be included in Appendix A.

Table (5-5) SCR Gaussian2/Constant model Before and After Training

	σ_1		C 1		σ_2		C2	
	BT*	AT	BT	AT	BT	AT	BT	AT
LSCR	**0.0013**	**0.0013**	**0**	**0**	**0.034**	**0.037**	**0.11**	**0.11**
NSCR	**0.22**	**0.22**	**0.69**	**0.68**	**0.085**	**0.088**	**0.78**	**0.78**
HSCR	**0.05**	**0.08**	**0.99**	**1.01**	**0.001**	**0.001**	**1.5**	**1.5**

*BT = Before Training, and AT = After Training.

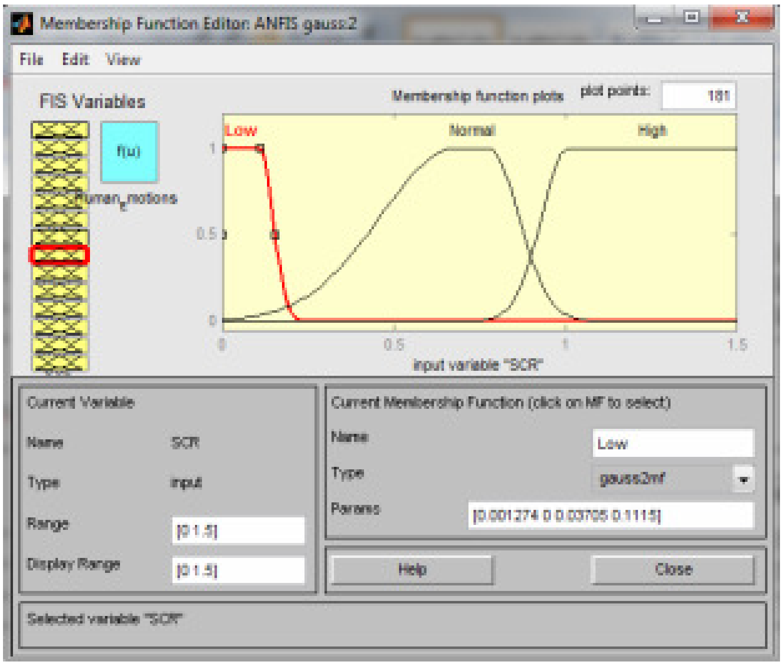


Figure (5-6) SCR parameters at the Gaussian2/Constant model before Training

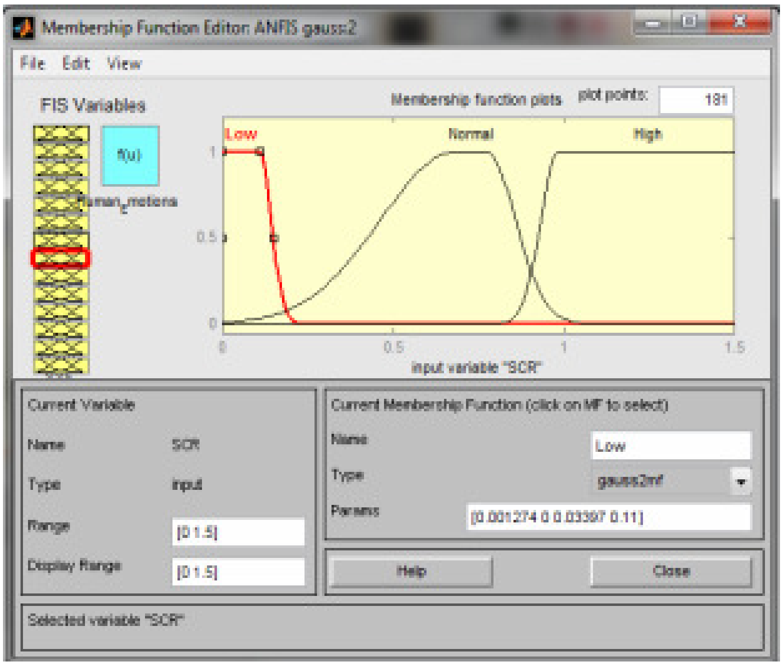


Figure (5-7) SCR parameters at the Gaussian2/Constant model after Training

The training results under the linear output function for Gaussian2 input function are shown in Figure (5 – 8) and summarized in Table (5 – 6). Note the parameters did not exhibit any change for this factor.

Table (5-6) SCR parameters at the Gaussian2/Linear model

	Sig 1		C 1		Sig 2		C2	
	BT*	AT	BT	AT	BT	AT	BT	AT
LSCR	**0.0013**	**0.0013**	**0**	**0**	**0.034**	**0.034**	**0.11**	**0.11**
NSCR	**0.221**	**0.221**	**0.69**	**0.69**	**0.085**	**0.085**	**0.775**	**0.775**
HSCR	**0.051**	**0.050**	**0.99**	**0.99**	**0.0013**	**0.0013**	**1.5**	**1.5**

*BT = Before Training, and AT = After Training.

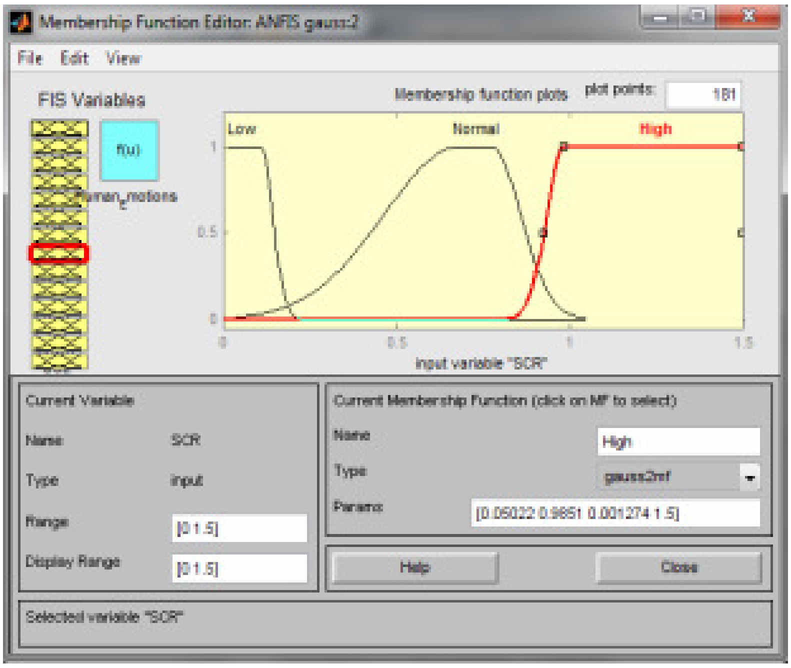


Figure (5-8) SCR parameters at the Gaussian2/Linear model after Training

Next we show the results for the Psigmf/Constant model before and after training (Figure (5 – 9, 5 – 10 and Table 5 – 6) the sigmoid function (psigmf) has four parameters (A1, C1, A2, C2). The model parameters exhibit several slight changes. For example, C1 changed from 0 to 0.021 for LSCR and from 0.93 to -0.83 for HSCR.

Table (5-7) SCR parameters at the Psigmf/Constant model

	A1		C1		A2		C2	
	BT*	AT	BT	AT	BT	AT	BT	AT
LSCR	**1465**	**1465**	**0**	**0.021**	**- 54.93**	**-54.93**	**0.15**	**0.19**
NSCR	**8.45**	**8.451**	**0.43**	**0.43**	**-21.97**	**-21.97**	**0.86**	**0.88**
HSCR	**36.6**	**36.62**	**0.93**	**-0.83**	**-1465**	**1465**	**1.5**	**1.5**

*BT = Before Training, and AT = After Training.

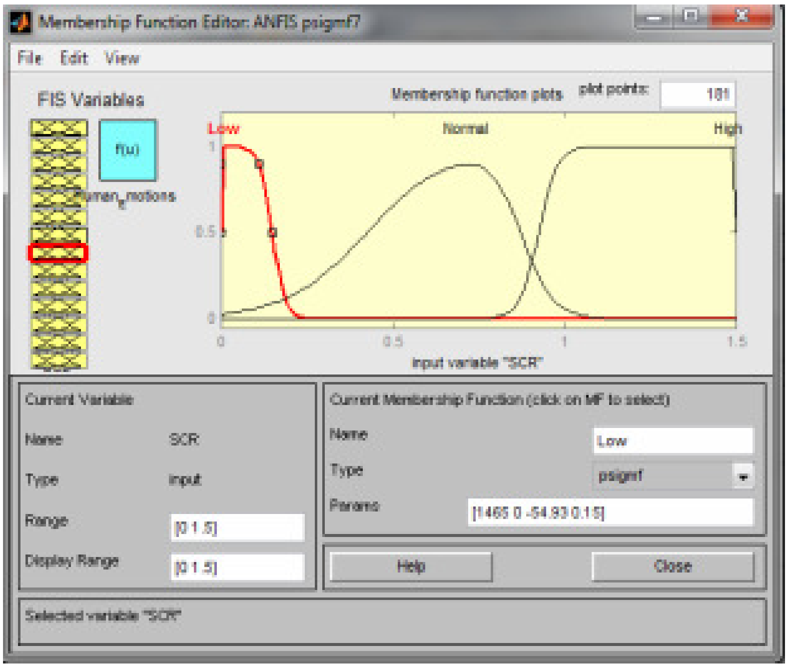


Figure (5-9) SCR parameters at the Psigm/Constant model before Training

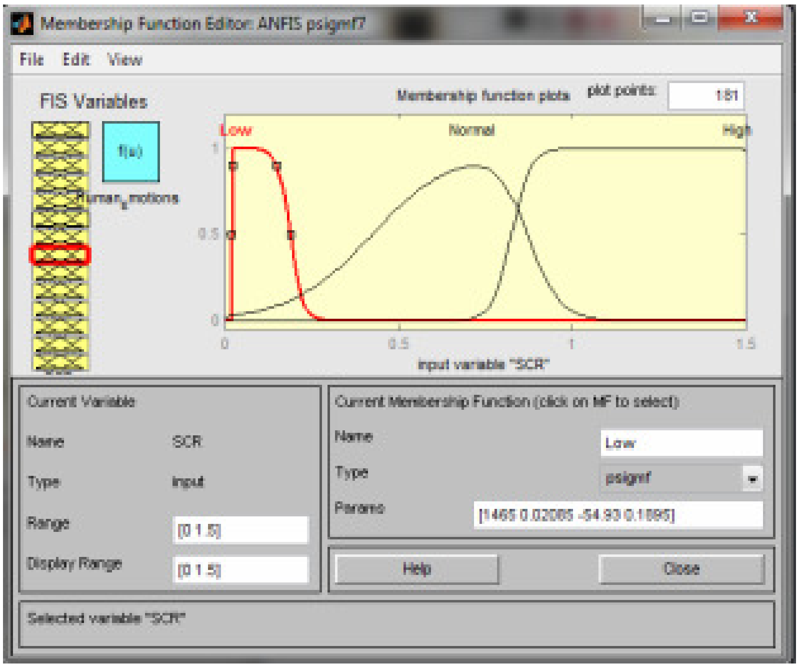


Figure (5-10) SCR parameters at the Psigm/Constant model after Training

The results for the Psigmf/Linear model are shown in figure Figure(5 – 11) and Table (5 – 8) the model did not exhibit any changes in the parameter value except for the C1 for LSCR, which changed from 0 to 0.012.

Table 5-8) SCR parameters at the Psigmf/Linear model

	A1		C1		A2		C2	
	BT	AT	BT	AT	BT	AT	BT	AT
LSCR	1465	1465	0	0.014	-54.93	-54.93	0.15	0.15
NSCR	8.45	8.45	0.43	0.43	-21.97	-21.97	0.86	0.86
HSCR	36.6	36.6	0.93	0.92	-1465	-1465	1.5	1.5

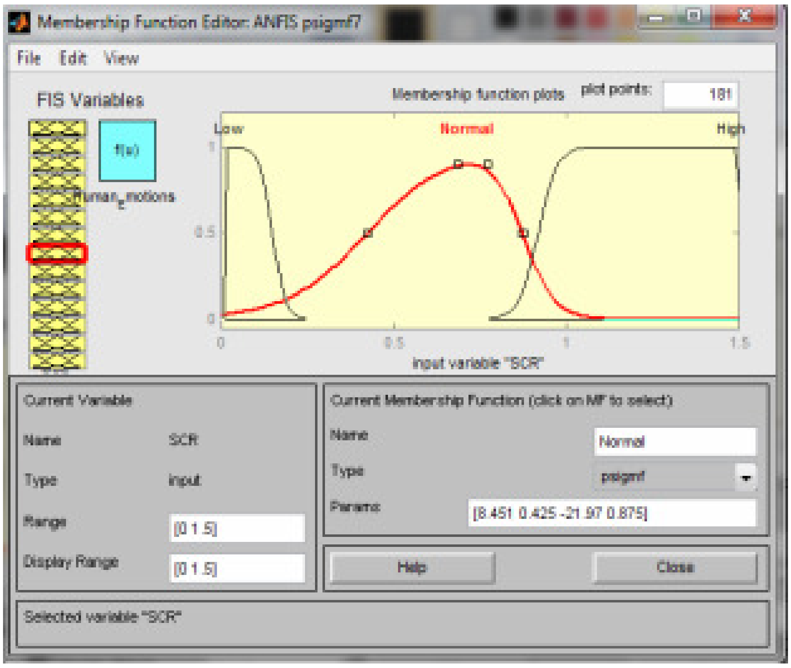


Figure 5-11) SCR parameters at the Psigm/Linear model after Training

It is evident that some of the parameters of the member functions had been changed some stayed the same. Note that the change in the parameter values is neither positive nor negative; no change implies that the initial choice of the parameters is in line with reality of the model. In other words, the established relation between the input factors and the output is consistent. The adjustment of the parameters takes place whenever the initial choice of the parameter is not proper.

The training of the models had a direct impact on the selected values of the output. The output ranges had been changed after training in all models. The initial output range was from 0 to 1 before training, but after training, the range became from 1 to 22.

2. Training Time

In this section, we measure the impact of training time on the performance of the models. In particular, we observe the error rate of the models under different numbers of epochs. An epoch in the ANFIS is one full cycle staring from the application of input at layer 1 of the model, until the firing weight of the rule is adjusted. At the end of an epoch, the error, which is defined as the difference between the desired output and the computed output value, is measured. In this section, the models are trained with different number of epochs 200, 300, 500, and 800 epochs. We will use, different types different training sets for the training NTA, CTA, and STA Figure (5 – 11), (5 – 12), and (5 – 13) show the error rates as function of the number of training epochs for the three different training sets.

Note that the larger the number of epochs the smaller is the error. The error rate decreased for all training data arrays. Note also the Sigmoid function Psigmf produced the lowest error rate. The results training under different epochs are summarized in Table (5 – 9). These results for training under different are obtained for the constant output function.

Table (5-9) Error values after training the models for constant models

Using NTA (Noisy Training Array)		
Model Name	Number of Epoch	The value of Error
Gaussian/Constant	800	4.9338
	500	4.9546
	300	4.9758
	200	4.9864
Gaussian2/Constant	800	5.5669
	500	5.7155
	300	5.7786
	200	5.8305
Psigmf/Constant	800	3.8699
	500	3.9032
	300	3.9467
	200	3.9836
Using CTA (Correct Training Array)		
Gassian/Constant	800	4.1283
	500	4.1992
	300	4.1685
	200	4.8193
Gaussain2/Constant	800	4.1283
	500	5.1915
	300	5.3289
	200	5.4145
Psigmf/Constant	800	3.837
	500	3.908
	300	3.878
	200	3.899
Using STA (Small Training Array)		
Gaussian/Constant	800	4.4025
	500	4.434
	300	4.4499
	200	4.4578
Gaussian2/Constant	800	4.4517
	500	4.8215

	300	5.043
	200	5.1611
Psigmf/Constant	800	3.2006
	500	3.4516
	300	3.564
	200	3.6435

The following charts will display the results of error values with the number of epochs for the constant output member functions.

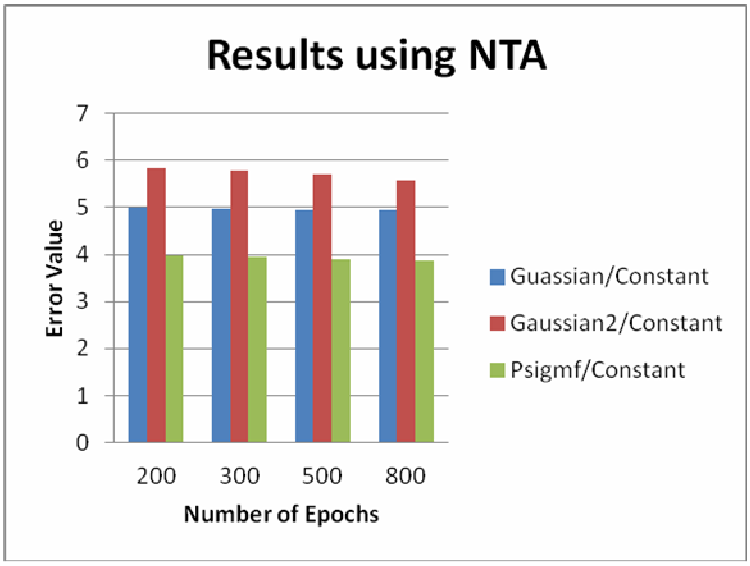


Figure (5-11) Epochs and error using NTA

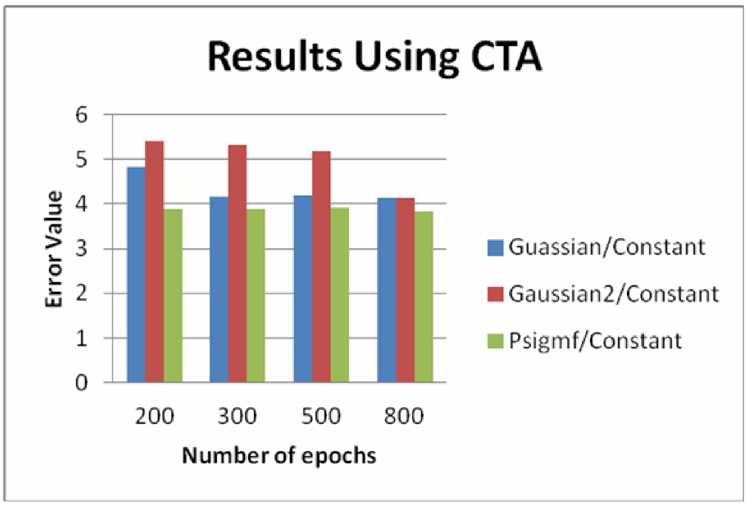


Figure (5-12) Epochs and error using CTA

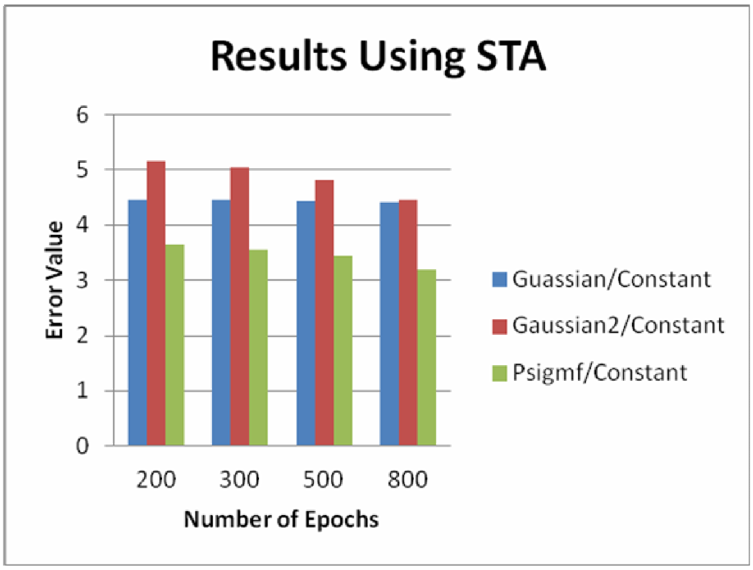


Figure 5-13) epochs and errors using STA

Table (5–10) summarizes the results for the error values under linear output member functions.

Table (5-10) Epochs and error at linear models

Using NTA (Noisy Training Array)		
Model Name	Number of Epoch	The value of Error
Gaussian/Linear	800	4.0731
	500	3.8969
	300	3.555
	200	3.6045
Gaussian2/ Linear	800	3.5996
	500	3.2359
	300	3.2125
	200	3.0242
Psigmf/ Linear	800	2.7247
	500	2.7594
	300	2.8191
	200	2.8555
Using CTA (Correct Training Array)		
Gassian/ Linear	800	2.0034
	500	2.8076
	300	2.921

	200	3.0102
Gaussain2/ Linear	800	2.399
	500	2.5219
	300	2.6212
	200	2.6808
Psigmf/ Linear	800	2.0034
	500	2.0618
	300	2.1202
	200	2.1698
Using STA (Small Training Array)		
Gaussian/ Linear	800	2.4569
	500	2.5483
	300	2.6286
	200	2.681
Gaussian2/ Linear	800	2.3201
	500	2.3919
	300	2.539
	200	2.2904
Psigmf/ Linear	800	1.9352
	500	2.0328
	300	2.1263
	200	2.3129

For comparison purposes, we summarize the results in the charts shown in Figure (5 – 14), (5 – 15), and (5 – 16). These results also reveal that the Sigmoid function generates the lowest error value and the training under Sigmoid produces the lowest error values. Figure (5 – 17) shows the performance of the Sigmoid under the three training arrays, for the linear output member function.

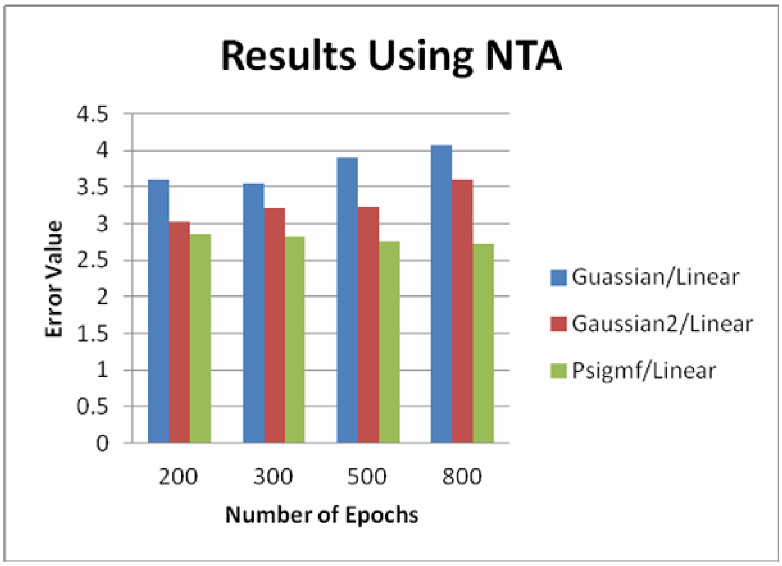


Figure (5-14) Epochs and error using NTA linear Model

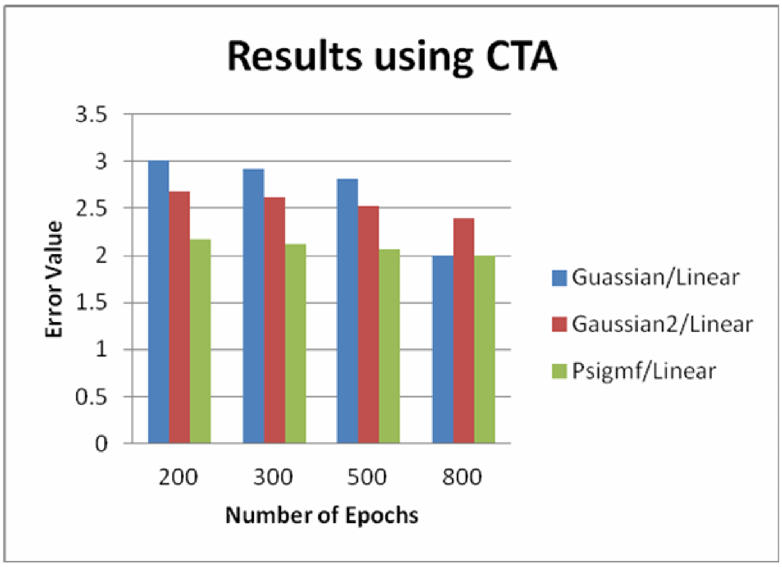


Figure (5-15) Epochs and error using CTA linear Model

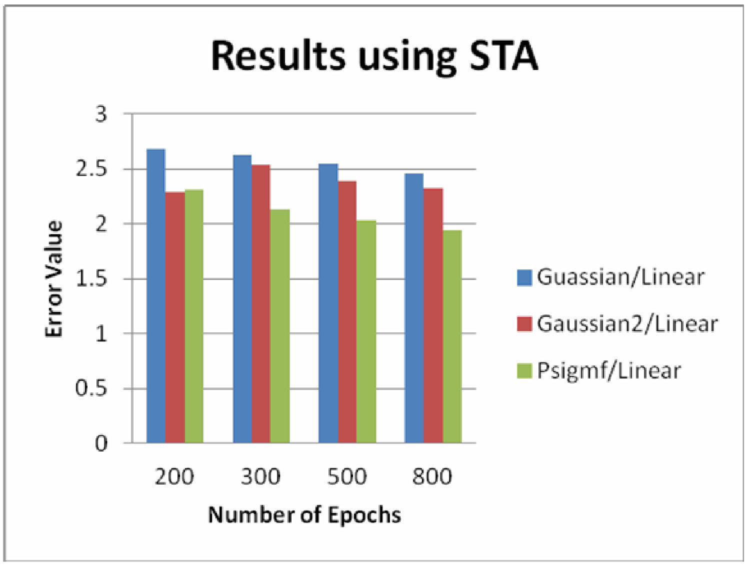


Figure (5-16) Epochs and error using STA linear Model

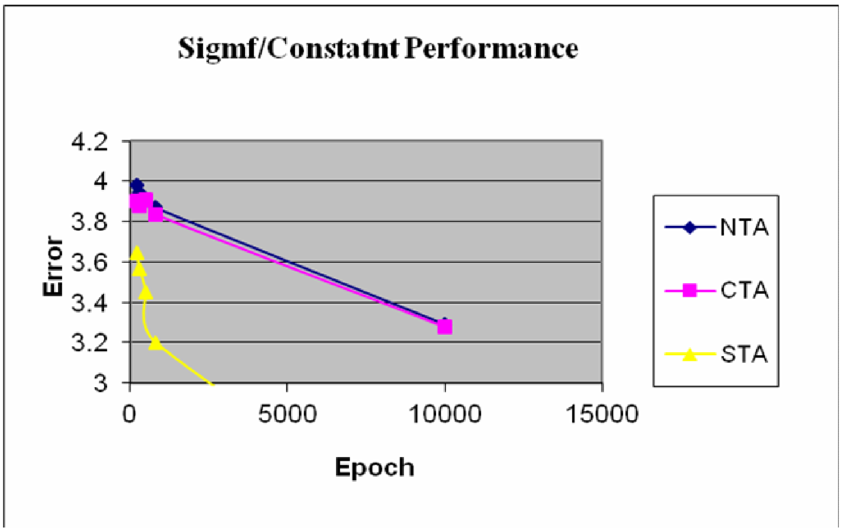


Figure (5-17) Shows the performance of the Psigmf/constant model under three training sets

5.5. Discussions

After training the models it has been noticed that both of the input and output variables had been changed. When the NTA, the error values were large and got the largest values at the constant output membership functions. Training under CTA data arrays produced smaller error values than those for NTA. The

STA training data produced the lowest error values. It can be concluded that the correctness and accuracy of the training data has an impact on the overall error values after the training is complete see Figure (5 – 17).

Also, the more training is done i.e. the larger number of epochs, the less value of the error. It had been noticed that for most of the cases the error values had decreased when the number of epochs increased.

The linear output models had less error values in most cases than the constant output models. It is interesting to report that one of the experiments showed an anomaly, where the error values increased after training under the Gaussian/Linear and Gaussian2/linear models using NTA data sets.

After training the system rules also change; thus the input values before training produce one emotion output, and after training the same input values may produce different emotion.

Table (5 – 11) shows four examples demonstrating the behavior of the models before training and after training using the psigmf/linear model. Input data is applied to the model before training and then the same data values are applied to the model after training, the CTA training data is used for 800 epochs. The last two rows of the table show the resultant human emotions before and after training. Note that for the first set of input data, the human emotion was described and detected as "surprise" corresponding to value "22" in the ANFIS model. After training, the same input combination produced the emotion of "fear" corresponding to the output value "6". The second input data produced "joy" emotion before and after training. The third input data produced "relief" emotion before training and "sadness" after training. The fourth input data produced "pride" and then changed to the "embarrassment" emotion.

Table (5-11) Shows the values of the input factor of the psigmf/Linear model

Factor	Input 1	Input 2	Input 3	Input 4
EEG	7.50	5.80	5.80	5.80
HR	70.00	99.55	99.55	99.55
HRV	0.08	0.11	0.11	0.11
PEP	550	275	275	275
SV	200	227.30	227.30	227.30
SBP	123.50	133.10	133.10	133.10
DBP	83.00	81.48	81.48	91.00
SCR	0.75	0.65	0.65	0.72
vt	650.00	492.90	492.90	492.90
Ros	0.50	0.70	0.70	0.70
RR	15.00	15.00	18.18	21.82
nSRR	2.50	1.93	1.93	1.93
SCL	12.50	14.20	14.20	14.20
FT	77.50	70.11	70.11	75.80
Emotion Before Training	**22.00 (surprise)**	**16.00 (joy)**	**20.20 (relief)**	**19.10 (pride)**
Emotion After Training	**6.0 (fear)**	**16.15 (joy)**	**7.49 (sadness)**	**5.62 (embarrassment)**

The choice of training data set has an impact on the outcome of the emotions. The previous example is generated with CTA data set. Using a different data set may very well produce different emotions output. This is consistent, however, with the fact that different categories of people may respond differently to emotions stimuli. Therefore, the training of the models with various data sets is important for the accuracy of the models. As such, in order for the model to be used properly to detect the emotions of a certain individual, it is important to know to which training sets category the individual belongs to. Table (5 – 12) shows the human emotions response to 10 different trials with different input values for each trial under a model that had been trained for 10,000 epochs with CTA, STA, and NTA using psigmf/Linear functions. The table demonstrates how the models behave under different training sets. The 10,000 epoch training produced the following error values: 2.85, 1.63, and 1.47 for NTA, CTA, and STA respectively. The following notations are used in the table:

- F = Factor name
- BT = the values of the human emotions output variables before training
- NTA = emotions output variables after training with NTA
- CTA = emotions output variables after training with CTA,
- STA = emotions output variables after training with STA.
- Columns numbered 1 through 10 are 10 different input arrays.

The first experiment (column number 1) shows 14 input values for the various factors. The result of applying these input values indicate that the human emotion before training the model is 22 which represents the emotion "suspense". The model is trained with three different arrays (NTA, CTA, and STA) for 10,000 epochs each. The output after training using NTA is 15.4, which represent the emotion "happiness". When the model is trained with CTA, the output is 6.48, which represents the emotion "fear". Using the STA training array, the detected emotion is "sadness crying" represented by the output 8.3.

The experiment is repeated 10 times, and the results are summarized in Figure (5-18).

Table (5-12) Human Emotions Response after train the Psigmf/Linear for 10,000 epochs with NTA, CTA, and STA.

F	1	2	3	4	5	6	7	8	9	10
EEG	7.5	7.5	7.5	7.5	7.5	7.5	14.66	14.66	14.66	4.432
HR	70	70	70	70	70	70	90.45	90.45	72.27	117.7
HRV	0.082	0.085	0.085	0.085	0.085	0.085	0.114	0.057	0.107	0.078
PEP	550	525	525	525	525	525	825	825	825	425
SV	200	200	200	281.8	281.8	63.64	300	300	300	300
SBP	124	123.5	123.5	123.5	123.5	113.9	113.9	126.7	126.7	145.9
DBP	83	89.86	81.48	81.48	87.57	87.57	80.71	80.71	80.71	86.05
SCR	0.75	0.239	0.239	0.239	0.784	0.784	1.057	1.057	1.057	1.057
vt	650	1017	1017	1017	1017	1017	1017	440.5	440.5	807.1
Ros	0.5	0.701	0.705	0.705	0.705	0.705	0.705	0.523	0.523	0.705
RR	15	14.55	14.55	14.55	14.55	14.55	14.55	14.55	14.55	20
nSRR	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	4.659
SCL	12.7	6.25	6.25	6.25	6.25	6.25	13.07	19.89	19.89	9.659
FT	77.5	89.43	89.43	89.43	89.43	89.43	78.07	78.07	78.07	88.3
BT	22 Suspense	20 Relief	16 Joy	17 Antic pleasure visual	21.1 Surprise	16.3 Joy	15.8 Joy	13.7 Contentment	12.8 Amusement	9.01 Sadness non crying
CA	6.48 Fear Imminent threat	11.3 Sadness Acute	15.4 Happiness	11.8 Affection	4.52 Embarrassment	15.7 Joy	15.2 Happiness	3.91 Disgust mutilation	7.13 Fear imminent	20.7 Surprise
NA	15.4 Happiness	16.1 Joy	16.1 Joy	16.1 Joy	16 Joy	16.1 Joy	16 Joy	10.6 Sadness Acute	9.54 Sadness anticipatory	16.1 Joy

SA	8.3 Sadness Crying	11.1 Sadness Acute	13.8 Contentment	10.7 Sadness Acute	10 Sadness anticipatory	15.9 Joy	12.7 Amusement	10.9 Sadness acute	8.29 Sadness crying	21 Surprise

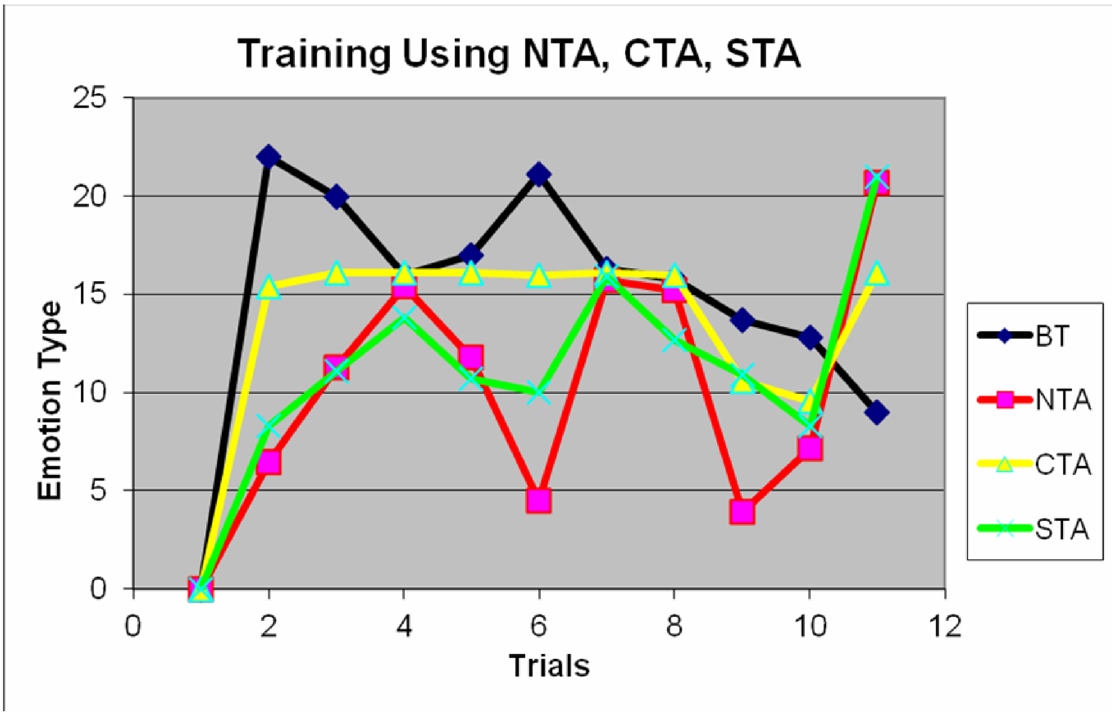


Figure 5-18) Training Using NTA, CTA, and STA

In Figure 5-18, the black dark line is the base line which represents the case before training. After training, the model is adjusted according to the given data in the training set. The choice of the training set and the accuracy of the data are crucial to the success of the model. Note that the emotions detected for each input array is different for different training sets. The red line (noisy data array) and the yellow line (correct data array) are the most diverse since the NTA is constructed by adding noise to the CTA array. However, it should be noted that there is no specific correlation between the values of different sets. The point here is that different training sets produce different models. In reality, there could be different training sets representing different human behavior and different human responses. So it is essential to know which category (or training set) an individual belongs to before attempting to define his/her current emotion.

Chapter Six

Chapter Six

6. Conclusions

- A neuro-fuzzy model for detection of human emotional status using 14 measurable human factors.
- The measured factors are converted into fuzzy variables using first layer of a neuro-fuzzy model.
- The fuzzy rules used in a set of rules to detect one of the twenty two different emotions.
- The models were trained and the output parameters representing emotions can be adjusted using an array of training data.
- The results presented in this study show that human emotions can be detected using a neuro-fuzzy model.
- A model can be trained and adjusted to match category of human behavioral response to emotion.
- The accuracy of the model is measured in terms of error value obtained between the expected output.
- The experiments in this study were conducted using MATLAB neuro-fuzzy tool.
- The experiments show that the model is sensitive to the choice of input membership functions.

- The sigmoid function is the most optimal in terms of trainability and producing low error values.
- Also the choice of Sugeno linear output function is more realistic than the constant output function.
- The Gaussian input membership function and the constant Sugeno output produce anomalous behavior, namely an increased error value while training.

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Appendix A

Psigmf/Linear

	A1		C1		A2		C2	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EEG								
DELTA	**146.5**	**146.5**	**0**	**0**	**-5.493**	**-5.493**	**3.5**	**3.5**
THETA	**1.569**	**1.569**	**4.25**	**4.25**	**-2.747**	**-2.747**	**7**	**7**
BETA	**1.569**	**1.569**	**8.75**	**8.75**	**-1.831**	**-1.831**	**12**	**12**
ALPHA	**1.831**	**1.831**	**12.5**	**12.5**	**-146.5**	**-146.5**	**15**	**15**
(HR)								
LHR	**21.97**	**21.97**	**20**	**20**	**-0.2197**	**-0.2311**	**57.5**	**57.5**
NHR	**0.3662**	**0.3662**	**52.5**	**52.5**	**-0.1373**	**-0.1373**	**80**	**80**
HHR	**0.2113**	**0.1912**	**97**	**97**	**-21.97**	**-21.97**	**120**	**120**
HRV								
VLF	**1.40E+04**	**1.40E+04**	**0.001**	**0.0009988**	**-149.7**	**-149.7**	**0.02165**	**0.05168**
LF	**173.3**	**173.3**	**0.01915**	**-0.001631**	**-686.6**	**-686.6**	**0.039**	**0.02955**
HF	**1099**	**1099**	**0.0375**	**0.03307**	**-1.40E+04**	**-1.40E+04**	**0.16**	**0.1604**
PEP								
LP	**1.997**	**1.997**	**0**	**-0.0001941**	**-0.01831**	**-0.03511**	**650**	**650**
NP	**0.005493**	**0.01033**	**500**	**500**	**-1.099**	**-1.099**	**1003**	**1003**
HP	**0.01099**	**0.009589**	**750**	**750**	**-1.997**	**-1.997**	**1100**	**1100**

(SV)								
LSV	**5.493**	**5.493**	**0**	**-1.92E-09**	**0.04291**	**-0.04103**	**80**	**80**
NSV	**0.02747**	**0.02726**	**100**	**100**	**-0.1099**	**-0.1099**	**225**	**225**
HSV	**0.09155**	**0.09155**	**270**	**270**	**-5.493**	**-5.493**	**400**	**400**
SBP								
LSBP	**46.75**	**46.75**	**100**	**100**	**-0.3433**	**-0.3433**	**113**	**113**
NSBP	**0.4578**	**0.4578**	**116**	**116**	**-0.4578**	**-0.4578**	**128**	**128**
HSBP	**0.3924**	**0.3926**	**127**	**127**	**-46.75**	**-46.75**	**147**	**147**
DBP								
LDBP	**137.3**	**137.3**	**75**	**75**	**-0.9155**	**-0.9155**	**80**	**80**
NDBP	**1.099**	**1.099**	**79.5**	**79.5**	**-1.099**	**-1.099**	**84.5**	**84.5**
HDBP	**0.9155**	**0.9161**	**84**	**84**	**-137.3**	**-137.3**	**91**	**91**
SCR								
LSCR	**1465**	**1465**	**0**	**0.0135**	**-54.93**	**-54.93**	**0.15**	**0.15**
NSCR	**8.451**	**8.451**	**0.425**	**0.425**	**-21.97**	**-21.97**	**0.875**	**0.875**
HSCR	**36.62**	**36.62**	**0.925**	**0.9188**	**-1465**	**-1465**	**1.5**	**1.501**
[illegible]								
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	**-10.99**	**-10.99**	[illegible]	[illegible]
[illegible]								
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

SCL								
LSCL	**87.89**	**87.89**	**0**	**0.000432**	**-5.493**	**-5.493**	**1.5**	**1.501**
NSCL	**0.2747**	**0.2747**	**10**	**10**	**-5.493**	**-5.493**	**20.5**	**20.5**
HSCL	**1.831**	**1.835**	**21.5**	**21.5**	**-87.89**	**-87.89**	**25**	**25**
FT								
LFT	**87.89**	**87.89**	**65**	**65**	**-1.099**	**-1.098**	**72.5**	**72.5**
NFT	**1.099**	**1.099**	**77.5**	**77.5**	**-1.099**	**-1.099**	**82.5**	**82.5**
HFT	**0.6103**	**0.6091**	**84.5**	**84.5**	**-87.89**	**-87.89**	**90**	**90**

Psigmf/Constant

	A1		**C1**		**A2**		**C2**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EEG								
DELTA	**146.5**	**146.5**	**0**	**0**	**-5.493**	**-5.493**	**3.5**	**3.5**
THETA	**1.569**	**1.569**	**4.25**	**4.25**	**-2.747**	**-2.747**	**7**	**7**
BETA	**1.569**	**1.569**	**8.75**	**8.75**	**-1.831**	**-1.831**	**12**	**12**
ALPHA	**1.831**	**1.845**	**12.5**	**12.51**	**-146.5**	**-146.5**	**15**	**15**
(HR)								
LHR	**21.97**	**21.97**	**20**	**20.01**	**-0.2197**	**-0.2227**	**57.5**	**57.5**
NHR	**0.3662**	**0.3662**	**52.5**	**52.5**	**-0.1373**	**-0.1373**	**80**	**80**
HHR	**0.2113**	**-0.08551**	**97**	**97**	**-21.97**	**-21.97**	**120**	**120**
HRV								
VLF	**1.40E+04**	**1.40E+04**	**0.001**	**-**	**-1497**	**-149.7**	**0.02165**	**0.05154**

				0.00732				
LF	**173.3**	**173.3**	**0.01915**	**0.03329**	**-686.6**	**-686.6**	**0.039**	**0.02036**
HF	**1099**	**1099**	**0.0375**	**0.02722**	**- 1.40E+04**	**- 1.40E+04**	**0.16**	**0.1606**
PEP								
LP	**1.997**	**1.997**	**0**	**- 0.00076**	**-0.01831**	**-0.03225**	**650**	**650**
NP	**0.005493**	**0.02398**	**500**	**500**	**-1.099**	**-1.099**	**1003**	**1003**
HP	**0.01099**	**0.01711**	**750**	**750**	**-1.997**	**-1.997**	**1100**	**1100**
(SV)								
LSV	**5.493**	**5.493**	**0**	**-2.14E-05**	**-0.04291**	**0.01777**	**80**	**80**
NSV	**0.02747**	**0.01999**	**100**	**100**	**-0.1099**	**-0.1099**	**225**	**255**
HSV	**0.09155**	**0.09155**	**270**	**270**	**-5.493**	**-5.493**	**400**	**400**
SBP								
LSBP	**46.75**	**46.75**	**100**	**100**	**-0.3433**	**-0.3374**	**113**	**113**
NSBP	**0.4578**	**0.4578**	**116**	**116**	**-0.4578**	**-0.4578**	**128**	**128**
HSBP	**0.3924**	**0.3787**	**127**	**127**	**-46.75**	**-46.75**	**147**	**147**
DBP								
LDBP	**137.3**	**137.3**	**75**	**75**	**-0.9155**	**-0.915**	**80**	**80**
NDBP	**1.099**	**1.099**	**79.5**	**79.5**	**-1.099**	**-1.098**	**84.5**	**84.5**
HDBP	**0.9155**	**0.8974**	**84**	**83.99**	**-137.3**	**-137.3**	**91**	**91.02**
SCR								
LSCR	**1465**	**1465**	**0**	**0.02085**	**-54.93**	**-54.93**	**0.15**	**0.1895**
NSCR	**8.451**	**8.451**	**0.425**	**0.4251**	**-21.97**	**-21.97**	**0.875**	**0.875**

HSCR	**36.62**	**36.62**	**0.925**	**0.827**	**-1465**	**-1465**	**1.5**	**1.503**
(VT)								
RAPIDL	**1.997**	**1.997**	**100**	**100**	**-0.2747**	**-0.26**	**140**	**140**
QUIETN	**0.01831**	**0.01831**	**350**	**350**	**-0.02197**	**-0.02197**	**625**	**625**
DEEPH	**0.01831**	**0.003207**	**750**	**750**	**-1.997**	**-1.997**	**1200**	**1200**
ROS								
LROS	**2197**	**2197**	**0**	**0**	**-61.03**	**-61.03**	**0.445**	**0.445**
NROS	**42.25**	**42.25**	**0.465**	**0.4653**	**-78.47**	**-78.47**	**0.565**	**0.5669**
HROS	**54.93**	**54.93**	**0.55**	**0.5488**	**-2197**	**-2197**	**1**	**1.003**
RR								
LRR	**109.9**	**109.9**	**5**	**4.999**	**-1.831**	**-1.83**	**8.5**	**8.5**
NRR	**0.6866**	**0.6866**	**11**	**11**	**-0.6866**	**-0.6866**	**19**	**19**
HRR	**0.6866**	**0.7193**	**19**	**19.01**	**-109.9**	**-109.9**	**25**	**24.98**
NSRR								
LNSRR	**439.4**	**439.4**	**0**	**0.01055**	**-5.493**	**-5.493**	**1.5**	**1.5**
NNSRR	**5.493**	**5.493**	**1.5**	**1.5**	**-5.493**	**-5.493**	**2.5**	**2.5**
HNSRR	**2.747**	**2.753**	**3**	**3.027**	**-439.4**	**-439.4**	**5**	**4.99**
SCL								
LSCL	**87.89**	**87.89**	**0**	**-0.01483**	**-5.493**	**-5.492**	**1.5**	**1.514**
NSCL	**0.2747**	**0.2756**	**10**	**10**	**-5.493**	**-5.493**	**20.5**	**20.5**
HSCL	**1.831**	**1.889**	**21.5**	**21.51**	**-87.89**	**-87.89**	**25**	**25.01**
FT								
LFT	**87.89**	**87.89**	**65**	**64.98**	**-1.099**	**-1.085**	**72.5**	**72.51**

NFT	**1.099**	**1.099**	**77.5**	**77.5**	**-1.099**	**-1.099**	**82.5**	**82.5**
HFT	**0.6103**	**0.6098**	**84.5**	**84.5**	**-87.89**	**-87.89**	**90**	**90**

Gaussian2/Constant

	σ 1		**C1**		**σ 2**		**C2**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EEG								
DELTA	**0.01274**	**0.01274**	**0**	**0**	**0.3397**	**0.3397**	**3.1**	**3.1**
THETA	**1.189**	**1.189**	**5.65**	**5.65**	**0.6795**	**0.6795**	**6.2**	**6.2**
BETA	**1.189**	**1.189**	**10.15**	**10.15**	**1.019**	**1.019**	**10.8**	**10.8**
ALPHA	**1.019**	**1.022**	**13.7**	**13.7**	**0.01274**	**0.01274**	**15**	**15**
(HR)								
LHR	**0.08493**	**0.08493**	**20**	**20**	**8.493**	**8.49**	**47.5**	**47.5**
NHR	**5.096**	**5.096**	**58.5**	**58.5**	**13.59**	**13.59**	**64**	**64**
HHR	**8.833**	**8.836**	**107.4**	**107.4**	**0.08493**	**0.08493**	**120**	**120**
HRV								
VLF	**0.000133**	**0.000133**	**0.001**	**0.001**	**0.01247**	**0.02386**	**0.00697**	**0.03376**
LF	**0.01077**	**0.04274**	**0.03183**	**0.137**	**0.002718**	**0.003022**	**0.0358**	**0.0183**
HF	**0.001699**	**0.003129**	**0.0395**	**0.03782**	**0.000133**	**0.000133**	**0.16**	**0.16**
PEP								
LP	**0.934**	**0.9343**	**0**	**0**	**101.9**	**101.9**	**530**	**530**

	3							
NP	**339.7**	**339.7**	**900**	**900**	**1.699**	**1.699**	**1001**	**1001**
HP	**169.9**	**169.9**	**950**	**950**	**0.9343**	**0.9343**	**1100**	**1100**
(SV)								
LSV	**0.3397**	**0.3397**	**0**	**0**	**43.49**	**43.49**	**28.8**	**28.8**
NSV	**67.95**	**67.95**	**180**	**180**	**16.99**	**16.99**	**205**	**205**
HSV	**20.38**	**20.38**	**294**	**294**	**0.3397**	**0.3397**	**400**	**400**
SBP								
LSBP	**0.03992**	**0.03992**	**100**	**100**	**5.436**	**5.436**	**106.6**	**106.6**
NSBP	**4.077**	**4.077**	**120.8**	**120.8**	**4.077**	**4.077**	**123.2**	**123.2**
HSBP	**4.756**	**4.759**	**132.6**	**132.6**	**0.03992**	**0.03992**	**147**	**147**
DBP								
LDBP	**0.01359**	**0.01359**	**75**	**75**	**2.038**	**2.039**	**77.6**	**77.6**
NDBP	**1.699**	**1.699**	**81.5**	**81.5**	**1.699**	**1.699**	**82.5**	**82.5**
HDBP	**2.038**	**2.047**	**86.4**	**86.4**	**0.01359**	**0.01359**	**91**	**91**
SCR								
LSCR	**0.001274**	**0.001274**	**0**	**0**	**0.03397**	**0.03705**	**0.11**	**0.1115**
NSCR	**0.2208**	**0.2219**	**0.685**	**0.6836**	**0.08493**	**0.08785**	**0.775**	**0.7775**
HSCR	**0.05096**	**0.07786**	**0.985**	**1.01**	**0.001274**	**0.001274**	**1.5**	**1.5**
(VT)								

RAPID L	**0.9343**	**0.9343**	**100**	**100**	**6.795**	**6.799**	**132**	**132**
QUIET N	**101.9**	**101.9**	**470**	**470**	**84.93**	**84.93**	**525**	**525**
DEEPH	**101.9**	**101.9**	**870**	**870**	**0.9343**	**0.9343**	**1200**	**1200**
ROS								
LROS	**0.000849**	**0.000849**	**0**	**0**	**0.03058**	**0.03058**	**0.409**	**0.409**
NROS	**0.04416**	**0.05309**	**0.517**	**0.5114**	**0.02378**	**0.04247**	**0.537**	**0.5509**
HROS	**0.03397**	**0.03486**	**0.59**	**0.5892**	**0.000849**	**0.000849**	**1**	**1**
RR								
LRR	**0.01699**	**0.01699**	**5**	**5**	**1.019**	**1**	**7.3**	**7.298**
NRR	**2.718**	**2.718**	**14.2**	**14.2**	**2.718**	**2.718**	**15.8**	**15.8**
HRR	**2.718**	**2.733**	**22.2**	**22.2**	**0.01699**	**0.01699**	**25**	**25**
NSRR								
LNSRR	**0.004247**	**0.004247**	**0**	**0**	**0.3397**	**0.333**	**1.1**	**1.099**
NNSRR	**0.3397**	**0.3397**	**1.9**	**1.9**	**0.3397**	**0.3397**	**2.1**	**2.1**
HNSRR	**0.6795**	**0.6932**	**3.8**	**3.789**	**0.004247**	**0.004247**	**5**	**5**
SCL								
LSCL	**0.02123**	**0.02123**	**0**	**0**	**0.3397**	**0.3397**	**1.1**	**1.1**
NSCL	**6.795**	**6.795**	**18**	**18**	**0.3397**	**0.3398**	**20.1**	**20.1**

HSCL	**1.019**	**1.019**	**22.7**	**22.7**	**0.02123**	**0.02123**	**25**	**25**
FT								
LFT	**0.021 23**	**0.02123**	**65**	**65**	**1.699**	**1.709**	**70.5**	**70.5**
NFT	**1.699**	**1.699**	**79.5**	**79.5**	**1.699**	**1.699**	**80.5**	**80.5**
HFT	**3.058**	**3.058**	**88.1**	**88.1**	**0.02123**	**0.02123**	**90**	**90**

Gaussian2/Linear

	σ1		**C1**		**σ 2**		**C2**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EEG								
DELTA	**0.01274**	**0.01274**	**0**	**0**	**0.3397**	**0.3397**	**3.1**	**3.1**
THETA	**1.189**	**1.189**	**5.65**	**5.65**	**0.6795**	**0.6795**	**6.2**	**6.2**
BETA	**1.189**	**1.189**	**10.15**	**10.15**	**1.019**	**1.019**	**10.8**	**10.8**
ALPHA	**1.019**	**1.021**	**13.7**	**13.7**	**0.01274**	**0.01274**	**15**	**15**
(HR)								
LHR	**0.08493**	**0.08493**	**20**	**20**	**8.493**	**8.493**	**47.5**	**47.5**
NHR	**5.096**	**5.096**	**58.5**	**58.5**	**13.59**	**13.59**	**64**	**64**
HHR	**8.833**	**8.835**	**107.4**	**107.4**	**0.08493**	**0.08493**	**120**	**120**
HRV								
VLF	**0.00013 3**	**0.00013 3**	**0.001**	**0.001**	**0.01247**	**0.01509**	**0.0069 7**	**0.0170 6**
LF	**0.01077**	**0.0148**	**0.0318 3**	**0.0447 8**	**0.00271 8**	**- 0.01404**	**0.0358**	**0.0201 7**
HF	**0.00169**	**0.00206**	**0.0395**	**0.0384**	**0.00013**	**0.00013**	**0.16**	**0.16**

	9	**6**		**1**	**3**	**3**		
PEP								
LP	**0.9343**	**0.9343**	**0**	**0**	**101.9**	**101.9**	**530**	**530**
NP	**339.7**	**339.7**	**900**	**900**	**1.699**	**1.699**	**1001**	**1001**
HP	**169.9**	**169.9**	**950**	**950**	**0.9343**	**0.9343**	**1100**	**1100**
(SV)								
LSV	**0.3397**	**0.3397**	**0**	**0**	**43.49**	**43.49**	**28.8**	**28.8**
NSV	**67.95**	**67.95**	**180**	**180**	**16.99**	**16.99**	**205**	**205**
HSV	**20.38**	**20.38**	**294**	**294**	**0.3397**	**0.3397**	**400**	**400**
SBP								
LSBP	**0.03992**	**0.03992**	**100**	**100**	**5.436**	**5.436**	**106.6**	**106.6**
NSBP	**4.077**	**4.077**	**120.8**	**120.8**	**4.077**	**4.077**	**123.2**	**123.2**
HSBP	**4.756**	**4.756**	**132.6**	**132.6**	**0.03992**	**0.03992**	**147**	**147**
DBP								
LDBP	**0.01359**	**0.01359**	**75**	**75**	**2.038**	**2.038**	**77.6**	**77.6**
NDBP	**1.699**	**1.699**	**81.5**	**81.5**	**1.699**	**1.699**	**82.5**	**82.5**
HDBP	**2.038**	**2.038**	**86.4**	**86.4**	**0.01359**	**0.01359**	**91**	**91**
SCR								
LSCR	**0.001274**	**0.001274**	**0**	**0**	**0.03397**	**0.03397**	**0.11**	**0.11**
NSCR	**0.2208**	**0.2208**	**0.685**	**0.685**	**0.08493**	**0.08497**	**0.775**	**0.775**
HSCR	**0.05096**	**0.05022**	**0.985**	**0.9851**	**0.001274**	**0.001274**	**1.5**	**1.5**
(VT)								
RAPID	**0.9343**	**0.9343**	**100**	**100**	**6.795**	**6.795**	**132**	**132**

L								
QUIETN	**101.9**	**101.9**	**470**	**470**	**84.93**	**84.93**	**525**	**525**
DEEPH	**101.9**	**101.9**	**870**	**870**	**0.9343**	**0.9343**	**1200**	**1200**
ROS								
LROS	**0.000849**	**0.000849**	**0**	**0**	**0.03058**	**0.03058**	**0.409**	**0.409**
NROS	**0.04416**	**0.04429**	**0.517**	**0.5169**	**0.02378**	**0.02392**	**0.537**	**0.5371**
HROS	**0.03397**	**0.03406**	**0.59**	**0.5899**	**0.000849**	**0.000849**	**1**	**1**
RR								
LRR	**0.01699**	**0.01699**	**5**	**5**	**1.019**	**1.018**	**7.3**	**7.3**
NRR	**2.718**	**2.718**	**14.2**	**14.2**	**2.718**	**2.718**	**15.8**	**15.8**
HRR	**2.718**	**2.714**	**22.2**	**22.2**	**0.01699**	**0.01699**	**25**	**25**
NSRR								
LNSRR	**0.004247**	**0.004247**	**0**	**0**	**0.3397**	**0.3397**	**1.1**	**1.1**
NNSRR	**0.3397**	**0.3397**	**1.9**	**1.9**	**0.3397**	**0.3397**	**2.1**	**2.1**
HNSRR	**0.6795**	**0.673**	**3.8**	**3.801**	**0.004247**	**0.004247**	**5**	**5**
SCL								
LSCL	**0.02123**	**0.02123**	**0**	**0**	**0.3397**	**0.3397**	**1.1**	**1.1**
NSCL	**6.795**	**6.795**	**18**	**18**	**0.3397**	**0.3398**	**20.1**	**20.1**
HSCL	**1.019**	**1.019**	**22.7**	**22.7**	**0.02123**	**0.02123**	**25**	**25**
FT								
LFT	**0.02123**	**0.02123**	**65**	**65**	**1.699**	**1.7**	**70.5**	**70.5**

NFT	**1.699**	**1.699**	**79.5**	**79.5**	**1.699**	**1.699**	**80.5**	**80.5**
HFT	**3.058**	**3.058**	**88.1**	**88.1**	**0.02123**	**0.02123**	**90**	**90**

Gaussian/Constant

	σ		**C**	
	Before	**After**	**Before**	**After**
EEG				
DELTA	**1.66**	**1.66**	**1.55**	**1.55**
THETA	**0.91**	**0.91**	**5.93**	**5.93**
BETA	**1.30**	**1.30**	**10.48**	**10.48**
ALPHA	**0.55**	**0.60**	**14.35**	**14.35**
(HR)				
LHR	**20.17**	**20.16**	**33.75**	**33.75**
NHR	**15.92**	**15.92**	**61.25**	**61.25**
HHR	**5.35**	**5.43**	**113.70**	**113.70**
HRV				
VLF	**0.02**	**0.05**	**0.00**	**-0.07**
LF	**0.00**	**-0.03**	**0.03**	**0.02**
HF	**0.05**	**0.06**	**0.10**	**0.10**
PEP				
LP	**327.00**	**327.00**	**265.00**	**265.00**
NP	**44.38**	**44.38**	**950.30**	**950.30**
HP	**63.70**	**63.70**	**1025.00**	**1025.00**
(SV)				

LSV	**55.07**	**55.72**	**14.40**	**14.40**
NSV	**27.60**	**27.60**	**192.50**	**192.50**
HSV	**45.01**	**45.01**	**347.00**	**347.00**
SBP				
LSBP	**8.24**	**8.24**	**103.30**	**103.30**
NSBP	**5.10**	**5.10**	**122.00**	**122.00**
HSBP	**6.12**	**6.13**	**139.80**	**139.80**
DBP				
LDBP	**3.14**	**3.14**	**76.30**	**76.30**
NDBP	**2.12**	**2.12**	**82.00**	**82.00**
HDBP	**1.95**	**1.97**	**88.70**	**88.70**
SCR				
LSCR	**0.08**	**0.09**	**0.06**	**0.06**
NSCR	**0.12**	**0.16**	**0.73**	**0.72**
HSCR	**0.22**	**0.10**	**1.24**	**1.28**
(VT)				
RAPIDL	**20.38**	**20.38**	**116.00**	**116.00**
QUIETN	**108.30**	**108.30**	**497.50**	**497.50**
DEEPH	**140.10**	**140.10**	**1035.00**	**1035.00**
ROS				
LROS	**0.20**	**0.20**	**0.20**	**0.20**
NROS	**0.03**	**0.06**	**0.53**	**0.52**
HROS	**0.17**	**0.17**	**0.80**	**0.80**
RR				

LRR	**2.00**	**2.04**	**6.15**	**6.16**
NRR	**3.40**	**3.40**	**15.00**	**15.00**
HRR	**1.19**	**0.90**	**23.60**	**23.64**
NSRR				
LNSRR	**0.81**	**0.86**	**0.55**	**0.56**
NNSRR	**0.42**	**0.42**	**2.00**	**2.00**
HNSRR	**0.51**	**0.09**	**4.40**	**4.49**
SCL				
LSCL	**0.81**	**0.83**	**0.55**	**0.55**
NSCL	**1.23**	**1.23**	**19.05**	**19.05**
HSCL	**0.98**	**0.99**	**23.85**	**23.85**
FT				
LFT	**4.03**	**4.04**	**67.75**	**67.75**
NFT	**2.12**	**2.12**	**80.00**	**80.00**
HFT	**0.81**	**0.74**	**89.05**	**89.06**

Gaussian/Linear

	σ		**C**	
	Before	**After**	**Before**	**After**
EEG				
DELTA	**1.66**	**1.656**	**1.55**	**1.55**

THETA	**0.91**	**0.913**	**5.93**	**5.925**
BETA	**1.30**	**1.295**	**10.48**	**10.48**
ALPHA	**0.55**	**0.5521**	**14.35**	**14.35**
(HR)				
LHR	**20.17**	**20.17**	**33.75**	**33.75**
NHR	**15.92**	**15.92**	**61.25**	**61.25**
HHR	**5.35**	**5.351**	**113.70**	**113.7**
HRV				
VLF	**0.02**	**0.01667**	**0.00**	**-0.01325**
LF	**0.00**	**-0.01459**	**0.03**	**0.01808**
HF	**0.05**	**0.05191**	**0.10**	**0.1001**
PEP				
LP	**327.00**	**327**	**265.00**	**265**
NP	**44.38**	**44.38**	**950.30**	**950.3**
HP	**63.70**	**63.7**	**1025.00**	**1025**
(SV)				
LSV	**55.07**	**55.72**	**14.40**	**14.4**
NSV	**27.60**	**27.6**	**192.50**	**192.5**
HSV	**45.01**	**45.01**	**347.00**	**347**
SBP				
LSBP	**8.24**	**8.238**	**103.30**	**103.3**
NSBP	**5.10**	**5.096**	**122.00**	**122**
HSBP	**6.12**	**6.115**	**139.80**	**139.8**
DBP				

LDBP	**3.14**	**3.142**	**76.30**	**76.3**
NDBP	**2.12**	**2.123**	**82.00**	**83**
HDBP	**1.95**	**1.952**	**88.70**	**88.7**
SCR				
LSCR	**0.08**	**0.08094**	**0.06**	**0.0547**
NSCR	**0.12**	**0.1238**	**0.73**	**0.7299**
HSCR	**0.22**	**0.2093**	**1.24**	**1.244**
(VT)				
RAPIDL	**20.38**	**20.38**	**116.00**	**116**
QUIETN	**108.30**	**108.3**	**497.50**	**497.5**
DEEPH	**140.10**	**140.1**	**1035.00**	**1035**
ROS				
LROS	**0.20**	**0.2043**	**0.20**	**0.2045**
NROS	**0.03**	**0.03271**	**0.53**	**0.5268**
HROS	**0.17**	**0.1742**	**0.80**	**0.7951**
RR				
LRR	**2.00**	**1.996**	**6.15**	**6.15**
NRR	**3.40**	**3.397**	**15.00**	**15**
HRR	**1.19**	**1.191**	**23.60**	**23.6**
NSRR				
LNSRR	**0.81**	**0.807**	**0.55**	**0.55**
NNSRR	**0.42**	**4247**	**2.00**	**2**
HNSRR	**0.51**	**0.51**	**4.40**	**4.4**
SCL				

LSCL	**0.81**	**0.8069**	**0.55**	**0.55**
NSCL	**1.23**	**1.232**	**19.05**	**19.05**
HSCL	**0.98**	**0.9767**	**23.85**	**23.85**
FT				
LFT	**4.03**	**4.034**	**67.75**	**67.75**
NFT	**2.12**	**2.123**	**80.00**	**80**
HFT	**0.81**	**0.8071**	**89.05**	**89.05**