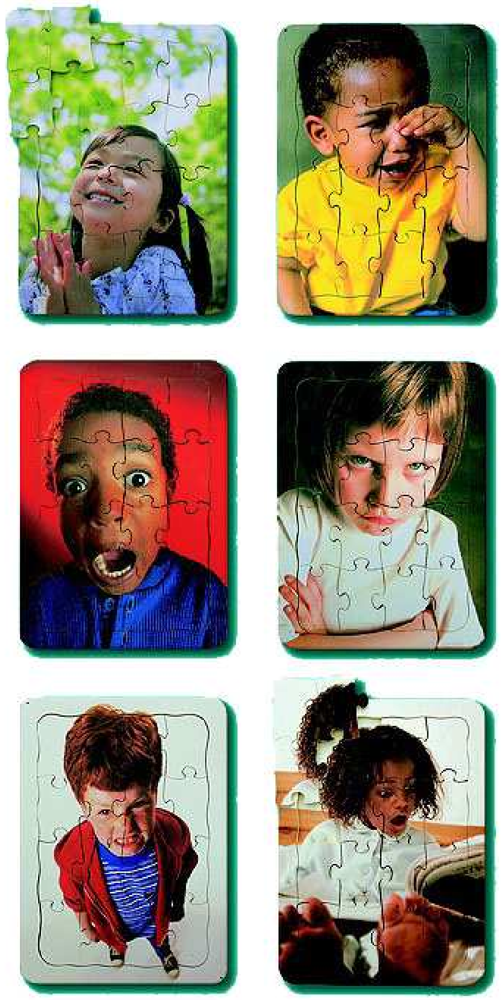


# Emotional Facial Expressions Recognition & Classification


Galateia Iatraki

Student number 1398741



Thursday, November 05, 2009



Master of Media and Knowledge Engineering

Man Machine Interaction Group

Faculty of Electrical Engineering, Mathematics and Computer Science

TU Delft Delft University of Technology

# Emotional Facial Expression Recognition & Classification

by Galateia Iatraki 1398741

Submitted for the degree of Master of Science in
Media and Knowledge Engineering

November 2009

Delft University of Technology
Faculty of Electrical Engineering, Mathematics and Computer Science
Master of Media and Knowledge Engineering
Man Machine Interaction Group

*Graduation Committee*
Prof. Drs. Dr. Leon J.M. Rothkrantz
Dr. ir. Pascal Wiggers
Ir. H.J. Geers

## ABSTRACT

Human machine interaction is not as natural as interaction among humans. That is the reason why is not yet possible to completely substitute face-to-face communication by human-machine interaction in spite the theoretical feasibility of such a substitution in several professional areas including education and certain medical branches. To approach the naturalness of face-to-face interaction, machines should be able to emulate the way humans communicate with each other.

Multi-media and man-machine communication systems could promote more efficient performance if machine understanding of facial expressions is improved. Based on this problematic issue, the current thesis is focused on the recognition of emotional facial expressions, finding interrelation between the facial expressions and labels and finally the classification of the expressions.

One of the parts of this project is an emotional database which will contain images of faces, their corresponding Action Units and their labels. The contribution of this database to the problem stated above is that it can be used by systems in order to recognize emotional facial expressions given one of the database data i.e. action units' combination.

The other part of the project, which is an expert system for emotional classification, will enable to classify emotional expressions, the ones included in the database and all the possible combinations of them.

# PREFACE

I want to take this opportunity to express my appreciation to all the people for their contribution and support they gave me to accomplish this thesis. Their support and their contribution during all this time were really meaningful.

First of all, I would like to thank my advisor Prof. Drs. Dr. Rothkrantz, for his help and guidance. His experience and ideas helped to reach the end of this project. I would also like to thank all participants who voluntarily participated in my experiment for data acquisition and application testing. I would also like to thank Zhenke Yang for answering my questions about expert systems and spend time for giving me advise and ideas.

I want to thank specially my parents, for their support for my decision of studying in Netherlands and also during the two years of the studies, even from a long distance.

Nevertheless, these two years were also full of new experiences and new people. An especial thank to my flat-mates, the old ones and the new ones, for the nice time we had and the very nice atmosphere in our house. Of course I am very grateful also for all my friends in Netherlands and Greece for their support but also the experiences and the fun time we had.

Last I want to thank all the people in the lab for making the time of studying more interesting and pleasant.

Galateia Iatraki
Delft, the Netherlands
October 2009

# TABLE OF CONTENTS

# LIST OF FIGURES

## LIST OF TABLES

# CHAPTER 1 Introduction

Interaction among humans is far more natural than human-machine interaction. That is the reason why is not yet possible to completely substitute face-to-face communication by human-machine interaction in spite the theoretical feasibility of such a substitution in several professional areas including education and certain medical branches. To approach the naturalness of face-to-face interaction, machines should be able to emulate the way humans communicate with each other.

Human communication has two main aspects: verbal (auditory) such as speaking, singing and sometimes tone of voice and non-verbal (visual) such as body language, sign language, paralanguage, touch, eye contact, or the use of text. The atomic units of verbal communication are words and for non-verbal phenomena like facial expressions, body movements, and physiological reactions. Although speech itself is often sufficient for communication (e.g. in a phone-call), non-verbal communication units can be useful in synchronizing the dialog, to signal comprehension or disagreement and to let the dialog run smoother, with less interruption.

Multi-media and man-machine communication systems could promote more efficient performance if machine understanding of facial expressions is improved.

## 1.1 Problem Overview

Most of the information that we have about facial expressions was shaped by our parents and our family. The faces of our parents and other people that took care of us as children were the first ones to see. Their faces may have been very expressive or very guarded in their facial expressions. People in our family may have shown emotions in their faces as most other people do, or one of them might have developed a strange or peculiar way of looking disgusted or afraid, and that may still influence our recognition of that emotion. As a child, some people have been specifically instructed not to look at the facial expressions of others, or at least certain facial expressions. For example, some children are told never to look at someone who is crying [9].

The number of the facial expressions that we use in our everyday life cannot be strictly specified due to the different surrounding and cultural background that each person has. Research on the facial expression analysis has focused more on the six basic emotional expressions (fear, anger, disgust, happiness, surprise and sadness). For these facial expressions conclusions about their universality have already been made. However, the emotional facial expressions used around the world are much more and some of them are combinations of more than one.

Based on the difficulty of recognition of several facial expressions from people of different backgrounds the focus of this thesis is to find a way to display a large variety of emotional facial expressions, validate them and produce rules in order to translate facial actions into emotional expressions.

## 1.2 Possible Applications

Facial expression recognition and classification can have many applications in various aspects of our everyday life. Many attempts have been made the recent years of using facial expression recognition in the fields of behavioral science, medicine and security and man-machine interfaces. In interaction of humans through computers and in human – computer interaction were face contact is important, like videoconference, games, affective computing and perceptual man-machine interfaces recognition of facial expressions can play a crucial role.

The recognition and generation of facial expressions can create a more human like communication. For example in computer games or other computer applications were avatars are used, a face of a widely recognized facial expression can produce a more natural communication. In the same example, the recognition of the user's emotion through facial expression recognition can be very usable. Another important aspect were facial expression recognition can be very useful is in medicine, for remote patient monitoring were non-verbal contact to the patient can be more direct and necessary.

## 1.3 Goal of the thesis

The goal of the current Master thesis is to create a database of emotional facial expressions, give the appropriate verbal labels and compare different ways of classification.

## 1.4 Research Questions

According to the theoretical problem overview that we gave we pose the following research questions:

a. *How to represent facial expressions?*

In this research the way that we are going to represent facial expressions is the Facial Action Coding System (FACS) [10]. FACS is the most widely used and versatile method for measuring and describing facial behaviors. Paul Ekman and W.V. Friesen developed the original FACS in the 1970s by determining how the contraction of each facial muscle (singly and in combination with other muscles) changes the appearance of the face. With the activation of a number of Action Units an emotion could be represented. In this project we will use the 3D Facial Expression Modeler, implemented by Anna Wojdel in TUDelft [23], in order to produce the faces and handle the Action Units involved as well as their intensity.

b. *How to label facial expressions?*

For labeling the facial expressions we will use emotional words. The emotions can be represented by facial expressions and by emotional words. We will combine these two kinds of data by finding for each facial expression the corresponding emotional word, that means the facial expression and the word that describe the same emotion.

c. *How to code facial expressions?*

The facial expressions are coded by the activated AUs and their intensities. Each facial expression can be coded by a set of numbers that represent the intensity level of the AUs.

d. *How to create a database of facial expressions?*

For creating a database of facial expressions we have first to produce the facial expressions as we mentioned above. After producing the data it is very important to validate them. The validation can be done by experts but also by non-expert participants.

e. *How to classify emotional expressions and emotional words?*

Classification of emotional facial expressions is a very popular topic in the field of human – computer interaction and several methods have been under research. One of the methods we will investigate in this project is the classification by an expert system on the rules of activation of AUs. Attempts of using an expert system as a classifier have already been researched by the group of MMI in TUDelft [18] but only for the six basic emotions. This project will be an attempt to create a more accurate system which will work for more than the six basic emotions.

Emotional words classification is also a common research topic. One of the most well – known approaches is to represent emotional words in 2D space according to their values of pleasantness and activation [20] [6] [22].

The answers to the questions above will enable us to achieve our goal and create the database of emotional labeled facial expressions. In the following paragraph we will give the methods used for completing our goal.

## 1.5 Methodology

In order to accomplish the goal of this project we followed some steps. The activities taken will be presented below:

1. *Literature research*

The first step we took was a literature study so as to have a complete overview of the methods we have to use in our project. It was also important to have a better understanding of the concepts of emotion, facial expressions in human face-to-face communication and the existing methods for the recognition and classification of those emotions and facial expressions.

2. *Data acquisition*

In this step we had to collect the data we needed for completing our database. Emotional words and photos of facial expressions were gathered from the literature and more photos of facial expressions were produced using the 3D Facial Expression Modeler (FEM) [23]. The process of design the final dataset included

3. *Data Validation*

After completing the data list we had to validate it. The validation was done in two ways. First we created two online user-tests, were the participants could and then we compared the results given by participants with

4. *Design the expert system*

Some of the data were used in order to build an expert system for emotion classification. The expert system takes as input combinations of Action Units and classifies them to emotions. The correlation of emotions and action units is based on the validated data from the previous methods.

## 1.7 Thesis outline

The rest of this report is divided in nine chapters.

In chapter two we will give a theoretical background for better understanding of some of the basic concepts used in this project.

Later, in chapter three, we explain how we gathered and validated the data for our database. The steps to create the final list of emotional words and the generation of facial expressions using the FEM [23] are being discussed. We present also the concept of the validation online user-test as well as the results.

Chapter four is about our study of the semantic of the distance between facial expressions and emotional words. We describe the methods used, the results and the comparison of the results.

In chapter five we give an overview of expert systems and more specifically of the CLIPS shell that we used.

In chapter six we describe how we computed emotions from Action Units; we give an overview of our algorithm.

The rules that we designed in CLIPS, based on our algorithm are explained in chapter seven.

In chapter eight we show how to run the expert system and test it.

The chapter nine includes the evaluation of the expert system and the final results.

Finally in chapter ten we give the conclusions of this thesis and some further recommendations.

# CHAPTER 2 Theoretical Background

## 2.1 Emotions

The critical role that emotions play in rational decision-making, in perception and in human interaction has introduced an increasing interest in recognition and reproduction of emotions in computers. In literature, many applications that could benefit from this ability have been explored as well as the importance of non-verbal communication in automatic systems. However, most of the research that has been carried out on understanding human facial expressions cannot be directly applied to an automatic dialog system, as it has mainly worked on static images or on image sequences where the subjects show a specific emotion with no speech included.


Figure 1 Expressing emotions by facial expressions

Real life emotions are often complex and involve several simultaneous emotions. They may occur either as the quick succession of different emotions, the superposition of emotions, the masking of one emotion by another one, the suppression of an emotion or the overacting of an emotion. These phenomena are referred as blended emotions. These blends produce "multiple simultaneous facial expressions". Depending on the type of blending, the resulting facial expressions are not identical.

Psychological studies have indicated that at least six emotions are universally associated with distinct facial expressions: happiness, sadness, surprise, fear, anger, and disgust [9] [10]. Several other emotions and many combinations of emotions have been studied but remain unconfirmed as universally distinguishable.

Figure 2 The six basic emotions

Theories about emotions stretch back at least as far as the Ancient Greek Stoics, as well as Plato and Aristotle. In Aristotelian theory of the emotions, Aristotle with the opportunity to develop his most sustained thoughts on emotions, not only does he define, explicate, compare and contrast various emotions, but also he characterizes emotions themselves. His observation is quite striking:

*Emotions are the things on account of which the ones altered differ with respect to their judgments, and are accompanied by pleasure and pain: such are anger, pity, fear, and all similar emotions and their contraries.*

Figure 3 Masks in ancient Greek theater showing intensely over-exaggerated facial features and expressions

We also see sophisticated theories in the works of philosophers such as René Descartes, Baruch Spinoza and David Hume. More recent theories of emotions tend to be informed by advances in empirical research. Often theories are not mutually exclusive and many researchers incorporate multiple perspectives in their work.

Emotion has been examined also from other areas of interest –biology (Charles Darwin) [5], psychology (William James) – all, as well as philosophy, included in psychological tradition. From the psychological tradition several definitions of emotion have been given. One of them is presented in the book “Emotions Revealed” by Ekman P. [8]:

*Emotion is a process, a particular kind of automatic appraisal influenced by our evolutionary and personal past, in which we sense that something important to our welfare is occurring, and a set of physiological changes and emotional behaviors begins to deal with the situation. Emotions prepare us to deal with important events without our having to think about what to do. Emotions produce changes in parts of our brain that mobilize us to deal with what has set off the emotion, as well as changes in our autonomic nervous system, which regulates our heart rate, breathing, sweating, and many other bodily changes, preparing us for different actions. Emotions also send out signals, changes in our expressions, face, voice, and bodily posture. We don't choose these changes; they simply happen.*

The psychological point of view should not be magnified, however some techniques and ideas made in this area can be useful in a more practical field of interest.

## 2.2 Facial Expressions

Facial expressions play an important role in our relations. They can reveal the attention, personality, intention and psychological state of a person [21]. They are interactive signals that can regulate our interactions with the environment and other persons in our vicinity [13]. Based on Darwin's work[5], as well as Ekman's [8, 9, 10], the research in the field of automatic facial expression analysis is focused more to six prototypic emotional facial expressions - fear, sadness, disgust, anger, surprise, and happiness - . However, these basic expressions represent only a small set of human facial expressions. In fact, human emotion is composed of hundreds of expressions and thousands of emotional words, although most of them differ in subtle changes of a few facial features.

## 2.3 Facial Expression measurement

In order to make the information retrieved from the face and facial expressions available for usage, the facial gestures should be described.

The Facial Action Coding System (FACS) developed by Ekman and Friesen [10] is the most commonly used system for facial behavior analysis in psychological research. Another way of describing facial actions is in geometrical terms, model-based approaches, by using the Facial Animation Parameters (FAPs) that describe the face motion.

### 2.3.1 The Facial Action Coding System (FACS)

The Facial Action Coding System (FACS), developed by Ekman and Friesen [10], is a meta-representation that allows describing facial expression prior to interpretation. FACS detects and measures a large number of facial expressions by virtually observing a small set of facial muscular actions. The system decomposes the face into 46 so called Action Units (AUs), each of which is anatomically related to the contraction of either a specific facial muscle or a set of facial muscles.

FACS, except the AU's definition, includes the rules for AU's detection in a face image. Using these rules, a FACS coder (a human expert that has been formally trained using FACS) is able to encode a shown facial expression in terms of the AUs that cause the expression.

Although FACS has proven to be a reliable way for describing and measuring a large number of facial expressions, there seem to contain many limitations. The training procedure of human experts, so they can manually score AUs, is expensive, time consuming and at some point subjective.

The above limitations enhance the need for a fully automatic system that can detect and classify AUs and all their possible combinations that can appear in the face.

### 2.3.2 The Facial Animation Parameters (FAPs)

The FACS model has recently inspired the derivation of facial animation and definition parameters in the framework of the ISO MPEG-4 standard. In particular, the facial definition parameter set (FDP) and the facial animation parameter set (FAP) were designed in the MPEG-4 framework to allow the definition of a facial shape and texture, as well as the animation of faces reproducing expressions, emotions, and speech pronunciation[4].

The FAPs are based on the study of minimal facial actions and are closely related to muscle actions. They represent a complete set of basic facial actions, such as squeeze or raise eyebrows, open or close eyelids, and therefore allow the representation of most natural expressions. All FAPs involving translational movement are expressed in terms of the facial animation parameter units (FAPUs). These units aim at allowing interpretation of the FAPs on any facial model in a consistent way, producing reasonable results in terms of expression and speech pronunciation. FAPUs correspond to fractions of distances between some key facial features [14].

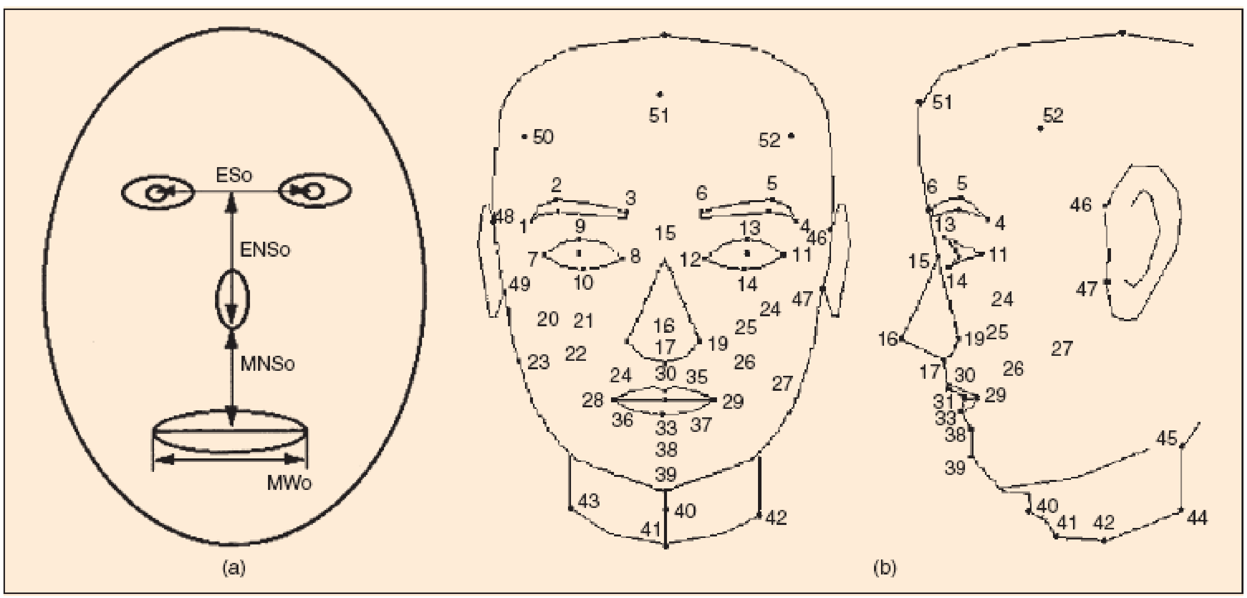



Figure 4 The Facial Animation Parameter Units (FAPUs) and the Facial Definition Parameter (FDP) set defined in the MPEG-4 standard

Using the MPEG4 parameters for the analysis of facial emotions has different advantages. In first place, the developed high-level analysis can benefit from already existing low-level analysis techniques for FDP and FAP extraction, as well as from any advances that will be made in this area in the future years. Besides, the low-level FAP constitute a concise representation of the evolution of the expression of the face. From the training database, and using the available FAP, spatiotemporal patterns for expressions will be constructed [14].

## 2.4 Facial Expression Representation (FEM)

Facial Expression Modeler (FEM) [23] is a system for the generation of facial expressions. It is implemented in C++ language on a PC platform. It uses multiplatform OpenGL and Qt GUI toolkits, and so it is available on both Windows and Linux operating systems (with the possibility of porting it to other systems as well). The 3D face model is built from triangular mesh modeled and textured in 3D Studio Max. The shape of the wireframe was built on the basis of an existing person's face. In order to create a texture two pictures of this specific person have been: a frontal and lateral view of the face. Both pictures were orthogonally projected on a cylindrical texture, and blended together. This software includes a parser to read ".ase" files exported from 3D Studio Max, and builds an internal 3D model which is displayed in the main window. The user interface consists of a window with 3D facial model and two controls for accessing facial expressions from the library, and editing them by editing the different AU controllers. This user interface is illustrated in the following figure:

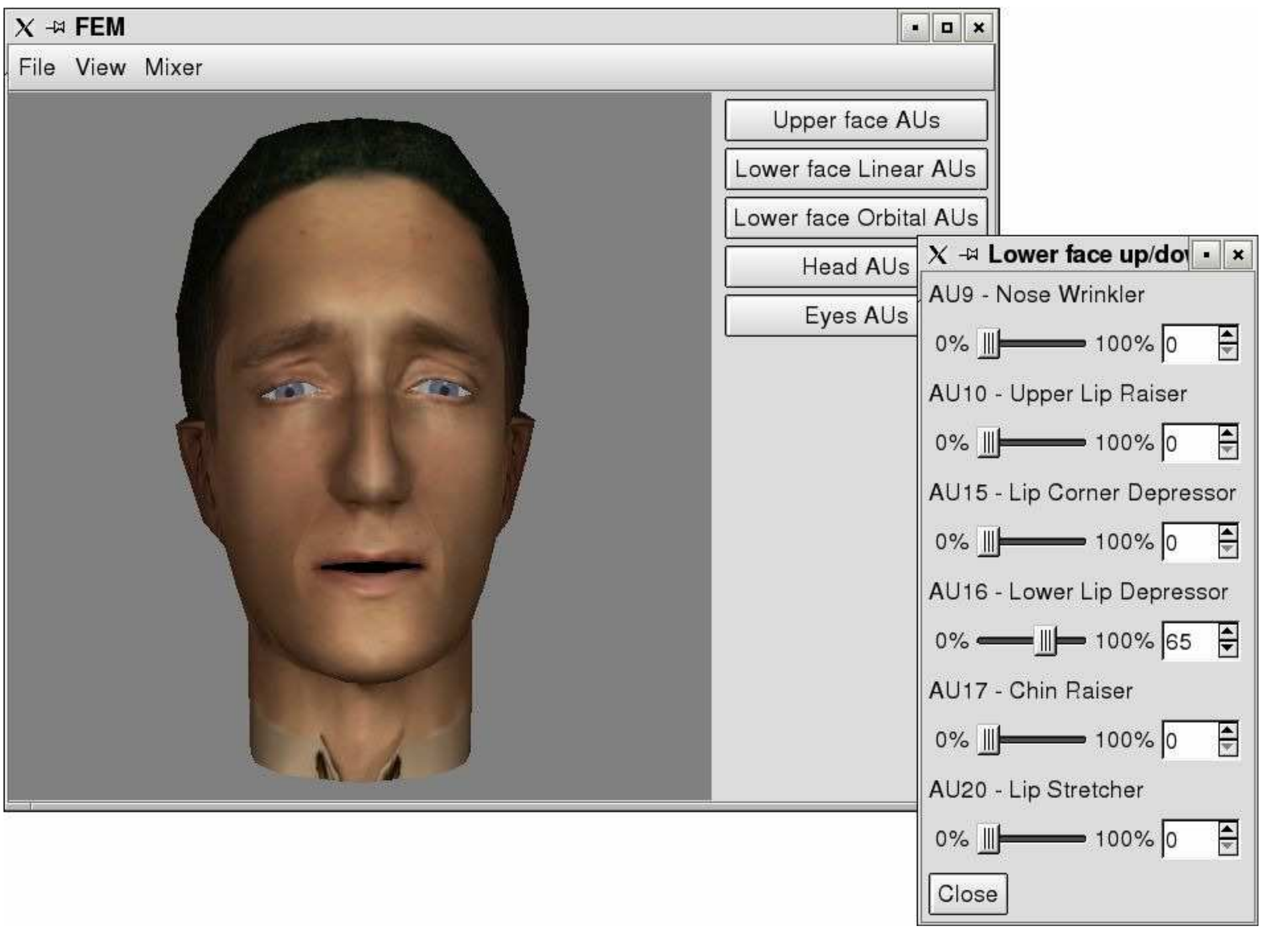



Figure 5 Example of using FEM

The facial model is based on FACS, but the user of this system does not have to be an expert in FACS in order to use the system itself. For the user a facial expressions script language was designed that wraps up the AU's in more intuitive terms. While designing a new facial expression, a user can make use of pre-defined facial expressions, which can be loaded from the library. It is assumed that each expression in the library is defined by a unique name, and that any given expression has a fixed set of AU's with their intensities.

The user can also create facial expressions and save them into the library. There is also an editor to modify an existing facial expression. In order to edit or to create new facial expressions, a user can access lower-level animation controls (using GUI elements that control all of the parameters corresponding to each AU). He can interactively move sliders and observe changes on the face resulting from activation of a given AU. These controls are divided into 5 groups of AU's: Upper face AU's, Lower face linear AU's, Lower face orbital AU's, Head AU's, Eyes AU's.

## 2.5 The pleasure and activation degree of emotional words

Research from Darwin forward has recognized that emotional states involve dispositions to act in certain ways. The various states that can be expressed are simply rated in terms of the associated activation level. Instead of choosing discrete labels, observers can indicate their impression of each stimulus on several continuous scales. Two common scales are valence(negative/positive) and arousal(active/passive). Valence describes the pleasantness of the stimuli, with positive (or pleasant) on one end, and negative (or unpleasant) on the other. The other dimension is arousal or activation; see Figure 6. The vertical axis shows activation level (arousal) and the horizontal axis evaluation (valence). A circumplex can be viewed as implying circular order, such that variables that fall close together are more related than variables that fall further apart on the circle, with opposite variables being negatively related and variables at right angles being unrelated (orthogonal).

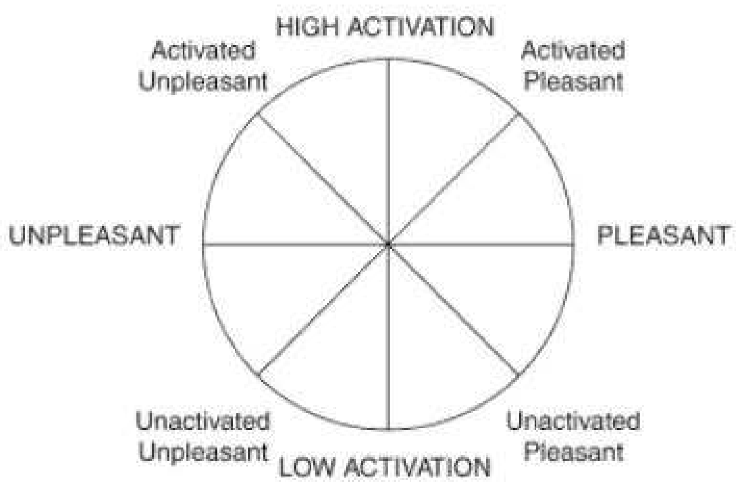



Figure 6 Activation-Evaluation space

We can identify the centre as a natural origin or the neutral state. The neutral state is a condition of readiness to respond. Emotional strength can be measured as the distance from the origin to a given point in the activation-evaluation space. An interesting implication is that strong emotions are more sharply distinct from each other than weaker emotions with the same emotional orientation. A related extension is to think of the six archetypal emotions as cardinal points in that space.

### 2.5.1 Emotional words classification by Russell and Desmet

In many researches on the English language a list has been defined of more than 200 words that are used to cover the full range of emotions. The meaning of these words contains a degree of pleasure and a degree of activation. This is also the same for sentences that contains some of these words; the sentence will then also have these degrees of pleasure and activation that appears because of the combination of these words. Recent attempts to analyze the degree of pleasure and the degree of activation of emotion words have been done by Russell [20] and Desmet [6]. Both depict these degrees on a 2D space of pleasure vs. activation. Russell used a psychological approach to plot emotional words, in a circular form called the Circumplex of Emotions, based on the changing of geometrical features of human expressions when expressing a certain emotion type (figure 7). He claimed that people can use the 2D space to analyse the emotion tendency of each word and their expression in a glance.

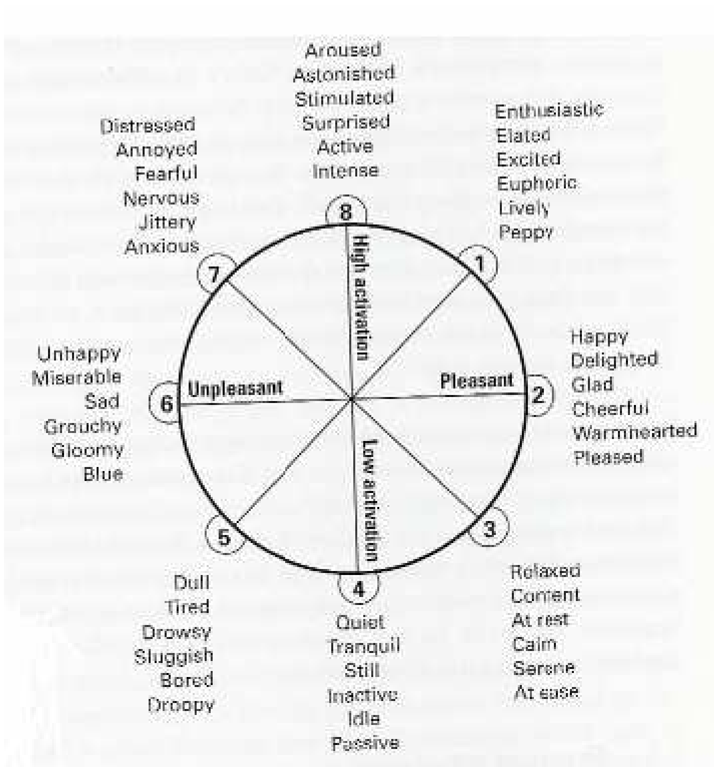



Figure 7 Russell's Circumplex of Emotions

Based on Russell's research, Desmet divided the 2D space into eight octants and conducted experiments. He used 347 emotion words. Through three experiments he collected 41 emotional words that were not ambiguous. He asked his participants to depict these words on one of the octants. In figure 8 we see how Desmet divided the 2D space in 8 octants and how plotted the 41 non ambiguous emotional words based on those 8 octants. Desmet claimed that these emotion words were used by people to express their emotion toward a product.

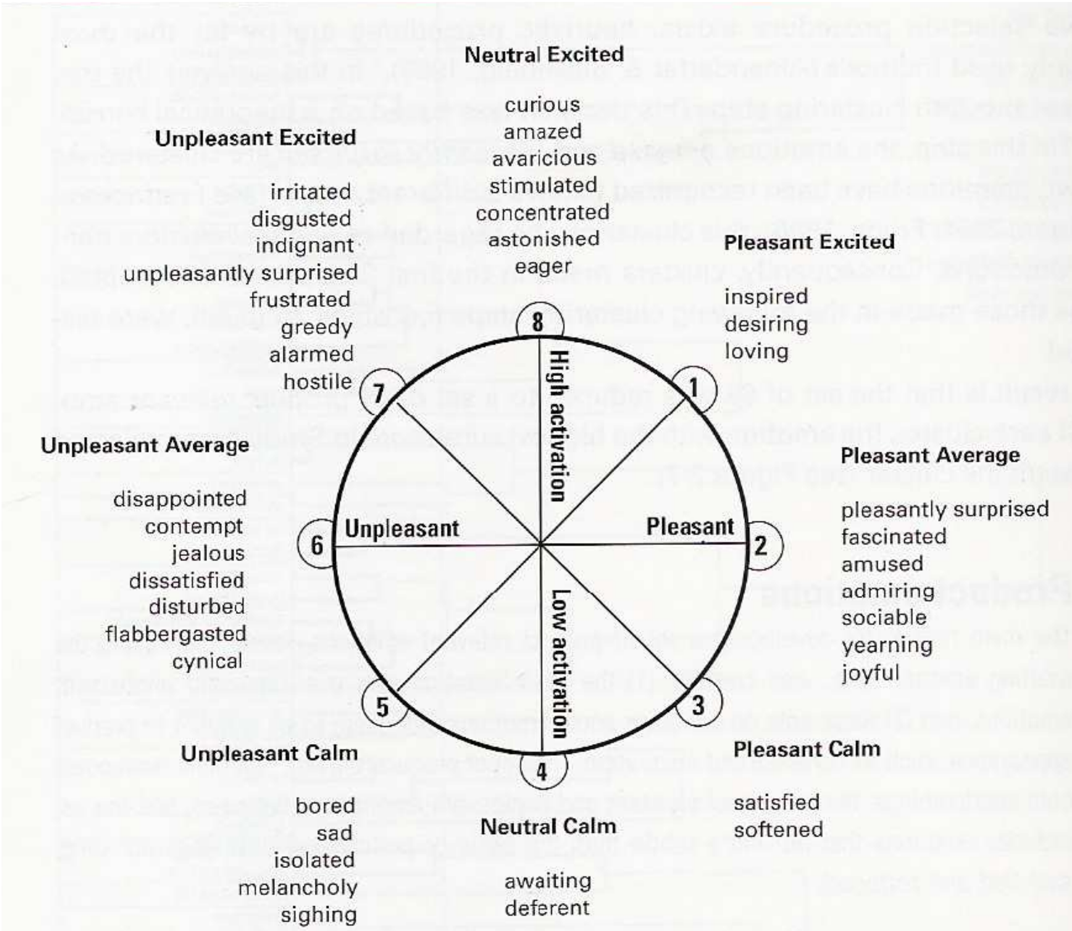



Figure 8 Desmet's classification

Both researches were performed to analyze quantitative values of emotion words based on the social value that was learnt during interaction with others or objects in daily life.

## 2.6 State-of-the-art in Facial Action Classification

In general, an automatic AU classification system consists of two steps: the facial feature extraction and the AU classification. In this research we will focus on the second stage, the classification. There are several approaches in AU classification which can be separated in two groups: the spatial approaches, where AUs are analyzed frame by frame, and the spatial-temporal approaches, where AUs are recognized over time based on the temporal evolution of facial features. The several automatic systems can differ in the feature extraction technique, the classification method or both.

### 2.6.1 The Spatial Classification Approaches

The Spatial Classification Approaches contain different methods such as neural networks, rule-based systems, Support Vector Machines (SVMs), template matching and rule-based method [19].

A whole different method is the Gabor wavelet or Gabor filter. A wavelet is a mathematical function used to divide a given function into different frequency components. A wavelet transform is the representation of a function by wavelets. The copies, so called “daughter wavelets”, are scaled and translated copies of the “mother wavelet”, a finite-length or fast-decaying oscillating waveform. Gabor filters are directly related to Gabor wavelets. There is no expansion applied to Gabor Filters as this is very time-consuming. Therefore a filter bank consisting of Gabor filters with various scales and rotations is created beforehand.

A Neural Network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing. In most cases a NN is an adaptive system that changes its structure, or weights, based on external or internal information that flows through the network. Training the neural network, especially when using spontaneous facial behavior is difficult due to the large number of possible AUs combinations.

Principal components analysis (PCA) is a technique used to reduce multidimensional data sets to lower dimensions for analysis. PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA involves the calculation of the eigenvalue decomposition or Singular value decomposition of a data set.

Support Vector Machines (SVMs) are a set of related methods used for classification and regression. They belong to a family of generalized linear classifiers. SVMs map input vectors to a higher dimensional space where a supervised learning classification regression linear classifiers separating hyperplane is constructed. The separating hyperplane is the hyperplane that maximizes the distance between the two closest support vectors of each class. The larger the distance is to the separating hyperplane from the support vectors the smaller the generalization error of the classifier will be. Support Vector Machines (SVMs) were compared to other techniques and the outcome was that the best performance was obtained when it was used on Gabor wavelet coefficients selected by AdaBoost.

A rule-based method was used in [19] with fast direct chaining inference procedure for AU classification. Based on the description of each AU in the FACS system, a set of rules are generated in terms of the feature representation, as well as some simple relationships among the AUs.

### 2.6.2 The Spatial-Temporal Classification Approaches

The Spatial-Temporal Classification Approaches include techniques as Hidden Markov Models (HMMs) and Bayesian Networks (BNs).

A Bayesian network (or a belief network) is a probabilistic model that represents a set of variables and their probabilistic independences. A HMM is a statistical model in which the system being modeled is assumed to be a Markov process with unknown parameters. A HMM can be considered as the simplest DBN.

### 2.6.3 Limitations of Facial Action Classification

Although there are many different approaches for facial action classification with interesting results, there also some limitations:

- Definition of emotions: The definition of emotions remains a critical issue. There is not one widely accepted definition but several definitions that have been given within different areas of interest.

- Labeling of facial expressions: The most typical method for labeling, is to show photographs of facial expressions to observers, who are asked to say what emotion they see in each face. The observers may be given a predetermined list of emotion words to choose from, or left to their own resources to reply with whatever emotion word comes to mind. That makes the labeling subjective as it is done by humans and also content dependent because they have to work on specific data. So far the labeling of six only emotions has been established. There are probably other emotions conveyed by the face-shame and excitement, for example, but these have not yet been as firmly established.

- Pure and blended emotions: Blended emotions, as it has been already explained are more complex than pure emotions, not identical and produce multiple simultaneous facial expressions. All these characteristics of the blended emotions make them difficult to analyze and till now most approaches in the field of emotion classification is about pure emotions and not blended emotions.

- Still pictures and video: In automatic AU coding, the use of still images is important for obtaining configurationally information about facial expressions. However the videos are necessary for studying temporal dynamics of facial behavior. The importance of both types of data makes difficult for the researchers to select the appropriate type for their approach. While in each case there are

- Emotions of a talking face: It is harder to describe emotions of a talking face because in case of speech some muscles of the face are moved changing the appearance of the face and making more difficult to understand which movements have to do with the expressed emotion and which have to do only with the speech.

- Spontaneous and acted emotions: Emotional expressions can be spontaneous or acted. The difficulty is to say which is which. There are many reasons for controlling facial expressions of emotion like cultural or group display rules that govern how people manage the appearance of their faces in public.

- Real life emotional facial expressions: In real the recognition of facial expressions is not always easy because of some conditions. These conditions are:
  1. orientation of the face
  2. occlusion because of glasses, moustache, beard etc
  3. light conditions.

# CHAPTER 3 Creating the non-verbal emotional database

*"A picture is worth a thousand words".*

An image may be more influential than a substantial amount of text. In our approach we wanted to determine emotions by pictures and by words. Unfortunately, there is no 1 to 1 correspondence between words and pictures. In our everyday life we learn how to interpret emotions and emotional facial expressions. However, sometimes is not easy to distinguish some emotions from the facial expression only. A very typical example of the ambiguity in emotional facial expressions is something that most of us have faced in our childhood in times that we were unrepentant about something we have done and our parents or teachers try to make us squirm about, and their response in our question "Why are you so angry?" is "I am not angry, just disappointed". That common example show that sometimes is not easy to recognize which emotion is being shown.

In our approach we aim to create an emotional database that will contain facial expressions and their most appropriate corresponding label. Our aim is to have the images of the faces an emotional word that describes that image. For each facial expression we will have the image of the face showing the expression and the list of Action Units that combine this expression. For each emotional word/label, important information we want to include in our database are the values of valence and arousal that we retrieved from Whissell's dictionary of affect in language (DAL) [22].

Table 1 Example of Whissell's dictionary values

| Word | Evaluation | Activation |
|---|---|---|
| cheerful | 2.5000 | 2.6250 |

| Emotional Words | Pleasantness Value | Activation Value | Facial Expression | Action Units |
|---|---|---|---|---|
| Happy | 3.00 | 2.75 |  | AU2 50<br>AU6 100<br>AU12 100<br>AU16 100 |

Figure 9 Example of information in the database

For creating the database as we described above we had to gather the data, validate them and examine their relations. The steps we had to take are described in the list below.

- Create a list of emotional words/labels and their pleasantness/activation values

- Generating the corresponding (3D) facial expression for each emotional word by using FEM, so that we will have the combination of AUs activated for each expression
- Validation of the pairs of emotional words/labels – facial expressions: after producing the facial expressions that represent the emotional words, we need to validate them and examine if there is a 1 to 1 correspondence in our dataset. For the validation we chose to design a user study that is being described in detail in 3.4.

In the following paragraphs of this chapter we will describe in detail the first three steps mentioned in the list.

## 3.1 Creating the list of emotional words/labels

The first step to create our database was to make the list of emotional words. The most important researches on the field of emotional words classification were the approaches of Russel and Desmet [20] [6] that we described in chapter 2.

Desmet [6], based on Russel's [20] work introduced a set of 41 product relevant emotions. This set of emotions does not provide a complete overview of all the emotions that a product can possibly elicit. First, it includes only those emotions that are often elicited by a product's assessment. The set would have included (partly) other emotions if it had been developed for product usage (e.g. using a malfunctioning computer), or ownership (e.g. owning an expensive car). Our appraisals are partly determined by our relationship with the particular product. Therefore, different emotions will emerge in different person-product relationships. The emotion shame, for example, which is not included in the current set, may be relevant in the context of product ownership (e.g. Thomas is ashamed of his old-fashioned shoes). Furthermore, the set does not represent all the emotions that can be elicited by a product's appearance, but only those that are often elicited by a product's appearance.

In order to enhance our database with emotional words that were not based on product validation we also gathered some data from the work of de Jongh [12]. The list provided contained except the emotional word and the appropriate facial expression generated by Face Shop, a facial expression modeler.

For each emotional word we had also to find the pleasantness activation values which would be included in the database and used also in the data analysis. The appropriate values were found in the Whissell's Dictionary of Affect in Language [22]. The Dictionary of Affect in Language (called DAL or Dictionary for short) is an instrument designed to measure the emotional meaning of words and texts. It does this by comparing individual words to a word list of 8742 words which have been rated by people for their activation, pleasantness and imagery.

The initial list of emotional words-labels was a combination of the two lists that were mentioned in the previous paragraph, the list of 41 product relevant emotions and the list of 43 emotional words used in the work of de Jongh [12].

After deleting the duplications introduced by merging the two lists and included the emotional words for the six basic emotions according to Ekman [8], we ended up with a list of 60 emotional words. We added the six basic emotions because they considered being the keystone in emotional expressions' research.

The next step, after finalizing the word list was to create the corresponding facial expressions.

## 3.2 Generating 3D examples using FEM

The next action we had to take was to generate the 3D emotional Facial Expressions which were corresponding to the emotional words included in our list. For each emotional word we produced the corresponding facial expression according to images found in literature and our knowledge and understanding of expected appearance for each emotion. For this activity we used the 3D Facial Expression Modeler (FEM) [23].

While working with FEM, we could use only one specified image of a 3D face. For generating a facial expression we had first to load the initial image of a neutral face which was opened in a 2D window. Then from the software's menu we could open some sub-windows which contained sliders, corresponding to Action Units. The sliders, each one with the appropriate Action Unit's name label, were divided in sub-windows according to the Action Units position.

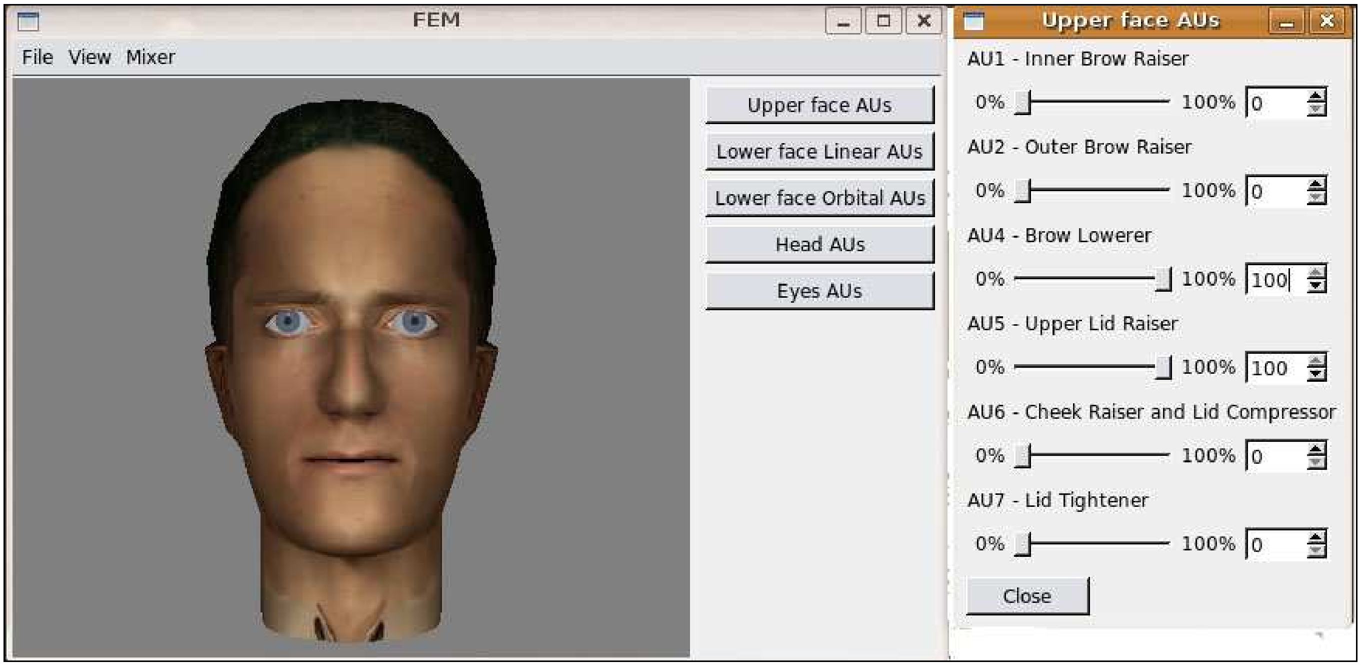



Figure 10 FEM user interface

The position of each slider is equivalent to action unit's intensity. Moving the slider from 0 to 100% we can show the intensity of the Action Unit and visualize the result, real time, in the face model.

For each emotional word we generated the corresponding facial expression based on images found in literature and in our understanding and knowledge on facial expressions.

The drawbacks of this procedure were that the photos found in literature were sketches and not photos of real people, the movements on the face were not based on the action units, and that made the simulation in FEM more complicated.

Initially, we generated more than one facial expression for each emotional word and we selected the most expressive. In table 2 we can see a part of the table containing the basic representation of emotions in terms of AUs intensities. The whole table that contains the 60 emotions of our database can be found in Appendix B.

Table 2 The basic representation of emotions expressed in terms of AUs intensities

| | AU1 | AU2 | AU4 | AU5 | AU6 | AU7 | AU9 | AU10 | AU12 | AU15 | AU16 | AU17 | AU18 | AU20 | AU22 | AU23 | AU24 | AU25 | AU26 | AU27 | AU28 | AU43 | AU54 | AU64 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| aggressive | 100 | 0 | 100 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 50 | 0 | 100 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| admire | 80 | 70 | 0 | 70 | 75 | 0 | 40 | 0 | 60 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 75 | 0 | 0 | 0 | 0 | 0 | 0 |
| afraid | 100 | 0 | 100 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| alarmed | 100 | 100 | 0 | 100 | 0 | 0 | 40 | 0 | 0 | 60 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| amazed | 60 | 100 | 0 | 45 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| amused | 30 | 40 | 0 | 0 | 100 | 0 | 40 | 0 | 100 | 0 | 30 | 0 | 40 | 80 | 0 | 30 | 0 | 27 | 0 | 0 | 0 | 0 | 0 | 0 |
| angry | 0 | 0 | 100 | 0 | 0 | 40 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 20 | 0 |
| annoyed | 0 | 80 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| anticipated | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 |
| avaricious | 0 | 80 | 40 | 55 | 70 | 0 | 0 | 0 | 0 | 0 | 20 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| awaiting | 0 | 0 | 20 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 |
| bored | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 50 | 0 | 0 |
| cautious | 0 | 70 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 | 0 |
| cheerful | 50 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| concentrated | 0 | 0 | 60 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| contempt | 0 | 100 | 70 | 0 | 0 | 0 | 70 | 0 | 0 | 40 | 0 | 40 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 20 | 0 | 0 |
| curious | 0 | 100 | 20 | 80 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 40 | 0 | 0 |
| cynical | 0 | 100 | 40 | 30 | 80 | 0 | 0 | 25 | 40 | 0 | 0 | 40 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 35 | 0 | 0 | 0 |
| dangerous | 0 | 0 | 80 | 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| defeated | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| deferent | 50 | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 |
| desire | 100 | 15 | 30 | 80 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| desperate | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 |
| disbelief | 0 | 100 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| disgust | 0 | 0 | 60 | 0 | 100 | 0 | 100 | 0 | 0 | 30 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 |
| dissapointed | 70 | 30 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| dissatisfied | 0 | 0 | 100 | 0 | 50 | 0 | 30 | 0 | 0 | 20 | 0 | 30 | 0 | 70 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| disturbed | 0 | 50 | 100 | 30 | 70 | 0 | 0 | 0 | 0 | 50 | 0 | 30 | 0 | 0 | 0 | 50 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

However, we needed a further testing of the produced faces, which was the next step in our research.

## 3.4 Validation of the pairs of emotional words/labels – facial expressions

As we have already mentioned, after creating the list of emotional words and their activation and pleasantness values, and generated the facial expressions using FEM we had to validate the pairs of emotional words/labels – facial expressions and examine if there is a 1 to 1 correspondence in our dataset.

For reaching our goal we designed a user test which we called Labeling User Test because the main idea is that users will be given images of facial expressions and list of emotional words and they will have to choose the appropriate word for the given image. In the following paragraphs we will describe our method in detail and the results of the Labeling User Test.

### 3.4.1 Labeling User Test

Our dataset consists of 60 emotional words and their corresponding labels. However, for the labeling user test we aimed to gather a big number of participants, without any specific knowledge on the field of emotion recognition and with a different cultural background. We realized that this goal was not easy to reach in case of the sixty emotional expressions and we should decrease the number of questions.

We decided to divide the list of sixty emotional words (labels) into groups. For performing this division we initially plot all the emotional words in 2D space according to their pleasantness and activation value given by Whissell [22]. In a later step we implemented the fuzzy c-means (FCM) algorithm [25] for initializing the clusters of the words in the 2D space.

In order to create the clusters of emotional words we implemented the fuzzy c-means (FCM) algorithm [25]. Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every data-point in the dataset belonging to every cluster to a certain degree. For example, a certain data-point that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another data-point that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster.

In figure 11 you can see the plot of emotional words in 2D space. Different shapes and colors of the data-points represent the different clusters produced by FCM algorithm.

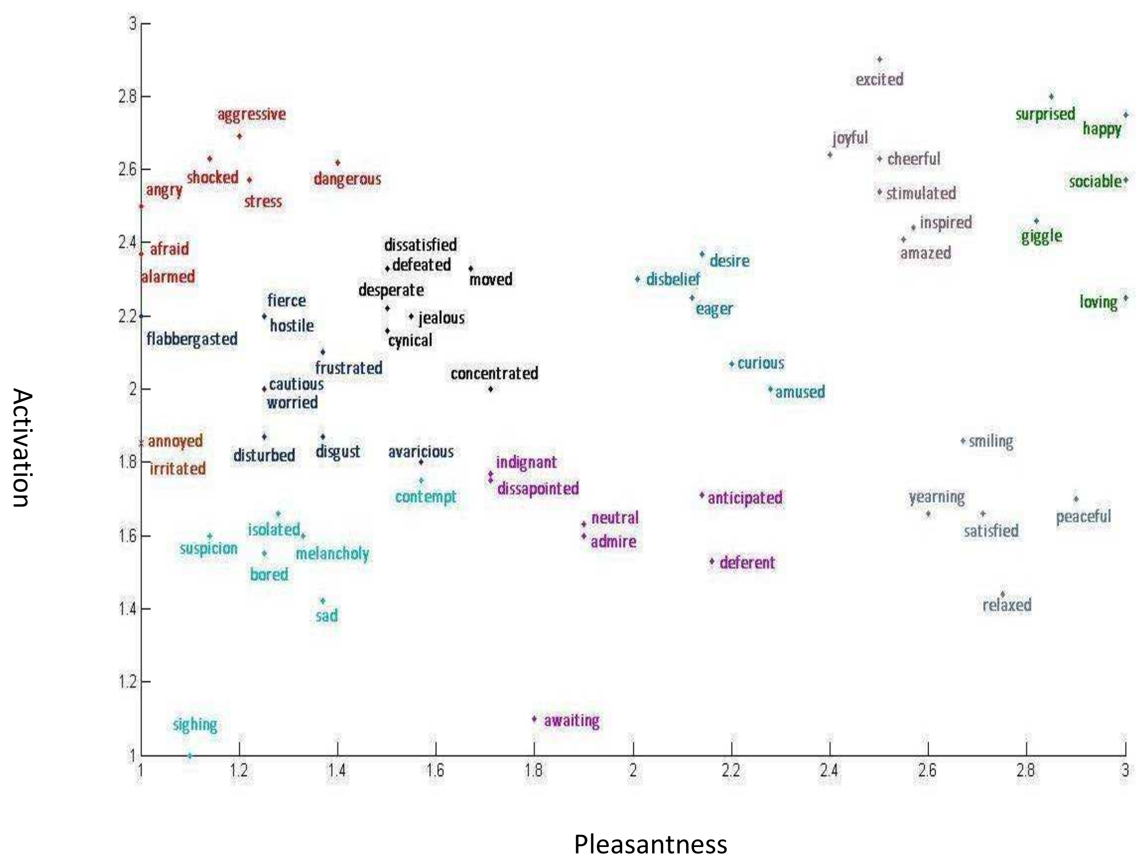



Figure 11 The 2D emotional space of the sixty emotional words characterized by pleasantness and activation

Table 3 The 10 clusters produced by FCM

| 1st cluster | 2nd cluster | 3rd cluster | 4th cluster | 5th cluster |
|---|---|---|---|---|
| indignant<br>disappointed<br>neutral<br>admire<br>anticipated<br>different<br>awaiting | dangerous<br>aggressive<br>shocked<br>stress<br>angry<br>alarmed<br>afraid | flabbergasted<br>hostile<br>fierce<br>frustrated<br>worried<br>cautious<br>disturbed<br>disgust<br>avaricious | surprised<br>happy<br>sociable<br>giggle<br>loving | irritated<br>annoyed |
| **6th cluster** | **7th cluster** | **8th cluster** | **9th cluster** | **10th cluster** |
| contempt<br>isolated<br>melancholy<br>suspicion<br>bored<br>sad<br>sighing | smiling<br>peaceful<br>satisfied<br>yearning<br>relaxed | excited<br>joyful<br>cheerful<br>stimulated<br>inspired<br>amazed | desire<br>disbelief<br>eager<br>curious<br>amused | dissatisfied<br>defeated<br>moved<br>desperate<br>jealous<br>cynical<br>concentrated |

For each of the sixty emotional words we had already produced the corresponding facial expression in the 3D modeler (FEM) [23]. For every cluster we chose the most expressive facial expression. Before forming the final dataset for the first online user test we decided to include all the six basic emotions which are consider the basis of research on the field of emotional facial expressions. For that reason the lists of emotional words of the second and fourth cluster were user twice. The second cluster includes angry and afraid, which belong both to the basic emotions, and the fourth cluster includes happy and surprised.

We ended up with the final data set for the first online user test which included 60 emotional words and 12 images of faces showing emotional expressions.

The online facial expressions labeling user test is an anonymous test. The only personal data we gathered from the participants are gender, age and nationality for statistical purposes.

The participants were shown one photo and a duplicated list of labels – emotional words. The first column of labels had the title first choice and the second one second choice. The intention of having two choices was that some facial expressions are possible to have ambiguous meaning according to some users. The first choice expresses the most suitable label from the list and the second choice gave to participants the option to select another label that they also found relative to the expression shown.

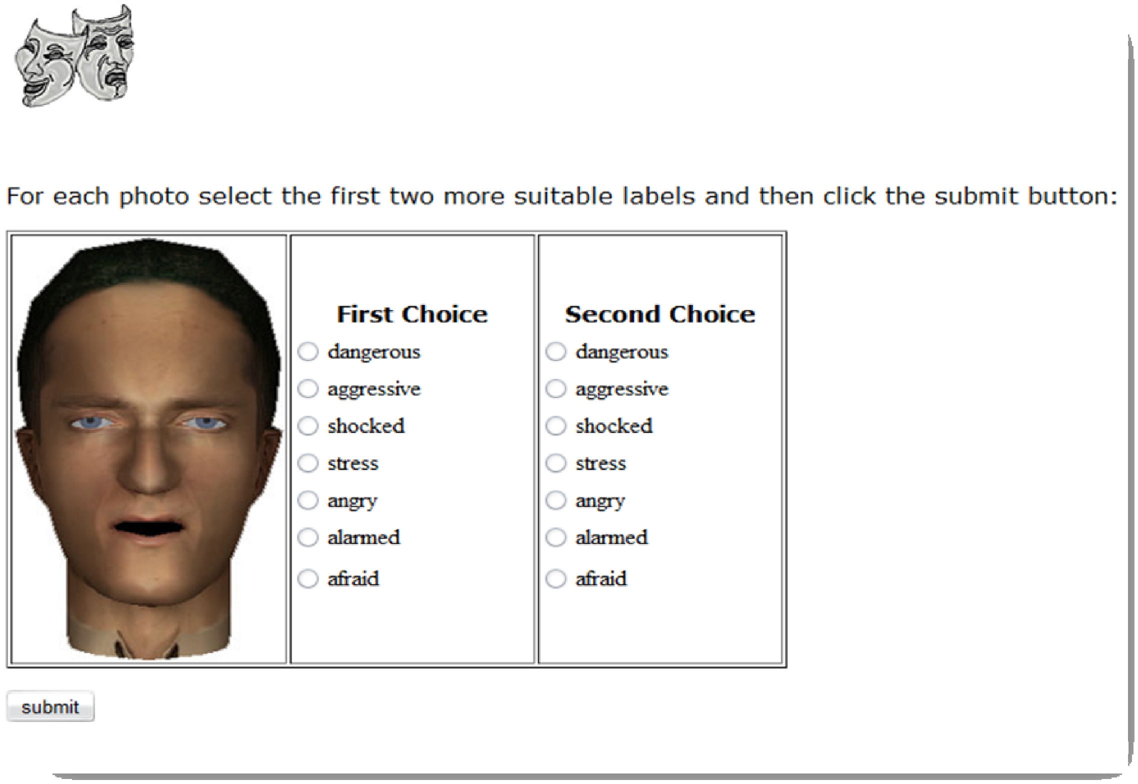



Figure 12 Example of the online facial expressions labeling user test

Our target group for the labeling user test was people from different cultural background. For completing that goal we focused on gathering people from TUDelft and especially students. The total number of participants was 25.

In the figures below you can see the personal information of the participants.

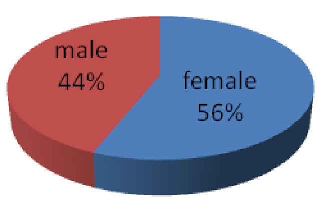



Figure 13 Gender of the participants

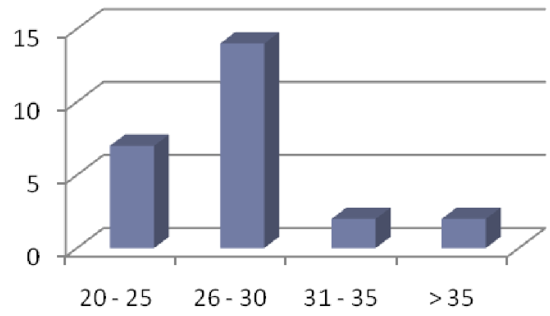



Figure 14 Age of the participants

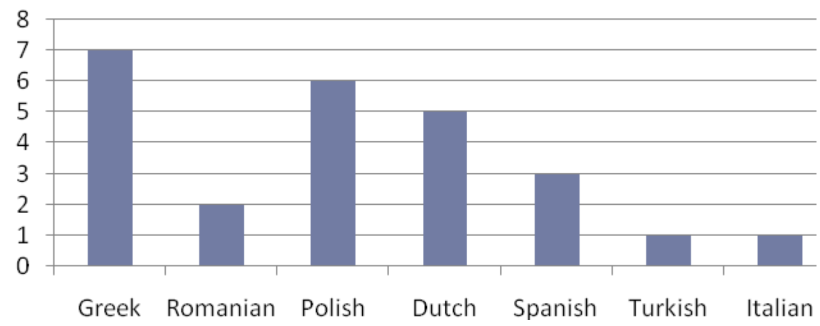



Figure 15 Nationality of the participants

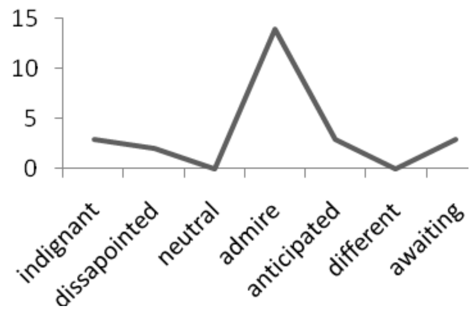
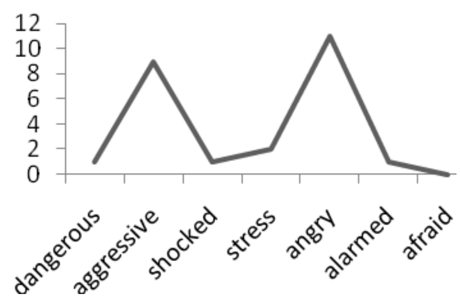
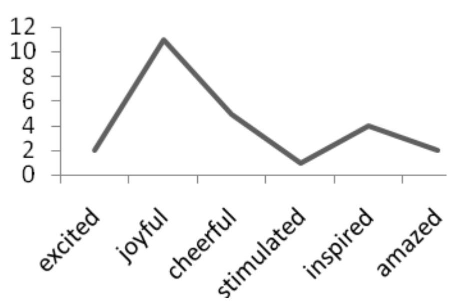
The distribution of the age of the participants is not very wide as most of them are students in TUDelft. However, we have a wide range of different nationalities which is very important in the research of facial expressions recognition as the cultural variations of emotions expressions has been investigated by a large number of researchers.

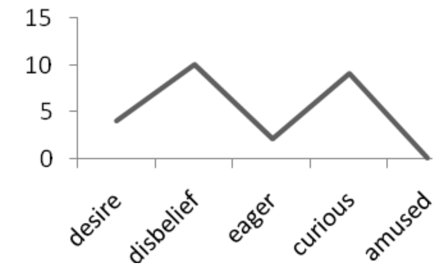
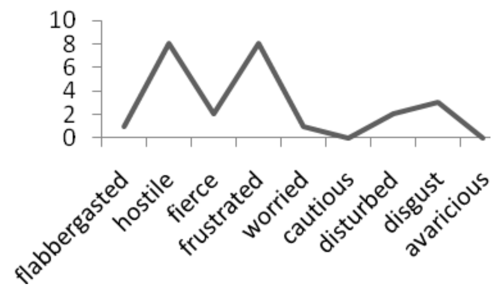
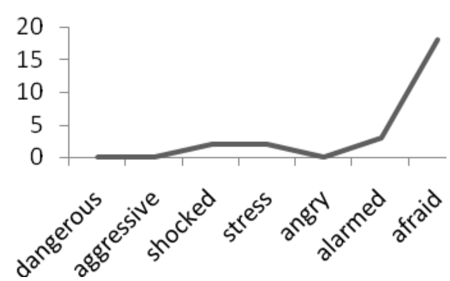
### 3.4.2 The results of the labeling user test

The purpose of the labeling user test was to validate the dataset of emotional words and the corresponding facial expressions and examine if we can find a 1 to 1 correspondence in our dataset.

In this paragraph we will explain the results of the labeling user test and we will discuss in which extend we manage to reach our goal.

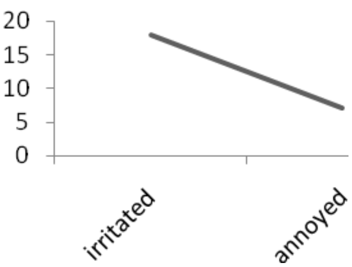
Table 4 Users scoring results for the labeling user test

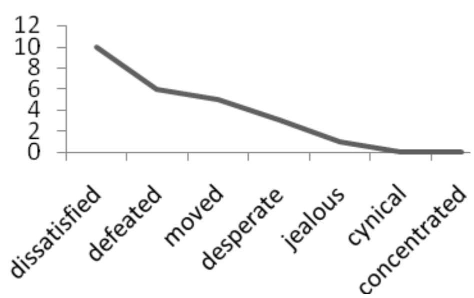
| Face produced in FEM | Results of the labeling user test | Our interpretation |
|---|---|---|
|  admire |   | In this graph we can clearly see one dominant peak for admire. That means that most of the participants gave the expected answer and there was no confusion. |
|  angry |   | In this graph we can see that we have two peaks. The highest represents again the preffered answer, however we can see that aggressive was almost in the same level. However, this is not discouranging because the semantics of the two words are very similar. |
|  cheerful |   | In this graph there is one peak which corresponds to joyful and not to cheerful. However, the two words have very similar meaning which makes hard to distinguish the right answer. |

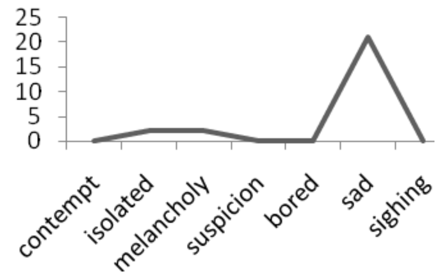
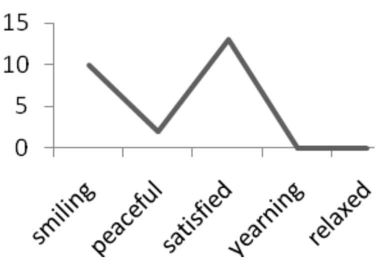
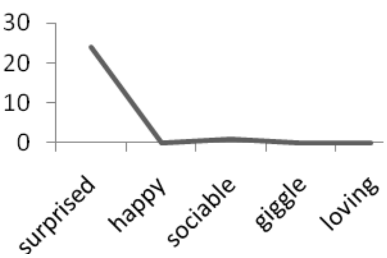
| | | |
|---|---|---|
| <br>desire |  | Here we have two peaks and neither is representing the expected answer. There is also on connection among the given answers and the expected one which makes us belive that the facial expression was not clear to the users. |
| <br>disgust |  | Here we have two peaks and neither is representing the expected answer. There is also on connection among the given answers and the expected one which makes us believe that the facial expression was not clear to the users. |
| <br>afraid |  | In this graph there is one only peak that represents the preferred answer. |

<table>
<tr>
<td>

happy</td>
<td>
</td>
<td>In this graph we can see once more very clearly that there is only one peak and corresponds to the expected answer.</td>
</tr>
<tr>
<td>

irritated</td>
<td>
</td>
<td>In this graph there is one only peak that represents the preferred answer.</td>
</tr>
<tr>
<td>

moved</td>
<td>
</td>
<td>As we can see the dominant peak is not the one representing the preferred answer. The expected answer is the third peak with not much difference from the second which shows that it was not clear to the users which emotion was shown.</td>
</tr>
</table>

| | | |
|---|---|---|
| <br>sad | <br> | The only peak that we can see in this graph is representing the correct answer. |
| <br>smiling | <br> | There are two peaks in this graph. The higher is not the preferred one but the second is the expected answer and we have to mention also that the meaning of the two words is similar so is expected that it can cause confusion. |
| <br>surprised | <br> | In this graph we can clearly see one dominant peak for surprise. That means that most of the participants gave the expected answer and there was no confusion |

Based on the results of the test we can see that people gave the expected answers for seven out of twelve facial expressions.

The line charts, in table 5, indicate that for the seven out of twelve emotions the results are satisfactory. In these cases the expected answer had been selected from more participants than the other possible words. However, five facial expressions were found confusing to find the corresponding label. The results for these five expressions can be found on the table below.

**Table 5 The results of the labeling test, for the five expressions**

| Expected answer | Test Results | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| moved | dissatisfied | defeated | moved | desperate | jealous | cynical | concentrated | | |
| | 10 | 6 | 5 | 3 | 1 | 0 | 0 | | |
| desire | desire | disbelief | eager | curious | amused | | | | |
| | 4 | 10 | 2 | 9 | 0 | | | | |
| cheerful | excited | joyful | cheerful | stimulated | inspired | amazed | | | |
| | 2 | 11 | 5 | 1 | 4 | 2 | | | |
| smiling | smiling | peaceful | satisfied | yearning | relaxed | | | | |
| | 10 | 2 | 13 | 0 | 0 | | | | |
| disgust | flabbergasted | hostile | fierce | frustrated | worried | cautious | disturbed | disgust | avaricious |
| | 1 | 8 | 2 | 8 | 1 | 0 | 2 | 3 | 0 |

The five expressions mentioned in the table, were not easy to recognize. Nevertheless, in some of the cases the expected answer and the given answer were very close in terms of meaning, for example in case of smiling the given answer was satisfied. Also in case of cheerful, were the given answer was joyful, there is not clear the expected difference of the two expressions. For the other three cases the main outcome of the test is that the facial expressions produced were not easy to recognize. On the other hand, the way of implementing the user test was also a factor for the unexpected results. The given lists of words for selecting the appropriate one were sometimes confusing and hard to distinguish the differences. The fact that the test was in English and none of the participants was not native English speaker, induce also in the unhoped results.

In general, we can say that the results of the labeling user test are encouraging. Most of the facial expressions were easily recognized and for the ones that leaded to confusing results we still can give some arguments. In the criticizing of the results we have also to take into account the nature of the test, which was more exacting than the usual type of facial recognition user test found in the literature. However, what is also clear from the results is that there is no 1 to 1 correspondence of emotional words and facial expressions. There are many cases were people were giving an answer different than the expected on but still the semantic was very similar so we there was not a clear separation.

# CHAPTER 4 Semantic of the distance between facial expressions and emotional words

One of our goals is to study the relations between the data of our database, and by data we actually mean the emotional words and the images of the facial expressions. Our hypothesis was that the semantic similarities of the emotional words correspond to the similarities of the facial expressions based on the Euclidian distances of vectors of AUs that compose the facial expressions. That means that the more similar expressions are closer.

Let us consider an example. If we raise the corners of the mouth a little bit (AU12), then the expression will be labeled as smiling/happiness. So the distance between neutral and smiling/happiness is close with respect to the Euclidian distance of vectors of AUs, but the semantic difference is huge. But, we hypothesis, that the correspondence in general is not as bad as in this specific example.

In order to test our hypothesis and study the relations of the emotional words and the corresponding facial expressions we decided to compare the results of data analysis techniques. We used three different methods and we compared the results. The first method was a user test, the Facial Expressions Comparison User Test, where the users have to score for the similarity level of all the possible pairs of different facial expressions. The results of these tests will be further explored using Multidimensional Scaling (MDS). This method is focused on the similarities of facial expressions. The second method is the Principal Component Analysis (PCA) of the Action Units intensities that are used for the representation of the facial expressions. The third method is the 2D plot of the pleasantness and activation values of the emotional words based on the values found in the Dictionary of Affect in Language (DAL) [22].

In the following sectors we will describe in more detailed the methods that we used and then we will discuss the results.

## 4.1 The methods

In this paragraph we will describe in more detail the computational methods we will use in the study of the relations between emotional words and the corresponding facial expressions.

### 4.1.1 Facial Expressions Comparison User Test

The second user test was a comparison test of the facial expressions that we created using the facial expression generator tool FEM. In this test we will use again the same subset of the 12 facial expressions that we used in the Labeling User Test. The 12 facial expressions were combined in 66 different pairs which users had to score based on their similarity level. For each pair the users had to score on a five point scale for their similarity level.

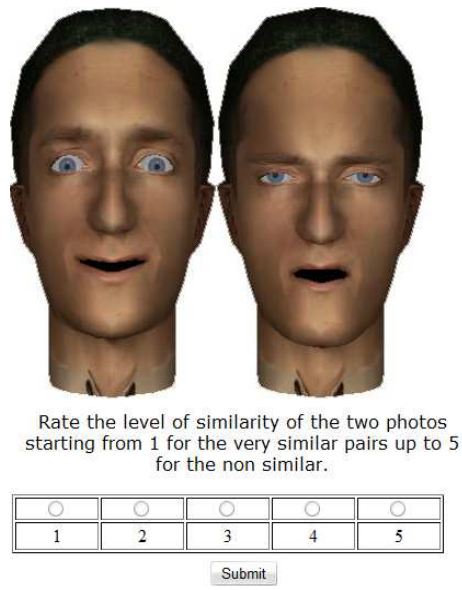



Figure 16 Example of scoring a pair of images in second user test

For the second test we had 15 participants. The 66 pairs of images were randomly divided in three groups so each participant had to score for 22 pairs of photos.

Our target group was again people from several cultural backgrounds so we focused on people that are working or studying in TUDelft. In the figures below you can see the personal characteristics of the participants.

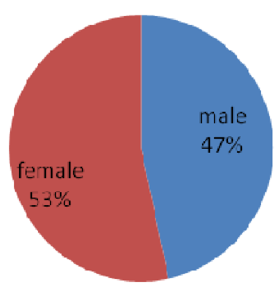



Figure 17 Gender of the participants

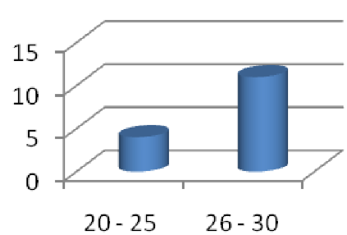



Figure 18 Age of the participants

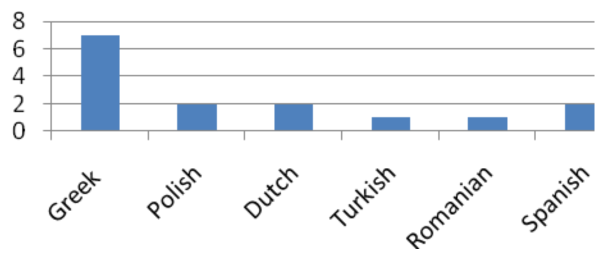



Figure 19 Nationality of the participants

As we can see from the diagrams above, the number of participants in this test was smaller, however enough for having some interesting results. The age distribution of the participants is not normal, due to the fact that most of them are students in TUDelft. Even though we had fewer participants in this online user test, we managed to have participants with different nationalities.

For each pair of facial expressions we had five scores and we calculate the mean values. In the table below you can see the results:

Table 6 Mean values of the similarity scores

| | admire | afraid | angry | cheerful | desire | disgust | happy | irritated | moved | sad | smiling | surprised |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| admire | 0 | 4.2 | 4.2 | 3.2 | 3.4 | 4.2 | 3 | 5 | 5 | 4.6 | 3.2 | 3 |
| afraid | 4.2 | 0 | 3.4 | 3.8 | 2 | 4.4 | 4.2 | 4.4 | 2.6 | 3.2 | 4.2 | 3 |
| angry | 4.2 | 3.4 | 0 | 4 | 4 | 3.8 | 4 | 4 | 4.4 | 3.6 | 4 | 3.6 |
| cheerful | 3.2 | 3.8 | 4 | 0 | 3.6 | 4.2 | 2.6 | 4.6 | 4 | 5 | 1 | 4.2 |
| desire | 3.4 | 2 | 4 | 3.6 | 0 | 4.2 | 3.4 | 4.4 | 2.8 | 3.8 | 2.6 | 3 |
| disgust | 4.2 | 4.4 | 3.8 | 4.2 | 4.2 | 0 | 4.4 | 3 | 4 | 3 | 4.6 | 4.4 |
| happy | 3 | 4.2 | 4 | 2.6 | 3.4 | 4.4 | 0 | 4.6 | 4.8 | 4.4 | 1.8 | 3 |
| irritated | 5 | 4.4 | 4 | 4.6 | 4.4 | 3 | 4.6 | 0 | 3.4 | 4 | 4.8 | 4 |
| moved | 5 | 2.6 | 4.4 | 4 | 2.8 | 4 | 4.8 | 3.4 | 0 | 2.2 | 4.2 | 3.8 |
| sad | 4.6 | 3.2 | 3.6 | 5 | 3.8 | 3 | 4.4 | 4 | 2.2 | 0 | 4.6 | 4.8 |
| smiling | 3.2 | 4.2 | 4 | 1 | 2.6 | 4.6 | 1.8 | 4.8 | 4.2 | 4.6 | 0 | 3.4 |
| surprised | 3 | 3 | 3.6 | 4.2 | 3 | 4.4 | 3 | 4 | 3.8 | 4.8 | 3.4 | 0 |

After calculating the mean values of the similarity scores, we continued with Multimodal Scaling (MDS) and further analysis of the results that we will discuss 4.1.2.

### 4.1.2 Multidimensional Scaling (MDS) for the facial expressions comparison user test results.

Multidimensional Scaling (MDS) is an explorative technique of data that allows us to obtain a representation of n-objects in a k-dimensional space, using information relative to “similarity” (or “dissimilarity) between each couple of objects. An MDS algorithm starts with a matrix of item–item similarities, and then assigns a location to each item in k-dimensional space, where k is specified a priori. For sufficiently small k, the resulting locations may be displayed in a graph or 3D visualization. This procedure does not organize the elements in exact way, but finds the configuration that approximates the observed distances in the best way. It uses several iterations that shift the objects to a space of selected dimension minimizing an error criterion.

#### *Computational Approach*

MDS is not so much an exact procedure as rather a way to "rearrange" objects in an efficient manner, so as to arrive at a configuration that best approximates the observed distances. It actually moves objects around in the space defined by the requested number of dimensions, and checks how well the distances between objects can be reproduced by the new configuration. In more technical terms, it uses a function minimization algorithm that evaluates different configurations with the goal of maximizing the goodness-of-fit (or minimizing "lack of fit").

*Measures of goodness-of-fit:* Stress. The most common measure that is used to evaluate how well (or poorly) a particular configuration reproduces the observed distance matrix is the stress measure. The raw stress value Phi of a configuration is defined by:

$$Phi = \sum_{ij} (d(Xi, Xj) - \delta(f(Xi), f(Xj)))$$

In this formula, d stands for the reproduced distances, given the respective number of dimensions, and δ (delta) stands for the input data (i.e., observed distances). The mapping f indicates a non-metric, monotone transformation of the observed input data (distances). Thus, it will attempt to reproduce the general rank-ordering of distances between the objects in the analysis.

There are several similar related measures that are commonly used; however, most of them amount to the computation of the sum of squared deviations of observed distances (or some monotone transformation of those distances) from the reproduced distances. Thus, the smaller the stress value, the better is the fit of the reproduced distance matrix to the observed distance matrix.

#### *Implementation*

The function *cmdscale* performs classical (metric) multidimensional scaling, also known as principal coordinates analysis. The c*mdscale* takes as an input a matrix of item-item similarities and creates a configuration of points. Ideally, those points are in two or three dimensions, and the Euclidean distances between them reproduce the original distance matrix. Thus, a scatter plot of the points created by *cmdscale* provides a visual representation of the original distances.

Use cmdscale to find a configuration with those inter-point distances. *Cmdscale* accepts distances as either a square matrix, or in a vector upper-triangular form produced by *pdist*.

[Y,eigvals] = cmdscale(D);

cmdscale produces two outputs. The first output, Y, is a matrix containing the reconstructed points. The second output, eigvals, is a vector containing the sorted eigenvalues of what is often referred to as the "scalar product matrix," which, in the simplest case, is equal to Y*Y'. The relative magnitudes of those eigenvalues indicate the relative contribution of the corresponding columns of Y in reproducing the original distance matrix D with the reconstructed points.

**Table 7 Matlab code for MDS implementation.**

```
%The 12 emotions used in our research.
emotions = {'admire','afraid','angry','cheerful','desire','disgust',      'happy','irritated','moved','sad','smiling','surprised'};

%The mean values of the scoring results in the second user-test.
D=[0 4.2 4.2 3.2 3.4 4.2 3 5 5 4.6 3.2 3
4.2 0 3.4 3.8 2 4.4 4.2 4.4 2.6 3.2 4.2 3
4.2 3.4 0 4 4 3.8 4 4 4.4 3.6 4 3.6
3.2 3.8 4 0 3.6 4.2 2.6 4.6 4 5 1 4.2
3.4 2 4 3.6 0 4.2 3.4 4.4 2.8 3.8 2.6 3
4.2 4.4 3.8 4.2 4.2 0 4.4 3 4 3 4.6 4.4
3 4.2 4 2.6 3.4 4.4 0 4.6 4.8 4.4 1.8 3
5 4.4 4 4.6 4.4 3 4.6 0 3.4 4 4.8 4
5 2.6 4.4 4 2.8 4 4.8 3.4 0 2.2 4.2 3.8
4.6 3.2 3.6 5 3.8 3 4.4 4 2.2 0 4.6 4.8
3.2 4.2 4 1 2.6 4.6 1.8 4.8 4.2 4.6 0 3.4
3 3 3.6 4.2 3 4.4 3 4 3.8 4.8 3.4 0 ];

[X,eigvals] = cmdscale(D);
plot (X(:,1),X(:,2),'.') ;
text(X(:,1),X(:,2),emotions)
```

In figure 20 you can find the plot generated:

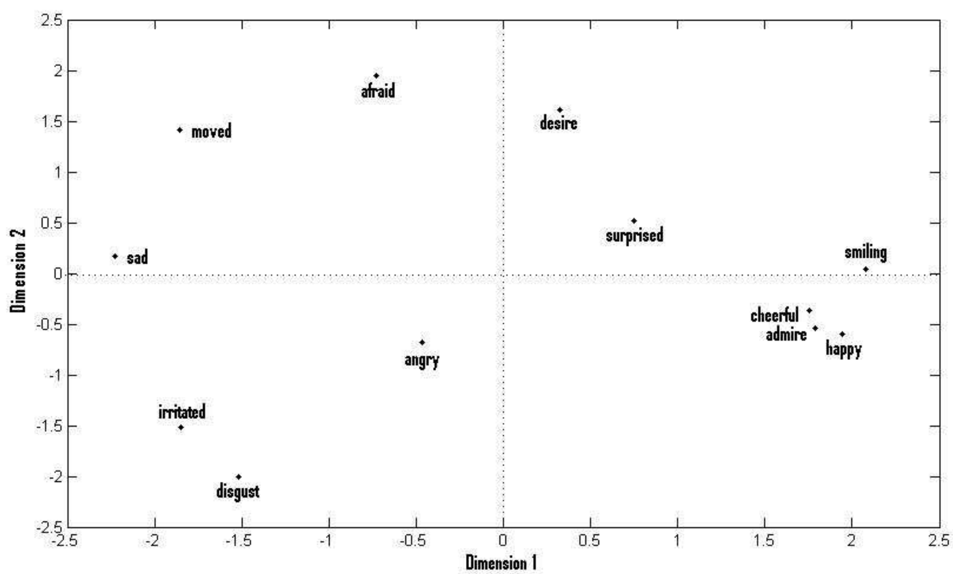



Figure 20 MDS plot

### 4.1.3 PCA analysis of Action Units Intensities' table.

The 12 emotional facial expressions of our dataset were coded in FAC'S by Action Units. Each one of the 12 facial expressions was coded by 20 Action Units.

The general idea of Principal Component Analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the dataset. This is achieved by transforming to a new set of variables, the principal components, which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variances.

PCA has been applied on the dataset (see table 8) that has been composed using the AU values obtained from the FEM system as described in Chapter 3. An example of this dataset is shown in the following table:

Table 8 The AUs matrix used in the PCA plot

| | admire | afraid | angry | cheerful | desire | disgust | happy | irritated | moved | sad | … |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AU1 | 80 | 100 | 0 | 50 | 100 | 0 | 0 | 0 | 90 | 100 | … |
| AU2 | 70 | 0 | 0 | 50 | 15 | 0 | 50 | 100 | 0 | 0 | … |
| AU4 | 0 | 100 | 100 | 0 | 30 | 60 | 0 | 85 | 0 | 100 | …. |
| AU5 | 70 | 100 | 0 | 0 | 80 | 0 | 0 | 100 | 45 | 0 | … |
| AU6 | 75 | 0 | 0 | 0 | 60 | 100 | 100 | 0 | 0 | 100 | … |
| AU7 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … |
| … | … | … | … | … | … | … | … | … | … | … | … |

In this table the columns represent the 12 basic representations of facial expressions and the rows represent the AU values of each representation as obtained from the FEM system.

### 4.1.4 Whissell's Dictionary of Affect in Language

Whissell [22] have developed the Dictionary of Affect in Language (DAL) in an attempt to quantify emotion in language. Volunteers viewed many thousands of words and rated them in terms of their pleasantness, activation, and imagery (concreteness). The DAL is embedded in a computer program which is used to score language samples on the basis of these three dimensions. The DAL has been applied to studies of fiction (e.g., Frankenstein, David Copperfield), of poetry (e.g., the work of Frost, Blake), drama (e.g., Shakespeare's tragedies and comedies), advertisements, group discussions, and lyrics (e.g., the Beatles). It has also been used in the selection of words for memory research.

Using a score system based of the three dimensions listed before, the Dictionary of Affect in Language (DAL) is an instrument designed to measure the emotional meaning of words and texts. It does this by comparing individual words to a word list of 8742 words which have been rated by people for their pleasantness, activation and imagery. Given a list of words (for example the words happy, sad and loving), the DAL scoring system will generate an analysis of the emotional meaning of these words. Figure 21 gives an example of a result of the analysis of three emotional words using the three different dimensions: pleasantness, activation, and imagery.

```
- <sentence>
  - <word>
      <token>happy</token>
    - <emotion>
        <measure type="DAL" valence="3.0000" activation="2.7500" imagery="2.2"/>
      </emotion>
    </word>
  - <word>
      <token>sad</token>
    - <emotion>
        <measure type="DAL" valence="1.3750" activation="1.4286" imagery="2.8"/>
      </emotion>
    </word>
  - <word>
      <token>loving</token>
    - <emotion>
        <measure type="DAL" valence="3.0000" activation="2.2500" imagery="1.2"/>
      </emotion>
    </word>
  </sentence>
```


Figure 21 Emotional text recognition using Whissell's Dictionary of Affect in Language

An example of the pleasantness and activation values for some of the 12 emotional words we used in this study is shown in table 9:

Table 9 Example of DAL values for emotional words of our database

| Emotion | Pleasantness | Activation |
|---|---|---|
| **afraid** | 1.00 | 2.37 |
| **angry** | 1.00 | 2.50 |

## 4.2 Comparing the results of the methods

In order to compare the results of the data analyzing techniques that we presented we plot the result of each one in 2D plot. In this paragraph we will discuss about our observations on these plots and the conclusions about our hypothesis.

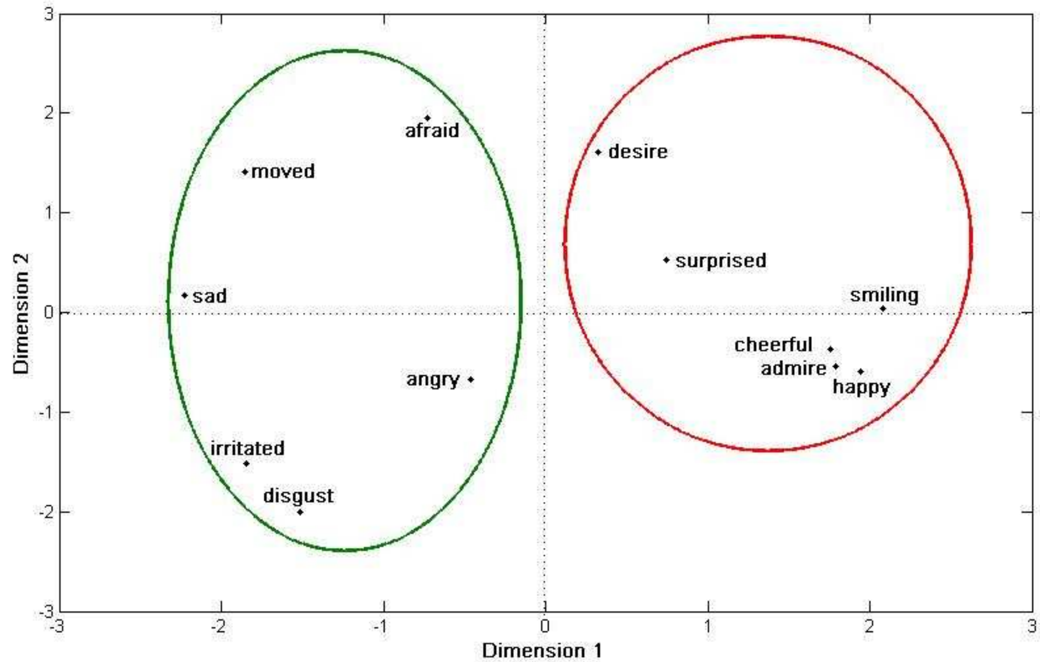



Figure 22 2D plot of MDS outcome

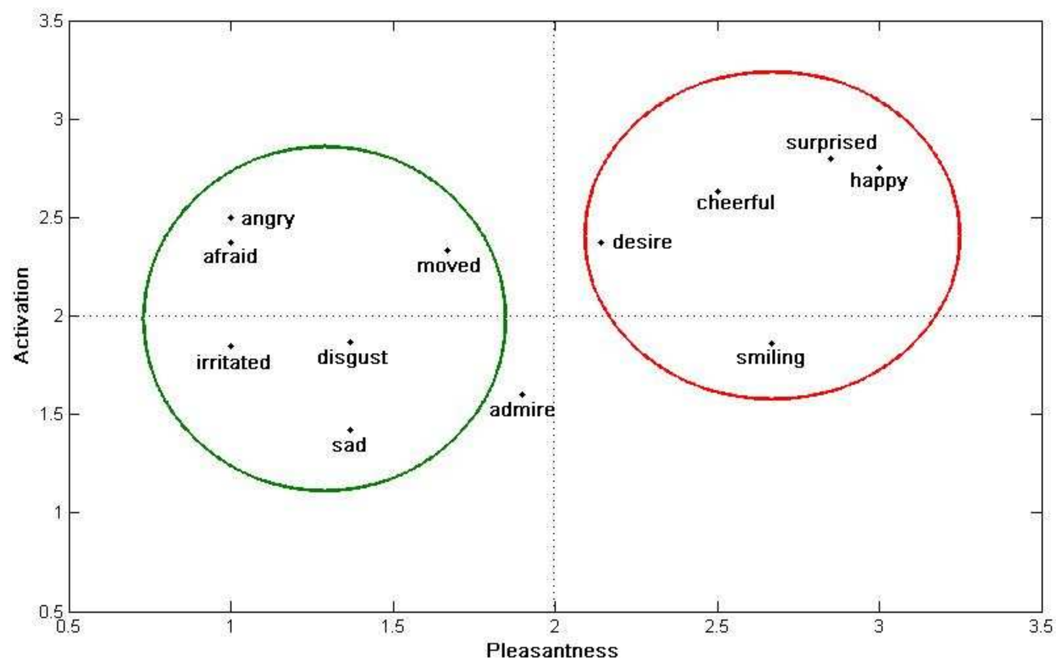



Figure 23 2D plot of pleasantness-activation values of emotional words based on DAL

After the implementation of the Multidimensional Scaling, we plotted the results in 2D in order to be able to investigate the clusters formed and compare them with other classification methods. The first comparison was with the 2D plot of the pleasantness and activation values of the

corresponding 12 emotional words. The values were gathered from the Dictionary of Affect in Language (DAL) [22].
The first observation we made was that the y-axis in both plots divides the data almost in the same way. The two groups are shown in the following figures (22) (23).

Group 1, includes afraid, moved, sad, angry, irritated and disgust and
Group 2, includes desire, surprised, smiling, cheerful and happy.

Only admire is in a different cluster in each plot. However, in figure (23) we can see that is almost in a neutral position in the middle. If we take into account that in the second plot x-axis is representing pleasantness, we can say that the two clusters represent the negative and the positive data.

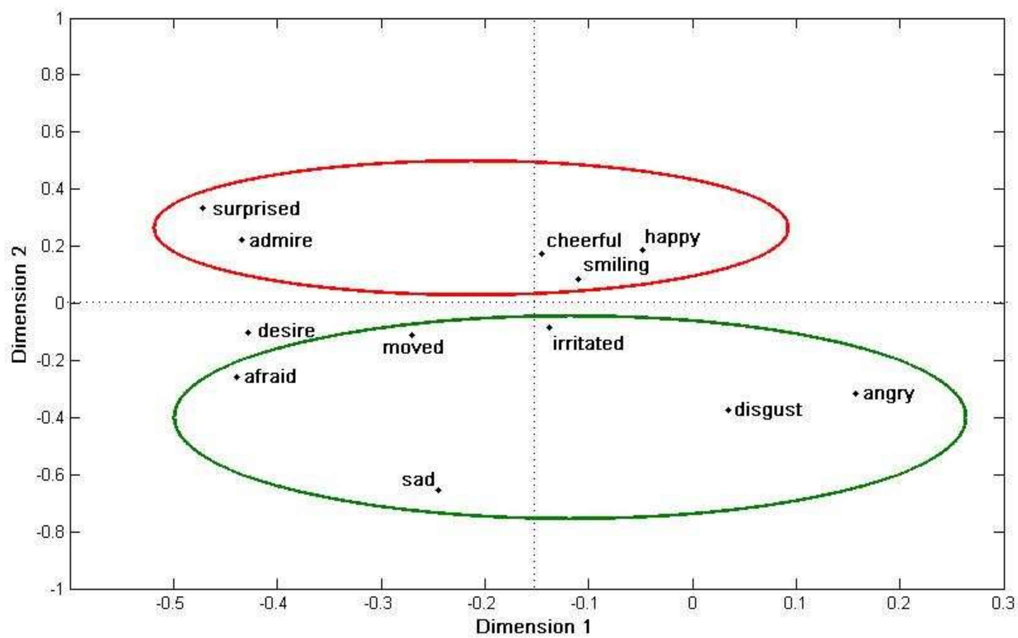



Figure 24 PCA results

In Figure24 we can see that we can find again the two basic clusters found in MDS plot and in the plot of the Whissell's scores presented in the previous paragraph. If we look more carefully in the PCA plot we can see also that the expression with semantic similarity are organized in subclusters, but is not always the case. For example, (cheerful, smiling, happy) can be considered as one cluster, which was expected.

In conclusion we can claim that the comparison of the three plots (MDS, PCA, Whissell's scores) gives us positive results. We can see some basic similarities and make a more general comparison. However, as we have already mentioned, we cannot go into detailed comparison because the MDS and PCA techniques used transform the data to new coordinate systems.

# CHAPTER 5 Expert Systems Overview

## 5.1 CLIPS

CLIPS was developed for NASA by the Software Technology Branch and the University of Georgia. It is available to the public and has several features which make it a desirable choice for producing expert systems. It offers the ability to integrate expert systems developed in CLIPS into the environment of a standard C/C++ program. This allows for quick prototyping and testing of expert systems alongside the development of a control program written in C/C++. An object-oriented programming language is also provided within CLIPS, called the CLIPS Object-Oriented Language (COOL).[20] CLIPS uses forward-chaining. It's an empty tool and has to be filled with knowledge. After that, it can develop a solution, starting from the facts. For this, CLIPS uses a LISP-like procedural language. CLIPS has the advantage of having an interpreted mode It is useful for checking syntax, and for trying several ideas about the way in which rules should be written.

CLIPS is designed to facilitate the development of software to model human knowledge or expertise. There are three ways to represent knowledge in CLIPS:

- Rules, which are primarily intended for heuristic knowledge based on experience.
- Deffunctions and generic functions, which are primarily intended for procedural knowledge.
- Object-oriented programming, also primarily intended for procedural knowledge. The five generally accepted features of object-oriented programming are supported: classes, message-handlers, abstraction, encapsulation, inheritance, and polymorphism. Rules may pattern match on objects and facts.

You can develop software using only rules, only objects, or a mixture of objects and rules.

## 5.2 Making rules

To accomplish useful work, an expert system must have rules as well as facts. A rule is similar to an "IF_THEN" statement in a procedural language like Ada, C, or Pascal. An IF THEN rule can be expressed in a mixture of natural language and computer language as follows:

```
IF certain conditions are true
 THEN execute the following actions
```

The name of the rule follows immediately after the keyword defrule. Although you can enter a rule on a single line, it's customary to put different parts on separate lines to aid readability and editing. CLIPS tries to match the pattern of the rule against a pattern entity. Of course, white space consisting of spaces, tabs, and carriage returns may be used to separate the elements of a rule to improve readability. Other comments begin with a semicolon and continue until the carriage return key is pressed to terminate a line. Comments are ignored by CLIPS.

```
(defrule duck "Here comes the quack"    ; Rule header
```

```
(animal-is duck)                        ; Pattern
     =>                                 ; THEN arrow
(assert (sound-is quack)))              ; Action
```

## 5.3 Limitations of CLIPS.

CLIPS has its limitations as well. In other expert systems like 'LOOPS', rule sets can be arranged in a hierarchy, embedding one rule set inside another, etc. In CLIPS, there's only a single level of rule sets, which make things less clear. Also, there's only loose coupling of rules and objects, and rules cannot easily be embedded in objects, as in for example Centaur. Furthermore, CLIPS has no explicit agenda mechanism and only forward chaining is available as basic control flow. If another kind of reasoning is to be implemented, tokens in working memory have to be manipulated. But despite these limitations, CLIPS is a good choice as the expert building tool to use in this project, especially since it can be used in conjunction with the other tools (OPEN-R SDK) that are used.

## 5.4 CLIPS vs JESS.

Since JESS is based on CLIPS, the syntax of both expert systems is roughly the same. The most important difference is the language it is based on. JESS is easily embedded in Java programs where CLIPS can be easily embedded in C/C++ applications. Other (minor) differences exist as well.

The CLIPS shell provides the basic elements of an expert system:

1. A fact-list and instance-list: this is global memory for data.
2. A knowledge-base: This contains all the rules.
3. An inference engine: for controlling the execution of rules.

Facts are data that usually designate relations or information like (is-animal dog) or (animals dog cat cow chicken). Rules can be applied on these facts in the form of IF-THEN rules. These rules are special because they 'fire' only once. Variables and wildcards can be used in the rules, and functions can be defined to manage the rules. Besides these basic properties, CLIPS has pattern matching abilities (the Rete Algorithm), extended math functions, conditional tests, object-oriented programming (COOL: Clips Object-Oriented Language) with abstraction, inheritance, encapsulation, polymorphism and dynamic binding.

JESS has the same basic properties as CLIPS, but its language lacks a few advanced features, for instance:

1. The CLIPS-user has a choice of seven strategies in rule-firing, while JESS only has the two most important ones.
2. The AND and OR conditional tests are not available in JESS in the left-hand side of rules.
3. JESS does not implement modules.
4. COOL: JESS lacks most COOL functions, but this is not really necessary since JESS is able to manipulate and directly reason about Java objects. Considering the Java language is already object oriented; the lack of COOL is only a disadvantage when CLIPS code has to be ported to JESS.

In general, these shortcomings are not really an obstruction. The most harmful shortcomings of JESS are however situated in the performance of Java, and the fact that it is still work in progress:

1. It is generally accepted that JESS is up to three times (depending on the application) slower than CLIPS. This is primarily due to Java itself, although the implementation of JESS might also contribute significantly.
2. The JESS parser is considered less robust than CLIPS. The main reason for this is that, unlike CLIPS, JESS is still work in progress. However, the quality of JESS is improving with every new version.
3. As a consequence of the absence of some features, CLIPS code is sometimes hard (or even impossible) to port to JESS. This will certainly be the case in bigger projects.

On the other side, JESS has some advantages over CLIPS as well:

1. The Java language implementation makes JESS the choice for developing web-based expert systems, although some people say they prefer to use CLIPS with C++ in a CGI script. If Java is preferred, however, JESS is a more efficient choice.
2. JESS enables the user to put multiple expert systems in one process. Java threads can be used to run these in parallel.

To summarize, CLIPS is still more complete and stable than JESS, but this might change in the future, since the JESS package is being improved constantly. Besides that, JESS also has the property of using Java, which in the long run might prove to be a big advantage over CLIPS.

# CHAPTER 6 How to compute emotions from Action Units

In this chapter we will explain how we used our database in order to produce the basic rules for our classification system. We will give our initial hypotheses, the representation of the emotions and the model we used for calculating the impact of the action units in each emotion. We will give the steps for generating our algorithm and we will explain the concept of the generated system.

The goal of our implementation is to produce a system that will calculate the impact of the AUs activation in the emotions of our database. Initially, we based the design of our system in the data gathered in our emotional database. We used the 60 emotional expressions as we described them in chapter 3. These data were validated by expert users in the pretest described in paragraph 3.4.1. Using these data we designed our algorithm.

As we described in chapter 3, our emotional database contains 60 emotional expressions. Each emotional expression contains the emotional word that describes the emotion, the combination of AUs that describe the corresponding emotional facial expression, the image of the face that shows the emotional expression as produced in FEM and the values of valence and arousal of the emotional word based on DAL [22].

The facial expressions in our database were produced in FEM and for that reason they are expressed in terms of Action Units. A set of 22 Action Units was used for the representation of the 60 emotional expressions. The impact of each AU in every emotion was expressed by its intensity level. The intensity level of each AU to an emotion can range from 0 % - 100 %. An example of the database for describing the emotion *n* is:

Table 10 Emotions basic representation in from our emotional database

| | $AU_i$ | $AU_j$ | .... | $AU_m$ |
|---|---|---|---|---|
| $Emotion_n$ | $I_i$ | $I_j$ | … | $I_m$ |

, where $AU_i$ – $AU_m$ is the set of the used Action Units for expressing the emotions, and

$I_i$ - $I_m$ are the corresponding intensities levels.

Before explaining the implementation details of our algorithm we will present the initial hypotheses which considered as the basis for our implementation:

1. Our database of 60 emotional expressions contains the basic representation for each emotion described in AUs. That means that the representation of each emotion in our database is considered as the most dominant expression of the emotion.
2. In each emotion representation the AUs with higher intensity are more important than the ones with lower intensity. That means that the activation or the inactivation of the AUs with higher intensity has stronger impact on the intensities of the emotions than the AUs with lower intensities.
3. We assume that all AUs contribute in a weighted linear way to the total intensity of the emotion.
4. With Intensity (I) we represent the activation level.

The model of the AUs and AUs combinations that describe the emotions was also an issue that we had to define before the implementation. We chose to use the additive model which means that the appearance changes of each separate AU are relatively independent and produce in the combination the sum of all these distinct changes caused by the separate AUs. When the combination of Action Units responsible for a set of appearance changes is additive, the decisions you need to make to score an AU are still relatively straightforward.

The next step was to design our algorithm for describing each emotion, calculate the total intensity of each emotion and find a formula for calculating the impact of AUs and random combinations of AUs in each emotion. As we explained in the beginning of this chapter, based on our database, each emotion is described by a set of AUs:

$$emotion_n = (AU_i,\ AU_j,\ \ldots AU_m),$$

each of these AUs has an intensity level that describes its impact in the specific emotion. That gives us the next formula which describes the total intensity of each emotion, which is calculated according to the additive model:

$$Intensity(emotion) = Ii + Ij + ... + \mathrm{Im} \qquad (1).$$

Having described the emotions of our database according to the AUs and calculate the intensity of the emotions we continued with calculating the impact of the activation of each AU and known combinations of AUs in each emotion. By known combinations we mean the ones that can be found in our database.

So, the affect of the activation of $AU_i$ with intensity $I_i$ on the $emotion_n$ is:

$$I(emotion) = \frac{Ii}{Ii + Ij + ... + \mathrm{Im}} \qquad (2).$$

and in case of the activation of more than one AUs with their corresponding intensities the equation (2) is :

$$I(emotion) = \frac{\Sigma I}{Ii + Ij + ... + \mathrm{Im}} \qquad (3),$$

where $\Sigma I$ is the summation of the AUs that are activated, the combination of them.

The equation (1) gives the total intensity of an emotion based on our data and only in case of the basic representation of the emotion. However, the equations (2) (3) are used in order to calculate the intensity of each emotion in case of a given random combination of activated AUs. So, given a combination we can find the intensity of each emotion. In a further step of our implementation we compare the resulted intensities values of the emotions and we end up with the emotion with the maximum intensity which is considered as the dominant emotion.

The pseudocode that describes the affect of the activation of $AU_i$ with intensity $I_i$ on the $emotion_n$ is given below:

*if*

*$AU_i$ is activated with intensity $I_i$*

*then*

$$I(emotion) = \frac{Ii}{Ii + Ij + ... + \mathrm{Im}}$$

In case that more than one AUs are activated the pseudocode describing the intensity of each emotion is:

*if*

*$AU_i$ is activated with intensity $I_i$*

*and AUj is activated with intensity $I_j$*

*and …*

*and AUn is activated with intensity In*

*then*

$$I(emotion) = \frac{Ii + Ij + ... + In}{Ii + Ij + ... + \mathrm{Im}}.$$

For example, in our database the emotion of happiness is expressed in the following combination of AUs:

**Table 11 Basic representation of the emotion happy**

| | AU1 | AU2 | AU4 | AU5 | AU6 | AU7 | AU9 | AU10 | AU12 | AU15 | AU16 | AU17 | AU18 | AU20 | AU22 | AU23 | AU24 | AU25 | AU26 | AU27 | AU28 | AU43 | AU54 | AU64 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| aggressive | 100 | 0 | 100 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 50 | 0 | 100 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| admire | 80 | 70 | 0 | 70 | 75 | 0 | 40 | 0 | 60 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 75 | 0 | 0 | 0 | 0 | 0 | 0 |
| avaricious | 0 | 80 | 40 | 55 | 70 | 0 | 0 | 0 | 0 | 0 | 20 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| awaiting | 0 | 0 | 20 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 |
| happy | 0 | 50 | 0 | 0 | 100 | 0 | 0 | 0 | 100 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| hostile | 0 | 100 | 100 | 100 | 100 | 0 | 100 | 0 | 0 | 40 | 0 | 0 | 30 | 0 | 0 | 50 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| indignant | 0 | 60 | 80 | 50 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| inspired | 80 | 85 | 0 | 40 | 60 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| irritated | 0 | 100 | 85 | 100 | 0 | 0 | 70 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 80 | 20 | 0 | 0 | 0 | 40 | 0 | 0 | 0 |

Based on our algorithm if *AU2* is activated, the level of intensity that the emotion happy will reach is:

$$\frac{50}{50+100+100+100} = 0.14 => 14\% \;\; of \;\; happiness$$

If *AU6* is activated then the intensity of happiness is:

$$\frac{100}{50+100+100+100} = 0.28 => 28\% \;\; of \;\; happiness$$

and if both *AU2* and *AU6* are activated the intensity of the emotion happiness is:

$$\frac{50+100}{50+100+100+100} = 0.42 => 42\% \;\; of \;\; happiness$$

As we showed in our examples the activation of different AUs, that are part of the basic representation of the emotions, cause different level of the emotions' intensity if their intensity value is not the same.

The algorithm presented is useful for analyzing all the possible combinations of AUs that can derive from our database. However, we identify one limitation that lead to continue one step further. The most important limitation is that our system could manage only data that exist in our database. In order to overcome this drawback and make a system that can manage also random AUs combinations we continued one step further where the we had to take into account the activation of AUs with random intensity levels and not only the ones found in our database.

As we described in the previous paragraphs, the intensity level of an emotion given an AU or a combination of AUs that are activated is given by

$$I(emotion) = \frac{\Sigma I}{Ii + Ij + ... + \mathrm{Im}} \qquad (3),$$

where $\Sigma I$ is the summation of the AUs that are activated. In that case the activated AUs are activated with their predefined intensity. If we have to calculate the intensity of an emotion when the intensity level of the individual activated AUs is random we have to compute a factor that will estimate what percentage of the basic intensity is attained. So, if the formula when using the basic intensities is the following:

$$I(emotion) = \frac{Ij}{Ii + Ij + ... + \mathrm{Im}},$$

where Ij is the intensity of AUj in the basic representation of $emotion_{n,}$ has to change into

$$I(emotion) = \frac{Ij * F}{Ii + Ij + ... + \mathrm{Im}} \qquad (4),$$

where F is the factor we have to calculate. As we showed in table 1, in the example of our dataset, the intensity of an AU can range from 0 to 100. That means that the random intensity can be higher or lower. In case that the random intensity of an AU that we want to calculate what impact has in $emotion_n$ is lower than the one on the basic representation then the factor F is:

$$F = \frac{Ir}{Ij} \qquad (5).$$

Where $I_r$ is the random intensity of $AU_j$ and $I_j$ is the intensity of $AU_j$ in the basic representation of the $emotion_{n.}$

In case that the random intensity of an AU that we want to calculate what impact has in $emotion_n$ is higher than the one on the basic representation then the factor F is:

$$F = \frac{1}{\frac{Ir}{Ij}} \qquad (6).$$

Where $I_r$ is the random intensity of $AU_j$ and $I_j$ is the intensity of $AU_j$ in the basic representation of the $emotion_{n.}$

So, in order to calculate the impact of any possible combination of AUs, activated in any intensity level, can be computed. We have to mention that in case of activation of an AU that is not part of the basic representation of $emotion_n$, there is no impact in the intensity of the emotion in any intensity level that the AU is activated.

The following parts of pseudocode describe the computation of the intensity of $emotion_n$ in case of random activation of AUs:

*if*

*$AU_i$ is activated with intensity $I_r$*

*and* $I_r < I_j$

*then*

$$I(emotion) = \frac{Ij * \frac{Ir}{Ij}}{Ii + Ij + ... + \mathrm{Im}}$$

*if*

$AU_i$ *is activated with intensity* $I_r$

*and* $I_r > I_j$

*then*

$$I(emotion) = \frac{\dfrac{Ij * \dfrac{1}{Ir}}{Ij}}{Ii + Ij + ... + \mathrm{Im}}$$

# CHAPTER 7 Design the rules in CLIPS

As we described in chapter 5 CLIPS needs rules in order to reason. For calculating the intensities of the activated AUs, the total intensities of the emotions and the impact of activated AUs in each emotion we had to implement some rules. Finding the dominant emotion as the final outcome is also implemented in rule. In this chapter we will explain the basic rules and we will give an example of running the system.

The most basic part of the system is the calculation of the impact that an activated AU has on each emotion. The initial facts that are needed for this rule are:

- the emotions of our database and their characteristics (name, value and total intensity of the basic representation)
- the input that we want to analyze, which is actually the activated AU and its intensity to be tested (in the code is presented as the variable *?c*)

So for all the possible combinations of emotion and AU the general syntax of the rules is:

```
(defrule emotion_n_AU_i
    (declare(salience      200))
    (activated     AU_i      ?c)
    ?x <- (emotion (name emotion_n) (value ?y) (total ?k))
    (not (done     emotion_nAU_i))
            (test (> ?c 0))
    =>
    (if   (>=  I_i  ?c)
            then
    (bind ?n (*  I_i  ( /  ?c  I_i)))
    )
    else
        (if  ( <  I_i ?c)
        then
        (bind ?n  ( *  I_i  ( /  1 ( /  ?c  Ii ))))
        )


    (modify ?x (value(+    ?y          ?n)))
    (assert (done emotion_nAU_i)))
```

The output of these rules is the modified value of each emotion, based on the activated AU and its intensity, which will be divided later with the total intensity of the basic representation of that emotion in order to get its activated intensity.

A specific example of this kind of rules is shown below, for the activation of AU1 and its impact on the emotion aggressive:

```
(defrule  aggressive_AU1
    (declare(salience        200))
    (activated  AU1  ?c)
    ?x <- (emotion (name  aggressive) (value ?y) (total  ?f))
    (not (done  aggressive  AU1))
    (test (> ?c 0))
    =>
        (if (>= 100 ?c)
        then
        (bind  ?n ( * 100 ( /  ?c  100)))
        )
        else
                (if  ( <  100  ?c)
                then
                (bind  ?n ( * 100 ( / 1 ( / ?c 100))))
                )
        (modify ?x (value ( + ?y ?n)))
        (assert (done          aggressive          AU1))
)
```

As we have explained also before, the sum of the values of the activated AUs has to be divided by the total intensity of the basic representation of the emotion in order to get the final intensity of the emotion that is the result of the activation of the AU or combination of AUs. This step is implemented in the rule presented below.

The initial facts that are needed for this rule are:

- the emotions of our database and their characteristics (name, value and total intensity of the basic representation), where the value is modified according to the AUs that are activated
- the final_guess, which is considered as the variable that will be used for keeping the final values of each emotion. The form of these facts can be: *(final_guess angry 0 1)*, which means that we have to insert as much final facts as the emotions we want to get results for.

```
(defrule final_emotion "find the finalized values for each emotion"
        (declare (salience 20))
        (emotion (name ?a)(value ?c)(total ?d))
        ?final_guess<-(final_guess ?a ?final_value ?final_total)
                =>
                (bind ?f (/ ?c ?d))
                (bind ?finall (/ ?final_value ?final_active))
                        (if (> ?f ?finall)
                         then
                          (retract ?final_guess)
                        (assert (final_guess ?a ?c ?d)))
)
```

Further on with another rule we print out the result:

```
(defrule print_final "print each emotion with the final value"
        (declare (salience 15))
        ?final_guess<-(final_guess ?final_emotion ?final_value ?final_active)
        =>
        (printout t "the final value of  "?final_emotion " is : "  (*(/ ?final_value ?final_active)100)% crlf) ) )
```

The final value is multiplied by 100 so that it will be given at the end in the form of percentage, for example *60%*.

The last step in our implementation is to find the dominant emotion, which means the emotion with the higher intensity level. Having computed the final values and intensities for each emotion we compare them end we end up with the maximum.

The initial facts that are needed for this rule are:

- the emotions of our database and their characteristics (name, value and total intensity of the basic representation), where the value is modified according to the AUs that are activated
- the max_guess, which is considered as the variable that will be used for keeping the values of the dominant emotion. The initial form of max_guess can be:

*(max_guess nothing 0 1).*

```
(defrule find_maximum "Select the maximum value from all the emotion values"
        (declare (salience 10))
        (emotion (name ?a)(value ?c)(total ?d))
        ?max_guess<-(max_guess ?max_emotion ?max_value ?max_active)
                =>
        (bind ?f (/ ?c ?d))
        (bind ?maxim (/ ?max_value ?max_active))
                (if (> ?f ?maxim)
                        then
                         (retract ?max_guess)
                        (assert (max_guess ?a ?c ?d))
                )
 )
```

Further on with another rule we print out the result:

```
(defrule print_maximum "print the emotion with the max value"
        (declare (salience 5))
         ?max_guess <- (max_guess ?max_emotion ?max_value ?max_total)
        =>

         (printout t "the emotion with the max value is: " ?max_emotion (*(/ ?max_value
        ?max_total)100)% crlf)
 )
```

The final value is multiplied by 100 so that it will be given at the end in the form of percentage, for example *60%*.

# CHAPTER 8 Testing the expert system

In this paragraph/chapter we will explain the testing process of the system. We will describe the input and output of the system and the steps for running the program in CLIPS.

As we explained in chapter 6 and 7 the main idea of the expert system is to calculate the impact of AUs combinations to the emotions of our database. That means that the input of the system should be the AUs and their intensity level and the output the total intensity of each emotion reached by the activation of the AUs.

In the chapter 6 we explained that the initial implementation of our system was designed in order to handle all the possible known combinations of AUs that could be found in the emotional database. However, in a further step we included the option of handling all the possible random combinations of AUs and calculating the total intensity of the known only emotions. So, the input can be any combination of AUs with random intensities.

In the previous chapter we also described the initial facts that we need in order to be able to run the expert system. As we mentioned, the emotions found in our database and their characteristics have to be used as an initial input to the system as well.

In order to improve the interaction with the expert system we tried to make the generation of the input files easier. We have to use two types of input files, one that contains the emotions and their characteristics of the emotional database and one that contains the AUs combination to analyze.

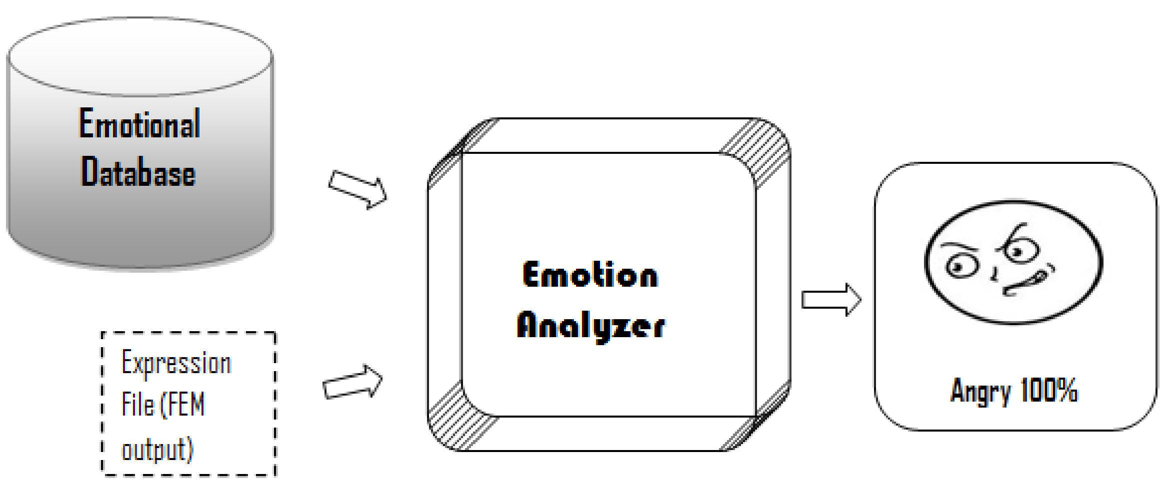



Figure 25 Overview of the system

The main parts of our system are:
*Emotional Database:* The extended emotional database consisted of 60 emotional expressions. For each expression the database includes the name of the expression, the activated Action Units and their intensity values.
*Expression File:* The output of the FEM, which is text file that describes the activated Action Units and their intensities. It is the input in our emotion analyzer.
*Emotion Analyzer:* The main part of the system, which is an expert system, implemented in CLIPS shell. The emotional analyzer 'reads' the expression files and displays the classified emotion.
*Classified Emotion:* Is the output of the analyzer, the classified emotion that displays in the systems console, which in our case is the CLIPS console.

We designed two text parsers, one that parser which takes as an input the data of the emotional database and gives as an output a list of all the emotions and their initial characteristics in the form that can be analyzed by CLIPS， and one that 'reads' the expression file and 'translate' it in facts, appropriate for being processed by the expert system.

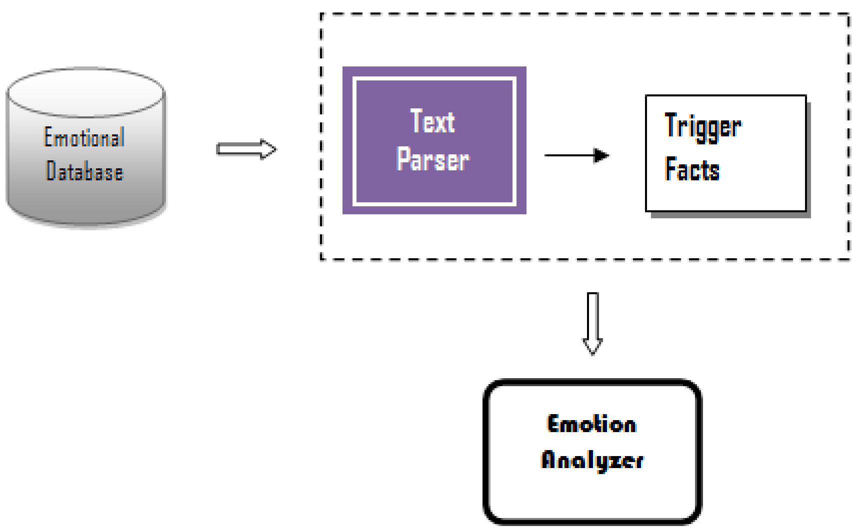



Figure 26 Parser that handles the data of the emotional database

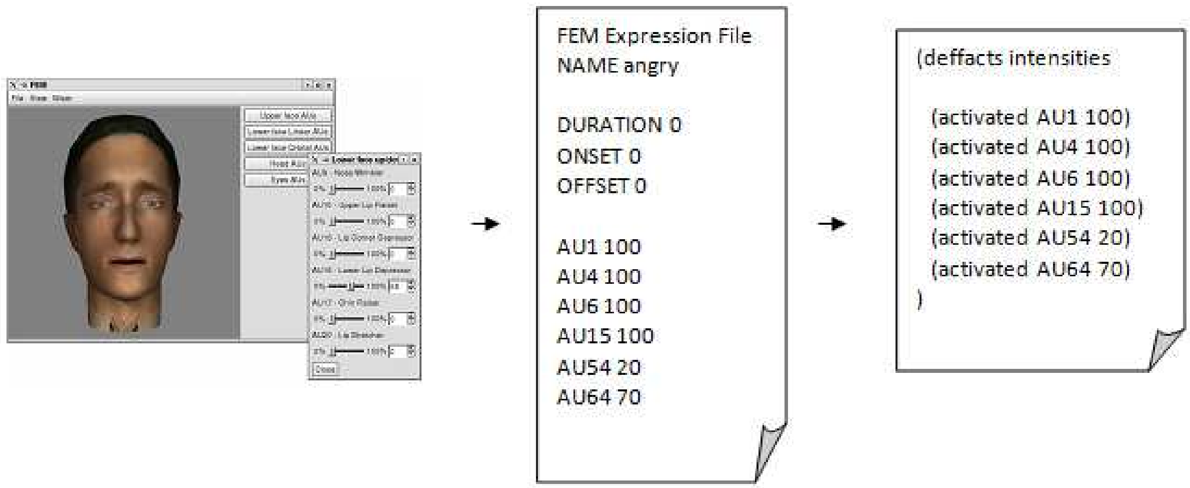



**Figure 27 A parser 'translates' the output of the FEM to CLIPS' facts**

The testing procedure will be explained by presenting a single run of the expert system. First the user has to describe the facial expression in terms of Action Units. This can be done by asserting the required data directly into CLIPS database. However, for a better visualization of the process and better interaction between the user and the system we used the FEM for producing the tested facial expressions.

After having launched the expert system, we load the files containing the first level rules, the second level rules, the trigger facts and the testing facts as they described above. Then we have to reset the system so that the appropriate facts, introduced by the rules, will be added in the facts list of the expert system. We can check the facts list by opening the facts window of CLIPS. Then we have to run the program in order to start the classification process and view the results. For testing our system we used the basic representations of the 12 validated facial expressions, used in our user tests described in chapter 3, and three variations of these expressions. For creating the variations we increased or decreased the intensity level of the involved action units. An example of the output of the classification system is shown in the figure (28).

```
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 11.6071428571429%
the final value of  afraid is : 8.0%
the final value of  cheerful is : 46.6666666666667%
the final value of  desire is : 6.66666666666667%
the final value of  happy is : 15.0%
the final value of  irritated is : 3.33333333333333%
the final value of  moved is : 14.8148148148148%
the final value of  sad is : 6.66666666666667%
the final value of  smiling is : 66.6666666666667%
the final value of  surprised is : 16.0%
the final value of  disgust is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: smiling66.6666666666667%
CLIPS>
```

**Figure 28 Experts system output**

# CHAPTER 9 Evaluation of the expert system

As we showed in the previous chapter the output of the expert system, given a combination of AUs, is the impact in the intensity of the emotions of our database. The expected outcome is the dominant emotion, were by dominant we mean the emotion with the higher intensity, and also the total intensities of other emotions of our emotional database. The hypothesis we made was that the emotions with the intensities closer to the dominants emotion intensity will be the ones that were consider as more similar to the dominant emotion based on the facial expressions comparison user test results described in 4.1.1. The results of test were plot after we implemented the Multidimensional Scaling technique (figure 20). So what we expect is that the emotions that are closer in the plot are the ones with the closer total intensities, based on the expert systems output.

For the evaluation procedure we used as input 12 files of AUs combinations. The 12 combinations are the basic representations of the subset of emotions from the 60 emotions found in the emotional database. The subset of the 12 emotions is the same used in the facial expressions comparison user test described in 4.1.1. In this chapter we will describe the output of 3 out of 12 input files, the expert systems output for the 12 files can be found in Appendix A.

## *Moved.clp*

The moved.clp contains the AUs combination that is the basic representation of the emotion moved based in our emotional database. In the output of the experts system shown in figure 29, we can see the impact of the activation of these AUs in the 12 emotions:

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 21.5020576131687%
the final value of  afraid is : 30.0%
the final value of  cheerful is : 15.4320987654321%
the final value of  desire is : 41.5384615384615%
the final value of  disgust is : 4.61538461538462%
the final value of  irritated is : 15.9663865546218%
the final value of  moved is : 100.0%
the final value of  sad is : 28.5714285714286%
the final value of  smiling is : 16.1616161616162%
the final value of  surprised is : 28.319783197832%
the final value of  happy is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: moved100.0%
CLIPS>
```

Figure 29 Output of the moved.clp execution

As we expected the dominant emotion is moved. We checked the first four emotions with higher intensity and we found:

*Moved 100%, Desire 41.53 %, Afraid 30.00 %, Sad 28.57 %.*

If we compare these results to the plot we can see that the closest emotions to the emotion moved are also the emotions desire, afraid and sad. So, the results of the experts system have similarities to the users scoring.

## Irritated.clp

The irritated.clp contains the AUs combination that is the basic representation of the emotion irritated based in our emotional database. In the output of the experts system shown in figure 30, we can see the impact of the activation of these AUs in the 12 emotions:

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 22.3809523809524%
the final value of  afraid is : 41.1111111111111%
the final value of  angry is : 30.8823529411765%
the final value of  cheerful is : 13.8888888888889%
the final value of  desire is : 23.6425339366516%
the final value of  disgust is : 46.2443438914027%
the final value of  happy is : 7.14285714285714%
the final value of  irritated is : 100.0%
the final value of  moved is : 37.972972972973%
the final value of  sad is : 27.5510204081633%
the final value of  smiling is : 8.18181818181818%
the final value of  surprised is : 48.780487804878%
the emotion with the max value is: irritated100.0%
CLIPS>
```

Figure 30 Output of the irritated.clp execution

As we expected the dominant emotion is irritated. However, we checked the first four emotions with higher intensity and we found:

*Irritated 100%, Surprised 48.78 %, Disgust 46.24 %, Afraid 41.11 %.*

If we compare these results to the plot we can see that the closest emotions to the emotion moved are not surprised, disgust and afraid but disgust, angry and sad. So, in this case we see that the results of the expert system do not agree with the users scoring.

## Happy.clp

The happy.clp contains the AUs combination that is the basic representation of the emotion happy based in our emotional database. In the output of the experts system shown in figure 31, we can see the impact of the activation of these AUs in the 12 emotions:

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 26.3425925925926%
the final value of  afraid is : 5.55555555555556%
the final value of  cheerful is : 63.3333333333333%
the final value of  desire is : 12.4615384615385%
the final value of  disgust is : 25.6410256410256%
the final value of  happy is : 100.0%
the final value of  irritated is : 8.40336134453782%
the final value of  sad is : 20.4081632653061%
the final value of  smiling is : 30.9090909090909%
the final value of  surprised is : 12.1951219512195%
the final value of  moved is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: happy100.0%
CLIPS>
```

Figure 31 Output of the happy.clp execution

As we expected the dominant emotion is happy. We checked the first four emotions with higher intensity and we found:

*Happy 100%, Cheerful 63.33 %, Smiling 30.90 %, Admire 26.34 %.*

If we compare these results to the plot we can see that the closest emotions to the emotion happy are also the emotions admire, cheerful and smiling. So, the results of the experts system have similarities to the users scoring.

We used the same process for the 12 emotions; all the results can be found in Appendix A. Comparing the expert system's outcome in all cases with the MDS plot (figure 19) we found out that only in case of the emotions moved, happy, afraid and desire the first four emotions with the highest intensity are the ones that are seem closer in the plot. However, in the other cases we could also find many similarities, for example in most cases the three out of the four emotions with the highest intensity are the closest as well in the plot.

## Results

Based on our evaluation, the expert system performs reasonable on emotion recognition of the facial expressions generated by FEM. In case of pure emotions the results are correct but in most cases facial expressions show blended emotions. Even human labelers have problems in labeling such emotions. Also the rules we implemented depend on values that have to be further researched in order to generate more accurate results.

# CHAPTER 10 Conclusions & Future Work

In this chapter we will present the conclusions of our projects and we will give some recommendations for future work.

## 10.1 Conclusions

The goal of this thesis, as it was stated in chapter 1, was to find a way to display a large variety of emotional facial expressions, label them, validate them and produce rules in order to translate facial actions into emotional expressions. In chapter 1 we also introduced a number of research questions that were established to meet this goal:

a. *How to represent facial expressions?*

For the representation of facial expressions we based on the Facial Action Coding System (FACS) [10]. FACS is the most widely used and versatile method for measuring and describing facial behaviors. Paul Ekman and W.V. Friesen developed the original FACS in the 1970s by determining how the contraction of each facial muscle (singly and in combination with other muscles) changes the appearance of the face. With the activation of a number of Action Units an emotion could be represented. In this project we used the 3D Facial Expression Modeler, implemented by Anna Wojdel in TUDelft [23], in order to produce the faces and handle the Action Units involved as well as their intensity.

b. *How to label facial expressions?*

For labeling the facial expressions we used emotional words. In chapter 3 we described how we created the list of emotional words, then we generated the corresponding facial expressions and finally we designed an online user test in order to validate the gathered data. Most of the facial expressions were easily recognized and for the ones that leaded to confusing results we still gave some arguments in section 3.4.2. However, what is also clear from the results is that there is no 1 to 1 correspondence of emotional words and facial expressions. There were also many cases where people were giving an answer different than the expected one but still the semantic was very similar so there was not a clear separation.

c. *How to code facial expressions?*

The facial expressions are coded by the activated AUs and their intensities. Each facial expression can be coded by a set of numbers that represent the intensity level of the AUs. In section 3.2 we explained how we generated 3D examples of facial expressions by using FEM and we gathered the data in a table were each emotion was described in terms of the activation level of each AU.

d. *How to create a database of facial expressions?*

The procedure for creating a database for facial expressions is actually what we already explained for the labeling of facial expressions. In chapter 3 we described in detail how we made the list of emotional words and then continued in generating the corresponding facial expressions. The validation was also a very important part for this task.

e. *How to classify emotional expressions and emotional words?*

We used an expert system for emotion recognition. In chapter 6 and 7 we described our algorithm and the basic rules of our system. The validation of the system in chapter 9 showed that the expert system performs reasonable on emotion recognition of the facial expressions generated by FEM. In case of pure emotions the results are correct but in most cases facial expressions show blended emotions. Even human labelers have problems in labeling such emotions. Also the rules we implemented depend on values that have to be further researched in order to generate more accurate results. For good results in this part of the process, we may be able to use probabilities. The right probabilities would greatly improve the performance of our implementation. But the approach we initially thought was by using CLIPS and not a probabilistic method. In conclusion we can say that an expert system can be used for emotion recognition but we can also compare the results with another tool.

For the emotional words classification we used the Whissell's score from dictionary of affect of language (DAL). Based on these values we could plot the emotional words in 2D space of pleasantness and activation. As we described in chapter 4 we used the values of DAL in order to validate our hypothesis that the semantic similarities of the emotional words correspond to the similarities of the facial expressions based on the Euclidian distances of vectors of AUs that compose the facial expressions. That means that the more similar expressions are closer. We designed one more user test, the facial expressions similarities user test and we plot the data by using Multidimensional Scaling (MDS). After comparing the results of MDS to Principal Component Analysis (PCA) on and Whissell's score for the corresponding labels/emotional words we found that we can see some basic similarities and make a more general comparison. However, as we have already mentioned, we cannot go into detailed comparison because the MDS and PCA techniques used transform the data to new coordinate systems.

## 10.2 Future Work

Based on the research reported in this thesis more opportunities for future research in this field can be summarized in the following parts: gather larger number of data, implement more user test with large number of participants and investigate more on the dominance of each AU on every emotion.

First of all, gathering a very large number of data is really important in this field of research and it can be always possible to use more. Gathering more emotional words and generating more facial expressions can give more accurate results and drive us in different conclusions. Generating more facial expressions for each emotion is also very important as there is not only one way to represent an emotion. Find more variations of the emotional facial expressions can be a further step in this research.

Having more data requires further testing for validation. In this project we tried to gather participants from different cultural background in order to investigate also the different way of perceiving emotions representation. However, the number of participants allows introducing uncertainty in the results.

Our algorithm, implemented in CLIPS, is a basic approach in the emotion recognition. One of our assumptions was that the AUs contribute in a linear way to the total intensity level of the emotions. The only differentiation we used was that the AUs with the higher intensity, used in the basic representation of the emotion, have more impact in the total intensity of the emotion than the ones with lower intensity. Nevertheless, further exploration should be done in this direction. Unfortunately we didn’t have any information about the dominance of each AU to each emotion.

# References

[1] Albecht, I., Haber, J., Kahler, K., Schroder, M., Seidel, H., “May I talk to you? :-) -Facial Animation from Text “

[2] Biyaye, M., “ Non-verbal Emotional Dictionary: Automatic generation of facial expressions from text input”, *Master Thesis in Man-Machine Interaction Group of TUDelft, Faculty of Electrical Engineering, Mathematics and Computer Science, 2009*

[3] Boucouvalas, A. C., “Real Time Text-to-Emotion Engine for Expressive Internet Communications”, *Ios Press, 2003, Amsterdam, The Netherlands*

[4] Cowie R., E. Douglas-Cowie et al.,“Emotion Recognition in human-Computer-Interaction”, *in IEEE Signal Processing Magazine January 2001 1053-5888/01 2001.*

[5] Darwin C., “The expression of the Emotions in Man and Animals”, *Chicago, IL: University of Chicago Press, 1872, 1965.*

[6] Desmet, P.M.A., “Designing Emotions”, *PhD thesis, Delft University of Technology, Department of Industrial Design engineering, 2002*

[7] Du, Y., Bi, W., Wang, T., Zhang, Y., Ai, H., “Distributing Expressional Faces in 2-D Emotional Space”, *CIVR’07, July 9–11, 2007, Amsterdam, The Netherlands, Copyright 2007 ACM 978-1-59593-733-9/07/000.*

[8] Ekman, P., “Emotions Revealed”, *Times Books Henry Holt and Company LLC, Copyright © 2003 by Paul Ekman.*

[9] Ekman P., Friesen, W. V., “Unmasking the face”, *Malor Books, Cambridge, MA 02238, Division of the Institute for the Study of Human Knowledge, Copyright © 2003 by Ekman P.*

[10] Ekman P., Friesen, W. V., & Joseph C. Hager, 2002, “Facial Action Coding System, The Manual”, *Published by Research Nexus division of Network Information Research Corporation, Copyright © 2002 Paul Ekman, Wallace V. Friesen, & Joseph C. Hager All Rights Reserved.*

[11] González Campins, E., “Automatic Smiley Labeling*”, Master Thesis, 2005*

[12] de Jongh, E. J., “FED: An online facial expression dictionary as a first step in the creation of a complete nonverbal dictionary”, *Master of Science thesis Delft University of Technology, Man-Machine Interaction group, June 2001*

[13] Pantic, M., Rothkrantz, L. J. M., “Facial Action Recognition for Facial Expression Analysis from Static Face Images”, *IEEE Transactions on Systems, Man, and Cybernetics, vol. 34, NO. 3, June 2004.*

[14] Pardas, M., Bonafonte A., “Facial animation parameters extraction and expression recognition using Hidden Markov Models”, *Signal Processing: Image Communication 17, 2002, 675–688.*

[15] Rothkrantz, L. J. M., Wojdel, A., “A Text Based Talking Face”, *P. Sojka, I. Kopeˇcek, and K. Pala (Eds.): TSD 2000, LNAI 1902, pp. 327–332, 2000, ©Springer-Verlag Berlin Heidelberg 2000*

[16] Rothkrantz, L. J. M., Fitrianie, S., “A Text Based Synthetic Face with Emotions”, *The research reported here is part of the Interactive Collaborative lexicon database. Information Systems (ICIS) project, supported by the Dutch Ministry of Economic Affairs, grant nr: BSIK03024*

[17] Rothkrantz L. J. M., Fitrianie, S., “Constructing Knowledge for Automated Text-Based Emotion Expressions”, *The research reported here is part of the Interactive Collaborative Information Systems (ICIS) project, supported by the Dutch Ministry of Economic Affairs, grant nr: BSIK03024, CompSysTech ‘06*

[18] Rothkrantz, L. J. M., Pantic, M., “Expert system for automatic analysis of facial expressions”, *Image and Vision Computing 18 (2000)881-905*

[19] Rubin, V. L., Stanton, J. M.,  Liddy, E. D., “Discerning Emotions in Texts”,

[20] Russell, J.A., “A Circumplex Model of Affect”, *Journal of Personality and Social Psychology 39: 1161–1178, 1980*

[21] Stathopoulou, I., Tsihrintzis, G.A., “An improved Neural-Netwrok-based Face Detection and Facial Expression Classification System”, *IEEE International Conference on Systems, Man and Cybernetics, 2004.*

[22] Whissell, C.M. "The dictionary of affect in language." In Emotion: Theory, Research and Experience, *Plutchik & Kellerman Eds. Academic Press,113-131*

23 - [23] Wojdel, A., “Knowledge driven facial modeling”, Master Thesis, *TUDelft & Technical University of Ł´od´z, 2005*

[24] *http://news.bbc.co.uk/2/hi/science/nature/8199951.stm*

[25] http://www-igbmc.u-strasbg.fr/projets/fcm/

# Appendix A

In Appendix A you can find the evaluation results of the 12 emotions expression files generated by FEM.

Table 12 Output of the angry.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  afraid is : 22.2222222222222%
the final value of  angry is : 100.0%
the final value of  desire is : 2.76923076923077%
the final value of  disgust is : 14.3589743589744%
the final value of  irritated is : 12.8151260504202%
the final value of  sad is : 24.4897959183673%
the final value of  surprised is : 0.0%
the final value of  smiling is : 0.0%
the final value of  moved is : 0.0%
the final value of  happy is : 0.0%
the final value of  cheerful is : 0.0%
the final value of  admire is : 0.0%
the emotion with the max value is: angry100.0%
CLIPS> |
```

Table 13 Output of the afraid.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 30.0%
the final value of  afraid is : 100.0%
the final value of  angry is : 29.4117647058824%
the final value of  cheerful is : 13.8888888888889%
the final value of  desire is : 53.2307692307692%
the final value of  disgust is : 9.23076923076923%
the final value of  happy is : 14.2857142857143%
the final value of  irritated is : 28.9495798319328%
the final value of  moved is : 54.7297297297297%
the final value of  sad is : 40.8163265306122%
the final value of  smiling is : 14.5454545454545%
the final value of  surprised is : 40.0%
the emotion with the max value is: afraid100.0%
CLIPS>
```

Table 14 Output of the admire.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 100.0%
the final value of  afraid is : 48.8888888888889%
the final value of  cheerful is : 70.5357142857143%
the final value of  desire is : 68.4761904761905%
the final value of  disgust is : 29.4871794871795%
the final value of  happy is : 48.7755102040816%
the final value of  irritated is : 30.2521008403361%
the final value of  moved is : 58.8803088803089%
the final value of  sad is : 31.6326530612245%
the final value of  smiling is : 54.1125541125541%
the final value of  surprised is : 71.9512195121951%
the final value of  angry is : 0.0%
the emotion with the max value is: admire100.0%
CLIPS> |
```

Table 15 Output of the irritated.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 22.3809523809524%
the final value of  afraid is : 41.1111111111111%
the final value of  angry is : 30.8823529411765%
the final value of  cheerful is : 13.8888888888889%
the final value of  desire is : 23.6425339366516%
the final value of  disgust is : 46.2443438914027%
the final value of  happy is : 7.14285714285714%
the final value of  irritated is : 100.0%
the final value of  moved is : 37.972972972973%
the final value of  sad is : 27.5510204081633%
the final value of  smiling is : 8.18181818181818%
the final value of  surprised is : 48.780487804878%
the emotion with the max value is: irritated100.0%
CLIPS>
```

Table 17 Output of the desire.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 44.4907407407407%
the final value of  afraid is : 46.6666666666667%
the final value of  angry is : 8.82352941176471%
the final value of  cheerful is : 22.2222222222222%
the final value of  desire is : 100.0%
the final value of  disgust is : 23.0769230769231%
the final value of  happy is : 21.4285714285714%
the final value of  irritated is : 21.0084033613445%
the final value of  moved is : 57.4662162162162%
the final value of  sad is : 38.7755102040816%
the final value of  smiling is : 28.1818181818182%
the final value of  surprised is : 48.5365853658537%
the emotion with the max value is: desire100.0%
CLIPS>
```

Table 16 Output of the cheerful.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 26.8518518518519%
the final value of  afraid is : 11.1111111111111%
the final value of  cheerful is : 100.0%
the final value of  desire is : 16.7692307692308%
the final value of  happy is : 37.1428571428571%
the final value of  irritated is : 8.40336134453782%
the final value of  moved is : 27.027027027027%
the final value of  sad is : 10.2040816326531%
the final value of  smiling is : 63.6363636363636%
the final value of  surprised is : 24.390243902439%
the final value of  disgust is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: cheerful100.0%
CLIPS>
```

Table 18 Output of the happy.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 26.3425925925926%
the final value of  afraid is : 5.55555555555556%
the final value of  cheerful is : 63.3333333333333%
the final value of  desire is : 12.4615384615385%
the final value of  disgust is : 25.6410256410256%
the final value of  happy is : 100.0%
the final value of  irritated is : 8.40336134453782%
the final value of  sad is : 20.4081632653061%
the final value of  smiling is : 30.9090909090909%
the final value of  surprised is : 12.1951219512195%
the final value of  moved is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: happy100.0%
CLIPS>
```

Table 19 Output of the disgust.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 13.3796296296296%
the final value of  afraid is : 13.3333333333333%
the final value of  angry is : 21.5686274509804%
the final value of  desire is : 15.6923076923077%
the final value of  disgust is : 100.0%
the final value of  happy is : 28.5714285714286%
the final value of  irritated is : 29.3637454981993%
the final value of  moved is : 16.2162162162162%
the final value of  sad is : 41.4965986394558%
the final value of  surprised is : 0.0%
the final value of  smiling is : 0.0%
the final value of  cheerful is : 0.0%
the emotion with the max value is: disgust100.0%
CLIPS>
```

Table 21 Output of the moved.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 21.5020576131687%
the final value of  afraid is : 30.0%
the final value of  cheerful is : 15.4320987654321%
the final value of  desire is : 41.5384615384615%
the final value of  disgust is : 4.61538461538462%
the final value of  irritated is : 15.9663865546218%
the final value of  moved is : 100.0%
the final value of  sad is : 28.5714285714286%
the final value of  smiling is : 16.1616161616162%
the final value of  surprised is : 28.319783197832%
the final value of  happy is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: moved100.0%
CLIPS>
```

Table 20 Output of the irritated.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 22.3809523809524%
the final value of  afraid is : 41.1111111111111%
the final value of  angry is : 30.8823529411765%
the final value of  cheerful is : 13.8888888888889%
the final value of  desire is : 23.6425339366516%
the final value of  disgust is : 46.2443438914027%
the final value of  happy is : 7.14285714285714%
the final value of  irritated is : 100.0%
the final value of  moved is : 37.972972972973%
the final value of  sad is : 27.5510204081633%
the final value of  smiling is : 8.18181818181818%
the final value of  surprised is : 48.780487804878%
the emotion with the max value is: irritated100.0%
CLIPS>
```

Table 22 Output of the sad.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 22.2685185185185%
the final value of  afraid is : 44.4444444444444%
the final value of  angry is : 35.2941176470588%
the final value of  cheerful is : 13.8888888888889%
the final value of  desire is : 44.6153846153846%
the final value of  disgust is : 42.3076923076923%
the final value of  happy is : 28.5714285714286%
the final value of  irritated is : 16.3445378151261%
the final value of  moved is : 57.2972972972973%
the final value of  sad is : 100.0%
the final value of  smiling is : 14.5454545454545%
the final value of  surprised is : 15.609756097561%
the emotion with the max value is: sad100.0%
CLIPS>
```

Table 23 Output of the smiling.clp execution

```
TRUE
CLIPS> (reset)
CLIPS> (run)
the final value of  admire is : 20.3703703703704%
the final value of  afraid is : 8.88888888888889%
the final value of  cheerful is : 61.1111111111111%
the final value of  desire is : 14.6153846153846%
the final value of  happy is : 20.0%
the final value of  irritated is : 5.04201680672269%
the final value of  moved is : 21.6216216216216%
the final value of  sad is : 8.16326530612245%
the final value of  smiling is : 100.0%
the final value of  surprised is : 17.0731707317073%
the final value of  disgust is : 0.0%
the final value of  angry is : 0.0%
the emotion with the max value is: smiling100.0%
CLIPS>
```

# Appendix B

In Appendix B you can find the table of the 60 emotions represented in terms of AUs intensities.

| | AU1 | AU2 | AU4 | AU5 | AU6 | AU7 | AU9 | AU10 | AU12 | AU15 | AU16 | AU17 | AU18 | AU20 | AU22 | AU23 | AU24 | AU25 | AU26 | AU27 | AU28 | AU43 | AU54 | AU64 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| aggressive | 100 | 0 | 100 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 50 | 0 | 100 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| admire | 80 | 70 | 0 | 70 | 75 | 0 | 40 | 0 | 60 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 75 | 0 | 0 | 0 | 0 | 0 | 0 |
| afraid | 100 | 0 | 100 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| alarmed | 100 | 100 | 0 | 100 | 0 | 0 | 40 | 0 | 0 | 60 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| amazed | 60 | 100 | 0 | 45 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| amused | 30 | 40 | 0 | 0 | 100 | 0 | 40 | 0 | 100 | 0 | 30 | 0 | 40 | 80 | 0 | 30 | 0 | 27 | 0 | 0 | 0 | 0 | 0 | 0 |
| angry | 0 | 0 | 100 | 0 | 0 | 40 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 20 | 0 |
| annoyed | 0 | 80 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| anticipated | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 |
| avaricious | 0 | 80 | 40 | 55 | 70 | 0 | 0 | 0 | 0 | 0 | 20 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| awaiting | 0 | 0 | 20 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 |
| bored | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 50 | 0 | 0 |
| cautious | 0 | 70 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 0 | 0 | 0 | 0 | 0 | 0 |
| cheerful | 50 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| concentrated | 0 | 0 | 60 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| contempt | 0 | 100 | 70 | 0 | 0 | 0 | 70 | 0 | 0 | 40 | 0 | 40 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 20 | 0 | 0 |
| curious | 0 | 100 | 20 | 80 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 40 | 0 | 0 |
| cynical | 0 | 100 | 40 | 30 | 80 | 0 | 0 | 25 | 40 | 0 | 0 | 40 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 35 | 0 | 0 | 0 |
| dangerous | 0 | 0 | 80 | 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| defeated | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| deferent | 50 | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 |
| desire | 100 | 15 | 30 | 80 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| desperate | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 |
| disbelief | 0 | 100 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| disgust | 0 | 0 | 60 | 0 | 100 | 0 | 100 | 0 | 0 | 30 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 |
| dissapointed | 70 | 30 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| dissatisfied | 0 | 0 | 100 | 0 | 50 | 0 | 30 | 0 | 0 | 20 | 0 | 30 | 0 | 70 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| disturbed | 0 | 50 | 100 | 30 | 70 | 0 | 0 | 0 | 0 | 50 | 0 | 30 | 0 | 0 | 0 | 50 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| eager | 0 | 100 | 100 | 100 | 100 | 0 | 100 | 0 | 0 | 40 | 0 | 0 | 30 | 0 | 0 | 50 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| excited | 50 | 50 | 0 | 50 | 50 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 |
| fierce | 0 | 100 | 50 | 70 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 30 | 0 | 100 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 |
| flabbergasted | 70 | 30 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 |
| frustrated | 30 | 90 | 90 | 70 | 40 | 0 | 0 | 45 | 0 | 30 | 20 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| giggle | 0 | 0 | 30 | 0 | 0 | 100 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| happy | 0 | 50 | 0 | 0 | 100 | 0 | 0 | 0 | 100 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| hostile | 0 | 100 | 100 | 100 | 100 | 0 | 100 | 0 | 0 | 40 | 0 | 0 | 30 | 0 | 0 | 50 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| indignant | 0 | 60 | 80 | 50 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| inspired | 80 | 85 | 0 | 40 | 60 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| irritated | 0 | 100 | 85 | 100 | 0 | 0 | 70 | 0 | 0 | 50 | 0 | 50 | 0 | 0 | 0 | 80 | 20 | 0 | 0 | 0 | 40 | 0 | 0 | 0 |
| isolated | 100 | 20 | 0 | 0 | 70 | 90 | 0 | 0 | 0 | 20 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| jealous | 0 | 30 | 100 | 0 | 0 | 0 | 20 | 0 | 0 | 80 | 15 | 0 | 0 | 0 | 0 | 50 | 40 | 0 | 0 | 0 | 20 | 0 | 0 | 0 |
| joyful | 20 | 25 | 0 | 0 | 0 | 60 | 0 | 0 | 100 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| loving | 30 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 |
| melancholy | 100 | 0 | 50 | 0 | 0 | 60 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 0 |
| moved | 90 | 0 | 0 | 45 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| neutral | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| peaceful | 20 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| relaxed | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 15 | 0 | 0 |
| sad | 100 | 0 | 100 | 0 | 100 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 70 |
| satisfied | 0 | 70 | 0 | 0 | 0 | 40 | 0 | 0 | 80 | 20 | 0 | 35 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 0 |
| shocked | 0 | 70 | 0 | 70 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| sighing | 60 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| smiling | 40 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| sociable | 40 | 30 | 0 | 0 | 40 | 0 | 0 | 0 | 50 | 10 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| stimulated | 0 | 50 | 70 | 0 | 100 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 70 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| stress | 50 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| surprised | 80 | 100 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 |
| suspicion | 0 | 100 | 100 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| worried | 80 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | 0 | 0 |
| yearning | 75 | 85 | 0 | 70 | 30 | 20 | 60 | 20 | 50 | 0 | 0 | 0 | 0 | 70 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 0 | 0 | 0 |