Detection of human emotions through the analysis of brain waves

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Abstract

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The recognition and communication through emotions and emotional states are an integral part in human interaction and omnipresent in daily life. Being involved in various areas such as cognition, learning and decision making, these concepts have been studied with great interest to be applied for Human Machine Interaction (HMI) and potentially for those with socioemotional impairments, such as children with ASD. This thesis addresses the development of a framework to measure and categorize emotional states by aid of pattern recognition with electroencephalographic (EEG) signals. For the investigation, the commercially available Emotiv EPOC headset was used. Three emotional categories, namely positively excited, negatively excited and calm have been selected to be recognized through the use of various processing and classification methods researched.

The framework has been verified with data from a publicly available EEG-database after which it has been tested on adults and children using emotionally loaded images. Experimental results were presented and discussed towards the performance and readiness of the framework for emotion recognition in adults and children.

The findings of this thesis contribute to the understanding of current challenges faced when working with visual stimuli, especially to be used for children. Some of these challenges include (i) designing a protocol to allow for unique emotion elicitation to avoid classification error, (ii) integrate efficient algorithms for the reduction of noise and (iii) agreeing upon universal evaluation standards to allow for a deeper evaluation of performance towards emotion recognition.

Declaration

I hereby certify that this report constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the report describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

Malte Trauernicht

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Chapter 1

Rationale

Social and emotional interactions play a vital role in most of human communication with others and are omnipresent in daily life. Nevertheless, some people suffer from lifelong developmental disabilities such as autism spectrum disorder (ASD) from which they are unable to understand fundamental social and emotional behaviour. ASD refers to a family of disorders with ranging degree of severity, from light to severe and are largely manifested as social deficits such as stereotyped movements difficulty in communication and interaction with people [9]. To date, about 1 in 88 children has been diagnosed with ASD in the United States and the average prevalence was found to be as high as 1% on other continents (Asia, Europe and North America) [10].

Current research in human-robotic interaction (HRI) has shown potential for robots to be used as therapy tools in order to stimulate social interaction and elicit novel social behaviours from autistic people, particularly young children and teenagers [11]. As one of the first application domains in the field of socially assistive robotics (SAR), robot therapy through HRI intends to improve engagement and joint attention skills for people with special demands. The educational significance in this domain results from the fact that while autism appears to be on the rise, there is currently no "cure" for people affected by ASD [12, 13]. And although a range of specialist education and behavioural programmes (often referred to as interventions) are developed, they often differ greatly in price, quality and suitability for the autistic child and thus alternative treatment possibilities are yet interesting for the children with ASD and associated parties, i.e. researchers, therapists, and the like [12, 14]. One of the possible advantages of using HRI is the opportunity to study the child's way of interacting with alienate situations, objects and environments and therefore results may show indications towards the triggers and processes of tantrums or disruptive behaviour as well as provide information about what elicits positive responses [15].

To this end, students and professors at the Universidade Federal do Espirito Santo (UFES/Brazil) are cooperatively working towards a system implementation of mobile robots, generating actions to interact with children in the ASD spectrum and a Brain Computer Interface (BCI) to analyse emotions through electroencephalogram (EEG) recordings. Main objectives of the joint project are to explore degrees of applicability of HRI as an intervention tool as well to study technical capabilities and implications of BCIs in autism research. Preliminary results have been found effective in the preservation of a safety distance during Child-Robot Interaction (CRI) and different interaction modes have been defined. Furthermore, several evaluation methods for the assessment of CRI have been proposed to quantify interaction results to be readily compared with other research conducted in a similar manner. Ultimately, paired with the detection of emotional states of autistic children during play and interaction, the system may be able to adaptively change its behaviour to maintain the motivation and stimulus of interaction.

Towards the development of the desired system as a treatment option and research tool, current work is focused towards the recognition and characterization of emotions through the analysis of brain waves with an EEG-based BCI. By doing so, universal models of emotions are utilized to allow the system to generalize over (more or less) generally acknowledged interpretations of emotions, instead of relying on pure subjectivity. In the method of automatically detecting emotions through EEG, there is a general consensus in the steps required for a BCI to arrive at an estimation of classes to be differentiated. This thesis explores the capability of several methods in different stages of emotion detection, stemming from various computational approaches to perform either signal conditioning, extraction or translation tasks, as these build the foundation of a BCI. Innately, the project is limited to the use of the commercially available Emotiv EPOC EEG-headset [16] which poses an additional constraint as the number of available electrodes is considerably less than in medical use. Nevertheless, using accessible user products will inevitably indicate its suitability for detecting emotions in children with autism and to be used in BCI research in general. In obtaining emotionally evoked signals, stimuli need to be carefully chosen, i.e. based on the context and purpose of use. Emotional elicitors are fundamentally different comparing adults with children and therefore has to be adapted by using appropriate methods [17]. Yet, there are a number of repositories of emotionally-annotated stimuli comprising of visual, auditory, physiological cues, individual or in combination. In this research the International Affective Picture System (IAPS) [6] has been proposed, based upon which experimental methods will be adapted to.

1.1 Motive

The fundamental problem in this research manifests itself in the complex nature of brain signals to be identified and correctly classified. Although recent studies have presented outstanding emotion recognition rates for healthy adult subjects as high as 92.8% using advanced recognition techniques [18, 19] and commercially available EEG devices [20], the situation fundamentally changes when dealing with children, moreover, those suffering from any form of ASD [21]. As a consequence, test procedures, amongst others, have to be carefully designed in order to fulfill its primary goals by also allowing for repeatability. With regard to what has been said, research in this project is thus directed towards a descriptive problem, i.e. investigating in existing emotion detection techniques and projecting these onto social-emotional impaired children. Providing a comprehensible description of the emotion recognition estimation process is intended to give insight in the complexity and amount steps required to arrive at a quantitative and statistical analysis by presenting crucial statistical figures.

The reason for research performed in this area arises from the inherent need of successful intervention methods and the shortage of comparative studies in BCI research towards autism and children in general. The current work addresses the challenge of creating a verified and validated platform for emotion recognition based on healthy adults and children to be later validated using autistic candidates. Thus, exploring the nature of emotions by means of available techniques it is not only beneficial for researchers and scientists but potentially for therapists, care-takers and even parents to understand fundamental triggers and processes emotional responses of the children. The outcomes of this research are thus a contribution to the field of affect detection in humans, specially children, aided by a developed platform to process and distinguish emotions in EEG as a pattern learning problem. The design and implementation of the system shall facilitate ongoing research of affect recognition in the context of children, and those in the ASD spectrum.

Thus, in taking all aforementioned parts into account, the following principal research question has been defined as:

> *To which extent, if at all, can selected feature extraction and machine learning techniques be viable methods for recognizing emotions in EEG for adults and children with the hardware limitations posed by the Emotiv EPOC headset?*

Further sub-questions associated have been identified as:

1. What are the main constraints towards affect recognition in children when the implementation for adults was verifiable?
2. What commercial value and impact does the system indicate towards the use with children and/or autistic individuals?

1.2 Document Overview

The remainder of this report is structured as follows:

Chapter 2, Background, briefly describes models and notions of emotions used in BCI research, followed by a fundamental description of EEG signals and their characterization by also mentioning computational methods for analysis of brain waves. Next, introductory knowledge to Brain-Computer Interfaces is presented, outlining the main types for emotion recognition as well as common evaluation metrics which are also used in this contribution.

Chapter 3, Situational & Theoretical Analysis, starts with a brief outline of autism research based on emotion detection and continuous by exploring essential stages of the emotion recognition estimation process. Furthermore, basic properties of different computational methods for signal conditioning and processing will be reported, as well as listing a state-of-the-art comparison for algorithms used in EEG-based BCIs. Lastly, the chapter will present the hypothesis drawn from the aforementioned information presented.

Chapter 4 is dedicated to the V-model approach as a concept of project development and presents the underlying development process towards affect recognition. This chapter deals with the decomposition and definition of requirements and design considerations before integrating and verifying these as a later stage. Moreover, the model with which emotion detection is believed to be achieved and how it is implemented is outlined in subsequent sections.

Chapter 5, Research Design, outlines the implementation steps, i.e. experimental, by providing details on how to verify and validate the proposed model.

Experimental Results in Chapter 6, display empirical findings on EEG data, followed by a detailed discussion of said results.

Conclusions and future recommendations based on determined limitations can be found in Chapter 7 and 8.

Chapter 2

Background

2.1 Emotions

The study of emotions has become a target of many research in the field of psychology, physiology, computing and engineering, with the formulation of theories and models of emotions as well as their origin, expression and characterization.

2.1.1 Brief History on Emotions

The question towards the nature of emotions and mood has intrigued mankind since the early days of philosophy or even earlier with the development of self-consciousness in increased human intelligence throughout evolution. Although scientifically arguable, one of the first well documented (i.e. written) sources include Aristotle's notion of emotion, stated in his work *Rhetoric* (1378b), translated into English by W. Rhys Roberts [22]:

> "The Emotions are all those feelings that so change men as to affect their judgments, and that are also attended by pain or pleasure. Such are anger, pity, fear and the like, with their opposites".

Although many attempts by prominent emotion theorists and researchers were made, defining the term "emotion" in scientific terms not reached a universal consensus yet, thus indicating the complexity and intricacy of a term that is highly dependent on context and subjective experience[23].

Modern theories theories of emotions had been proposed in the 19^{th} and 20^{th} centuries,, relating emotional expression and experience, as the James-Lange Theory and the Cannon-Bard Theory [24]. Previous to the theory proposed by the American North psychologist and philosopher William James and by the Danish psychologist Carl Lange, it was believed that the emotion would be evoked by a situation and that the organism would change in response to emotion. The James-Lange theory proposes that the emotion occurs in response to physiological changes in the body [25]. Contradicting the theory of James-Lange, the American North physiologist Walter Cannon and his student Philip Bard proposed that emotion occurs from the appropriate activation of the thalamus in response to a situation [26, 27]. In general, James and Lange claimed that different patterns of somatovisceral activity can produce different emotions and Cannon and Brand claimed that different emotions can produce different patterns of somatovisceral activity.

To date, a emotion can be defined as a type of affect causing specific sets of changes in the somatic and/or neurophysiological activity, involving changes in the neurophysiological and hormonal responses, and in the facial, body and vocal behaviour [17]. It can either be understood as states or entire processes. Regarding emotions as a mental state (like happy or angry), it causes certain behaviours as a result of interacting with other mental states. Understood as a process, it can be divided into two intervals: the perception of the stimulus to trigger a bodily response, and the expression of that response as changes in bodily parameters like heart rate, breathing, facial expressions, and the like [28]. Freud's research in clinical psychology has shown that some aspects of emotional states can be reported and that others cannot. Emotions are usually directed to certain objects, unlike humor, which tends to be more diffuse. Emotions also tend to be of short duration, lasting of the order of seconds or minutes, however, other emotional reactions such as humor and especially the attitudes they tend to be more long duration [17].

2.1.2 Emotion representation categories

According to research in psychology, two major approaches to affect categories are the most used in the assessment community: the basic emotions, strongly anchored by Darwinian and Jamesian theories and continuous representations, a result from cognitive theory [29].

- **Darwin:** from a biological viewpoint, basic emotions are the result of a natural selection process and thus have important survival functions. As a Darwin proponent, Ekman described a number of six universal basic emotions identifiable in the facial expressions of individuals of all cultural and linguistic backgrounds which have now extended to a total of 15 families. Plutchik proposed eight basic emotions: anger, fear, joy, acceptance, curiosity, surprise, disgust and sadness which extended by another 8 advanced emotions each composed of 2 basic ones as depicted below in Figure 2.1 [30].

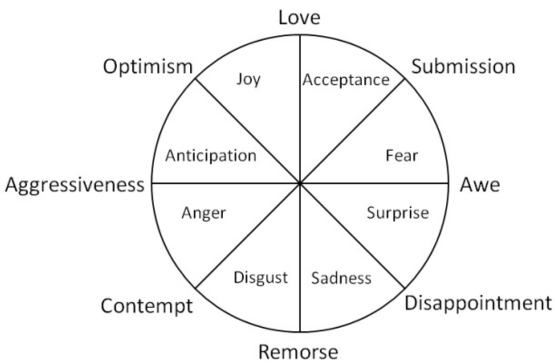


Figure 2.1: Wheel of emotion by Plutchik [1]

- **Cognition:** the idea of a continuous representation of emotions results from the theory assuming a possession of an individual representation of emotions and is referred to as Russell's model[29, 2]. Nowadays, there is an agreement on two, bipolar, fundamental dimensions: valence and arousal. Valence, ranging from positive to negative, represents the pleasantness while arousal represents the awakeness and alertness of the emotion (calm versus excited) [31]. In this way, emotion-related terms and be positioned in a circumplex shape, as a result of a numerical composition of its valence-arousal dimension (Figure 2.2 and 2.3).

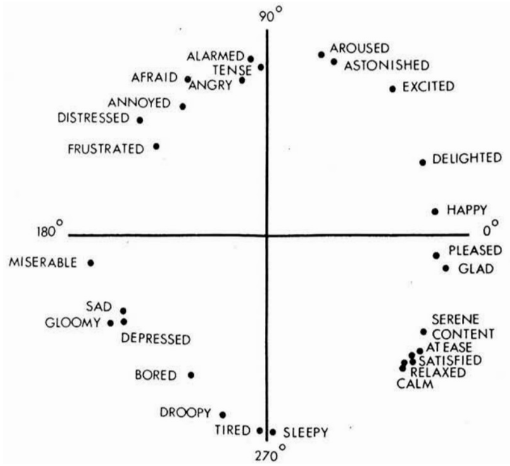


Figure 2.2: Circular scaling of Russell's circumplex model of emotion (taken from [2]).

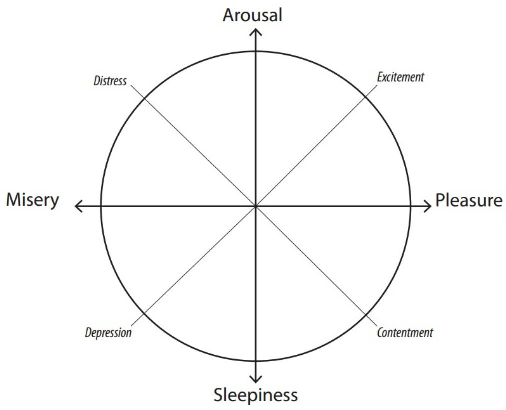


Figure 2.3: Arousal-valence model used in this thesis (adapted from [2]).

Mehrabian proposed a model which is based on a three-dimensional PAD (*Pleasure-Arousal-Dominance*) representation, adding an additional dimension to distinguish between the subject's level of control, declared as *dominance* [32]. The term "pleasure" is interchangeable with the term "valence" in Russell's model.

For the project at hand, the second approach (i.e. Russell's model, Figure 2.3) was chosen due to its suitability to represent emotions without using labels but just a coordinate systems that includes emotional meaning, and because of its computational advantage as compared to other approaches [29]. In here, each quadrant is a 2D representation of an affective state for which the indication of the positions of certain emotions is based on emotion labeling.

2.2 Emotions in the Brain

The brain, as the center of the human nervous system, controls all vital functions of the human body. At its largest and most highly developed part, the cerebrum, it is divided by a longitudinal fissure into halves (hemispheres)-left hemisphere and right hemisphere which intercommunicate via a neural fiber bundle, the corpus callosum. Each containing 5 discrete lobes, the brain coordinates specific functions with multiple or single areas of the brain in both hemispheres which is also referred to as brain lateralization.

A critical role in emotional expression and interpretation plays the limbic system, a complex set of highly interconnected brain structures with many pathways. Although the exact nature of the limbic system is yet to be explored it was proposed that it supports autonomic effector mechanisms associated with emotional states as well as the modulation of emotional quality induced by the stimulus [33]. One of the subcortical key structures is the amygdala which plays a critical role in emotion processing and control of major affective activities, like affection and love but also fear and anxiety when triggered. Furthermore, research shows that lesions of the amygdala and other limbic damages can produce changes in the emotional behaviour. Projections by the amygdala are sent to the hypothalamus which is mostly responsible for activating certain metabolic processes and the secretion of hormones. However, due to the fact that the limbic system is an internal brain structure it cannot directly be measured as a scalp recording.

Recalling the cerebral functions for emotion recognition, multiple brain regions have been associated with particular contributions to the emotional processing and the consciously experienced feelings. The spatial location of the different brain regions is shown in Figure 2.4.

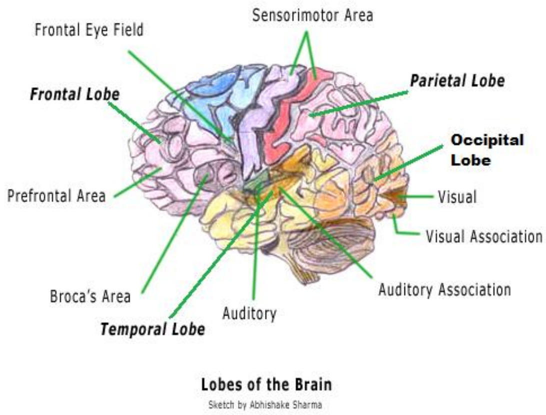


Figure 2.4: Cross section of the human brain and physical location of the different lobes.

Frontal lobes, comprising of various distinct areas, are majorly involved in planning and executing learned behaviour. Yet, regions such as the medial frontal cortex (or prefrontal lobe) has been found active for motivational, cognitive and emotional processes. The orbital part of the frontal cortex is said to be the emotional control center to administer processes like judgement, social behaviour and even determines personality [17].

Parietal lobes have found to be involved with activities in recognition, orientation and other perceptions of awareness. Temporal lobes are integral to auditory perception, components of language as well as being highly involved in memory. Visual-spatial processing is mainly performed in the occipital lobes as they include the primary visual cortex.

2.3 EEG Recording

As an electroencephalogram, we consider the measured neuronal activity in both frequency and amplitude generated from the human brain. Measured against a "reference site" which is comparably non-active, the brain region under study is recorded by an electrode as an oscillating signal reflecting the electric potential from the group of neurons situated in close proximity [34, 35].

2.3.1 Short History of the EEG

The first use of EEG signals for the study of electrical activity of a human being dates back 70 years and was performed by the German neurologist Hans Berger in 1924. Ever since the technology has been development and gained far reaching implications for the study of human brain activity in general and particularly how the brain changes as a response to changes in emotion [17]. Nowadays, modern recording equipment, empirical studies of EEG, and the availability of sufficient computational power for computers give rise to the ability to detect even very subtle changes in the electric potentials recorded and to distinguish between resting state and stimulus conditions between the two hemispheres of the brain (e.g. cerebral laterality), amongst others. Allowing for more and more subtle changes to the be detected enables scientists and researchers to study the origin of various human cognitive and emotional processes as well as to find individual differences in brain function and brain activity [34].

2.3.2 Rhythms of the Brain

EEG signals are measured as potential differences over time between an active electrode and reference electrode placed on the scalp. Brain signals occur as electric oscillations of neuronal populations and can be classified according to their frequency, also referred to as brain rhythms. Well known frequency bands include delta (δ, 0.5–3Hz), theta (θ, 4–7Hz), alpha and mu (α, μ, 8–12Hz), beta (β, 12–30Hz), and gamma (γ, 30–100Hz) [7]. These rhythms have been found in correlation to different states of human behaviour and thus their analysis proved successful for the use of emotion recognition and other BCI applications [36]. Figure 2.5 shows the different rhythms based on their frequency content.

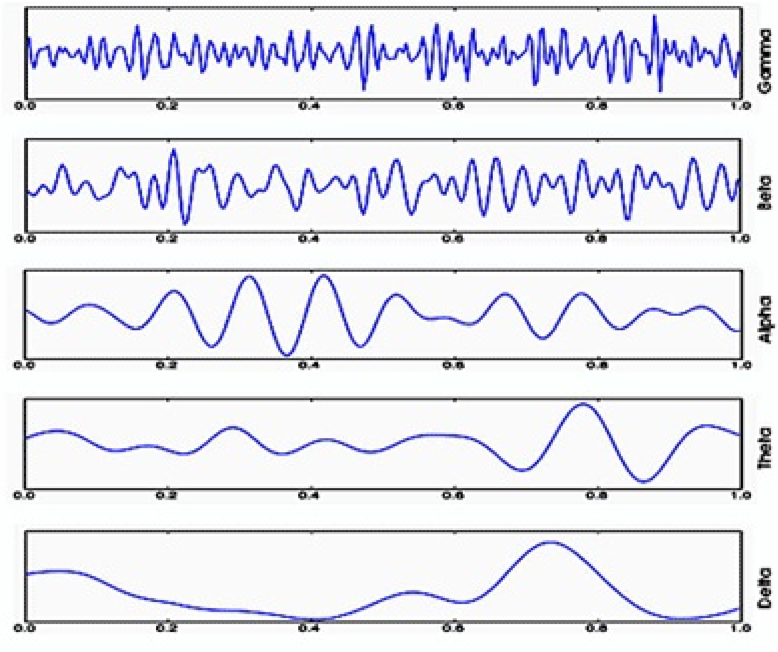


Figure 2.5: Brain wave oscillations over a time period of one second.

With respect to children, theta wave oscillation come within the range of 4–7 Hz and are usually found in larger amounts in young and older children as compared adults in awake states. Gamma brain waves can be observed throughout the entire brain and are associated to problem solving tasks for both, adults and children. For adults, also certain motor function such as muscle contraction or perceptions of visual auditory stimuli have been associated to gamma waves. Alpha activity can be found over the occipital region in the brain and primarily reflect visual processing and has also be found to be involved in memory brain functions and mental effort [7]. Mu rhythms are found in the same frequency range as alpha but is linked to motory rather than mental tasks. Lastly, beta waves are found in the frontal and central regions and evident during motor activities. During absence of motor activities, beta oscillations appear to be have a symmetrical distribution in the brain which changes with the onset of motory tasks to be performed [7].

2.3.3 Electrodes

Electrode Placement: the 10-20 System

In an attempt to make replicable setups and to reduce the uncertainty of what is being measured where, standardized sets of electrode locations have been developed. One of the most internationally recognized methods to describe the location of scalp electrodes on the scalp in the context of recording EEG signals is the "10-20 system" [37]. The numbers associated with the name indicate that the

> " ... first electrode placed should be separated from the landmark with a distance of 1/10 of the total distance from one landmark to the other, while the rest of the electrodes should be separated by 1/5 of the total distance. [36]"

Each electrode has a uniquely specified id which is a combination of characters and numbers. Characters are encoded for the specific region (lobe) of the brain and numbers are associated with a position of that particular lobe. Furthermore, they also indicate on which side of the homologous hemispheres of the brain the electrode is located. Even numbers represent right hemisphere whereas odd numbers encode for left hemisphere. An illustrative example of the electrode montage is presented in Figure 2.6.

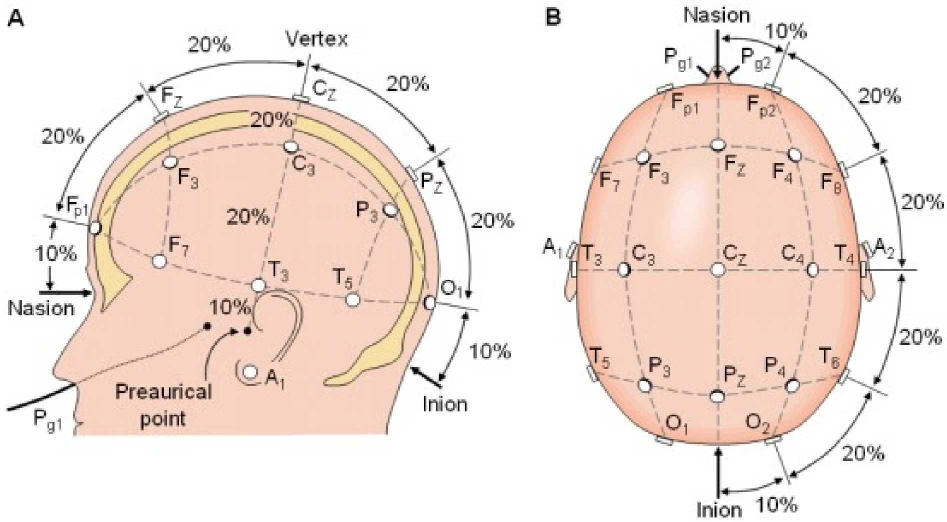


Figure 2.6: 10-20 system of electrode placement. The characters stand for frontal (F), temporal (T), occipital (O), parietal (P) lobe and cerebellum (C)

In most clinical applications, 19 recording electrodes (plus ground and system reference) are used. Additional electrodes can be added to the standard set-up when there is need for increased spatial resolution for a particular area of the brain. These high-density arrays can contain up to 256 electrodes more-or-less evenly spaced around the scalp.

Monopoles and Dipoles

For the measurement of EEG signals unipolar or bipolar electrodes can be used. In the former case, each electrode is compared to either a neutral electrode or to the average of all electrodes as a reference. In the bipolar case, the difference between an individual pair of electrodes is measured [38].

The device used in this research, Emotiv EPOC wireless headset uses a fixed reference pair (CMS and DRL electrodes) which form the basis for the electrical measurements. The reference location is around P3 region for the default reference location, and on the maxillary process behind the ear in the alternate location, as shown in Figure 2.7 [16].

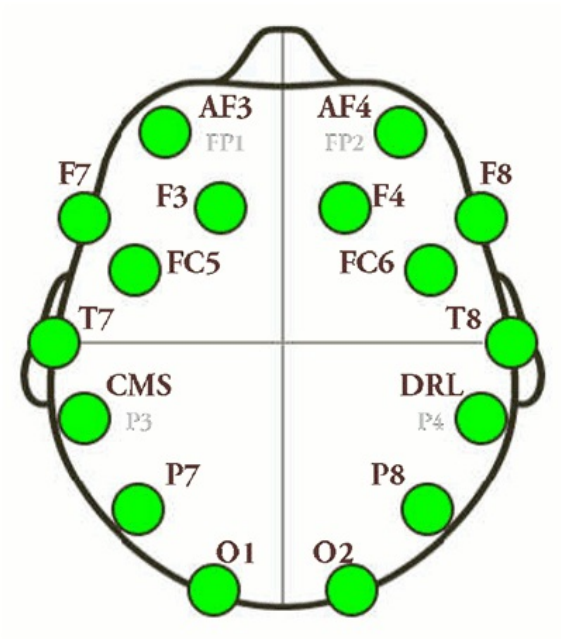


Figure 2.7: Scalp locations covered by Emotiv EPOC.

According to [36], the focus of valence research has been centered on the difference between both hemispheres which suggests a bipolar montage for the detection of these features. However, in order to be able to compare amplitudes and latency for alpha and beta waves to determine arousal states, a unipolar montage is suggested. The Emotive EPOC headset comes with a set of monopole electrodes, suitable for the determination of affective states in the arousal spectrum. For the emotional valence recognition based on the difference in hemispherical activity bipolar recordings can be obtained by referencing electrodes of interest to each other.

2.3.4 Referencing

One of the major challenges with EEG recordings is the need of referencing bio-potentials, i.e. relating the activity of a recording site to a "neutral" – or reference site. Since a completely inactive (zero-potential) site has not been found on the human body, any activity at the reference site will directly affect the current voltage recording [39]. Yet, there are several means to address the reference problem by employing a common reference (CR) electrode from which relative potentials to other recording sites are measured, or through reference-free techniques. The former approach refers to re-reference techniques or electrode montages such as vertex (Cz), linked-ears, linked-mastoids, ear lobes, C7 reference, bipolar references, and tip of the nose [40]. Amongst reference-free techniques, common average reference (CAR), weighted average reference and source derivation are the most frequently used methods and enjoy the advantage of not suffering from problems directly associated with the physical reference utilized [41].

2.4 The Computer and the Brain

Detecting and recognizing emotional information for the study and development of systems to improve communication among individuals and machines has emerged in recent decades and is becoming considerably popular [42, 43]. Advances in cognitive neuroscience and brain imaging technologies have made it possible to directly interface with the human brain in order to build communication systems that do not depend on its regular output channels such as peripheral nerves and muscles [3]. This has lead researchers to explore the possibility of building a brain-computer interface (BCI) to enable humans to interact with their surroundings through the detection, recognition and interpretation of electroencephalographic (EEG) activity [7]. This is particularly interesting for people suffering from severe neurological or neuromuscular impairments who are intrinsically restricted in conventional augmentative communication channels.

The fundamental aim of EEG-based BCI is to turn mental activity into command outputs for a computer to carry out the user's intent. Popular approaches in achieving this aim are the use of classification algorithms (e.g. neural networks) in comparison to lesser used regression models (e.g. classical statistical analysis) [44]. Given the nature of a BCI as a pattern recognition system, it discriminates sets of brain patterns into different classes according to its features (or targets). These features are derived from inherent signal properties containing discriminative information to reflect similarities from a particular class and distinguish it from other classes. In point of fact, the overall performance rate of a BCI depends on the effective combination of both, feature extraction and classification methods.

2.4.1 Electrophysiological sources of control

Current BCIs come in a variety of different design possibilities owing to their respective purpose of use. Moreover, in order to interpret users' intent, BCIs need to obtain control signals i.e. patterns of brain activity that can be used for communication and control [3]. Over the course of research, a number of physiological phenomena of brain signals have been decoded enabling the BCI to interpret user intentions, some of which are listed along with their main features in Table 2.1. A detailed discussion of these electrophysiological sources of control has been presented in [7].

Signal	Physiological phenomena	Number of choices	Training	Information transfer rate
Visual evoked potentials (VEP)	Brain Signal modulations in the visual cortex	High	No	60-100 bits/min
Slow cortical potentials (SCP)	Slow voltages shift in the brain signals	Low	Yes	5-12 bits/min
P300 evoked potentials	Positive peaks due to infrequent stimulus	High	Yes	10-60 bits/min
Sensorimotor rhythms (SMR)	Modulations in sensorimotor rhythms synchronized to motor activities	Low	Yes	3-35 bits/min

Table 2.1: Summary of control signals (adapted from [7])

In brief, distinctive EEG patterns, produced by different types on mental activity are classified by the BCI and used as control input in order to gain control over the BCI. These types of mental activities together with the corresponding EEG pattern produced are tagged as electrophysiological sources of control are distinguished by the regions of activity. Examples of control input signals for BCIs are shown in Figure 2.8.

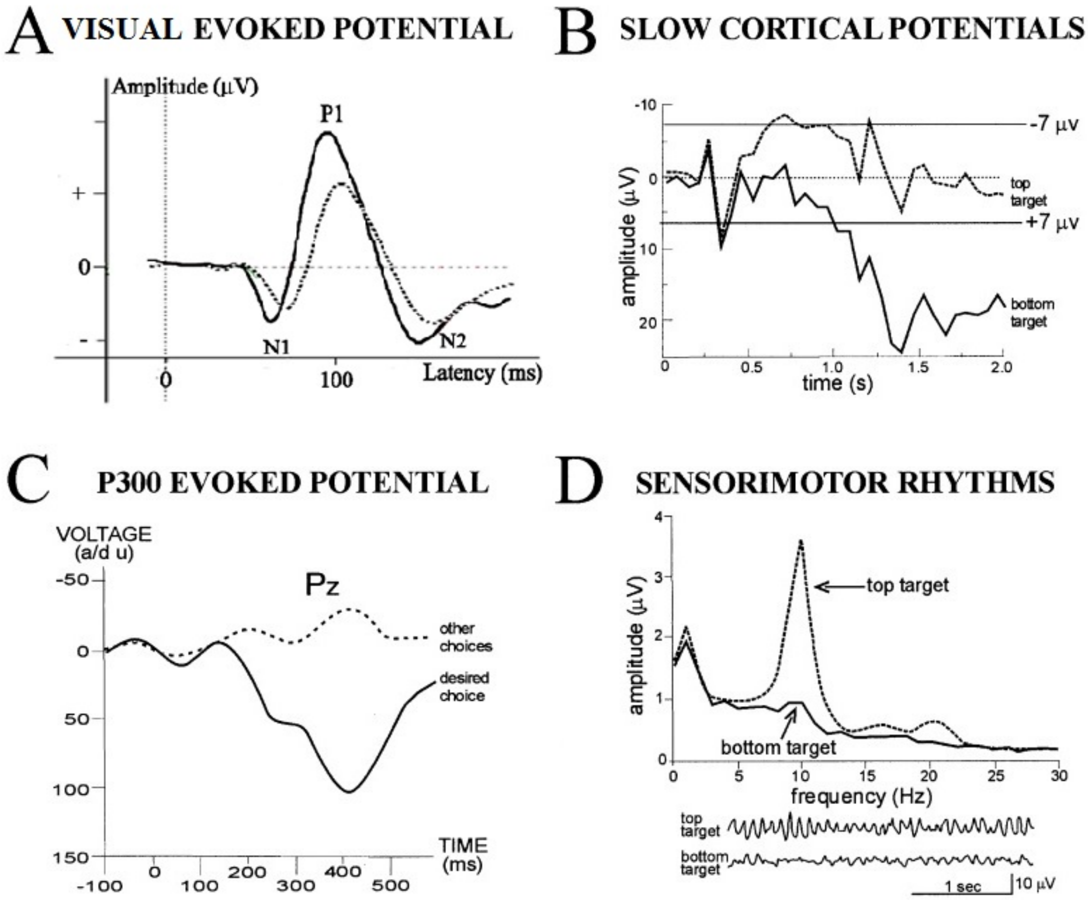


Figure 2.8: Present-day non-invasive human BCI systems. (Adapted from [3]). (A) Example of visual evoked potentials (VEPs) with positive and negative peaks of varying latency and amplitude. (B) Slow Cortical Potential to move cursor toward a target at the bottom (more positive SCP) or top (more negative SCP). (C) Example of an averaged P300 response for a presented matrix of possible choices for the user on a screen. Only the desired choice by the user evokes a large P300 potential. (D) Sensorimotor rhythm BCI recorded over sensorimotor cortex. Uses μ or β rhythms to move a cursor to a target at the top or bottom of the screen.

In brief, present-day BCIs with VEP control signals make use of measurable electrical potential fluctuations that are recorded in an occipital manner above the primary visual cortex. These are caused by a visual stimulation of the eye retina. This stimulation either occurs either through light flashes or a so-called checkerboard pattern with contrast reversal. In this way, the BCI does not require any training since VEPs rely on inherent brain patterns created independently from the user's intention. Information transfer rates, indicating the amount of information communicated per unit of time, show that VEPs can reach as high as 60-100 bits/min which corresponds to roughly 6–12 words a minute when using keyboard interfaces [7].

Slow cortical potentials (SCP), generated in the cortex, are the result of slowly shifting potentials with durations ranging from 0.5–10.0 s, typically measured at the vertex referred to linked mastoids [3]. After filtering, measured activity is presented back to the user on a computer screen with usually two choice boundaries and the final selection is performed with the vertical movement of a cursor corresponding to the currently measured voltage level. Because SCPs can be voluntarily modulated, training is required to achieve higher accuracy than in a one-trial configuration. Current SCP-BCI systems achieve accuracies of 65–90% on a two-choice basis, able to write 0.15–3.0 letters/min. Altough at low rates, theses systems are greatly appreciated by people unable to communicate with conventional technologies [3].

The P300, or oddball paradigm, relies on the generation of peaks in the EEG at about 300 ms, when exposed to infrequent or emotionally significant visual, auditory or somatosensory stimuli in a subset of routine stimuli. These positive voltage peaks are harnessed from the parietal cortex and do not require the need of being actively trained by the user to be elicited. Current P300 systems yield performances of up to 60 bits/min and has considerably grown in the last decade of research [3, 45].

Amongst other activity from sensorimotor cortex, mu and beta rhythms appear as idle oscillations in the mu (7–13 Hz) and beta band (13–30 Hz). Their association with the particular cortical areas that are directly connected to the brain's motor output channels suggests their applicability for EEG-based BCI communication [3]. Movement planning or execution has shown a distinct decrease in mu and beta rhythms, also known as "event-related desynchronization" or ERD, which can be readily read out and also voluntarily modulated by training.

2.4.2 BCI Types

By making use of the aforementioned control signals current BCIs can be largely categorized into three types: (i) directly controlled or indirectly controlled, (ii) synchronous (cue-paced) or asynchronous (self-paced) and (iii) exogenous and endogenous. The different types of BCIs are presented in Table 2.9, by also listing the dedicated control signals as well as attributed advantages and disadvantages. Furthermore, it shall be noted that BCIs can also be distinguished as dependent, i.e. peripheral or motoric actions from the user that are needed to be communicated, or totally independent of muscle activity whatsoever [3]. However, being very similar to the nature of exogenous and endogenous BCIs and exhibiting analogous advantages and drawbacks, they will not be particularly mentioned here.

Directly and indirectly controlled BCIs as "classical" paradigms, bypass the natural outputs of the brain, e.g. peripheral nerves and muscles to directly interface with the mental activity of the brain through EEGs. Mapping controlled mental activity onto an artificial output channel, for example with sensorimotor imagery [46], can be used to obtain multi-valued control signals. However, the power of direct control comes at a price of apparent resource and control conflicts. Being limited in parallel conscious communication with conventional (manual) human-computer interface (HCI) and the BCI, may cause problems for the user. Besides, leaving the option for both, conscious control from the user and interpreted control from the BCI may create a conflict of resources.

In distinction to direct control, indirect BCIs are based on conscious modulation of brain activity through the exposure of external stimuli. The most documented and successfully applied method in this regard are P300 spellers which have been well adapted for EEG-based BCIs [3, 47, 48].

Being a subset of directly and indirectly controlled BCIs, recent research efforts have proposed to further categorize into active, reactive and passive BCIs, allowing for additional application possibilities [49, 50]. Active and reactive BCIs derive their outputs from brain activity either dependently by user control (active) or independently through external stimulation (reactive) and therefore matching the template of directly or indirectly controlled BCIs. Passive BCIs, accounting for other BCI types, create an implicit communication interface, i.e. the user does not try to control his brain activity and, instead, assimilates to an input, which can be used to adapt control or applications towards the user's affective state [51]. Nonetheless, distinct frontiers between the different subcategories may yet be difficult to establish. Prominent applications of implicit and explicit interaction include, amongst others, adaptive automation, affective computing and video games.

Exogenous and endogenous BCIs distinguish one another from the nature of signals used as an input. Whereas exogenous BCI uses external stimuli such as visual or auditory evoked potentials (VEP or AEP, respectively) to induce neural activity, endogenous BCI is based on self-regulation of brain rhythms, i.e. does not require any external stimuli [52]. The advantage of using endogenous over exogenous BCIs results from the restriction of exogenous BCIs to present predefined control choices instead of voluntary cursor control in a two-dimensional space, as in the case of an

BCI		Category	Paradigms	Advantages	Disadvantages
Directly	*Active*	Endogenous Asynchro-nous	- Mental tasks - SMR - SCP	- Independent of any stimulation - Can be operated at free will - Useful for users with sensory organs affected - Suitable for cursor control applications - No requirement to wait for external cues - Offers a more natural mode of interaction	- Very time-consuming training (months or weeks) - Not all users are able to obtain control - Multichannel EEG recordings required for good performance - Lower bit rate (20–30 bits/min) - Much more complicated design - More difficult evaluation
Indirectly	*Reactive*	Exogneous Synchronous	- P300 - SSVEP	- Minimal training - High bit rate (60 bits/min) - The user can avoid generating artifacts since they can perform blinks and other eye movements when brain signals are not analysed - Only one EEG channel required	- Permanent attention to external stimuli - May cause tiredness in some user - Does not offer a more natural mode of interaction
Other	*Passive*	Exogenous Synchronous Other configurations possible	- Emotional states	- Direct communication with technical system - Offers the most natural mode of interaction - Can improve performance of other BCI types	- One-trial emotion recognition, requires high accuracy rate - Highly subjective towards: user characteristics environmental influences

Figure 2.9: Main differences between directly and indirect BCI approaches.

endogenous BCI. Relying on internal brain signal regulation also benefits to applications for users with advanced stages of ALS who show sensory impairments.

Synchronous and asynchronous BCI approaches rely on different data processing modalities as the basis of operation. Synchronous interfaces allow user interaction only in fixed time windows, specified by the BCI (system initiation). Most BCI systems use evoked responses with determined stimulus onset and duration time as a trigger for initiation, therefore making exogenous control interfaces a suitable candidate for synchronous configurations. However, synchronous paradigms also allow even endogenous inputs to be used when precise correlation is not needed [53]. Another advantage of synchronous interfaces is that they simplify the design and evaluation of the signal by simply disregarding any brain activity outside the set time window and mental activity is known in advance as associated with specific cues [54]. Asynchronous interfaces do not make use of time windows, hence the user performs a mental task to trigger the interaction (user-initiation). This allows for self-paced interaction and thus offering a more natural mode of communication in comparison to its synchronous counterpart. Nonetheless, because of the continuous analysis of brain signals, endogenous inputs require high recognition rates for mental tasks to be performed to avoid "false positive" errors. For general-purpose-problems, asynchronous interfaces show promising results, but for interactions involving discrete selections in a timed window, synchronous paradigms are best suited [53].

2.5 BCI evaluation

Evolving from a growing interest in BCI research, as seen through the emerging number of new articles, events and research groups, there is an increased pressure to report improved performance as recent articles openly mentioned [55, 56, 57]. However, different groups use different methods for reporting performance, and it is essential that (1) the evaluation procedure is valid from a statistical and machine learning point of view, and (2) this procedure is described and defined in sufficient detail.

For the performance evaluation of a BCI, a number of measures are commonly used. To measure performance, a number of metrics need to be defined upon which performance is measured. On a basic level, these include the number of correct classifications and the number of mistakes made by the classifier. Other metrics in reporting BCI results include classification accuracy, Cohen's kappa k, sensitivity and specificity, positive and negative predictive value, the F-measure and the r2 correlation coefficient [58].

2.5.1 Evaluation Criteria

Once potentially classifiers have been constructed and implemented, several performance measures can be studied in order to find the most suitable classifier for a particular task. Amongst a variety of measured, knowledge of the accuracy for a given system is of paramount importance in both the application of the classifier and also in comparison with others [59]. Next to domain-dependent quality indicators, the following evaluation criteria are the most commonly used:

Speed and *robustness* of classifiers refer to the computational load posed in generating and using the classifier model as well as the ability to make correct predictions given noisy data, therefore making them two very useful indicators.

Moreover, some classifiers might be well able to perform on a limited data set with limited or few amounts of features to be distinguished but fail to perform well on large data sets. Thus, the *scalability* of a system to perform efficiently given large amount of data can also be investigated. Other practical assessments include the *interpretability* and *simplicity* of the model used and thus increasing the level of understanding and proof rule compactness [60].

2.5.2 Predictive Accuracy and Error Rate

The predictive (classification) accuracy refers to the probability of performing a correct classification. It can be estimated from dividing the number of correct classifications by the total number of trials, i.e.

$$p = \frac{\sum C_{i,i}}{N}, \tag{2.1}$$

where $C_{i,i}$ is the i^th diagonal element of a confusion matrix which contains the information about the actual and predicted classifications done by the classification system. N is the total number of trials and $e = 1 - p$ is the probability of making an incorrect classification, referred to as error rate or misclassification rate. It is important to note that accuracy and error rate do not take class balance into account, i.e. if one class occurs more frequently than another, the accuracy may be high even for classifiers that cannot distinguish between classes [43].

To provide a quantitative performance representation for classifier behaviour in class recognition, a semi-global performance matrix, known as the Confusion Matrix, can be used. Introduced by Kohavi and Provost, the matrix shows predicted versus actual classifications of different label values [61]. This allows for an evaluation of which classes are being correctly and incorrectly classified. For the context of this study, a general multiclass confusion matrix can be denoted as in Equation 2.2:

$$M = \begin{bmatrix} RR_{1,1} & RR_{1,2} & ... & RR_{1,N} \\ \vdots & \vdots & \vdots & \vdots \\ RR_{2,1} & RR_{2,2} & ... & RR_{2,N} \\ \vdots & \vdots & \vdots & \vdots \\ RR_{N,1} & RR_{N,1} & ... & RR_{N,N} \end{bmatrix}, \tag{2.2}$$

where $RR_{i,j}$ corresponds to the total number of entities in class C_i which have been classified in class C_j. Main diagonal elements (i.e. $RR_{1,1}$, $RR_{2,2}$, ..., $RR_{N,N}$) show the total number of correctly identified samples in class C_i. Using this, the global performance for a particular classifier A can be computed, as defined in 2.3:

$$RR^A = \frac{1}{N} \sum_{i,j=1}^{N} RR_{i,j} \tag{2.3}$$

Although it is convenient to use a confusion matrix containing all information on the outcome of a classification procedure, it is usually less practical to compare multiple confusion matrices. As a result, a lot of studies use scalar performance measures, which can be quickly achieved from the confusion matrix. Amongst others, the most frequently used metrics in BCI research include aforementioned classification accuracy, Cohen's kappa k, sensitivity and specificity, the F-measure and the correlation coefficient r^2 [43].

2.5.3 Cohen's kappa

Cohen's kappa k refers to a statistical measure for the agreement of categorical items. It is used to measure the degree of agreement between true class labels and classifier outputs and it is scaled between 0 (pure chance agreement) and 1 (perfect agreement). The formula for kappa coefficient is:

$$k = \frac{p - p_0}{1 - p_0}, \tag{2.4}$$

where p_0 is the level of chance and denotes the accuracy under the assumption that all agreement occurred by chance. Further, p_0 can be estimated from the confusion matrix by

$$p_0 = \frac{\sum C_{i,:} C_{:,i}}{N^2}, \tag{2.5}$$

where $C_{i,:} C_{:,i}$ are the $i^t h$ row and column of the confusion matrix, and N is the total number of trials. As a rule of thumb values of Kappa from 0.40 to 0.59 are considered moderate, 0.60 to 0.79 substantial, and 0.80 outstanding [62].

The Kappa statistic has demonstrated usefulness as a metric when dealing with imbalanced distribution of classes, i.e. skewing of the class distribution. This was also demonstrated by [63], also using data from affective sources which further supports the decision to include it in this study. However, apart from the aforementioned sources, very little data is found in literature reporting this classification agreement measure upon which comparisons can be performed. It has therefor been concluded that a moderate agreement of classification will suffice as a base to be further developed upon in future works.

2.5.4 Sensitivity and Specificity

Metrics Sensitivity and Specificity in BCI research are used to measure in-sample proportions of correctly classified positive targets (true positives) and the proportion of correctly rejecting a negative result (true negatives). Thus, the sensitivity of a classifier can be defined as

$$Se = \frac{TP}{(TP + FN)}, \tag{2.6}$$

where TP refers to a *true positive* and FN to a *false negative* event. Consequently, specificity can then be defined as

$$Sc = \frac{TN}{(TN + FP)}, \tag{2.7}$$

with TN being a *true negative* result and FP denoting a *false positive* event. These values can be easily retrieved from a confusion matrix, as well as the earlier introduced metrics, indicating its usefulness in evaluating classifier performances, by also accounting for random chance effects [43].

2.5.5 Resampling

In machine learning, there are many widely used resampling methods to test the reliability of the error estimates. The methods that may be of interest for the project are *k-fold* and *leave-one-out cross-validation* (LOC) because they are widely used and less computer intensive because of their simplicity to apply.

In k-fold crossvalidation the dataset is simply split into K subsets. All but one subset (the so called "hold out" set, or subset l) will be used to train the classifier function. Afterwards, the trained function is then used to the classify trials in the i^{th} hold out set and this operation is repeated K times, with each set being held out once. The second method, leave-out-one cross validation, is almost identical to the first with the exception that each hold out set comprises of only 1 trial. As a result, every trial is omitted from the training set exactly once [43].

Chapter 3

Situational & Theoretical Analysis

In this chapter, we will look at essential parts and features that will make up an EEG-based BCI including: signal acquisition, signal-processing or enhancement, feature extraction and translation algorithms, also referred to as classifiers. A conceptual schematic is shown in Figure 3.1.

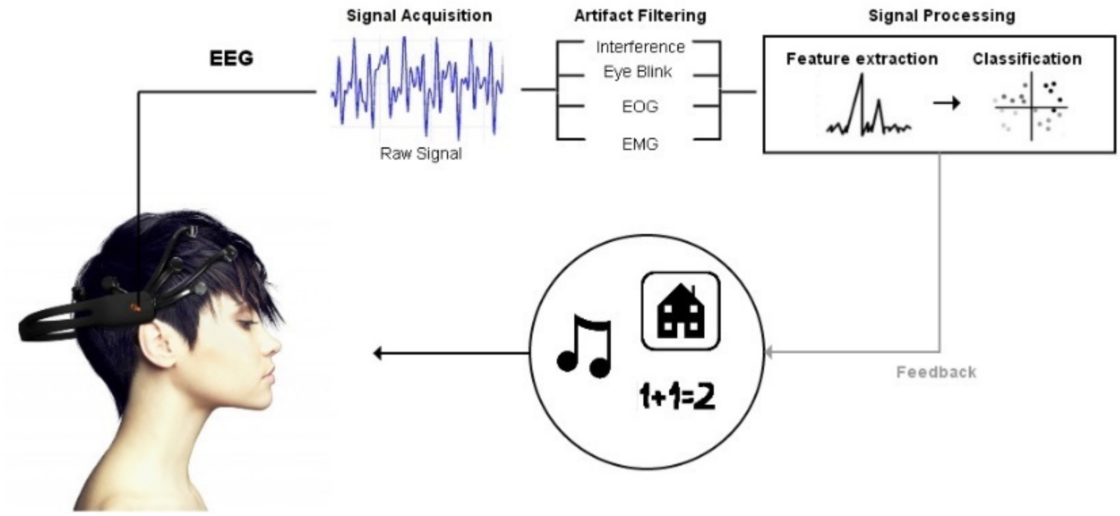


Figure 3.1: Emotion recognition estimation process.

There is a great extent of literature devoted to the topic of signal processing for bio-electric signals, especially brain signals, which is why only general concepts will be discussed and relevant information for the project. In event processing and analysis, we commonly distinguish between real-time online and offline data processing. Online processing usually refers to an algorithm that processes data (including events) element-by-element without having the complete data set from the start. Since time is mostly a critical factor, online algorithms mostly comprise of simple equations in order to process the events fast. Offline algorithms, in contrast, have given the entire problem set from the beginning and therefore allow for more computationally demanding processes to be performed, as processing time may not play a critical role. Another advantages evolves from the fact that offline data sets can be stored and reused at a later stage of development or tested against new methods. In this way, it is possible to track the evolution of algorithm performances and/or computational demands.

3.1 Emotion elicitation

3.1.1 Influence of Modality

There are two approaches on how emotions can be elicited, i.e. internally (by the user) or externally (as a response towards stimuli). In the former case, the test subject is asked to imagine a particular kind of emotion which he or she has to recall from memory (e.g. by thinking of an experience in the past). The latter approach tries to evoke emotions in the subject by using affective images, sounds, semantic cues, or a combination of modalities. Whether to use the former or latter method depends on the hypothesis of research and type of experiment planned. In comparing both approaches, the former one poses many additional challenges since memories cannot be separated to appear purely visual or auditory but occur as a complex mixture being processed in the human brain in different regions. It is seems therefore natural to present preselected, context laden images instead of relying on subjective memory thought alone.

Affective Pictures

Amongst recent research, several works have been investigating in affective reactivity through ERPs towards auditory and visual stimuli. Over the course of time some repositories with emotion-annotated stimuli such as the International Affective Picture System (IAPS) have been created and also validated for different cultures, Brazil amongst others [6, 4]. Affective pictures from this database are ranked according to their "valence" dimension, i.e. attraction-aversion behavior and their "arousal" dimension, representing the intensity or level of activation. Emotional states may therefore represented in a two-dimensional affective space, with the level of arousal on the x-axis and valence on the y-axis, respectively, as shown in Figure 3.2. Using this affective space dimension, one is able to select and distinguish between emotional states depending on the purpose and application of the system. Given the complexity of the task to evoke and process emotions in general and the expectation to face additional challenges with children, it is suggested that a categorization in three classes will suffice to draw important conclusions from for the development toward higher class recognition. As indicated in Figure 3.3, the three emotional categories defined in this project can be projected on the valence/arousal space, labeled "PE" for positive/excited, "NE" for negative/excited and the whole space in the low (≤ 5) arousal space, here simply referred to as "C" (calm).

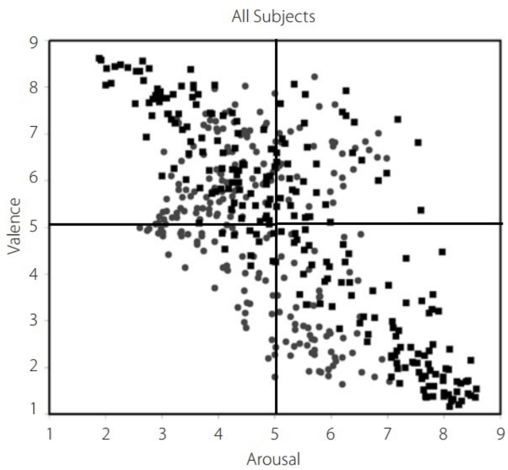


Figure 3.2: Dimensional representation of emotional states in a Brazilian sample consisting of 448 university students (from [4]).

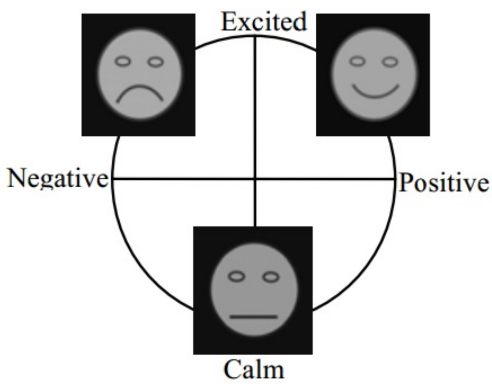


Figure 3.3: Emotional classification according to arousal and valence.

Obviously, these three emotional states do not make up for all areas in the two-dimensional valence-arousal space. Nevertheless, as explained by [64], only few emotions may evoke strong calm/negative or calm/positive responses and therefore only few parts of this space are really relevant. Furthermore, several works using this particular division of affective space have shown the ability to be applied in emotion recognition tasks [65, 66, 20].

Significant differences in emotional reactions towards affective patterns have not been found between healthy children, adolescents and adults which allows the use of similar picture material to be used for multiple age groups [67, 68].

3.1.2 Arousal: Beta/Alpha Ratio

Since the pictures used are provided in a measure of arousal and valence, it is necessary to define the terms in relation to the electrical activity as well as frequency bands they are associated with in the different regions of the brain. In literature, we find as a measure of arousal, the ratio of beta and alpha brainwaves as recorded by the EEG. In general, the alpha rhythm is the prominent EEG wave pattern of an adult who is awake but relaxed with closed eyes and exhibits greatest measurable amplitudes in the occipital and parietal regions of the cerebral cortex but also have characteristic rhythms in all other regions [69].

Beta rhythms occur in individuals who are are alert and attentive to external stimuli or exert specific mental effort, or paradoxically, beta rhythms also occur during deep sleep, REM (Rapid Eye Movement) sleep when the eyes switch back and forth [41]. This inverse relationship has been suggested by recent researches that investigated in electrical differences toward resting state potentials to stimulus conditions from the two hemispheres and other physiological activity associated to the event of stimulation [70].

3.1.3 Valence: Asymmetric Hemispherical Activation

Psychophysiological as well as scientific for the past decades have examined relationships between emotion and asymmetries in EEG over the frontal cortex and the cortical hemispheres [71]. It has been found that induced negative emotion produces a shift toward left hemisphere dominance in perceptual tasks whereas positive emotion tends to activate this part more than the right hemisphere. High alpha activity (8–12 Hz in the EEG frequency band) is associated with low brain activity and conversely, low alpha activity presents high brain activity paired with a reduction of beta wave [36]. Hence, it is hypothesized that hemispherical inactivation has direct implications with a negative shift of mood and vice versa, right frontal inactivation is linked towards positive response. In terms of brain signals, a cortical inactivation is associated with an increase in alpha activity and a relative decrease in beta waves. The reverse applies when an activation of hemispheres occurs. This hypothesis has been supported by many researches, some of which are listed in [72].

Studies related to the asymmetric hemispheric activation with autistic children and their TD counterpart have been conducted as early as 1982 by Warrenburg and Fuller to measure alpha activity in language and visou-spatial tasks from both parietal lobes [73]. Findings in spatial-tasks did not show significant differences, however, they exhibited greater right-hemisphere dominance during language tasks than normal subjects. Performed motor imagery tasks also presented asymmetry between test groups as autistic subjects showed greater right-hemisphere activation during motor imagination whereas normal subjects displayed the opposite. To this extend, researchers suggest that a reduction in cerebral asymmetry can be associated with a general lag or retardation and not just a selective left-hemisphere dysfunction [73].

Regarding the scalp electrode positions for measuring alpha activity levels, prefrontal lobe electrode positions (F3/F4 and Fpz) are the preferred choice due to the highest detection of EEG power spectral activities in the alpha band when subjects are exposed to emotional stimuli [36, 74, 75]. In comparison to autistic individuals, middle-range (8–10 Hz) alpha frequencies showed reduced power across various brain regions, including the frontal, occipital, parietal, and temporal cortex [76] but greater relative power in 3–7 Hz and 13–17 Hz during resting state [77].

3.2 EEG Signal Preprocessing

As shown in the picture earlier (Figure 3.1), raw EEG data needs preprocessing, or filtering in order to remove the unwanted DC components and drifts that result from the impact of environmental factors such as the presence of electromagnetic fields , amongst others. For this reason, a number of filters can be applied to reject signal bands and focus on the range of signals desired. A low pass filter can be applied to remove high frequency components, as EEG signals are rarely studied with signals above 90Hz which corresponds to the Gamma range [41]. There are many preprocessing techniques such as the Common Average Reference (CAR), Canonic Signed Digit (CSD), Independent Component Analysis (ICA), Common Spatial Patterns (CSP) to name a couple, each of which has its distinctive advantages and drawbacks.

3.2.1 Artifact Reduction

Regarding the non-linear, noisy nature of EEG signals, they pose additional challenges to be dealt with to increase the performance of BCIs. Signal contamination, also referred to as artifacts, can be of various origin and can be broadly classified into two classes: non-physiological (or technical) artifacts and those of physiological nature. Artifacts of non-physiological nature include power-line interference, changes in electrode impedance, etc., whereas the physiological artifacts are usually associated with ocular, muscular and heart activity, hence referred to as electrooculography (EOG), electromyography (EMG) and electrocardiography (ECG) artifacts respectively [78]. EOG artifacts are caused by eye movements or blinking, each of which produces distinct amplitude patterns over brain signals. Electrocardiography artifacts result from rhythmic heart muscle contractions and introduce cyclic signal patterns in the EEG. Finally, EMG signal disturbances occur with muscular activity and can have large impacts on the EEG signal quality. Research has shown that at particular locations of the scalp, i.e. frontal, temporal and occipital regions, EEG signals can even be surpassed by EOG and/or EMG activity [79, 78].

Handling noise sources can be approached in several ways and the choice of method will often depend on the nature of the artifact aimed to be reduced. Among simple methods exist artifact avoidance and artifact rejection which refer to ways and means to obtain cleaner signals by, for instance, asking the subject not to move or blink throughout the experiments, or having an expert system looking at parts of the signal to discard [80]. More effective approaches are those of automated artifact detection algorithms to deal with inherent epoch contamination, given that artifact amplitudes are high enough. Common stochastic methods for removing artifacts are Blind Source Separation (BSS), Principal or Independent Component analysis (PCA, ICA), Canonical Correlation Analysis (CCA) as well as linear filtering and regression models [3, 81]. Besides, deterministic methods such as Empirical Mode Decomposition (EMD) and Wavelet Transform (WT) have been successfully utilized for EMG and partially EOG rejection [78, 82, 83]. Results show that the performance of artifact correction methods strongly depends on the level of contamination and of the fundamental EEG signal source configurations and therefore need to be chosen carefully. In comparison to rejection methods, artifact removal intends to remedy contaminated signals while keeping the underlying neurological phenomenon intact.

Next to the large variety of sophisticated artifact removal techniques mentioned, a number of less complex and computationally more efficient methods exist to be readily employed for basic artifact reduction.

3.3 EEG Signal Analysis

The methods for EEG analysis can be distinguished as *Parametric* and *Non-parametric*. The latter approach makes use of the assumption that during short time periods, the EEG signal can be regarded as stationary. Given this condition ,rhythmic as well as spectral properties of the signal can be readily studied. Popular methods for spectral characteristics estimation often include the Fourier Transform and other fourier-related transforms, as well as interval analysis. However, the limitations lie in the poor time-frequency resolution and technical problems with Fourier transforms, whereas the analytical characterization suffers from the presence of noise and artifacts [70]. Moreover, disadvantages associated to the spectral analysis result from the requirement of long observation times (up to 30 seconds and more) to achieve good spectral estimates from the underlying signal. This requirement often conflicts when trying to analyze rhythmic changes over time and other spectral properties, hence the responsiveness of the system. Parametric methods, on the other hand, make use of stochastic models involving specific parameters to represent EEG signals. With taking the non-stationarity into account, various linear and nonlinear methods have been developed although linear approaches are often preferred due to reasons of simplicity and lesser statistical uncertainty resulting from estimations based on spectral properties such as the power spectrum [70].

In general, when dealing with the design of a EEG-based BCI system, a number of critical feature properties must be considered [44]:

- **Outliers and noise:** EEG data is inherently noisy and can contain many outliers when processed, associated to the poor signal-to-noise ratio or due to various non-cerebral signals superimposing the EEG. Non-cortical signal contamination may come from measurement inaccuracies, muscle or eye blink artifacts, and others.
- **Non-stationarity:** Inherent sources of the EEG signal dynamics stem from metastable states in the neural assemblies during brain activity that rapidly change in time [84]. These non-stationaries may be of valuable information content but make it specially difficult spectral analysis or linear methods to detect.
- **High dimensionality:** Due to the complexity of the signals, EEG features may often be represented in higher dimensions, as they are extracted from different channels at different time instances. Higher dimensions also impose limitations towards linear methods that try to generalize over the problem at hand. Dimensionality reduction of the feature vector may therefore be considered.
- **Time information:** As emotions and brain activity patterns in general are related to specific time variations of the EEG, it is appropriate to include features containing this kind of information for the analysis of time series.
- **Small training sets:** Since acquiring large trial sets is usually a very extensive and time consuming endeavor for both, the researcher and test subject, it is suggested to work with small training sets. Besides, computational load for data processing is reduced which may be of lesser importance for offline but crucial for online applications.

3.3.1 Feature Extraction

Due to the vast complexity of the brain, relevant patterns of interest are more and more studied by the aid of computational methods for effective quantitative interpretation of EEG data that otherwise would have been performed visually. Within the research many methods to extract features from EEG data sets have been invented, which can be largely categorized into four groups: (i) dimension reduction, (ii), spatial, (iii) temporal and (iv) spectral domain. Because brain signals are often measured through multiple channels, not all collected information from selected channels may be relevant for the extraction of features. Dimension reduction techniques such as principal component analysis (PCA) or independent component analysis (ICA) may become applicable to sort out notoriously redundant and extract relevant features by also reducing the computational load. Since the original EEG signal is a time domain signal, the analysis of time characteristics can be used to analyze components that can be directly seen in the EEG recording such as event-related potentials (ERPs) reflecting emotional states [85]. In emotion recognition, many researches have presented the usefulness of statistical time domain properties as simple and effective statistical descriptors such as means, differences and standard deviations over raw signals or entropy [86, 87, 66].

Frequency domain based approaches rely on time frequency transformations. The extracted information are now based on events or patterns within the frequency domain to be analyzed. A popular example allowing for a quantitative analysis of the spectral decomposition in EEG signals is Power Spectral Density (PSD) via Fourier Transformation. Although generally used on under the assumption of stationarity, this method has shown promissory results for determining emotions from brain signals [88, 89]. Other methods, such as the Short-Time Fourier Transform (STFT), make a priori assumptions on the signal characteristics to be analyzed. This method, when sufficient information about the signal is present, may achieve very good results but is largely restricted in areas where little or no prior assumptions can be made. Thus, it appears impractical to be used for recognizing emotions where many uncertainties about the specific signal content are present. Also, the length of windows as a division signals into small segments to estimate their individual parameters often affects the accuracy of estimated features, thus aggravating classification results [7].

Next to purely time and frequency domain dependent features, methods have been developed to synergize spectral and temporal information. A powerful, nonparametric method introduced in late 1980's is the Wavelet Transform (WT). Comparable to a mathematical microscope, this tool performs a multi-resolution analysis so that the signal can be analyzed in different time scales. In EEG studies, this method has been successfully used to investigate oscillations of very small scale and neural rhythms [90]. Moreover, the joint time-frequency resolution obtained by WTs can remedy some of the drawbacks associated with EEG signal decomposition as in FFT and STFT through its variable window size and time-filtering properties [70]. Though imposing additional computational and memory requirement for finding optimal wavelet coefficients, it makes an excellent method for the capture of even transient features from non-stationary signals which is the case in EEGs, more importantly, emotions [90]. Wavelets have therefore been a frequent candidate in emotion detection on EEG's with good results in combination with various classification algorithms [91, 19, 18], and partially in Section B.4.

Drawing from the works presented above, we aim to investigate broadly the usefulness of features for emotion detection in the different signal domains, i.e. time domain, frequency domain and a combination of both. Hence, *Statistical Features of Time Series* (SFT), *Power Spectral Density* (PSD) and *Wavelet Power Spectrum* (WPS) will be part of this investigation. Nevertheless, for completeness of this section and to give an overview of the most frequently used feature extraction algorithms for EEG-BCIs, a table is presented in Appendix A. Also, for the brevity of this chapter, mathematical details of all discussed methods will not be included in this section but necessary information on the principles is given in Appendix A.

Feature Selection

One of the key factors for the classification performance of acquired data subsets is feature selection. In this process, irrelevant and redundant features are removed by retaining a crucial set of features sufficient enough to make a good classification possible. Besides, it inherently reduces the data dimensionality which has the positive effect of accelerating the classification process as well as to produce a more compact classification rule [92]. With regard to the here proposed system, however, it was decided against sophisticated feature selection methods since the sample and feature (sub-)sets may already be small and because it adds an additional layer of complexity. In recognizing the vast amount of variables and challenges present, comparing different feature selection methods may be considered for future work on this matter.

3.3.2 Classification

For online applications, a general objective is to keep computational loads minimal by classifying more emotions with fewer electrode channels used. With regard to emotion recognition algorithms, yet most systems rely on offline simulations, some of which are summarized in Appendix B.4, comparing feature extraction types and classification methods by the emotion types recognized and achieved accuracy. To date, there are many developed approaches towards emotion classification, however, the most used algorithms can be divided into four categories: (i) linear and (ii) nonlinear classifiers, (iii) neural networks, (iv) combinations of classifiers. With regard to the scope of this thesis, individual descriptions of every classification method and analysis will not be provided here.

In general, linear, as compared to nonlinear classifiers usually exhibit superior robustness when handling emotion data sets due to the reduced number of parameters to specify [7]. This reduces the chance of over-fitting the data especially when the knowledge about the data is limited and tune parameters cannot be well estimated. Noisy data may decrease the signal quality significantly for which even linear systems can fail. Regularization, at this point, may help to bound the impacts of noise and high variability, as well as reducing the classifier complexity [7]. However, facing large data sets where little is known about its properties, nonlinear methods are better suited finding underlying data structure. Popular linear classification methods, amongst others, include (Bayesian) Linear Discriminant Analysis ([B]LDA), Fisher Discriminant Analysis (FDA) and Support Vector Machines (SVMs) [93, 94]. An advantage of LDA its performance to extremely fast evaluations of unknown inputs performed by the calculations of distances between a new sample and the mean of training data samples in each class. Moreover, the classifier is said to be stable, i.e. small variations in the training set may not affect the performance considerably which is preferred when the equality between features cannot be guaranteed. As compared to Bayesian methods it also produces higher prediction accuracies, in general, but comes at a price of potentially performing low on complex, nonlinear data [44].

In learning nonlinear decision boundaries between classes, various methods have been developed and applied for various types of BCIs. Frequently used nonlinear classifiers in EEG-BCI are: k-Nearest Neighbours (k-NN), learning vector quantisation (LVQ), kernel SVMs, quadratic discriminant analysis (QDA) and Mahalanobis distance (MD). K-Nearest Neighbors, according to an extensive survey carried out by Rani et al. [95], is one of the most widely used techniques in affective studies to classify EEG data containing particular emotional affects/states. Moreover, another research has verified KNN's effectiveness in the classification of EEG data by claiming a good ability of the classifier to deal with difficult probability densities based on its discriminant analysis [96]. It is therefore a suitable candidate for the emotion recognition task presented in this project.

Other powerful tools for finding nonlinear decision boundaries of classes are so called artificial neural networks, (ANN) which essentially mimic the human brain structure of interconnected neural nets to process information. The most common application of neural networks is supervised classification with the MultiLayer Perceptron (MLP) being the most popular architecture [44]. Providing a number of suitable characteristics such as small training set requirements, fast operation, ease of implementation and the ability to learn and generalize over any continuous function given a sufficient number of neurons, makes it a very attractive algorithm for various tasks. However, since MLP's are universal approximators, they are usually very prone to overfitting the training set which makes them fail to generalize on unknown data. More often than not, this is the case with noisy and non-stationary input features, as it is the case with EEG data . Defining the optimal architecture and tuning parameters for the MLP to learn appropriately often requires a substantial amount knowledge for the various coefficients and inner MLP options to be determined.

Despite the popularity of MLP, several other neural network architectures have been developed based on various approaches, e.g. LVQ, Fuzzy ARTMAP, Radial Basis Function (RBF) and Multiple Back-Propagation (MBP) methods [44, 97]. Information about all of the above mentioned classification methods in the context of emotion recognition be retrieved from works summarized in Appendix B, Section B.4. In the discussion of emotion recognition by indicating the numerous works listed, every classification algorithm comes with a specific set of advantages and disadvantages related to the context in which they are placed to perform and with various signal processing methods they have been combined with.

Although most research efforts have investigated in single unit classifiers, recent trends show increased interest in assembling different classifiers in various ways. Novel classifier combination strategies propose cascading translation algorithms to reduce error margins, class voting, or meta-classification, which are referred to as Boosting, Voting and Stacking, respectively [44].

Drawn from the various researches reviewed above and as presented in Appendix B.4, the final selection of classifiers for this project has been made upon the following:

- Support Vector Machines (SVM)
- Multilayer Perceptron (MLP)
- k-Nearest Neighbors (KNN)
- Learning Vector Quantization (LVQ)
- and Linear Discriminant Analysis.

All of these classification methods have been used in emotion recognition for two or more classes and also in the context of affective pictures.

3.4 Hypothesis

To date, high classification accuracy BCI systems close to absolute (100%) do exist for 2–6 emotions (as shown in Appendix B.4, however, tested with a specific subject, channel or data(sub-)set in both emotion recognition tasks and other [93, 98, 99]. The success of these systems is mostly attributed to a high number of electrodes used, advanced filtering techniques as well as tailored signal processing steps (i.e. handpicking from mentioned feature extraction and classification methods). Generally speaking, per-subject differences in classification accuracy are high and the BCI is therefore dependent on how well the subject is utilizing the system.

With regard to the specific population of children, however, not many studies have been dealing with the development of emotion recognition systems through affective pictures but rather investigated in the various verbal, physiological and behavioral differences between adults and children [67, 68]. Others have used visual stimuli to elicit event-related potentials, as in the case of this research, but for the purpose of comparing latencies and amplitudes of the induced brain waves and not emotion recognition through pattern learning [100, 10]. Similar studies have been performed for children with ASD. Prominent approaches towards emotion recognition are the use of facial or vocal stimuli for subjects with ASD and looking at event-related potentials or P300 phenomena in order to compare latencies, amplitudes or abnormalities [101, 102, 103].

Nonetheless, given the maturity of methods used in modern BCI systems for emotion recognition as outlined in Section 3.3.1 and 3.3.2, it is hypothesized that an emotion recognition platform can be developed, verified under controlled, laboratory conditions to be eventually tested with children. Given the lack of studies that have been conducted on children affect recognition, this work proposes the selection and comparison of popular signal processing and translation algorithms to be studied for the use with young individuals. Approaching this idea, the previous analysis of feature extraction methods and the state-of-the-art literature review suggest the use of multiple methods to be evaluated against each other. This idea is followed by the inclusion of three different feature extraction and a total number of five classifiers.

In order to find a numerical criterion for the rejection or acceptance the hypothesis, we decided to achieve a moderate classification agreement between the three determined classes "positive/excited" (PE), "negative/excited" (NE) and "Calm" (C). Recalling from Section 2.5.3, this corresponds to a kappa coefficient of $k = 0.4$. Solving the equation 2.4, with a random chance effect of $p_0 = 33.3\%$ for three classes, this yields an accuracy of $p \approx 60\%$.

The outcomes of this investigation will be matched against these two values to indicate whether the hypothesis can be accepted or would require reconsideration based on a rejection event.

Chapter 4

Conceptual Model

4.1 Overview

This chapter entails information about the concept model from which various system and functional requirements are established. It follows the V-model approach for project development by outlining inter-dependencies throughout the development process and introducing loop iterations when system requirements are mismatched. Based on this approach, we aim to identify the most appropriate design of our BCI system to be eventually tested on the intended user group of adults and children. The main steps of the V-model are presented in this chapter for which an illustration and accompanied description can be found in Appendix C.

4.2 Decomposition and Definition

The subsequent sections decompose the project according to the requirements and specifications set by the research team and other stakeholders such as caretakers and parents of the selected user group. Furthermore, this section aims at the agreement on interrelationships, roles and responsibilities for the system and the agreement on key performance measures and how the system will be validated at the end of project development. A short overview of all parties involved including their respective need and responsibility toward the project is provided in Appendix C.1.

4.2.1 System Level Requirements

In specifying *what* the system is supposed to do, the needs of all research team members were fused and translated to the quantifiable measures. This led to set of system level as well as functional and non-functional requirements the developed platform shall be able to exhibit and maintain.

On a system level, the principal requirements were defined as in Section 3.4. Furthermore, in order to guarantee the usability of the developed platform, a number of sub-requirements as in the following list have been summarized:

- Offering a structured approach for analysis by providing reproducible results.
- Produce meaningful output of signal data.
- Offer stable environment.
- Be user friendly.
- Be effective.

In discussing these items, the need for a structured approach for analysis comes with the fact of dealing with a data sets from various test candidates to be processed in multiple steps. Also, taking effectiveness into account, a logical structure and intuitive interface allow for more effectiveness when walking through the steps of analysis and finding potential flaws in the system. Nonetheless, the system will not be designed for anyone as it requires adequate knowledge about EEG data and its analysis methods.

Providing meaningful data output from the EEG signals is crucial for the understanding of affect as a physiological expression of emotion through the use of multi-channel EEG devices. A stable environment is of great importance for the verification of the framework to be tested with multiple subjects, adults as well as children. This requirement, however, cannot be fulfilled when testing outside the laboratory under highly varying environmental conditions.

Functional Requirements

As a functional requirement, the acquisition of signals has to be performed from all channels prior to the pre-processing stage and being stored as a local data file containing all experimental data. In this way, data sets can be reused when system modifications were performed affecting the system performance. Next, the system must perform pre-processing steps, as EEG data is typically polluted by artifacts, noise, electrode drift or popping. Thus, the system must provide means to clear contaminated data either manually, by inspection, or automatically. Revisiting Section 3.2 and 3.2.1, the following steps can be applied:

- Signal Acquisition
- Basic pre-processing
  - Re-reference filter
  - Bandpass filter
- Inspect data, visual inspection
- Segmentize data
- Feature extraction
  - Outlier reduction
- Feature vector concatenation
- Classification

As for data down sampling, this step can be used for faster processing of data and is usually performed with high frequency acquisition tools in which the sample rate does not add to the precision of calculations anymore. Since the EPOC Emotiv headset comes innately with a 128 Hz sampling frequency, further downsampling will not be necessary. Re-referencing, as mentioned in Section 2.3.4, can improve the signal quality and Signal-to-Noise (SNR) and can be performed on various locations with different methods [40, 41]. Amongst those, common average reference (CAR) was proposed due to its suitability as a reference-free method for EEG signals by being computationally light. Furthermore, artifacts that occur in all channels and thus being unlikely of physiological nature can be successfully remedied using this technique [104]. Bandpass filtering allows for filtering specified frequencies or frequency ranges from the data so that the can be focused on the area (or frequencies) of interest.

Although in ideal environments data inspection is superfluous, these conditions are never met and therefore visual inspection of plotted voltages against time can reveal important information. Amongst others, data inspection will mostly be directed towards any unexpected signal occurrences such as glitches, artifacts or other noise sources. Visual inspection will become necessary for the verification of (sub-)systems to work according to the requirements.

Data segmentation, as means to resize the data into smaller pieces becomes necessary when fed to particular analysis methods such as computing the power spectral density of a particular signal band. In here, the FFT, for instance, time domain windows require the selection of the data length in order to be performed for the reduction of leakages, naturally occurring when FFT is applied to non-periodic signals, as in case of EEGs. Since the pattern of the underlying emotional signal is unknown, it is impractical to reinspect the feature set as a result of extraction. Nevertheless, since the classification result depends on the quality of features to discriminate, possible outliers in the feature vector may affect the result. Reducing these is necessary to reveal the data pattern which is most prominent in the data set.

Fusion at the feature level is necessary when combining information content to construct an augmented feature set. For this, the feature need to be appended as arrays to be provided as training data for the classification.

Non-functional Requirements

Non-functional requirements for this project include:

- Robustness & Fault tolerance,
- Portability & Adaptability,
- Modifiability & Extensibility,
- and Usability of the system.

To begin with, the system should avoid invalid user input causing the system to crash or malfunction. To this end, the developed interface has to allow for only valid input options or the choice of selecting predefined outputs (e.g. list boxes or pop-up menus). In case of unavoidable risks, false input has to be properly handled by notifying the user about errors made. Portability & adaptability concern the use of software environments used. In this project, the system is designed on "Matlab" from Mathworks, a platform independent, high-level technical computing language frequently used amongst researchers from various fields. Although listed, this requirement is regarded as less critical. Furthermore, modifiability & extensibility refer to the option of changing the software or interface structure in an attempt to improve the performance, increase functionality or be used for similar experiments. Considering a modular design composed of small, interchangeable building blocks, allows for a quick adaption or extension of the hardware and software components and enhances understanding of the functional components. The usability and ease of use of the system remains necessary when creating an intuitive interface for test candidates as well as for other users that will continue to develop the system or implement it in other experiments, applications and the like.

At last, the development of a test protocol to collect data under identical test conditions and without the presence of bias posed through factors such as time of day or external interference has to be considered. Although important, the effect of "day dependencies" as coined by Picard et al. [105] will not be investigated through the lack of flexibility in acquiring subjects on particular days.

4.2.2 System Design

Based on the system requirements mentioned above, the system design can be created, comprising of a high-level design on the overall framework of the system and more detailed specifications for the hardware and software components to be developed.

On a high-level, emotion recognition algorithms are part of a currently developed mobile robotic system, named MARIA (Mobile Autonomous Robot for Interaction with Autistics) to be used as a potential intervention and research tool for children with autism. Other parts include the autonomous navigation and control of the mobile robot platform (PIONEER 3-AT), the development of a face detection algorithm with commercially available webcams, as well as the creation of child-robot interaction modes and their respective analysis towards success and suitability. A schematic, including a ludic image of the current robot is presented in Figure 4.1.

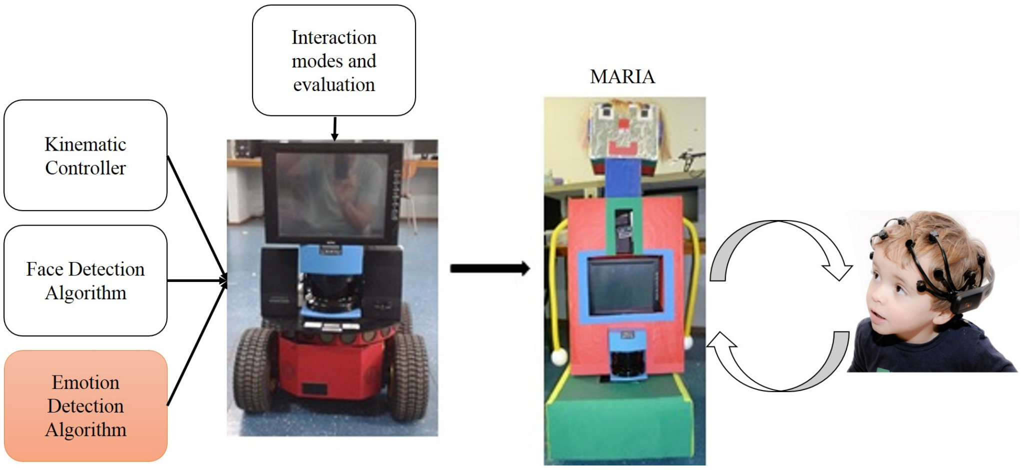


Figure 4.1: High-level system overview MARIA (Mobile Autonomous Robot for Interaction with Autistics)

In concert with all other components, the emotion detection algorithm developed in this work (indicated in red) shall in future be used to detect affective states in a child-robot interaction in order to be able to assess developed interaction modes, and/or stimuli presented to the child. Regarding the proposed system in this work, the overall process of recognizing emotions consists of a number of consecutive steps as displayed in 3.1 and dedicated (sub-)sections. For the execution of tests, however, additional steps need to be included to obtain data for the verification and validation of components and (sub-)systems. Figure 4.2, provides an overview of the overall system architecture, including the emotion recognition concept and some details of tasks performed per building block of acquisition and (pre-)processing. A closer look in testing and verifying all components will be provided in the next section 4.3.

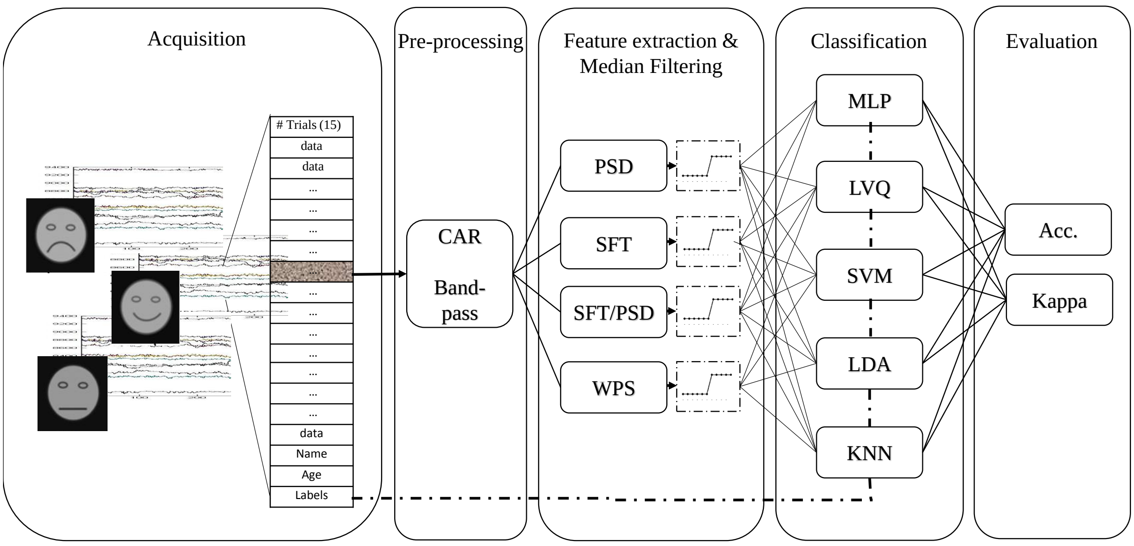


Figure 4.2: Conceptual schematic of emotion recognition system.

4.3 Integration and Test

This section discusses the integration of system and functional components as well as the developmental iterations needed during the testing phase of this project. It includes a short description about the necessary hardware components needed and extends to detail the major software development needed prior to the conduction of experiments. A basic flowchart outlining this process is shown in Figure 4.3.

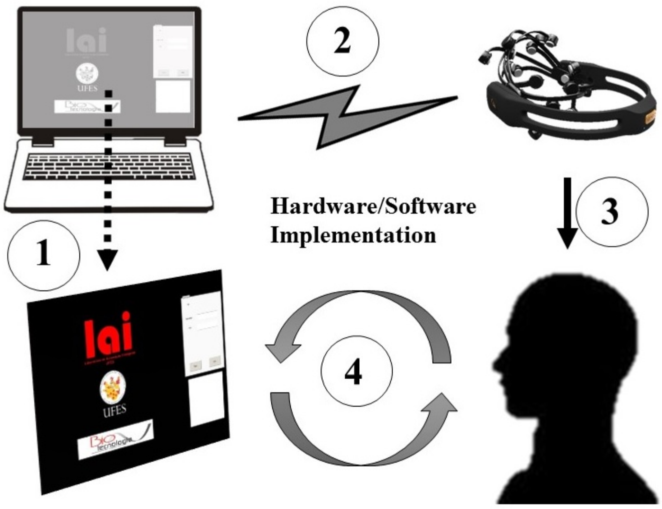


Figure 4.3: Hardware/Software implementation steps.

4.3.1 Implementation and Unit/Device testing

Hardware and Software components

Hardware components to be used for this project mainly comprise of a computer to present the graphical interface running on linux (Ubuntu 12.04.4) with Matlab 8.01 (R2013a) and the EPOC Emotiv headset as well as a USB wireless receiver dongle to receive channel information.

Regarding the software development, a number of steps were executed to arrive at a final interface to interact with the test subject in the experiments. These include the development of an interface using emotionally-annotated pictures in a developed protocol outlined in Section 5.3.2 (1), the establishment of a stable data connection between the computer and the EPOC Emotiv headset (2), as well as the development of an automated signal enhancement and processing routine, as depicted conceptually in Figure 4.2. Challenges in (2) are present when trying to read out the acquired signals from Emotiv associated with every channel as well as indicating the contact quality of every electrode since the data is encrypted and thus not readily available. Also, a method needed to be developed being able to read raw data on demand from Matlab, synchronized to the presentation of emotional images. To solve the former problem, we utilized and modified the only open-source project (emokit) developed to enable gathering raw data from the Emotiv EPOC headset, instead of relying on inbuilt software procedures which have found to slow the data exchange on Windows systems. On-demand acquisition via Matlab was achieved by creating a sniffer protocol to fetch the samples from the Emotiv buffer when needed.

Component Testing

Step (3) and (4) in Figure 4.3 refer to testing of the subsystems, i.e. graphical interface and Emotiv EPOC headset connection and communication. To test the headset, all electrodes were attached, data acquisition timed and signals visually inspected to spot apparent glitches, drifts and other abnormalities (e.g. transmission interruptions, delays, etc.).

Once the Emotiv EPOC headset functioned properly, the implementation in the graphical interface was tested and again inspected for timing issues with the data acquisition or signal contamination. We also investigated in the effective range of the wireless connection until failure and different synchronization methods with the images to reduce computational load and decrease data acquisition delays otherwise present.

Testing of the software components was performed in stages which are indicated in Figure 4.4. In here, every label represents a new stage in development, requiring all of the aforegoing stages to be properly functioning. On the raw data, bandpass and CAR filter methods were applied for basic signal enhancement (1). Afterwards, the different feature extraction methods were developed and tested on re-referenced and filtered sample data (2). Finally, all classification methods proposed in the project were included sequentially (3). Testing classifiers was performed using ideal (dummy) data for a linearly separable case and then a multi-class (three-class) problem.

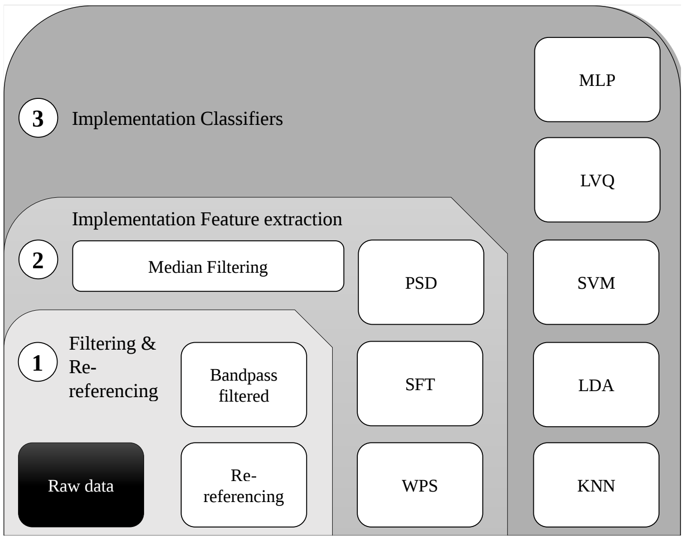


Figure 4.4: Stage-by-stage testing.

4.3.2 Integration and Verification

The verification of subsystems and will be performed at the completion of the implementation stage and indicates the readiness of the subsystems to be validated in the final stage. Basic pre-processing can be performed in one sweep, i.e. reference and bandpass filtering. Re-referencing, as stated in Section 2.3.4 subtracts the average of the complete scalp pattern for every specific electrode at sample time t. For bandpass filtering, a digital Butterworth filter was applied with determined coefficients using Matlab's *fdatool* function.

Yet, with regard to the verification of feature extraction methods, no standard procedure exists to ensure the correctness of all extracted features from the signal segment of interest. In most cases, the inspection of extracted features is mostly performed visually and heavily depends on the user's expertise [106]. This step usually requires in-depth knowledge for both, the intrinsic behavior of EEG signals during affective processing as well as a thorough understanding of operations performed during feature extraction and their interpretation. To give an example, in P300 studies, we aim to find positive peaks at a latency of 300ms after stimulus presentation and so time domain feature extraction methods can be easily verified when analyzing the particular region of interest, i.e. P300 environment. Studies with steady-state VEPs are interested in finding specific frequencies towards the visual stimulation for which frequency domain techniques can be readily applied [7].

In emotion recognition, we lack information about the particular response elicited since it may occur with various latencies, amplitudes and regions.

However, it is also possible to verify the correctness of selected features indirectly, i.e. through the comparison of classifier performances using features of known datasets. Rather than calculating individual features on a theoretical basis, we can use data containing features and their associated labels from open-source databases and compare the results from a single or multiple classifiers. This has the advantage to quickly verify the similarity or difference of results suggesting to accept, reject, or adapt the features or feature subsets chosen. As a prerequisite, however, it has to made sure that the translation algorithms are verified which is usually less problematic due to the existence of feature extracted, labeled signals, publicly available for the scientific use in BCI studies.

The working of the classifiers was verified through the use of the publicly available BCI competition III data set provided by Fraunhofer FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller, Benjamin Blankertz), and Campus Benjamin Franklin of the Charité - University Medicine Berlin, Department of Neurology, Neurophysics Group (Gabriel Curio) [99]. It consists of recordings from five healthy subjects, who during recording sessions, were instructed to perform one of three motor imagery tasks, indicated through visual cues for 3.5 s: left hand, right hand, right foot. Given are continuous signals of 118 EEG channels and markers that indicate the time points of 280 cues for each of the 5 subjects.

Based on this data set, the working of classifiers was then tested using the provided feature vector of 217 elements from 7 channels extracted by Wavelet Power Spectra analysis, as presented in a novel study accepted by the IEEE Engineering in Medicine & Biology Society (EMBC) [5]. In this study, a neural model for an adaptive BCI system based on software agents was proposed by using the aforementioned data set and similar preprocessing. The performance of different classifiers, including the techniques used in this project (SVM, k-NN, MLP, and LVQ), was investigated and provide the ground for comparison. Classification outcomes were compared to the ones achieved in literature and inner settings of the classifiers changed until a substantial agreement, i.e. $p \geq 74\%$ and $k = 0.61$ was met. A higher kappa and accuracy were chosen due to reasons of dealing with a binary classification problem to verify the platform against. Although no comparable result data is available for the LDA classifier, it is still tested on the data provided. To guarantee valid results for making predictions regarding new data, the data set were further randomly partitioned into training and independent test sets via k-fold cross validation. In this study, the complete data set was divided into 5 parts, and one of them was used as training data set for adjusting the parameters of the prediction model, also referred to as "leave-one-out" cross-validation. It is repeated 10 times for the validation of the system.

Subsequently, and when acceptable classification performance on the provided feature set has been achieved, the here suggested extraction methods are used on the dataset. This step was performed in a similar manner to the neural model presented in [5], as depicted below in Figure 4.5.

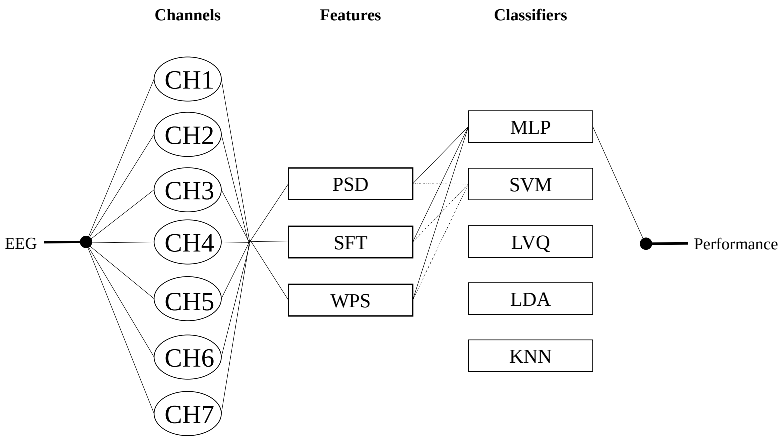


Figure 4.5: Neural model representation with combined PSD, SFT and WPS feature vector and MLP classifier (adapted from [5]).

Each feature set and an assembly of all features are used to train the BCI. On the whole, the classifiers will be accepted when the classification performance resembles the agreement obtained in [5] and presented shown in Figure 4.1.

Features	# elements	**SVM**		**KNN**	
		Acc.[%]	Kappa	Acc.[%]	Kappa
WPS	217	**91.7**	**0.83**	**90.0**	**0.80**
		MLP		**LVQ**	
		Acc.[%]	Kappa	Acc.[%]	Kappa
		90.0	**0.80**	**89.7**	**0.80**

Table 4.1: Verification data of classifier results for WPS and all elements.

4.3.3 System Validation

After the BCI system has passed system verification, it is ready to be employed with the experimental protocol and test subjects, all of which is described in the following section according to the developed protocol which is presented in 5.3.2. During this phase, the deployed system is validated towards its effectiveness in meeting its intended purpose and original needs identified in concept of operations, Appendix C.1 and Section 4.2.1. Moreover, the presented hypothesis in Section 3.4 is compared towards the achieved results, indicating the success of the project to recognize emotions in individuals with autism. The project can be concluded successful, when the system level requirements and functional requirements are met. The degree of fulfilled non-functional requirements further presents the state of the BCI system as a whole, providing information about the potential to be used in commercial, and/or medical applications. A summarizing list of all requirements including their individual acceptance criteria is presented in Table 4.2.

System level requirement	**Acceptance criterion**
Number of emotions	3 (PE, NE, C)
Accuracy	$\geq 60\%$
Kappa	≥ 0.4
Functional requirement	
Signal Acquisition	operative
Basic pre-processing:	
Re-reference filter	operative
Bandpass filter	operative
Inspect data, visual inspection	usable signal
Segmentize data	operative
Processing:	
Feature extraction	operative
Outlier reduction	operative
Classification	operative
Non functional requirement	
Robustness & Fault tolerance	if possible
Portability & Adaptability	preferable
Modifiability & Extensibility	preferable

Table 4.2: Emotion recognition project requirements .

Chapter 5

Research Design

5.1 Overview

Up to now, we have discussed the underlying theory behind brain-computer interfacing by looking at its essential components, i.e. electrophysiological signals of control, EEG acquisition and processing. We have also outlined popular translation algorithms for recorded EEG information and reviewed their performance for emotion recognition of various experiments found in recent literature. Finally, we have shown the project definition, implementation and verification processes by means of the V-model as the underlying engineering model. This chapter entails the experimental BCI setup developed to answer the research questions by defining the data collection process, i.e. selecting visual stimuli and creating appropriate test protocols for adult and child candidates. Furthermore, necessary experimental steps for the verification of the system are outlined.

5.2 Subjects

This work includes the participation of 14 children (7 girls and 7 boys) with age range between 7 and 11 years (mean age of 8.4 ± 1.1 SD for boys, and 9.14 ± 1.2 SD for girls); right-handed; without the use drugs and without traumatic experiences or phobias. Furthermore, two adult subjects have participated for initial tests to verify the working of the system and achieve first performance results as adult subjects. One male, 23, and one female subject, 22, both right handed and under similar medical conditions as the children, took part in the investigation.

5.2.1 Ethical Aspects

This research project is in line with the ethical issues inherent in research involving human beings, established in Resolution 196/96 of the Health National Council and its complementary norms. Information collected will be confidential. Privacy and confidentiality will be ensured, as well as protecting the identity of participants. Signing of the consent will also be a prerequisite for data collection by all legal guardians of children who accept and allow participation in the experiments, after being informed about goal of the research. Similarly, adult participants approved their participation in the research. The letter of consent for participation in the research can be found in Appendix D.3.

5.3 Data collection

5.3.1 Stimuli Set Construction

Revisiting Section 3.1.1, visual stimuli have been the preferred choice of many studies revolving around the problem of emotion recognition in humans with promissory results [105]. For the selection of emotionally provoking pictures, a number of internationally acknowledged databases exist, basing their stimuli sets on the aforementioned valence-arousal scale and performed validation studies, usually using a broad sample size between 60 to approximately 100 participants or more [6, 107, 8].

To induce emotions, 15 emotion-evocative stimuli were selected from the IAPS database, spread over the extremes of the emotion map. This selection was performed by first selecting pictures from IAPS and instrumenting them via empirical thresholds on valence, arousal and dominance scores, as defined in 5.1:

	Inclusion criteria		
Emotional State	Valence	Arousal	Dominance
postive excited:	**>7.0**	**>5.0**	**>5.0**
negative excited:	**<5.0**	**>5.0**	**≤5.0**
calm:	**4.0–7.0**	**≤5.0**	**>4.0**

Table 5.1: Inclusion criteria for emotional states.

Particular images on redundancy or particularity of context with respect to the target group (e.g. violent or erotic pictures) were then removed. As a result, for each emotional state, i.e. positive/excited, negative/excited and calm (neutral), 5 stimuli have been selected for these classes. These stimuli including their descriptions and their ordering is listed in Appendix D.1. Preliminary test runs with adult candidates, however, revealed that the classification performances were far below expectations since it was tested under laboratory conditions, i.e. little or no external noise factors, full concentration and no movements during the trials. Also, the first test candidates indicated that the stimuli selected were weak and tiring and thus may have appeared indistinguishable between each other for the classifiers. In order to circumvent this and to verify the proof of principle for the emotion recognition system, an alternative database has been chosen for adults with strong emotionally loaded pictures (e.g. animal mistreatment, degrees of violence, etc.). Again, a selection of 5 pictures with very high, very low or indifferent valence and arousal scores for each category has been created which is listed in AppendixD.1. Based on these images the verification of the concept has been performed.

5.3.2 Acquisition Protocol and Procedure

Upon arrival of the participant, he or she was familiarized with the experimental procedure, the meaning of the self-assessment scale (SAM) and used equipment. A full list of the instructions given throughout the experiment is provided in Appendix D.2. After the sensors were placed on the scalp of the participant and their signal quality verified, the participant was asked to initiate the experiment by pressing the start button on the screen when he/she felt ready, shown in Figure 5.1 and 5.2.

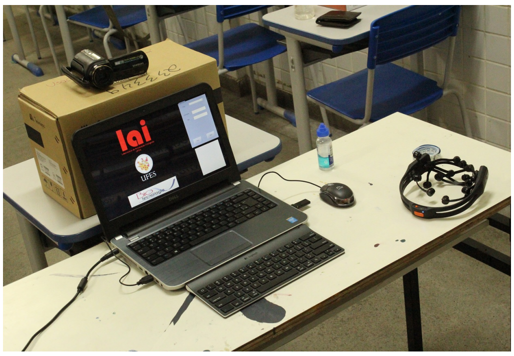


Figure 5.1: Experimental setup at EMEF.

Figure 5.2: Execution of experiment, signal verification and acquisition process.

For the acquisition of data, a test protocol was developed, by also targeting the expected subject behaviour in order to reduce as many noise and artifact sources as possible prior to any processing steps. For this case, a total of 15 trials was performed, each consisting of a number of steps, as presented in 5.3:

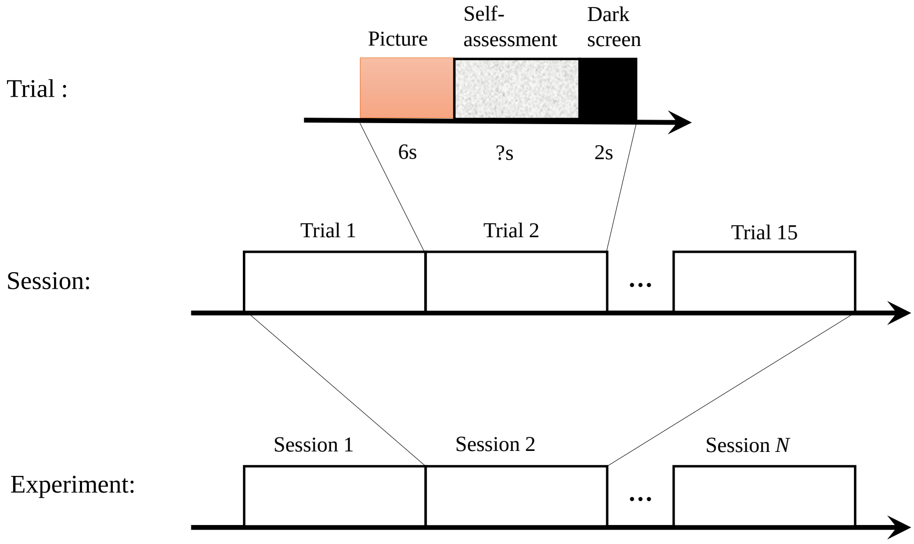


Figure 5.3: The protocol of data acquisition for typically developing and ASD individuals.

1. User initiation starts a simulation of 15 pictures, randomly selected from the list presented above for a duration of seconds per trial in which EEG data will be captured.

2. When presentation time has elapsed, the SAM evaluation screen will be shown for as long as the participant needs to give his emotional rating. No entry errors will be caught during this period in order to ensure data completeness.

3. An idle, black screen will be shown to for 2 seconds to "cool down" from the rating task and to mentally prepare for the upcoming picture to be shown which completes the trial.

Depending on the time each user takes for running through the self-assessment, a whole session lasts around 3.5 - 5 minutes which is believed to be sufficiently short for keeping the subject at a high level of concentration. Besides, the time of image presentation found in literature seems to vary between 2.5 and 30 seconds for which 6 seconds of exposure seems to be a legit choice [108, 36].

Participant Self-Assessment

Every presented picture was followed by an evaluation screen showing scales of Self Assessment Manikins to assess subjective rating as a measure of excitation arousal and pleasure, represented as a nine level graphic picture scale, as shown in Figure D.2. In studies of emotion recognition based on the IAPS, the images were often organized relaying scales of arousal and valence [109]. The graphical interface used in the experiment is shown in Appendix D.1.1 and further includes another SAM scale rating levels of "dominance" the subject feels toward each individual picture.

This method was be utilized to address the validity of selected emotional pictures when used in the context of children. During the experiment, the evaluator is asked to select on of the SAMs on each axis, yielding a discrete evaluation triple per trial. The evaluator indexes will later be used for the training and testing of the classifiers. It shall also be noted that this evaluation process may be closer to the actual "ground-truth" of emotions since it asks the subject to assess the individual emotional states evoked through the picture himself and is not biased by an empirical average drawn from a sample, as in the case of IAPS. Nevertheless, IAPS labels can still be used to compare the emotional perception of the selected stimuli, as derived from the individual evaluation triples.

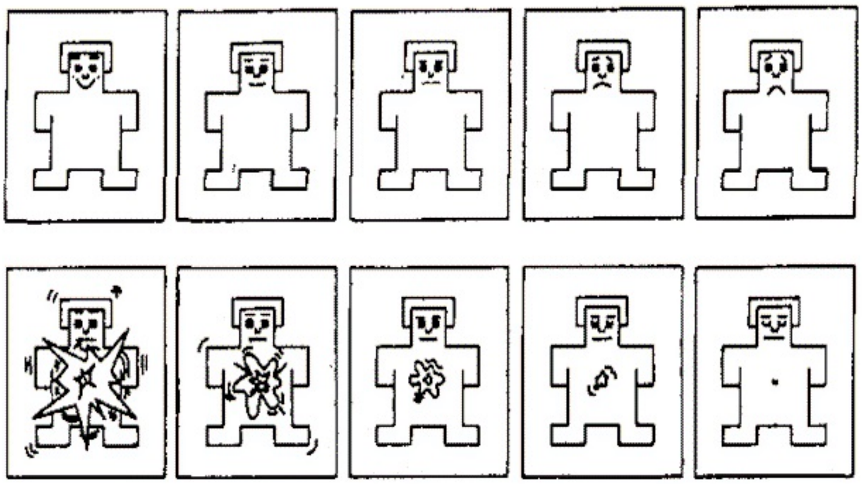


Figure 5.4: The nine level Self Assessment Manikin scale (adapted from [6]).

5.3.3 Materials and Setup

The provided emotion recognition system records EEG data using the Emotiv EPOC wireless headset [13]. This Emotiv headset has 14 electrodes locating at A_{F3}, F_7, F_3, FC_5,T_7, P_7, O_1, O_2, P_8, T_8, FC_6, F_4, F_8 and AF_4 following the American EEG Society Standard, as depicted in Figure 5.5. Furthermore, it does not require a moistened cap to improve conduction.

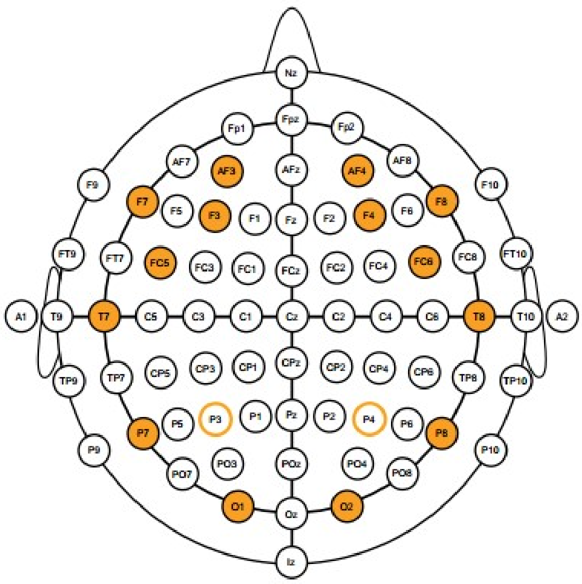


Figure 5.5: Emotiv EPOC electrode montage (solid orange) in the 10-20 system representation. The orange circles are the reference nodes.

Real time data acquired by the Emotiv Epoc headset is sent to a model in Simulink, a graphical extension tool in Matlab for the modelling, simulating and analysing multi-domain dynamic systems. A Simulink block receives the EEG data in a vector format and it can be used for further processing in the Simulink environment. Basic input signal filtering of all channels was performed using a equiripple bandpass filter design with stopbands at 2 and 50 Hz and -80dB attenuation as well as bandpass frequencies at 3 and 49 Hz. Moreover, zero-phase digital filtering has been applied to further reduce noise by preserving the main signal features without induced phase shifts.

The EEG data were recorded using a laptop (Intel Core i5, 1,60GHz x 4) and stimuli presented on the 15.6" screen with 60 Hz frame rate. Subjects were seated approximately 80 cm from the screen. Testing and verification of the equipment and system was performed in the laboratory environment of UFES whereas the experiment itself took place in the facilities of the local, municipal primary school for tests with TD individuals and at AMAES for subjects with ASD.

5.4 Preprocessing

5.4.1 Channel selection

Drawing from works in [36, 74, 76] the processing of emotions, also in comparison to autistic children, can be measured predominantly on the frontal, temporal and parietal lobes of the brain which would correspond to the channels F_3, F_4, C_3, C_4, T_3, T_4, P_3 and P_4 of the 10-20 standard, on an 8-electrode basis. With regard to Emotiv EPOC device, only two of these channels (i.e. F_3 and F_4) exist on the direct location. Thus, in investigating in the aforementioned regions with the Emotiv EPOC headset, the remaining six electrodes needed to be chosen as close to the suggested electrodes as possible. As shown in Figure 5.5, the electrodes in closest proximity are FC_5, FC_6, P_7, P_8. Additionally, electrodes T_7 and T_8 have been selected as substitution for T_3 and T_4 to add information from the temporal lobe. Although most of the analysis will be focused on the analysis of these 8 channels, initial processing for feature extraction will be performed on the complete data set in order to see whether the removal of particular electrode, hence complexity of the data set, will increase the classification outcomes. Subsequently, a thorough analysis on electrode information content and possible electrode configurations for performance enhancement will be performed afterwards. Finding an optimal subset of channels will also indicate possible limitations of the utilized Emotiv EPOC headset and therefore partially answer our research question towards feasibility of the headset and readiness of the complete emotion recognition system. 2 channels were removed prior to feature extraction, i.e. A_{F3} and A_{F4}, which have to been found very prone to artifacts resulting from the forehead, i.e. frowning or eye blinks, as well as other movements such as chewing or head motions. As a preparation for the aforementioned analysis, we formalize the problem of an optimal channel subset, by defining the set comprising of the remaining 12 channels available as

$$C_{tot} = F_7, F_3, FC_5, T_7, P_7, O_1, O_2, P_8, T_8, FC_6, F_4, F_8, \tag{5.1}$$

with a subset C_{tot} being the set of c channels selected for feature extraction. To investigate in the brain regions playing an active role in emotion elicitation and propagation, we defined 9 different electrode sets to be compared against or an investigation of possible patterns to be found across the participants which can be described with current literature or deviates from what has been found so far. The different channel distributions defined, along with a short descriptive reasoning, are listed in Table 5.2.

Label	Electrodes	Description
C_{tot}	$\mathrm{F}_7, F_3, FC_5, T_7, P_7, O_1, \mathrm{O}_2, P_8, T_8, FC_6, F_4, F_8$	To investigate in the Emotive EPOC system as a whole. Also indicates whether information richness enhances or deteriorates the emotion recognizability.
C_R	Right Hemisphere: $\mathrm{P}_8, T_8, FC_6, F_4, F_8$	Evaluate influences of asymmetric hemispherical activation, as referred to in Section 3.1.3. It also may support the notion of the right hemisphere being superior in expressing emotions than its left counterpart [110].
C_L	Left Hemisphere: $\mathrm{F}_7, F_3, FC_5, T_7, P_7$	
C_8	$\mathrm{F}_3, FC_5, T_7, P_7, \mathrm{P}_8, T_8, FC_6, F_4$	Defines the suggested electrode configuration similar to a 8-electrode configuration also found in literature [111].
C_6	$\mathrm{F}_3, FC_5, P_7, P_8, FC_6, F_4$	According to literature, distinct temporal and spatial signal responses can be determined from particularly these areas [110].
C_4	$\mathrm{F}_3, FC_5, FC_6, F_4$	Investigation of purely frontal and fronto-cortical information.
C_F	F_3, F_4	Plays an important role in the genesis and especially expression of affective. states, as mentioned in [36]. Therefore, finding the individual contribution of this region is attempted. Also, processing time is largely reduced, indicating if emotion recognition is possible with low computational cost.
C_P	P_7, P_8	Individual contribution of the parietal region in emotion recognition.
C_O	O_1, O_2	Individual contribution of the occipital region in emotion recognition.

Table 5.2: Defined channel configuration for a quantitative investigation in the contribution of brain regiones for emotion recognition.

5.4.2 Artifact Removal

In order to minimize the risk of signal contamination through artifacts trough eye blinks or other types of movement, all trials were visually inspected for any kind of abnormalities that may significantly decrease the signal quality. Data sets, containing large distortions over various channels were discarded completely while those sets with particular channel contamination were noted to be processed at a later step of data sets evolving from specific channel selections. This procedure was repeated for all test subjects from which 7 subjects had to be removed from the data pool because of too many signal contamination throughout 5 or more trials and thus, leaving 7 child participants for further analysis. Nevertheless, the risk of outliers in individual trials yet exist which may effect the testing performance of the classifier due to training on distorted signals. To address this problem, noise reduction through median filtering was performed which can effectively remove pulse noises by preserving detail and smoothens the signal [112]. Instead of filtering the raw signals, however, it was proposed to remove outliers resulting from extracted features as they may directly affect the class recognition performance. A closer look on the effect of this method is presented in Section 6.

Although visually inspected signal may not present major contamination, occurrences of artifacts and occasional outliers may persist to exist. Removing a complete trial because of minimal signal disturbance is not a feasible option since it further reduces the amount of information to conduct an analysis upon. Therefore, a simple method has been developed to indicate the amount of contamination per channel and trial which can be of valuable information when analyzing the information content throughout different channel configuration mentioned earlier. A simple rejection method has been proposed by computing the median of each channel in a trial, given order statistics

$$Y_1 = min_i X_i, Y_2, ..., Y_{N-1}, Y_N = max_i X_i.$$

, where Y_i is the i^{th} order statistic . The statistical median of the sample can therefore be defined by

$$Median(M) = \frac{1}{2}\left(Y_{N/2} + Y_{1+N/2}\right), \tag{5.2}$$

where N is an even number of samples which is the case for this project as $14*128 = 768$ samples are provided per channel. The median is then subtracted from the input signal to obtain the differences $\Delta_i, \Delta_{i+1}, ..., \Delta_N$. Then, the median for the positive as well as the negative differences was recomputed and then multiplied by factor 2 and a specified criterion to indicate positive and negative signal outliers of the signal, defined as

$$Threshold_+ = (1 + Criterion) * 2M_+,$$

for positive signal outliers, and

$$Threshold_- = (1 + Criterion) * 2M_-,$$

for negative signal peaks. Any signal sample exceeding the threshold is considered an outlier, since we expect the signal to behave within the threshold boundary of two times the median and the defined extra margin. The last step is to divide summed positive and negative outliers by the total number of samples to achieve the proportion of contamination within a trial. If this proportion exceeds the specified criterion, the trial may not be producing high classification rates. We will use this to investigate what amount which particular channels are affected by outliers and other distortions and will help to interpret classification performance.

5.4.3 Feature Vector Formation

As touched upon in Section 3.3.1, the number of features extracted describe particular characteristics of the underlying signal and directly affect the classification output. A poor representation of the original signal, i.e. using a low number of features, may not be enough information for the classifier to correctly generalize over unknown data whereas a large feature vector imposes a high complexity on the problem and results in greater computational loads. In trading off between these extremes it is usually attempted to describe a signal with the lowest number of features necessary to achieve a good classification rate. Large feature sets usually do not necessarily add more information content, instead redundancy is very likely to occur. Besides, given the diversity of feature extraction to be tested upon various classifiers in this project makes it very impractical to test for every possible permutation. It was therefore chosen to use as little as one feature extraction method up to a combination of three feature vectors, depending on the size of resulting features per method.

For the feature vectors to be fed to the classification block, the data sets of length p were first concatenated to form one single vector, in case multiple extraction methods were chosen.

$$x_{vec} = (a_{1,1}, a_{1,2}, \cdots a_{1,p-1}, a_{1,p}, b_{1,1}, b_{1,2}, \cdots b_{1,1-p}, b_{1,p})^T, \tag{5.3}$$

where b represents the different feature sets of size p.

5.5 Classification

5.5.1 Generalization

Recalling from Section 2.5, the ability of a classifier to generalize over untrained data validates its performance, provides information about the strength of the model selected and indicates potential overfitting. For the validation of classifiers, usually three distinct subsets of the complete data vector are defined: a training set, a validation set and a testing set. The training set is used as a set of examples for teaching the algorithm on what to discriminate and to adjust weights on, for instance, the neural network. Validation sets are often put into practice to minimize overfitting, i.e. to verify that any increase in accuracy over the training data set actually yields an increase in accuracy over a data set that has not been shown to the network before, or at least the network has not trained on it. If the accuracy over the training data set increases, but the accuracy over the validation remains unchanged or decreases, it shows that the classifier is overfitting the data and the training should be stopped, also referred to as *early stopping*. Eventually, the testing data set is used to confirm the predictive power of the classifier upon its architecture and its determined weights [113]. As a rule of thumb, a simple 50-25-25 split can be applied which has proven to work well if sufficient data points are available.

Given the relatively small number of trials per session, however, it is considered impractical to adhere to this rule as it would only yield a number of 7 training sets and 4 data sets for validation and testing. Given a three-class problem, each of these sets would contain no more than 2 sets per class at most, only allowing for minimal adjustments of the model parameters before tested on unknown trials. As a result, the complete set of preprocessed trials was divided into two distinct subsets: one training set B_{train} and one test set B_{test}, for which its desired outputs to the three class problem are shown in Table 5.3.

Class	**Category**	**Desired Output**
1	Positive Excited	$(1\ 0\ 0)^T$
2	Negative Excited	$(0\ 1\ 0)^T$
3	Calm	$(0\ 0\ 1)^T$

Table 5.3: Desired output vectors from the classifiers.

For the training of patterns, a 70/30 split data was chosen, 12 trials for training and 3 for testing, respectively. The reason to omit the validation set is largely owing to the fact that the test set may not represent all three classes and thus a trained three-class classifier would be validated on a binary problem instead by surely producing a large classification error. In order to circumvent this problem, *5-fold cross validation* was proposed with $l = 10$ number of runs, thus producing a total number of $k * l = 50$ resampling iterations. As explained in 2.5.5, k, equally sized, partitions are created of which a single subsample is retained for model testing as validation data and the other partitions are used as training. This cross-validation is then repeated k times (the *folds*) by using each subsample exactly once as the validation set. Repeating the whole cross-validation cycle 10 times ensures that every class will have been trained and tested upon to avoid the possibility of class mismatching.

5.5.2 Classification Performance

Revisiting Section 2.5, a direct measure of performance of the individual classifiers is the amount of correctly determined classes in the test data set divided by the total number of classes in the set which can be denoted as in Equation 5.4

$$p = \frac{\sum C_{i,i}}{N}, \tag{5.4}$$

where $C_{i,i}$ is the $i^t h$ diagonal element of a confusion matrix which contains the information about the actual and predicted classifications done by the classification system and N is the total number of trials. This results in a value between 0% and 100% and is commonly named as *accuracy* or *classification rate* of the classification system. Moreover, since the number of identifiable classes is three, an accuracy of 33.3% corresponds to a complete random classification event.

Chapter 6

Results

This chapter is dedicated to the analysis of the obtained data and the final results of the study. The first section is focused towards the verification of subsystems, i.e. feature extraction methods and classifiers to prove their working under optimal conditions. Next, test results of adult participants are presented to evaluate the emotion recognition performance for different feature extraction and classification method configurations. Supplementary results comparing the performance differences towards IAPS and the alternatively proposed database GAPED are presented in Appendix E. Based upon the best extraction set found in adults to identify emotions, the analysis was performed for all 5 classifiers and different feature vectors corresponding to various electrode subsets. In presenting the results, the (sub-)systems will be validated towards its functional and nonfunctional requirements, as mentioned in Section 4.3.3 and are used to formulate an answer to the initially phrased research questions in Chapter 1.

6.1 Verification Results

As indicated in the V-model (Appendix C), the integration of software and hardware components is an iterative process, i.e. adjustments become necessary when acceptance criteria are not met or other risks evolve that may negatively influence the systems performance at a later stage. Thus, in order to advance to the final system validation step, all subordinate steps require verification and/or revision.

6.1.1 Feacture Extraction and Classification Methods

The verification of feature extraction and classification methods has been achieved in two steps:

1. Using an open-source, raw EEG dataset as signal input to extract the various features and
2. use single vectors or concatenated combinations of features for the classification performance analysis.

Outcomes of the former step are verified against achievements in literature whereas the latter will be matched towards the requirements posed in this project, i.e. an accuracy rate of $\geq 0.74\%$ with a cohen coefficient k of $k = 0.61$. Table 6.1 exhibits the average performance results of classification methods based on 217 wavelet feature elements produced and 5–fold cross-validation with 10 repetitions.

Features	# elements	**SVM**		**KNN**		**LDA**	
		Acc.[%]	k	Acc.[%]	k	Acc.[%]	k
WPS	217	**93.54**(+1.84)	**0.87**(+0.04)	**83.3**(-6.7)	**0.67**(-0.13)	**86.9**	**0.74**
			MLP			**LVQ**	
		Acc.[%]		k	Acc.[%]		k
		79.4(-10.6)		**0.61**(-0.19)	**81.4**(-8.3)		**0.63**(-0.17)

Table 6.1: Classification results on BCI competition III data set using Wavelet features.

As shown above, the achieved accuracies range from 79.4% (MLP) to as high as 93.54% (SVM) by even outperforming the proposed SVM in literature by +1.84% but yielding lower results for the other classifiers. The performance for LDA could not be compared to literature values but show good result for the binary classification. All methods show a substantial agreement between true class labels and classifier outputs. Drawing from these results, the architecture of the classifiers was accepted to be implemented for recognizing emotions.

Following this verification step, we aimed to produce similar output by creating own feature sets of similar magnitude using the same dataset but and the here proposed feature extraction methods, i.e. PSD, WPS and statistical features. Since one of the proposed is identical to the one presented in [5], the results of this method can be readily compared give a direct indication of whether the performance is of similar magnitude or deviates largely from the ones stated in literature. The classification outcomes for all feature extraction methods and all classifiers with the same cross-validation method as mentioned above, are summarized below in Table 6.2.

Features	# ele-	**MLP**		**SVM**		**LVQ**		**LDA**		**KNN**	
	ments	Acc.[%]	k	Acc.[%]	k	Acc.[%]	k	Acc.[%]	k	Acc.[%]	k
SFT	70	80.7	0.61	92.2	0.84	85.14	0.70	90.9	0.82	86.10	0.72
PSD	35	84.5	0.69	86.39	0.72	**73.57**	**0.47**	88.1	0.76	**74.86**	**0.50**
WPS	217	82.0	0.64	91.75	0.84	89.36	0.79	**62.4**	**0.28**	88.9	0.78
All	322	80.0	0.60	93.90	0.88	89.46	0.79	**75.25**	**0.51**	88.82	0.78

Table 6.2: Classification results on BCI competition III data set using features of proposed extraction methods.

As shown in the table above, all extraction methods perform well on the dataset for finding discriminative information for each class with one or more classifiers. In fact, only LDA in two cases, and LVQ as well as KNN presented a smaller kappa agreement for extracted features with PSD and WPS which are highlighted in Table 6.2. Nevertheless, since we are interested in finding the best feature extraction/classification pair, this result indicates that these combinations may not produce preferable outcomes. With regard to SVMs, however, almost all feature extractor combinations yielded a high accuracy and true class agreement, claiming a strong performance of this classifier to work well with binary class generalization which was also repeatedly reported in literature, as reviewed by [44]. Furthermore, it shall be noted that whereas SVMs increase in performance with more information availability, linear discrimination seems to suffer from information richness but seems to perform just as good with a lower number of elements as SVM. All in all, given these results it was concluded that all feature extraction and classification work and therefore this verification step was found completed.

6.2 Adult participants

6.2.1 Emotion recognition

Although emotional responses toward pictures have shown consistent patterns in literature for both, adults and child participants (Section 3.1.1), it was observed through preliminary tests with adults and suggested IAPS images, that the stimuli had a very tiring effect on the participants. This was orally confirmed by the subjects themselves as they expressed a lack of attention because of the repetitive sequence i.e. pictures and SAM evaluation in alternation. The results of classification suggested similar, as it was only possible to achieve a maximum mean recognition accuracy of 44.67% with a corresponding mean kappa value of $k = 0.19$ and three classes for the best feature subset which in this case was PSD+SFT for both subjects. This result suggests a very low variability in the measured signals, too little for the classification methods to derive well defined decision boundaries for the three categories. Besides, this is in line with findings of works in physiological and behavioural responses to affective pictures between adults and children. In a comparative study, McManis et al. [67] reported that the removal of highly arousing visual material due to screenings by teachers and principals reduced the affective reaction of adults which is a similar finding here, given that the most extreme pictures have been disregarded. For the sake of completeness, individual results of this preliminary tests can be reviewed in Appendix E.1.

Therefore, an alternative stimuli set, as mentioned in Section 5.3.1 was developed to see whether a different set of visual stimuli would yield a different emotion recognition performance. At the same time, a digital, nonlinear median filter was introduced on the extracted feature (sub-)set to see whether possible outliers during feature extraction may enhance the signal information content. Essentially, a median filter looks at its proximity neighborhood, specified through a parameter n, and replaces the current value by the median of the compared numbers, given by n. Despite dealing well with signal outliers (e.g. noise peaks) on raw signals, median filters are not commonly used on signal feature subsets. Yet, their use has been found effective in increasing the classification outcome as a result from experiments, by also employing the alternative stimuli set. For both users, in the following referred to as *User1* and *User2*, the classification rate with respect to the complete 12-channel set C_{tot}, increased to an average of 53% with the combination pair of SFT and PSD with the LVQ classifier, along with a kappa coefficient of 0.15. Details are given in Appendix E.2.

Furthermore, a closer look at particular channel distributions, as mentioned in Section 5.4.1, revealed a big difference in the information content for the classifiers to be able to find discriminative features which may have been the result of emotional responses. Figure 6.1 shows the resulting classification outcomes for all five classifiers based on the individual, or concatenation of particular features extracted, for all 9 electrode configurations. Note that the letters A, R, L, F, O and P represent the electrode locations on the scalp as channel, i.e. $A = C_{tot}$, $R = C_R$, $L = C_L$, ... , $T = C_T$.

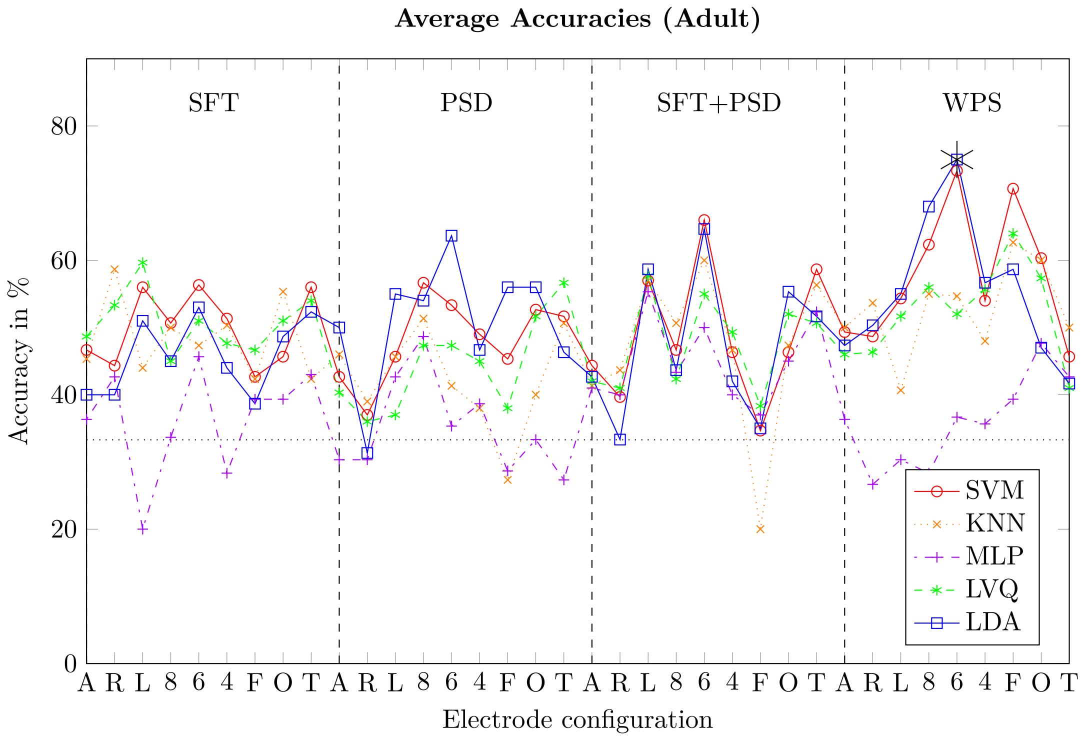


Figure 6.1: Overall classification results of all classifiers on all feature sets in 9 electrode configurations.

From the Figure, we see that purely statistical features do not achieve a good performance, on average, by fluctuating around $45 - 50\%$ accuracy for all classifiers, except MLP. Retrieved information from the analyzed power spectra (high alpha and low beta spectrum, 8-15Hz) showed better results than statistical features with a peak accuracy of 64.67% for linear discriminant analysis and about 60% for the support vector machine. Besides a further increase in accuracy for combined features (PSD + SFT, 66.0%), we observe that discriminative information is well retrieved from the channel subset C_L, corespondent to the electrodes placed on the left hemispheric brain regions and subset C_6, achieving the best result for this feature set. Yet, features in the Wavelet Power Spectrum seem to carry the most information content for classifying the three emotion categories in our setup, since an average accuracy of 73.33% for SVM and 75.00% for LDA was achieved. Further, the agreement between predicted and true classes as indicated by the kappa coefficient, were also higher (0.48 for SVM and 0.56 for LDA) then compared to the rest. Similar to the combined feature set, best results were found in C_6 suggesting that affective states in adults for three categories may be possible to only detect by measuring the frontal as well as the parietal area of the brain.

All in all, with respect to the achieved performances in adults users in emotion recognition, the system proves to be working well on a WPS/LDA (or SVM) combination pair using the C_6, channel subset for three emotions. The found maximum average accuracy of 75% and a kappa coefficient of 0.56 support this claim and clearly fulfill the system requirement defined in Section 4.3.3. Drawn from the knowledge gathered on the best feature extraction and classification method, we will use this information to be compared with child subjects in the following section.

6.2.2 Electrode configuration

Below, two Figures 6.2 and 6.3 are shown with to display the results for the different channel contributions as described in Section 5.4.1. The shown plots are excerpts from the overall performance presented in Figure6.1, from which the best classifier (SVM) has been selected based on SFT+PSD (left) as well as WPS features (right).

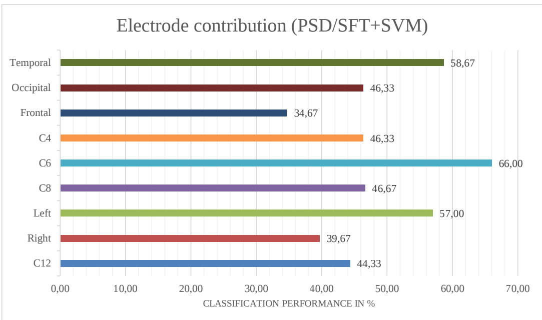


Figure 6.2: Averaged electrode contribution of combined feature set with support vector machine classifier.

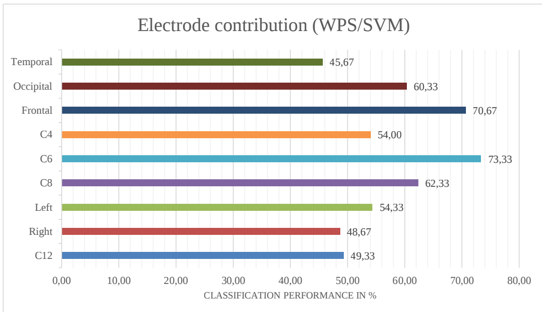


Figure 6.3: Averaged electrode contribution of WPS feature set with support vector machine classifier.

With regard to the complete channel set (C_{tot}), excluding the pre-frontal electrodes AF_3 and AF_4, we see that the emotion recognition rate is ($\leq$ 50%) which is a weak performance when comparing to particular subsets shown. Generally, when using only channel subsets, the classification performance can be enhanced significantly. For example, this is the case of C_6, exhibiting a significant increase in accuracy as compared to other subsets. C_6, covering parts of the frontal and fronto-cortal area of the brain as well as temporal, seem to enclose more emotional information in the time-frequency domain as compared to extracted features gathered in the alpha and low-beta band by (PSD). The investigation of individual electrode pairs in frontal, occipital and temporal region further suggests that more recognizable and distinguishable features from wavelets are drawn from the frontal and lesser from the occipital and temporal signals. Similar findings have also been reported in literature, describing the strength of an emotion by an increase in the beta/alpha activity in the frontal area, coupled with a rise in beta activity in the parietal lobe [36, 114]. According to this dataset, the inverse seems to hold for features from the frequency power spectrum over the high alpha/low beta band since mean average shows the occurrence of pure chance over the frontal but higher over occipital and temporal regions. According to [115], high temporal beta activity is connected to the amplification of responses towards negative emotions which may coincide that more candidates have labeled the images as negative then positive but almost equal to calm. However, proof of claim cannot be supported statistically given the current dataset.

In analyzing further discrepancies among the channel outcomes, we can now look at the individual contamination of channels and trials based on different margin criteria, as described in Section 5.4.2. The table below exhibits the individual channels presenting degrees of contamination when the threshold margin is varied and the amount of trials that would have been rejected based on the criterion. Through testing, we found that a criterion ≤ 0.15 results in the suggested rejection of almost all trials, therefore it was not considered feasible to be included in the analysis. A good criterion for the sensibility of outliers was achieved by a value of 0.15, i.e. 15% of the signal contamination being affected by high variations.

Criterion	**15[%]**		**20[%]**		**25[%]**	
User	**Reject**	**Channels**	**Reject**	**Channels**	**Reject**	**Channels**
1	0	T7 O1 O2 T8	0	T7 O1	0	None
2	4	F7 T7 P7 O1 O2 P8 T8 FC6 F4	0	T7 P7 P8 T8	0	T7
Average in %	26.67	$\geq 2\times$:O1 O2 T7 T8	0.00	$\geq 2\times$: T7	0.00	$\geq 2\times$: None

Table 6.3: Degree of trial and channel contamination based on sample margin rejection criteria.

From Table 6.3, we see that at a 15% rejection criterion, four trials from $User2$ would be consdiered affected and suggested to be excluded when in order to increase classifier performances. It is also shown that several channels present high levels $\geq 15\%$ of contamination, amongst others, channels of the frontal and parietal area of the scalp. This may indicate the low performance of the C_4 and C_8 channel subsets, containing electrode from this particular regions. A rejection of four trials would also mean an exclusion of for trials to be learned for $User2$ which corresponds to almost a complete class to be left out for training, given the case that all rejected trials would be equally labeled. Such a great class imbalance is very unlikely to counteract by standard cross-validation and resampling techniques.

6.2.3 Classifier Analysis

Almost independent from any feature set, classification via Multi-Layer Perceptrons was very weak, more often than not even below the associated threshold for a random event classification of 33.33%. In searching for an answer to this behaviour, numerous factors may play a role:

- size of the training data,
- number of hidden layers,
- lack of knowledge of the underlying problem.

First, the space of training samples to feed the neural network defines the space of generalization for the trained model. When the data is much different from the obtained model, or class of models, the generalization on data is impossible. Good generalization may be possible from attempts of interpolation, however not from extrapolation. That being said, insufficient data for learning may not fill the entire space the model has to be valid for which it results to fail. This phenomena is referred to as the 'Curse of Dimensionality' and has been reported as a common problem on noise and non-stationary EEG data [36]. Second, since MLP is a universal approximator, starting with zero knowledge about the process it will be modeled upon, many decisions for network parameters are drawn from experience, existing literature on the existing problem or by trial-and-error. Since extensive testing on optimal training parameters was not decided feasible, several parameters were chosen based on system defaults in Matlab's Neural Network Toolbox. In general, the number of hidden layers and neurons in a hidden layer increase the flexibility of a system to adjust its weights but comes at the cost of additional complexity in the training algorithm [116]. Clearly, the lack of knowledge toward the underlying nature of brain signals, specially emotions, make it difficult to give a good, intuitive guess about which parameters to choose or which tuning methods to apply. Moreover, accounting for the subjectivity of emotions to be experienced and expressed, one had to adjust the model on every individual to be tested, thus creating a great effort which is impractical when trying to generalize and make use of the concept "emotion" as control input in BCI'S, for instance.

6.3 TD participants

6.3.1 Emotion Recognition

Knowledge presented in the previous chapter has been utilized to focus the analysis on the combined feature subset SFT+PSD and Wavelets with the four classification methods proofing good generalization results, i.e. SVM, KNN, LVQ and LDA. From the pool of the 8 remaining child subjects, the same analysis has been performed as shown above, enabling to readily compare the outcomes and spot potential differences. A similar analysis in this context refers to the same (pre-)processing as in the adult case and that although remaining outliers from the visually inspected data remained. Removing many ($n \geq 5$) would essentially reduce the training and test for the classifiers which, instead, would significantly increase the chance of a class not being trained at all. Likewise to the aforegoing analysis, each classifier performed a 5-fold cross-validation and 10 repetitions on the original sample. This creates the base for the following analysis of performance results.

The following Figure 6.4 shows the averaged classification of all users based on selected feature sets and for all electrode (sub-)sets, indicated on the x-axis as abbreviations, identical to Figure 6.1. Note that everything below the dashed horizontal line (33.3%) represents a null classification, i.e. a random classification event. Numerical details are presented in Appendix E.3.

Needless to say, as compared to the adult counterparts, this result significantly deviates, comparing best accuracies from Figure 6.1 and here. Neither a clear tendency of wavelet power spectrum information nor particular classifiers seemed to exhibit superior performance over the given data set. Highest indicated results were obtained by a PSD+SFT/KNN pair with 50.38% accuracy and yet low true class agreement of $k = 0.17$. Results with extracted wavelet features, on average, yielded accuracies of 45.81% for KNN and 40.95% with LDA. This result greatly deviates from the expectation of wavelet features to retrieve suitable information content in the signal for discriminating three classes, as it was proven with adult candidates. Also, the signals have been visually inspected prior to signal processing in order to reduce the amount of evitable error during signal processing and classification. In finding a suitable answer to this behaviour, there are multiple starting points from which to investigate in potential flaws or limitations of the system. A more detailed error analysis is therefore provided in Section 6.3.3.

6.3.2 Electrode Configurations

The individual channel distributions do also not present any significant differences from other configurations. Minor differences amongst the $C_{tot} - C_4$ configurations are certainly associated with random effects rather than emotional response information for both feature sets coupled with

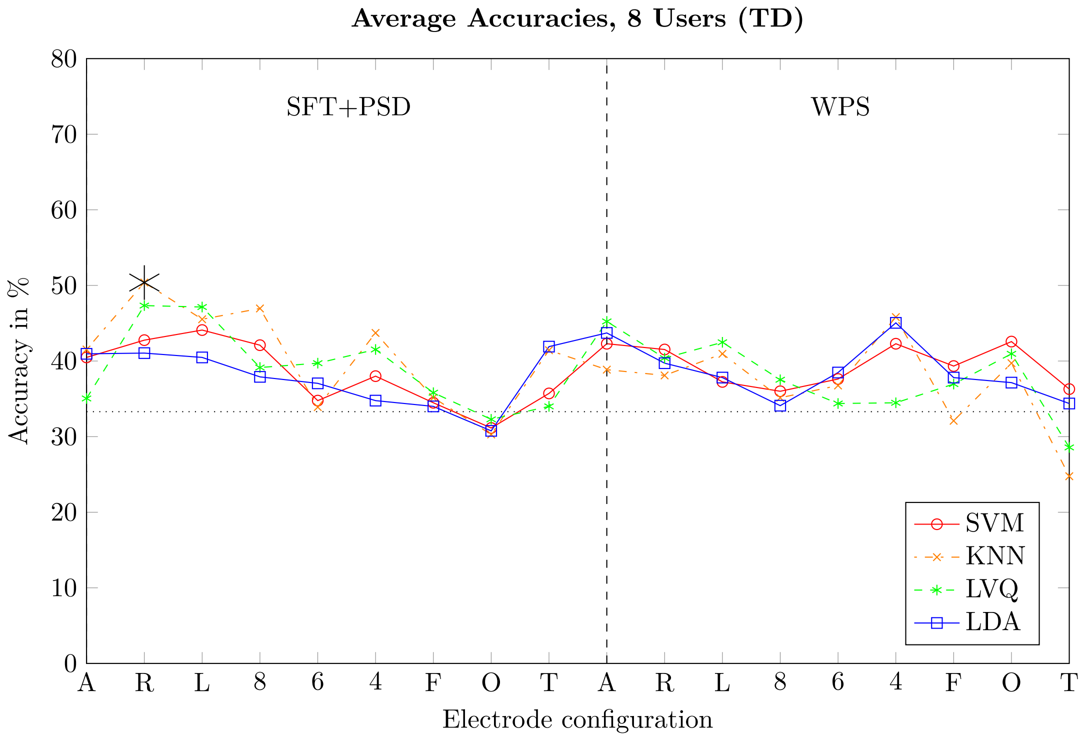


Figure 6.4: Average classification result of children with preselected feature extraction methods tested on all electrode configurations.

the highest performing classifiers KNN, as shown below in Figure 6.5 and 6.6. With the exception of information drawn from electrode over the right hemisphere which actually may contain relevant emotional content towards negative stimuli, indicated by various findings in literature [110, 114, 117]

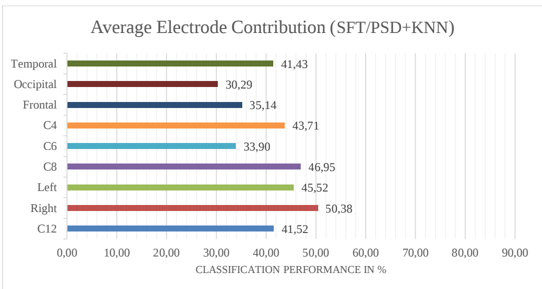


Figure 6.5: Averaged electrode contribution of combined feature set with k-nearest neighbor classifier.

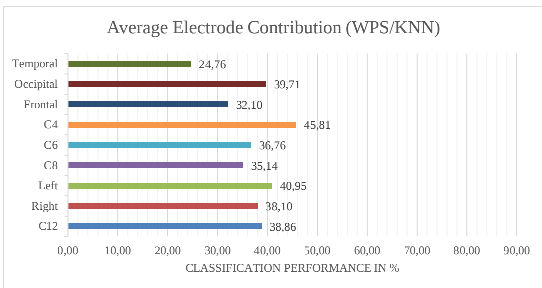


Figure 6.6: Averaged electrode contribution of WPS feature set with k-nearest neighbor classifier.

Because the results can be almost considered to be stemming from random classification events, a more thorough electrode analysis toward the functioning of brain regions with emotional content is therefore omitted. Instead, we can look perform the signal analysis for contaminated signals analogous to the adult user case. Table 6.4 shows the outcome of this analysis with respect to the three different criteria for possible signal rejection mentioned earlier.

The table shows that compared to the adult signals (26.7%), almost 40% of the trials (labeled "Reject") would be rejected from the algorithm at a 15% criterion of input signal contamination per channel in all trials. This value significantly lower at the 20%-level but also means that the overall

Criterion	15[%]		20[%]		25[%]	
User	**Reject**	**Channels**	**Reject**	**Channels**	**Reject**	**Channels**
1	9	F7 T7 P7 O1 O2 P8 T8 F4 F8	2	F7 P7 O1 T8 F4	0	F7 P7 O1 T8
2	7	P7 O1 O2	1	P7 O1 O2	1	P7 O1 O2
3	6	T7 P7 O1 O2 T8 F8	2	T7 O1 O2 T8	0	T7 O1 T8
4	9	F3 P7 O1 O2 P8 T8 F8	2	P7 O1 O2 P8 F8	0	P7 O1
5	2	O1 O2 P8 FC6 F8	2	O1 O2 P8 FC6 F8	2	O1 O2 FC6 F8
6	7	T7 P7 O1 O2 T8 F8	3	T7 P7 O1 O2 T8 F8	0	T7 P7 O1
7	1	F7 FC5 T7 P7 O2	1	FC5 O2	1	FC5 O2
Average in %	39.05	$\geq 4\times$:O1 O2 P7 T8 F8	12.38	$\geq 4\times$: O1 O2 P7	3.81	$\geq 4\times$: O1 P7

Table 6.4: Degree of trial and channel contamination child EEG data based on sample margin rejection criteria.

signal contamination is higher which might relate back to misclassification events as a result of this contamination. Besides, numerous channels remain prevalent even after increasing the margin to include more data samples. Particular channels from almost all sites of the measurable brain region via Emotive EPOC are affected and some of them even occur throughout every trial and even every experiment. Mentionable here are the occipital electrodes and although not directly involved in emotion processing, they affect the classification performance of the EPOC headset when used as a whole. Paired with the fact more data takes longer to process, this is why they might be often omitted in emotional recognition studies. Other affected electrode sites which do play an active role in the emotion activation and processing, are the parietal as well as the frontal electrodes P_7 and F_8, respectively. The contamination of signals stemming from these regions has a direct link to the loss of information for the emotional recognizability since they are found active in analyzing emotional arousal during affective-pictures stimuli [118, 115].

6.3.3 Error Analysis

Inter-subject findings

To investigate in the reasons for unsatisfactory recognition outcomes, we first look at inter-subject differences to obtain insight in individual variations of participants that contribute to this result. Naturally, when averages are taken over a small sample size, outliers or highly biased data directly affects the calculated mean. It is therefore of interest to localize and elaborate on those examples since they may yield important information about systems overall concept and design and clearly an indicator for iterations necessary in the design process, as outlined in Section 4.2.2. Retrieved from the data set, we obtain two results over the extremes of the performance spectrum, presented in Figure6.7 for the best and Figure 6.8 for the worst performance.

It is seen that although the average appears low, there are significant differences between the individual participants with respect to both, classifier performance and electrode subset. Whereas in the best result an accuracy of 80% and $k = 0.61$ was achieved with a SFT+PSD/KNN combination over the right hemisphere, the same setup only achieved 44.67% and $k = 0.18$ for the worst result. Conversely, superior performance results were achieved over the C_8 channel subset for the, on average, lowest performing candidate of the sample pool. Furthermore, comparing the best performing configurations in adult candidates with those here, we also find deviations. Features of the Wavelet Power Spectrum did not show any performance enhancements and also the expected superiority of SVM and LDA as compared to other methods cannot be proven on this dataset.

These significant discrepancies in the findings present above require a closer analysis than simply looking at the level of agreement between the ground truth labels as defined by the SAM assessment

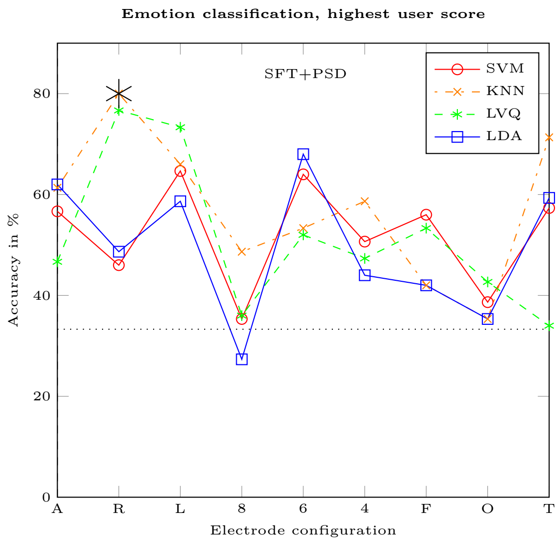


Figure 6.7: Emotion recognition result, highest user scores.

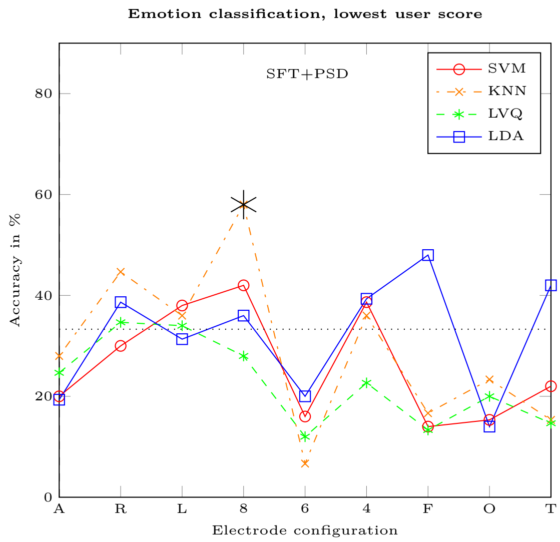


Figure 6.8: Emotion recognition result, lowest user scores.

and the machine learning classifier ratings. For doing so, we can use a number of standard statistical measures that take into account random chance effects and evaluate the inter-rater agreement between the "ground truth" labels and the corresponding classification result. Recalling from Section 2.5.4, we can look at the sensitivity and specificity of a system for the different classes given and readily compare rater agreements for all classes. The following tables (Tables 6.5–6.6) exhibit the cross tabulation (confusion matrix) results for the two subjects presented above, along with their respective statistical outcomes. Table 6.5 (lef) is based on the best accuracy achieved through SFT+PSD/KNN pair, measured over the right hemisphere. This is compared to the user with the weakest results under the same conditions.

		Predicted			
	Class	PE	NE	C	All
Actual	PE	**0**	0	0	0
	NE	0	**66**	14	80
	C	0	16	**54**	70
	All	0	82	68	150

		Predicted			
	Class	PE	NE	C	All
Actual	PE	**26**	14	10	50
	NE	10	**22**	8	40
	C	13	28	**19**	60
	All	49	64	37	150

Table 6.5: Confusion matrices of classification outcomes for the best (left) and worst (right) user.

Se	*Sc*	Acc.%	kappa
0.00	1.00	1.00	0.00
0.83	0.77	0.80	0.60
0.77	0.83	0.80	0.60

Se	*Sc*	Acc.%	kappa
0.52	0.77	0.69	0.29
0.55	0.62	0.60	0.14
0.32	0.80	0.61	0.12

Table 6.6: Trial statistics for the best (left) and worst (right) user.

All metrics presented above were derived from the respective confusion matrices according to the equations 2.1–2.7 introduced in Section 2.5.1 for both users. Thanks to the confusion table, we can now look at the classifiers performance based on its actual predictions rated against the true condition, or "ground truth". This was not possible with the aforegoing analysis only taking into account the correctly identified classes from the total sample space for that particular class. Clearly, the reason for the great discrepancy in performance between subjects lies in the number of classes that the classifier was effectively tested upon. In discussing the confusion matrix presented in Table 6.5, no class 1 objects, i.e. image labeled as positive/exciting (PE) has been identified by KNN, simply because it was not been present in the test set throughout cross-validation. Therefore, the classifier, as indicated through the column sums, is very biased towards the two remaining classes NE and C for which its sensitivity and specificity are reasonably high. Although the overall kappa coefficient is acceptably high, it considers the reduced version of a two-class problem which is neither intended nor very useful for applications based on emotional responses. With regard to the other user, we find all classes present in the tested data, although again being marginally unbalanced towards class 3 (C). Furthermore, this class presents the lowest sensitivity ($Se = 0.32$) but highest specificity ($Sc = 0.80$) of the classifier, meaning that it is likelier to correctly reject this class than to correctly classify it (Table 6.6). Besides, the kappa coefficient as the total agreement between all true class labels and the predicted classifier output is low ($k \leq 0.30$) suggests that all agreement tend to occur rather by chance effect. That being said, although accuracies are $0.61 - 0.69$ per class, the confusion matrix does not represent a meaningful classifier. As shown from the examples above, it is crucial to include other performance metrics such as the kappa coefficient to be able to detect incorrect classification behaviour as in the case of the subjects of investigation. Whereas kappa can provide an overall agreement rating between classes, the confusion matrix can be useful to evaluate possible biases and unbalanced test sets, amongst others.

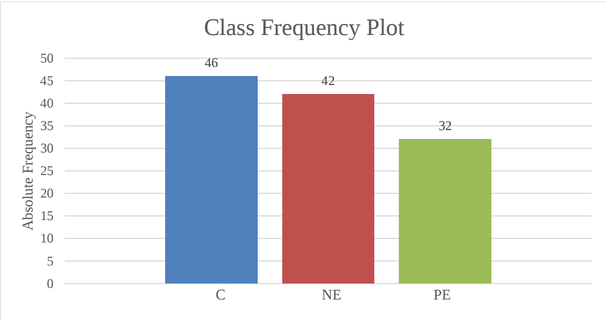
By recalling Section 6.2.3, we add to the discussion that for the weak performance of the classifiers, sizeable biases in the classes can be accounted. Although showing superior generalization ability for SVM and LDA in sufficiently high data sets, nearly any classifier is majorly affected by the amount and quality of training it receives. To counteract the shortage of trial data it may therefore be beneficial to allow for an extension of the experiment in order to achieve equal trial sizes. Observations during the experiment with adults and or children, coupled with the here presented indicator of channel contamination can be used as a quality indicator, even while the experiments are performed through the very little processing time required. However, since it was not able to be implemented given constraints of time, this suggestion may be picked in future work using the platform

Emotion elicitation

In this study we used a subset of images from evocative pictures of the IAPS. Using the database has the advantage of selecting from a pool of images which have been extensively evaluated by a large number of participants to validate valence/arousal values as well as ensemble means and variances. Nevertheless, since emotions are subjective and can hardly generalized, the induced feeling of a participant from a picture may greatly differ from the response expected [29]. Self-assessment should account for that bias by allowing the subject to rate the emotional response individually, through the use of acknowledged rating scales. This is advantageous when used for EEG-based emotion recognition, as the classifier is trained on data labeled by the subjects own perception which is closer to the "ground truth" of an emotion . With respect to the findings, however, it is surprising that the overall recognition was closer to a random events than identifying certain recognition patterns. In finding an answer to this, we identified multiple reasons:

1. The number of categories for training and testing is not distributed evenly, i.e. a strong bias exists towards either of the classes to be tested upon.
2. The SAM rating scale is not understood correctly by the participants and the image rating produces a wrong label output.
3. SAM is correctly understood by the participants but the selected stimuli are simply too weak to evoke the expected emotional state.
4. Other, not SAM-related factors during the experiment to influence the signal quality.

Evidently, as presented in the confusion matrices (Table 6.5), we find that classes were not equally trained and tested which makes the classifier more prone to errors as a particular class may be overtrained or not learned at all when little or no training sets for that class exist. The latter case automatically transforms three 3-class recognition task into a 2-class problem for which linearly discriminating classifiers usually perform well [44].



Class	Class Indication Matrix						
PE		x	x		x	x	x
NE	x	x	x	x	x	x	x
C	x	x	x	x	x	(x)	x
User	1	2	3	4	5	6	7

This is the reason why in particular cases the classification rate was extremely high as compared to other users. From the Figure **??**, it is evident that the classes are not well distributed with more images being identified as "Calm" and "Negative". Referring to classification, an imbalance of classes in the training, specially given the small sample size, we expect a non-steady behaviour of classification even though the test set might contain well distributed, i.e. all three classes. It is therefore of high importance to have a more or less evenly distributed training set or to employ resampling techniques that "oversample" the minority class and "undersample" the majority class in order to establish class equality [119]. K-fold cross-validation, as performed in this study partially accounts for this effect but cannot function when none of the true class labels are associated with a minority class. Table **??** demonstrates the existence of such situations in our data set as two of the subjects did not rate any picture as "positive" and once only 1 C-label was delivered, thus creating a great bias towards classes PE and NE. Certainly, this accounts partially for the marginal overall but occasionally strong performance in recognizing two classes shown earlier.

Although not able to experimentally verify, the possibility of the misunderstanding the SAM evaluation is present and may lead to failure in the recognition process. This is why it is best practice to verify the selected modality of emotion elicitation, here visual images. An indication for the researcher whether he constructed a well balanced stimuli set, can be obtained via comparison of subject vs. expected assessment. To illustrate this, the following Graph (Figure 6.9) shows the IAPS expected vs. the averaged participant label distribution of selected stimuli in the valence-arousal space according to their valence/arousal rating.

As expected, for IAPS we observe the spatial distribution of all pictures their associated valence/arousal space. The average of SAM evaluations, however, presents a quite different distribution of images where most of the PE images are found in the NE and C class space by also deviating from the average IAPS valence/arousal values. Likewise, NE and C class items are rather found in inverted positions to each other, i.e. more "Calm" pictures have been given high arousal values and "Negative/Exciting" valued low arousal. This finding does not necessarily mean a low classification outcome per se as it depends on the individuals actual emotional association, but it does tell that the expected emotional response may not be evoked by the picture selected and thus, making it hard to match activated brain regions to particular images being shown. This finding truly suggests the revision of the stimuli set and/or the need for more clarity on SAM scores for the subjects in an attempt to rule out mislabeling due to lack of understanding which,

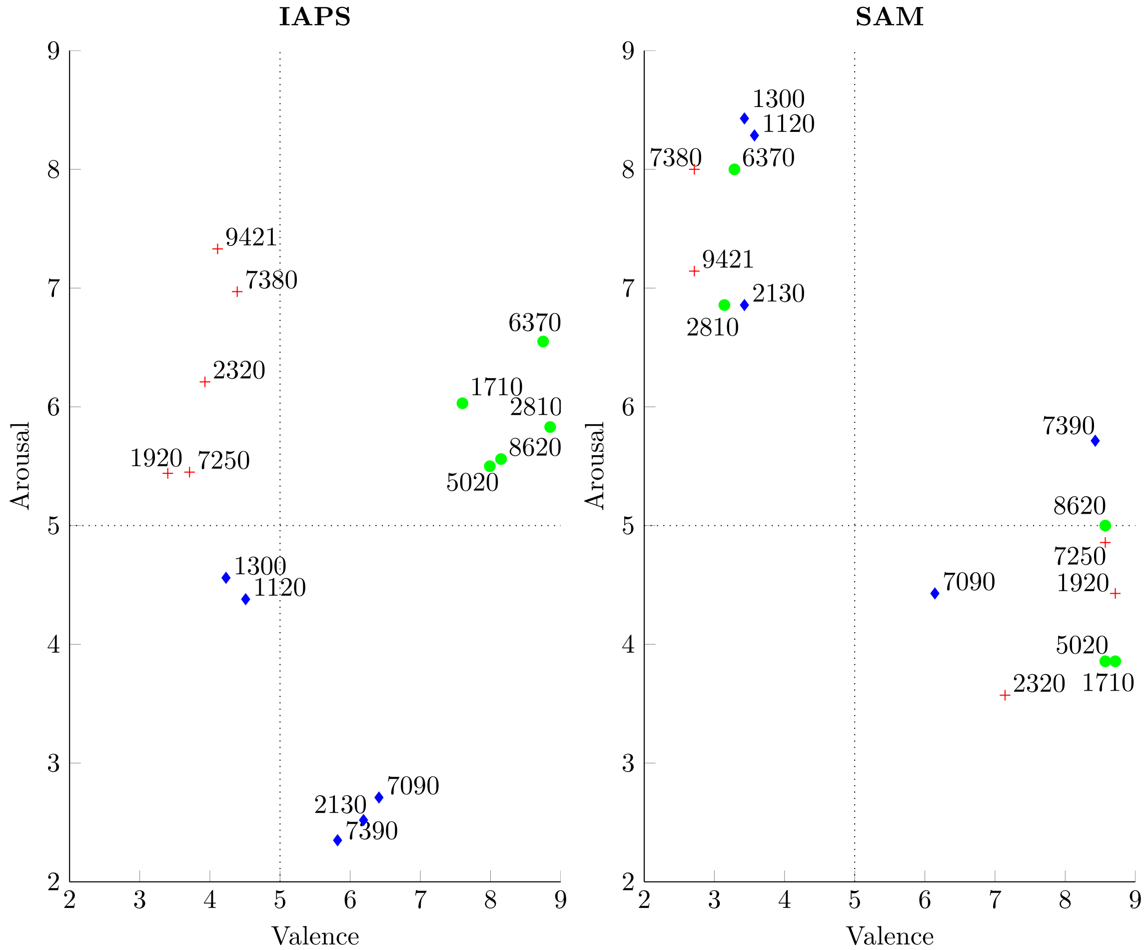


Figure 6.9: IAPS vs. SAM validation of stimuli.

inevitably, will cause the emotion recognition system to rely more on random classification rather than pattern learning. Because dealing with children imposes additional challenges in terms of age, gender or the personal state to affect the experiment, it is of paramount importance to have well-balanced, verified stimuli selection.

Given the case that SAM was well understood and presents the closest emotional association of the children with the self-assessment manikins, then the images may simply be too weak to elicit affective responses. This, as mentioned earlier was expressed by adult candidates who were tested on this stimuli set, along with feelings of tiredness through the monotonous, repetitive manner of showing the pictures. One way to address this problem is by asking the participant to simultaneously "feel" the emotion presented by conscious thought. This may deviate from the from the idea of detecting emotions not as an action but reaction, it might be beneficial in the study of active brain regions connected with voluntarily evoked emotions.

6.3.4 Overall System Validation

To reflect on the contribution of this work, we look back at the various system level as well as functional and non-functional requirements to be matched with the current outcomes (Table 6.7).

System level requirement	**Acceptance criterion**	**Fulfilled?**
Number of emotions	3 (PE, NE, C)	**partial**
Accuracy	$\geq 60\%$	**partial**
Kappa	≥ 0.4	**partial**
Functional requirement		
Signal Acquisition	operative	yes
Basic pre-processing:		yes
Re-reference filter	operative	yes
Bandpass filter	operative	yes
Inspect data, visual inspection	usable signal	**conditional**
Segmentize data	operative	yes
Processing:		
Feature extraction	operative	yes
Outlier reduction	operative	**conditional**
Classification	operative	yes
Non functional requirement		
Robustness & Fault tolerance	if possible	**no**
Portability & Adaptability	preferable	yes
Modifiability & Extensibility	preferable	yes

Table 6.7: Emotion recognition project requirements .

Given the recognizability of three emotional states in adults but not in children has led to the conclusion for a partial fulfillment of the system level requirements. It shall be mentioned that dealing with brain signals as such is an ambitious endeavor given the sheer endless number of variables associated. Furthermore, emotions are known to be very subjective and may largely deviate from any expectation without apparent reasons. Additionally, dealing with children by introducing even more uncertainties formed a very ambitious challenge.

Nevertheless, having found root causes for the weakness of performance provides a base of knowledge to continue this line of research. To this end, a complete and verified platform for emotion recognition has been developed including almost of the functional and non-functional requirements stated above which are integral for the affect recognition process. In mentioning those being conditionally fulfilled, it shall be mentioned that the inspection of data has yet been performed manually by looping through every trial for every user. Also, since the underlying pattern of interest for emotion recognition is mostly unknown, a "usuable"-labeled signal may not always be true owing to the lack of expert knowledge in EEG signal analysis. Outlier reduction has yet functioned as an analytic tool to add a statistical decision layer on the data which makes it easier to interpret data and finding potential causes for error.

Toward non-functional requirements, the system is yet prone to misselect noisy and or similar signal data which will remain a challenge in future use, unless appropriate preprocessing methods or the automated selection of relevant information has been found.

Chapter 7

Conclusions

This final chapter summarizes the findings of this contribution by answering the research questions as stated in chapter 1 and matches obtained results against the acceptance criterion mentioned in Section 3.4.

Main research question:

> *To which extent, if at all, can selected feature extraction and machine learning techniques be viable methods for recognizing emotions in EEG for adults and children with the hardware limitations posed by the Emotiv EPOC headset?*

From the results obtained in Section 6, we find that for three-class emotion recognition in adults we achieve an average accuracy of $p = 73.33\%$ and a corresponding kappa of $k = 0.48$ for support vector machines and even $p = 75.00\%$ with a kappa of $k = 0.56$ in linear discriminant analysis using features of the wavelet power spectrum. In matching these results with the acceptance criterion of $p \geq 60\%$ and a class agreement of $k = 0.4$, we can conclude that emotion recognition with the Emotive EPOC headset is possible for three emotional classes. Furthermore, from the various signal processing and machine learning methods tested, we suggest the use of a feature extraction and classification pair of wavelet features in combination with either support vector machines or linear discriminant analysis. Feature vector formation of statistical features of time series in conjunction with information from power spectra (PSD) yielded average accuracies $\geq 60\%$ with the same classifiers, however, it failed to meet the required class agreement and thus needed to be rejected.

Drawn from the results of younger subjects, the hypothesis needs to be rejected given an overall mean accuracy of $p = 50.38\%$ and a very low class agreement of $k = 0.17\%$. Nevertheless, the error source was found and verified to be causing this result by class imbalances on a small training set and multiple noise-affected channels throughout various trials. These affected trials, in return, can account for the classification error which is even magnified when contaminated trials belong to a minority class as a result from the individual SAM evaluation. This was verified as only 4 out of the 7 subjects actually indicated the presence of three emotional classes, according to their SAM assessment. Amongst the rest, a recognizable bias was present towards "negative" as well as "calm" emotions evoked by the stimuli set.

Moreover, this research investigated in the content of channel information for emotion recognition for 9 different channel pairs and subsets, evaluated against the respective classification outcome. Results from the adult group provide argument for a channel subset of 6 channels, namely F_3,FC_5,P_7,P_8,FC_6 and F_4. Measuring from frontal and parietal regions of the brain, this may well be in line with frequently reported findings of affect processing toward visual stimuli. Projecting this theory onto the children, however, did not find supportive ground, mainly due to the reasons of likely signal contamination and class imbalances.

Research sub-questions:

> *What are the main constraints towards affect recognition in children when the implementation for adults was verifiable?*

Given the fact that the system performed well on both, data from an external database as well as real signals from adults, computational constraints and/or misselection of feature extraction and classification methods is less likely. However, when looking at the very acquisition of data, a number of important findings and observations from the experiments have been achieved which can be summarized as the following:

- A large number of trials (7 out of 14) needed to be rejected due to excessive artifact presence associated with inherent movement of the child although being reminded to omit. Signals are mostly disturbed by eye blinks for which the most affected channels (AF_3 and AF_4) have been removed from processing but other sources such as head movements and frowning remain. Besides, the number of artifacts frequency increased over the period of the experiment.
- Yet, no EEG databases for emotion recognition in child exist so that the verification of (sub-)systems is performed on adult data, thus altering the conditions to be met with children afterwards.
- Children have a very different emotional perception as indicated by the class bias but more obvious through the inter-subject comparison of SAM. Stimuli validation with children prior to the tests is therefore of paramount importance in order to guarantee that the participant at least recognizes the emotion to be evoked.
- Different environmental conditions may play a role with regard to attention, mood and comfort, possibly affecting the emotional state of mind. Laboratory conditions are preferred but usually not possible due to the agreement with teachers and or guardians.
- The number of "clean" trials obtained is integral for the performance of classification. This study concludes that 15 trials may in theory suffice but practically less feasible due to aforementioned signal contamination. Nevertheless, acquiring more trials is usually problematic because of the associated load for the subject or time available.

What added value and impact does the system indicate towards the use with children and/or autistic individuals?

Extending the research of emotion recognition from adults and typically developing children to the user group of autistic individuals may have various benefits as mentioned in Section 1. Although the system has yet to be successfully tested on the healthy control group with acceptable performances, it does fulfill many functional and non-functional requirements which can facilitate the progression of research to reach this level. As compared to other commercial EEG's, the Emotiv EPOC headset is wireless and needs substantially less preparation although achieving good electrode contact quality requires some training.

Chapter 8

Recommendations and Future Work

This chapter entails the lessons learned from investigation performed and outlines opportunities to be considered for future work in the field of emotion recognition with adults and children.

One of the most important lessons learned during the development and throughout conducted experiments is the importance of the constructed stimuli set along with the achieved signal quality and trial size. On the one hand, if the stimulus is too weak, it may be easily confused with other classes and the classifier effectively trains similar signal patterns for multiple classes, causing it to perform weak. On the other hand, even the trials with the most emotionally evocative images depend on the signal quality and number of total trials obtained. We therefore encourage pay close attention to the number of trails needed to avoid class imbalances, the validation of the stimuli set, preferably per individual subject and aim to reduce as much signal distortion during experiments as possible. To address the latter, a number of more advanced artifact removal techniques such as stochastic or deterministic algorithms can be used which have shown promissory results in literature [3, 82, 83].

Yet, by far not all feature extraction and classification methods suitable of dealing with non-stationary and nonlinear EEG signals have been considered or embraced. As a possible alternative, the analysis of time series through higher-order crossings as well as novel time-spectral signal analysis have a attracted recent attention for affect computing by showing good performance results [120, 121].

In approaching the question of how stronger emotions can be evoked for the analysis suitable processing methods, the author suggests to investigate in potential signal enhancements through the use of multiple modalities, e.g. the use EEG signals and auditory stimuli in association with emotion-annotated pictures.

Frequently throughout literature, the performance of a system is mostly expressed solely through the classification accuracy. However, as shown in Section 6, it is of great importance to evaluate the ground truth agreement of predicted classes, as performed by the coefficient kappa. Systems might perform well by reducing the number of complexity and thus presenting a high individual class agreement but less classes in general. Clearly this calls for an agreement of evaluation standards among the research community to make results more comparable. Similar concerns have been raised by [63] calling for a small shift in paradigms towards the evaluation and statistical discussion of EEG based emotion recognition.

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Appendices

Appendix A

Signal Processing Methods

A.1 Common Average Reference (CAR)

CAR has been proposed as a method for providing an inactive reference. The underlying principle of this spatial filter type is the mean calculation of all EEG channels and its subtraction from selected output channels:

$$CAR = (AF3 + F7 + F3 + ... + F4 + F8 + AF4)/14 \tag{A.1}$$

If the potential on the head is generated by point sources and electrodes are equally spaced over the subject's head, the CAR results in a spatial voltage distribution with a mean of zero [39]. Therefore, by averaging a set of similar or replicate measurements, the signal-to-noise-ratio (S/N) can be increased.

Several studies provided evidence for the potential of CAR to be used in EEG measurements for BCI applications by comparing different reference techniques on different datasets for both offline and online applications [40, 123]. Given the shown potential and the ease of implementation for EEG-based BCIs, CAR filtering is used as part of the signal pre-processing for this project.

The implementation of CAR filtering has been realized in Matlab and is applied upon the incoming data from the EEG channels.

A.2 Selected Feature Extraction Methods

This section contains principle information about the feature extraction algorithms used in this project. In order to find the best feature set for the classification of our problem, we selected methods from several domains for signal analysis, i.e. time-, frequency- and the combined time-frequency space.

A.2.1 Time Domain Analysis

Statistical Features of Time Series

For biomedical signals such as EEG, a number of typically measured statistics can be used to extract basic information about the signal as features for the translation algorithm. Amongst the most typically computed statistical features are means of raw and normalized signals, standard deviation and the means of the absolute values of the first and second differences of either raw or normalized data. For the project at hand, the latter mentioned means of differences of raw signals are computed as

$$F(n) = \frac{1}{N-1} \sum_{n=1}^{N-1} |X_{n+1} - X_n| \tag{A.2}$$

and

$$F(n) = \frac{1}{N-2} \sum_{n=1}^{N-2} |X_{n+2} - X_n| \tag{A.3}$$

, where: X_n represents the value of the n^{th} sample of the raw signal. Since all other feature extraction methods rely on frequency domain properties, we additionally introduce the aforementioned time features for sake of comparison and to combine features from these domains.

A.2.2 Spectral Analysis

Power Spectral Density

The Power Spectral Density is among the methods applied in characterizing brain activity patterns in EEG signals and has already been used in many researches to study emotion recognition [118, 89]. The underlying principle of spectral analysis is a theorem stating that any function in time is essentially a superposition of wave forms with different frequencies.

Let $A_{fi} \sin 2\pi f_i t + \theta_i$ be the sinus wave at time t with amplitude A_{fi}, frequency f_i and phase θ_i and so any function of time denoted by, for example, eeg(t) can be written as:

$$eeg(t) = \sum_{all frequencies f_i} A_{f_i} sin(2\pi f_i t + \theta), \tag{A.4}$$

when suitable coefficients for A_{fi} (amplitudes) and θ_i (phases) are chosen. The power spectrum can be computed as the square of the amplitudes A^2_{fi} as a function of the frequency f_i and is commonly used as a measure of how strongly a certain frequency f_i or typical frequency bands of interest (delta, theta, alpha, mu, beta and gamma) contributes to the signal. The term "typical" about these notorious bands because unique combinations of these bands are found to encode for cognitive states, behaviour, location on the brain, etc., as highlighted by Nunez and Srinivasan [125]. Spectral components of interest for the analysis were the complete alpha band (8–13Hz) as well as low beta wave components (13–15Hz). From this frequency spectrum the power spectral density was estimated through the transformation of the signal data points by means of Fourier Transformation.

A.2.3 Time-Spectral Analysis

Wavelet Power Spectrum

Although computing power spectral densities for EEG-based emotion recognition is a very popular method amongst the available feature extraction algorithms, it assumes stationary of the signal over time periods. However, given the nonstationary, dynamic behaviour of EEGs, this would constrain teh Fourier Transformation to extract salient features which may be valuable for affect recognition [91]. Other, non-parametric methods of feature extraction can account for signal non-stationaries as they are found in the joint time-frequency domain, such as Wavelet features. Rather than analyzing the signal data set as a whole, wavelets provide a measure for the local frequency analysis and thus providing information that is likely to be obscured by other alternative time-frequency methods like Fourier analysis. The wavelet power spectrum is computed through a so-called wavelet transform $\psi(t)$, which, as a function of time can be defined as

$$\psi(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a} \right), \tag{A.5}$$

where a denotes a scaling parameter for the frequency represented by the wavelet and b a shifting factor, i.e. the center point of the wavelet [151]. At arbitrary scales between sampling intervals containing the time series, we refer to the continuous wavelet transform (CWT) of a function of time, $f(t)$, expressed as:

$$W(f) = \int_{-\infty}^{\infty} f(t) \overline{\psi(f)}, \tag{A.6}$$

where factors a and b still determine scale and center of the wavelet [151]. Given the continuous wavelet transform, we are able to obtain the wavelet power spectrum by essentially squaring the CWT as $P_W = W(f)^2$.

In this study, we performed the full spectrogram over the frequency band 2-32Hz with a scaling factor of 1Hz and a "Morlet" wavelet function which characterizes the overall wavelet shape and covers the domain under study. Computations were carried out in Matlab with obtained wavelet analysis codes, freely available on the internet.

Appendix B

Classification methods

This section outlines some of the most popular classification methods used in BCI research as well as in this thesis, and is divided into four different categories: linear classifiers, neural networks, nearest neighbor classifiers and combinations of classifiers. Core principles as well as the most important properties and their BCI applications are mentioned.

B.1 Linear Classifiers

Linear classifiers, as being one of the most popular methods for BCI applications, use discriminant algorithms with linear functions to distinguish between two or multiple classes. Those most frequently used in EEG research with BCIs are Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). Depending on the statistics of the dataset, LDA or SVMs may be the preferred choice for classification between classes.

B.1.1 Linear Discriminant Analysis

Linear classifiers, as being one of the most popular methods for BCI applications, use discriminant algorithms with linear functions to distinguish between two or multiple classes. Those most frequently used in EEG research with BCIs are Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). Depending on the statistics of the dataset, LDA or SVMs may be the preferred choice for classification between classes [127, 44].

When dealing with two-class problems, the class of the feature vector will be associated with the class that the vector lying in, separated by the hyperplane B.1. LDA groups objects into mutually exclusive groups based on their features and defines a line to discriminate between two, a plane between three and a hyperplane between three and more classes.

The strategy to find the best separating (hyper-)plane is to seek for the maximum interclass difference between to data points of different classes and to minimize the interclass variance. Multiclass (N > 2) problems usually introduce more than one hyperplane which are determined in a "One Versus the Rest" (OVR) manner, i.e. separating individual classes from all others. Posing

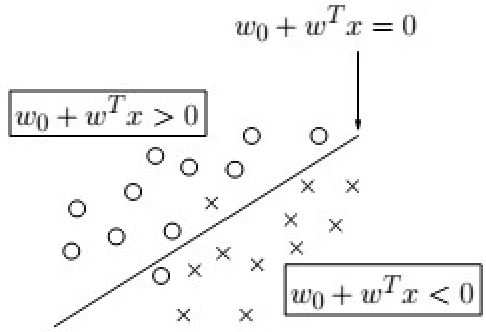

Figure B.1: A hyperplane which separates two classes: the "circles" and the "crosses" low computational demands and being easy to use, LDA has been successfully used for a range of BCI systems including P300 spellers, asynchronous or motor imagery based BCIs [44].

B.1.2 Support Vector Machines

Similar to LDA, an SVM also applies discriminate hyperlanes to detect periods. Distinguishable, however, is the attempt of the SVM to maximize margins from the closest data training points which function as the nearest preparation facts, as shown in Figure B.2.

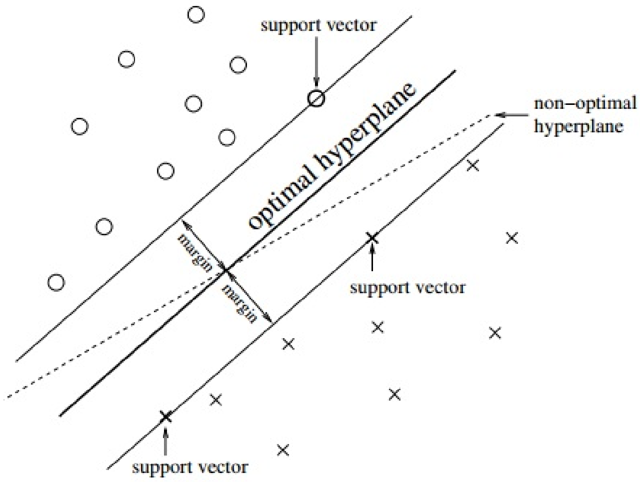

Figure B.2: SVM to find the optimal hyperplane for generalization.

An SVM classification using linear decision boundaries is referred to as a linear SVM. In a simple, binary class problem with separable data, the best hyperplane is found as the one with the largest margins between the two classes. Then, the *support vectors* are those data points that are closest to the separating hyperplane as indicated in the figure. From a mathematical perspective, following Hastie, Tibshirani and Friedman, the training data comprises a set of points (vectors) x_i for some dimension d, where $x_i \in R^d$ and their corresponding categories(or labels) y_i for which $y_i = \pm 1$ [154]. In finding the best hyperplane, we define the decision boundary as

$$w^T x + b = 0, \tag{B.1}$$

where $w \in x_i \in R^d$, and $w^T x$ is the inner dot product of w and x and b is a real number. Anything above the decision boundary should have label 1, i.e., x_i such that $w^T x$+b>0 will have the corresponding $y_i = 1$. Similarly, anything below the decision boundary should have a label -1, i.e., x_i such that $w^T x$+b<0 will have the corresponding class $y_i = -1$. For computational convenience, the problem is usually formulated as a dual quadratic programming problem which takes positive Langrange multipliers a_i multiplied by each constraint, and subtract them from the objective function to eventually arrive at its dual formulation:

$$L_D = \sum_i a_i - \frac{1}{2} \sum_{i,j} a_i a_j y_i y_j x_i \cdot x_j, \tag{B.2}$$

which assumes a stationary point the Lagrangian over w and b and setting the gradient to 0, hence

$$w = \sum_i a_i y_i x_i \tag{B.3}$$

$$0 = \sum_i a_i y_i. \tag{B.4}$$

To create non-linear decision boundaries, the "kernel trick" is often used which essentially maps the data to another, unknown space of generally higher dimensionality, using a kernel function $K(x, y)$ [154].

B.2 Neural Networks

Artificial Neural Networks (ANN) are, next to linear classifiers, one of the most frequently employed translation algorithms used in BCI research [44]. Neural Networks (NN), inspired by the functioning and construction of the human brain comprising of neural assemblies, attempt to learn relationship between input and output without any knowledge of the underlying model. In trying to mimic low-level functions of the human brain, neural networks can be described as suggested by Haykin [128], following the originally proposed definition by Aleksander and Morton (1990).

> "A neural network is a massively parallel, distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:
>
> 1. Knowledge is acquired by the network from its environment through learning process.
> 2. Inter-neuron connection strengths, known as synaptic weights are used to store the acquired knowledge."

In BCI research, the paradigm of neural networks has been successfully exploited for various tasks, including the determination of nonlinear decision boundaries and thus making it suitable for problems of higher complexity and multiclass approaches [113].

The method used in this thesis, namely that of a Multilayer Perceptron (MLP) is amongst existing NN designs the most versatilely applied and is described in the following.

B.2.1 MultiLayer Perceptron

Multilayer percpeptrons have been used in cases where no linear separability is possible, i.e. single perceptrons fail to find solutions to distinguish between classes. In general, MLP consist of input layer, one or more hidden layers to realize a hyperplane discriminant function and an output layer (Figure B.3).

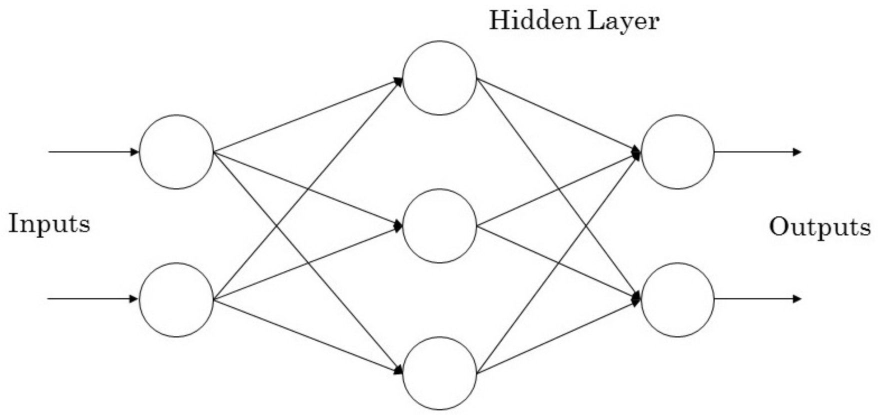

Figure B.3: A generalized Network. Input signals propagate through the middle (hidden) layer(s) to the output layer.

The training of such a network is usually accomplished by a highly popular algorithm known as the Back-Propagation Learning Algorithm. The underlying principle of this algorithm is to

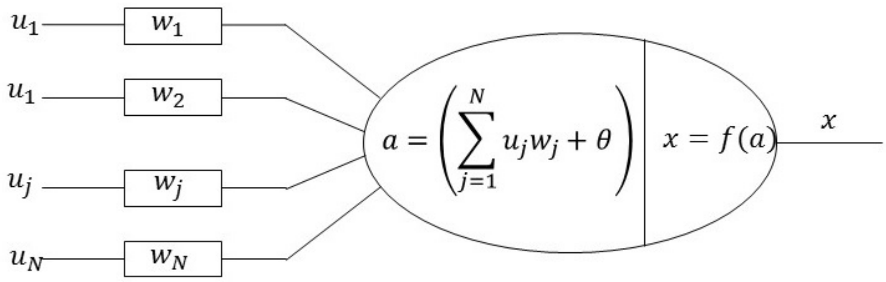

Figure B.4: An artificial neuron with N inputs, a weighting function and output(s).

perform error-correction by learning from examples and adjusting the weights between neurons that determine the final classification decision of the perceptron [113]. This algorithm can pass through the different layers in a forward or backward manner, depending whether initial weights shall remain fixed or be adjusted with respect to the output magnitude.

Given an artificial neuron as depicted in Figure B.4 with N inputs, denoted as u_1, u_2, ... u_N, we associate individual weights w_1, w_2, ... w_N, to arrive at an activation function given by the formula:

$$a = \sum_{j=1}^{N} u_j w_j + \theta \tag{B.5}$$

, where inputs and the weights are real values and θ represents the *threshold* in the artificial neuron, similar to the function of a synapse in the human brain. Negative a values correspond to inhibitory whereas positive values indicate excitatory connections. θ, when positive, is referred to as *bias* and moves the position of the decision boundary, i.e. the threshold for distinguishing classes. At its output, the neuron produces a function of its activation which, in biological neurons, is analogous to the firing frequency and can be expressed as:

$$x = f(a) \tag{B.6}$$

Sometimes it is useful to express the activation of a neuron in vector notation as

$$a = \mathbf{w}^T \mathbf{u} + \theta \tag{B.7}$$

, where the j^{th} element of the input vector $\mathbf{u}$ is u_j and the j^{th} element of the weight vector of w is w_j. The product $\mathbf{w}^T\mathbf{u}$ denotes the inner product of the vectors $\mathbf{w}$ and $\mathbf{u}$ and finally result in a scalar value to determine the threshold value together with the bias, if specified.

B.2.2 Learning Vector Quantization

Vector quantization is a form of competitive learning in neural networks. The goal to achieve is to "discover" the underlying data structure of the input by looking at how the data is clustered [141]. A supervised LVQ neural network consists of two layers: one competitive layer and one output layer, with neurons in the competitive layer being also referred to as subclasses. Every subclass is associated with weights similar to the input vector. Then, in a "winner-takes-it-all" manner, a subclass with the best match to an applied input vector will make the output inherit the class associated to that neuron. Neurons in the competitive layer may belong to the same class in the output layer but a individual neuron in the competitive layer only corresponds to a single class. A graphical representation of the concept is shown below in Figure B.5.

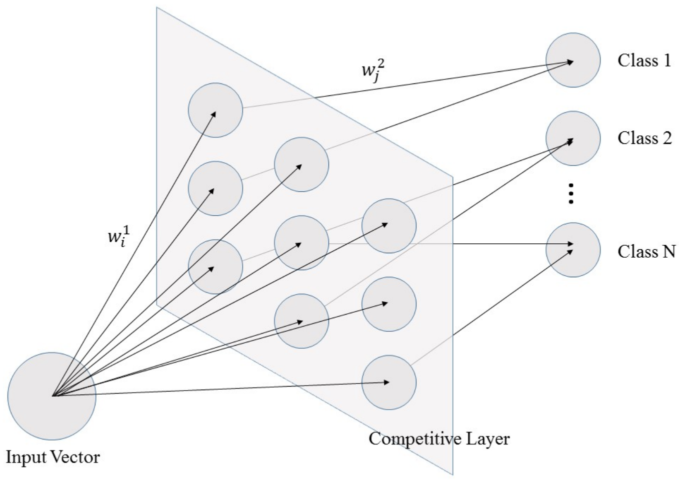

Figure B.5: Structure of a learning vectore quantization network.

B.3 Nearest Neighbor Classifiers

Nearest neighbor classifiers employ the simple idea of assigning a feature vector to a particular class according to its nearest vector(s) surrounding [44]. In case of the k-NN algorithm, class association for an unknown feature vector is determined by the nearest neighbors in the training set. k is a metric distance parameter and determines an encircled boundary to look for its nearest neighbor(s). k-NN, when k is chosen sufficiently high, it can approximate any function which is useful for the creation of nonlinear decision boundaries. To give an example for classification, whenever we have a new point to classify, we find its K nearest neighbors from the training data. Given a simple 2-class problem and $k = 5$ by having three instances of class C1 and two instances of C2, a new instance $\mathbf{x}$ would be labeled as C1, since it forms the majority of classes in the neighborhood as defined by the parameter k. A graphical illustration of the aforementioned example is shown below Figure B.6.

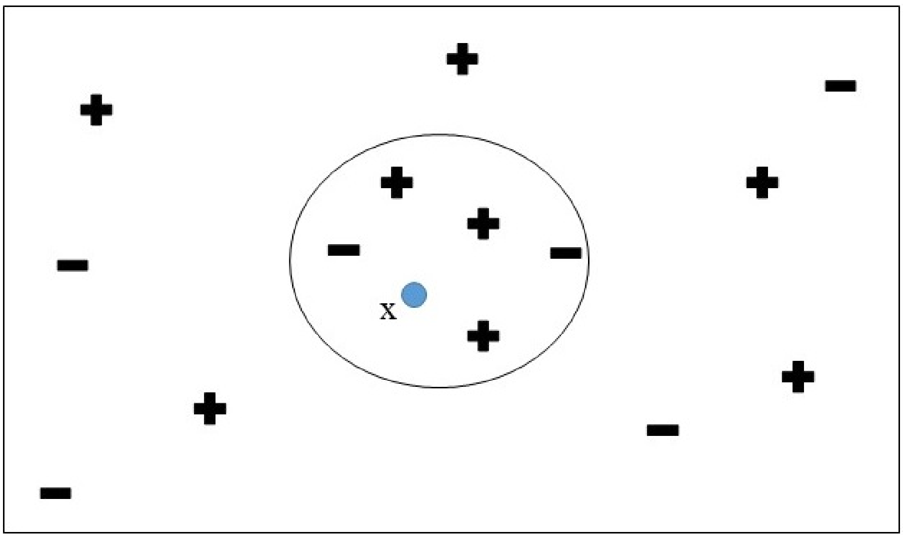

Figure B.6: If $k = 5$, then the new instance x will be classified negative because it is the majority of its nearest neighbors.

It is worth noting that kNN is a "supervised" classification method in that it uses all the class labels of the training data. Commonly, the classifier is based on the Euclidean distance between a test sample and a specific training sample but other measures such as Minkowski and Mahalanobis Distance exist [44].

B.4 State-of-the-art

The following table presents a state-of-the-art summary about recent investigations in the domain of emotion recognition via EEG-BCI. Data sets were tested based on various modalities, signal processing and classification methods. The performance accuracies for the investigated emotional states are mentioned along with the associated reference to the particular work. Note that this table has been adapted from [140] for which listed literature references correspond to. A copy of the work presenting this table can be requested on demand.
[1]

[1]Feature extraction and classification acronyms: Asymmetric12 (ASM12), Power Spectral Density(PSD), Support Vector Machine (SVM), Multilayer Perceptron (MLP), ANalysis Of VAriance (ANOVA), Sequential Forward Search (SFS), Sequential Backward Search (SBS), Principal Component Analysis (PCA), Fisher Discriminant (Fisher), Linear Discriminant Analysis (LDA), k-Nearest Neighbor (KNN), Statistical Features of Time Series (SFT), Wavelet Transform (WT), Higher Order Crossings (HOC), Quadratic Discriminant Analysis (QDA), Mahalanobis Distance (MD), Neural Networks (NN), Short Time Fourier Transform (STFT), Quadratic Discriminant Function (QDF), Fisher Discriminant Analysis (FDA), Sequential Floating Forward Search (SFFS), Fisher Projection (FP), Radial Basis Function (RBF), Fast Fourier Transform (FFT), Multiple BackPropagation (MBP)

	Protocol	Data Set	Pre-processing	Features	Classification	Accuracy	Ref.
Auditory		4 emotions	1-100 Hz band pass, 60 Hz notch, EOG	ASM12	SVM	92.73±2.09%	[142]
				PSD24	MLP	69.69%	
		4 emotions on valence/ arousal model	Low passed Normalized Artifact reduction (EMG)	ANOVA SFS SBS PCA Fisher	LDA kNN MLP	≈ 80% for all classifiers Up to 92% with feature reduction	[143]
	Pre-labelled emotional music	4 emotions	STFT, 50% hanning window	PSD ASM12	Multi-class SVM	Valence: 94.86 ± 1.76% Arousal: 94.43 ± 2.12% All: 90.52 ± 2.16%	[87]
Visual	Affective faces	5 emotions on valence/ arousal scale	Band-pass butterworth	SFT	QDA	62.3%	[120]
				WT	kNN	67.81%	
				HOC	SVM	83.33%	
					MD	<50%	
		4 emotions	Not mentioned	SFT	NN	individual features: 49.17%-85.00% Combination: 50.83% - 90.00%	[122]
	Affective pictures		Band-pass 4-45Hz, Laplacian reference signal	STFT ST	QDA	76.66%	[144]
	IAPS	2 emotions	Downsampling	PCA	Linear SVM	76.00%	[153]
					RBF SVM	80.0%	
		6 emotions	Not mentioned	None	MLP	Arousal: 96.58% Valence: 89.93%	[145]
	Guided imagery technique [146]	8 emotions	Normalization	Fisher PSD	DFA QDF	80% - 90% for different subsets	[147]
			Smoothing	SFFS SFFS-FP	DFA QDF	81.25% for all 8 emotions	[105]
Audio-visual	IAPS & IADS	4 emotions	Band-pass limited to α and β frequencies + PCA	(hybrid) Alpha/beta ratio band power	FDA	Modality: 82.1% Arousal: 92.3% Valence: 92.3%	[36]
		6 emotions	SL + Normalization	WT	kNN	79.14%	[148]
				SFT	LDA	74.52%	
	Induced by movie clips	6 emotions	Normalized for each emotion	None	kNN	71.6%	[97]
					DFA	74.3%	
					MBP	83.7%	
Multimodal	Multi modal	5 emotions	50 Hz low-pass filter	SFT	SVM	41.7% For 5	[149]
					NN	31.7% emotions	
					SVM	66.7% For 3	
					NN	63.9% emotions	
		4 emotions	Not mentioned	FFT, WT, PCA, SF	NN	67.7%	[150]

Table B.1: State of the art classification accuracy in offline emotion recognition BCIs.

Appendix C

Project Development Process

For the development of the project toward a suitable BCI implementation for emotion recognition, the V-model product-development process was used. This model is widely applied due to its simplicity and straightforwardness and has become a common standard in software development [129]. In this research, the V-model will be used as a measure of for design and test outcomes to be matched with originally specified targets and requirements as well as adding validation traceability to the development. The V-model structure for the current project has been developed as depicted in Figure C.1:

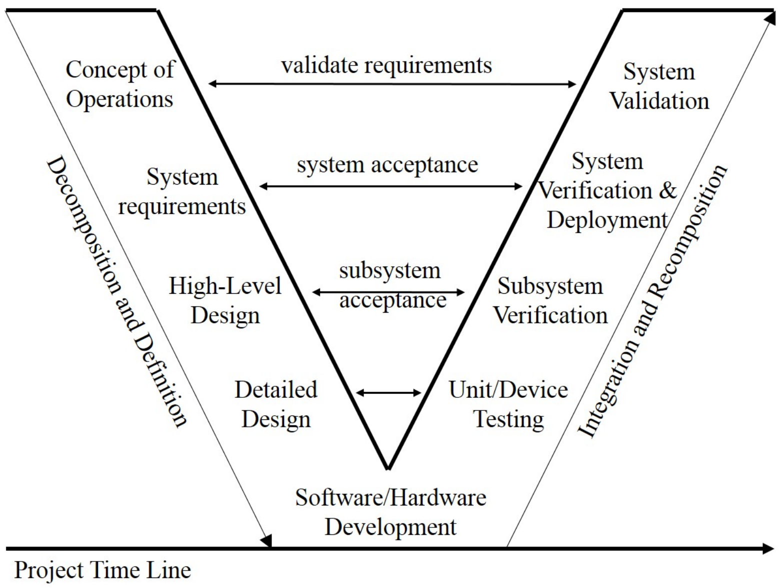

Figure C.1: V-model Project Development.

The left side of the model decomposes functional requirements and creates system specifications to be implemented in a preliminary hardware/software system design. At its notch, the system shall be in a prototypical stage upon which testing, verification and validation is performed in the right part of the V-model. Detected flaws or requirement mismatches have to be remedied by going back to the system or software design stage in order to improve the model or hardware/software setups. This loop has to be continued until the specified specifications are met.

C.1 Concept of Operations

For the development of functional and non-functional requirements, system capabilities need to be identified to be understood and agreed of all project stakeholders. Primary stakeholders include research members at UFES to jointly work towards the high-level project goal mentioned in 1 and the private, non-profit, special education service for autistic children named AMAES (Associação dos amigos dos autistas). In the latter case, new treatment options are sought by the association to be used in intervention programs and educational tools. Experiments to be conducted were agreed upon by the said association as well as by the Escola municipal de ensino fundamental experimental da UFES (EMEF-UFES), a public, municipal secondary school located at UFES.

Secondary stakeholders include funding partners, namely CNPQ (Conselho Nacional de Desenvolvimento Cientifico e Tecnológico) and CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior), expressing their natural interest to successfully complete the research investigation by the presentation of various findings along the set project timeline as well as end results. An overview of participating stakeholders including their needs and associated responsibilities is presented in Table C.1.

Primary Stakeholders	Needs	Responsibility
AMAES	Intervention tool for interaction for children with ASD	Provision of test candidates (ASD)
EMEF	Intervention tool for interaction for children with ASD	Provision of test candidates (TD)
Prof. Teodiano Bastos	Portable system for emotion recognition Robot for CRI with children in ASD spectrum	– Supervision – Guidance and expertize – Project Management
Javier Castillo	EEG acquisition protocol Test data for signal processing	– Device communication – System compatibility – Knowledge input: Signal extraction & classification – Guidance and Supervision
Christiane Goulart	Emotion recognition (3 emotions, high accuracy) Testbench (Interface)	– Research influence of modality – Experimental protocol
Secondary Stakeholders		
CNPq	presentation of findings	financial support
CAPES	presentation of findings	financial support

Table C.1: Stakeholder matrix

The core group to execute the concept of operations will compose of the research members listed above, each of who follows their own line of research in the collaboration. Nevertheless, for the validation of the system, a number of key performance measures had to be identified and agreed upon ensuring clarity amongst the core members. As in many of current BCI systems, two widely used performance measures, namely classification accuracy and Cohen's kappa k have been selected due to their broad comprehension in EEG-based BCI research and other fields. Moreover, a basic validation plan was created which includes testing iterations with adults prior to conducting experiments on the intended user groups of children. This is to prove that the system can be performed under static, controlled laboratory conditions and performs well.

Appendix D

Experiment

D.1 Visual Stimuli

The following table (Table D.1) describes the final construction set for the evocation of the three specified emotions: positive/excited (PE), negative/excited (NE) and calm (C). The table shows a small description per stimulus, its corresponding slide and valence, arousal and dominance score. Furthermore, the inclusion criteria defined in this project is displayed per emotion. Stimuli presented in Table D.2 have been proposed to induce strong emotions for adults and were used in the project to verify the recognizability of emotions through the concept developed. All pictures listed in Table D.1 were collected from IAPS [6], whereas those of Table D.2 were extracted from GAPED [8]. Note that IAPS uses a rating scale of 1–9 whereas GAPED measures its valence and arousal between 10 and 100.

	Description	Slide No.	Valence Mean	Arousal Mean	Dominance Mean
	Inclusion criteria		**>7.0**	**>5.0**	**>5.0**
PE	3 Puppies	1710	8.85	5.83	7.65
	Dolphins	1920	8.75	6.55	7.24
	B-day Cake	7250	7.99	5.5	7.11
	Popsicles	7390	8.15	5.56	7.25
	Circus Horse	8620	7.6	6.03	6.11
	Inclusion criteria		**<5.0**	**>5.0**	**≤5.0**
NE	Snake	1120	4.39	6.97	3.68
	Pit Bull	1300	4.11	7.33	3.56
	Masked Man	6370	3.93	6.21	3.78
	Roach/Pizza	7380	3.71	5.45	5.00
	Soldier	9421	3.4	5.44	3.05
	Inclusion criteria		**4.0–7.0**	**≤5.0**	**>4.0**
C	Ang. Woman	2130	4.23	4.56	4.86
	Girl Reading	2320	6.19	2.52	6.07
	Boy Screaming	2810	4.51	4.38	5.92
	Flowers	5020	6.41	2.71	6.55
	Book	7090	5.82	2.35	6.71

Table D.1: Valence, arousal and dominance means for selected pictures from IAPS.

D.1.1 Test sequence

The Figure below (D.1) shows routine of the interface to alternate between the emotional stimuli to be presented for 6 seconds and afterwards the SAM evaluation screen for as long as the user needs to evaluate his or her emotional state (usually around 4–8 seconds).

D.2 Information for Test Subjects

This section contains the information that participants have received prior and during the experiment. This document is a translated version in English from Brazilian Portuguese, since

	Description	Slide No.	Valence Mean	Arousal Mean
	Inclusion criteria		**>70.0**	**>10.0**
PE	Baby	P017	88.43	29.74
	Lake	P063	94.09	12.59
	White beach	P072	92.98	19.13
	Heather field	P107	85.22	26.68
	Panda bear	P122	92.90	22.85
	Inclusion criteria		**<50.0**	**>50.0**
NE	Killed lamb	A083	7.08	82.56
	Slaughtered cow	A100	1.72	82.48
	Emaciated child	H036	9.22	83.40
	Pilloried women	H063	5.67	81.86
	Emaciated kids	H077	0.78	91.29
	Inclusion criteria		**40.0–70.0**	**≤50.0**
C	Cupboard	N035	54.51	18.36
	Window sill	N039	49.43	17.89
	Tape	N045	53.57	14.80
	Lightbulb	N061	49.54	10.67
	Light	N091	53.99	12.07

Table D.2: Valence and arousal means for selected pictures from GAPED [8].

this is the mother language of all participants. The original version is available on request.

Protocol

Guiding the participant through experiment was performed as follows:

1. Introduction: "You will sit down in front of the computer and, through its screen, you will see some pictures. After each, paper-pencil dolls called 'manikins' will be shown. Using these manikins, say what you feel when you see the pictures."

2. Clarification of what stimuli presented: "The photos you see may make you feel joy, excitement, sadness, relaxed, fear, disgust ... Each child may have different feelings, because each one feels a thing. There is not a wrong answer, what you feel when you see the photo is the right answer."

3. Explanation SAM: There are 3 sets of manikins which demonstrate:

   (a) the state of unhappiness to the happiness;

   (b) the state of calm to excitement;

   (c) the state of control or comfort to the state without control or uncomfortable."

   "After seeing the photo, you mark the manikin's face of joy, if you felt happy, glad, joyful, good, hopefully. If you do not feel happy or sad, mark the manikin's neutral face, which is neither smiling nor sad.

   When you see a picture and if you feel calm, relaxed or sleepy, you mark manikin with closed eyes. Already manikin that demonstrates be wide awake and excited, you mark it if you feel very lively, active, wide awake, agitated.

   Here, it is noticed that manikins are small and they grows up and becomes bigger and bigger. When you see the picture and feel bullied, without control, uncomfortable, trying to escape the situation, feeling yourself as a little person, feel you need someone to help you or protect you, you mark the little doll. If you feel big, safe and comfortable, when you feel you do not need the help of anyone or company, you mark the largest doll.

   You can mark the dots between manikins if you felt something between them."

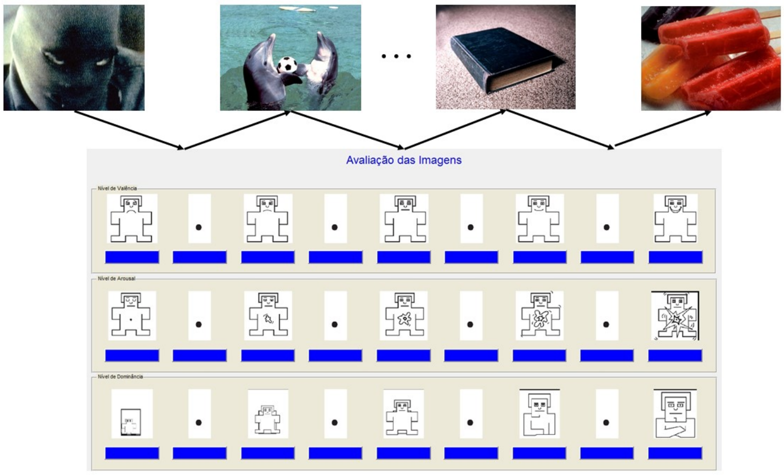

Figure D.1: Test sequence with SAM evaluation.

4. Practicing before the test: "Let's see some photos in the paper and you'll say what you feel, marking the manikins".

5. Questions before test: "If you have any remaining questions, please ask me now."

D.3 Letter of Consent

This is shown as proof to be conform with the Resolution 196/96 of the Health National Council and its complementary norms

TERMO DE CONSENTIMENTO LIVRE E ESCLARECIDO

NOME DO PACIENTE:
DATA DE NASCIMENTO:
RESPONSÁVEL:
ENDEREÇO:
TELEFONE:

Eu, ____
portador(a) do registro e identidade número__________________________, responsável pelo paciente____,
declaro que li e concordo com as afirmações abaixo relacionadas:

1. Título da Pesquisa: Detecção e Caracterização de Estados Emocionais por EEG em Crianças com e sem Autismo e Interação com Robô Móvel.

2. Pesquisadores Responsáveis*:* Dr. Teodiano Freire Bastos Filho e Christiane Mara Goulart.

3. A pesquisa consiste na aquisição de sinais eletroencefalográficos (impulsos elétricos gerados no córtex cerebral) e exposição de fotografias validadas internacionalmente, as quais desencadeiam estados emocionais.

4. A pesquisa será realizada com os sinais captados do córtex cerebral, através de equipamento comercial de eletroencefalograma.

5. A pesquisa não envolve riscos, pois o exame realizado não requer sedação ou anestesia, bem como não envolve qualquer procedimento invasivo.

6. Terei direito a desistir de participar da pesquisa a qualquer momento sem que isto traga prejuízos a mim ou à pessoa sob a minha responsabilidade.

7. Terei direito a todas as informações pertinentes à pesquisa, mesmo que isto comprometa a minha participação na mesma.

8. Autorizo a divulgação e publicação dos resultados dos exames exclusivamente para fins acadêmicos e científicos.

Confirmo que li e entendi todas as instruções que me foram repassadas pelos coordenadores desta pesquisa e, portanto, dou meu consentimento livre e esclarecido para participar da mesma.

Vitória, ____ de _____________ de 2014.

____
Paciente ou Responsável

____
Pesquisador Responsável

Figure D.2: Letter of consent template for participation approval.

Appendix E

Experimental Results

This chapter provides the various experimental results as referred to in the body of the thesis.

E.1 Verification Results IAPS

The following Table E.1 contains the data achieved for all the feature extraction methods and all classifiers to detect three emotional states. The highest result is highlighted and achieved by a combination of features (PSD+SFT). The data has been obtained from two healthy, adult subjects according by the use of the experimental protocol presented in Section 5.3.2.

Features	# elements	**MLP**		**SVM**		**LVQ**		**LDA**		**KNN**	
		Acc.[%]	k	Acc.[%]	k	Acc.[%]	k	Acc.[%]	k	Acc.[%]	k
SFT	96	31.67	-0.02	31.67	0.06	40.0	0.18	36.33	0.09	33.67	0.05
PSD	48	33.67	0.03	34.00	0.07	28.67	0.05	39.33	0.11	25.33	-0.06
WPS	372	24.67	-0.05	21.67	-0.01	26.67	-0.01	25.67	0.00	24.67	-0.05
SFT+PSD	144	33.00	0.00	35.67	0.11	41.67	0.22	**44.67**	**0.19**	40.33	0.11

Table E.1: Overall (C_{12}) classification result on IAPS stimuli for adult subjects.

E.2 Verification Results GAPED

Results on the alternative database GAPED and two users. The shown results are based on the classification result using a 12-channel (C_{12}) electrode configuration, excluding electrodes AF_3 and AF_4 from the original 14 channel set.

Features	# elements	MLP Acc.[%]	MLP k	SVM Acc.[%]	SVM k	LVQ Acc.[%]	LVQ k	LDA Acc.[%]	LDA k	KNN Acc.[%]	KNN k
SFT	96	39.00	0.04	42.00	0.04	52.33	0.13	34.33	-0.07	**53.00**	**0.15**
PSD	48	30.33	-0.05	42.67	-0.08	40.33	-0.04	50.00	0.10	46.00	0.03
WPS	372	28.00	-0.05	39.33	-0.19	49.33	-0.01	34.67	-0.21	49.33	0.04
SFT+PSD	144	41.00	0.03	44.33	-0.02	42.00	-0.05	42.67	-0.01	41.33	-0.07

Table E.2: Overall (C_{12}) classification result on GAPED stimuli for adult subjects.

Table E.3 exhibits all outcomes from adults and the individual channel configurations, introduced in Section 5.4.1. Classification was performed based on SFT/PSD features and WPS. The highest result is highlighted in the table.

Features	Electrodes	SVM Acc.[%]	SVM k	MLP Acc.[%]	MLP k	KNN Acc.[%]	KNN k	LVQ Acc.[%]	LVQ k	LDA Acc.[%]	LDA k
[SFT PSD]	Ctot	44.33	-0.02	41.00	0.03	41.33	-0.07	42.00	-0.05	42.67	-0.01
	CR	39.67	-0.09	40.00	0.01	43.67	0.02	41.00	0.05	33.33	-0.12
	CL	57.00	0.21	55.33	0.23	57.00	0.19	57.67	0.24	58.67	0.23
	C8	46.67	-0.02	43.33	0.04	50.67	0.00	42.33	-0.03	43.67	-0.02
	C6	**66.00**	**0.33**	50.00	0.13	60.00	0.25	55.00	0.21	**64.67**	**0.31**
	C4	46.33	-0.01	40.00	0.02	46.67	0.01	49.33	0.07	42.00	-0.07
	CF	34.67	-0.19	37.00	-0.06	20.00	-0.31	38.33	-0.06	35.00	-0.10
	CO	46.33	-0.04	45.00	-0.02	47.33	0.04	52.00	0.06	55.33	0.15
	CT	58.67	0.21	52.33	0.05	56.33	0.28	50.67	0.15	51.67	0.08
WPS	Ctot	49.33	0.01	36.33	0.03	50.00	0.07	46.00	0.03	47.33	-0.01
	CR	48.67	0.07	26.67	0.01	53.67	0.21	46.33	0.11	50.33	0.10
	CL	54.33	0.12	30.33	-0.01	40.67	-0.01	51.67	0.14	55.00	0.18
	C8	62.33	0.24	28.33	0.00	55.00	0.22	56.00	0.19	68.00	0.42
	C6	**73.33**	**0.48**	36.67	0.10	54.67	0.20	52.00	0.18	**75.00**	**0.56**
	C4	54.00	0.16	35.67	0.14	48.00	0.17	55.67	0.26	56.67	0.27
	CF	70.67	0.40	39.33	0.09	62.67	0.26	64.00	0.30	58.67	0.21
	CO	60.33	0.24	47.67	0.12	60.00	0.25	57.33	0.20	47.00	0.07
	CT	45.67	-0.03	42.67	0.02	50.00	0.03	41.00	-0.03	41.67	-0.10

Table E.3: GAPED stimuli classification result of all electrode configurations for adult subjects for PSD/SFT and WPS features.

E.3 Classification Results IAPS with children

The following Table E.4, shows the average classification results of children based on the IAPS stimuli and the concatenated SFT/PSD features as well as features from the wavelet spectrogram. The highest classification result is highlighted.

Features	Electrodes	SVM Acc.[%]	SVM k	MLP Acc.[%]	MLP k	KNN Acc.[%]	KNN k	LVQ Acc.[%]	LVQ k	LDA Acc.[%]	LDA k
[SFT + PSD]	Ctot	40.48	0.04	39.71	0.04	41.52	0.07	35.05	-0.06	40.95	0.05
	CR	42.76	0.07	43.33	0.07	**50.38**	**0.17**	47.33	0.12	41.05	0.06
	CL	44.10	0.09	39.71	0.05	45.52	0.11	47.14	0.17	40.48	0.07
	C8	42.10	0.06	37.52	0.00	46.95	0.09	39.14	0.04	37.90	0.00
	C6	34.76	-0.02	37.81	0.01	33.90	-0.03	39.71	0.04	37.05	0.03
	C4	38.00	0.01	40.48	0.04	43.71	0.09	41.52	0.08	34.76	-0.02
	CF	34.48	-0.08	35.24	-0.03	35.14	-0.04	35.81	-0.03	34.00	-0.08
	CO	31.14	-0.07	35.90	-0.04	30.29	-0.10	32.29	-0.04	30.76	-0.08
	CT	35.71	0.00	38.00	0.01	41.43	0.06	34.00	0.00	41.90	0.07
WPS	Ctot	42.29	0.06	39.05	0.03	38.86	0.01	45.24	0.09	43.71	0.05
	CR	41.52	0.07	39.24	0.04	38.10	0.01	40.38	0.02	39.71	0.03
	CL	37.24	-0.02	38.67	0.05	40.95	0.08	42.48	0.04	37.81	0.00
	C8	36.00	-0.03	37.81	0.03	35.14	-0.03	37.52	-0.03	34.10	-0.05
	C6	37.62	0.02	37.43	0.01	36.76	0.02	34.38	-0.01	38.48	0.01
	C4	42.29	0.05	36.76	0.00	**45.81**	**0.11**	34.48	-0.04	45.05	0.09
	CF	39.33	0.02	36.00	0.02	32.10	-0.08	36.95	0.00	37.81	-0.02
	CO	42.57	0.06	38.29	0.03	39.71	0.05	40.95	0.06	37.14	-0.02
	CT	36.29	-0.01	31.24	-0.04	24.76	-0.17	28.57	-0.05	34.38	-0.03

Table E.4: IAPS stimuli classification result of all electrode configurations for child subjects for PSD/SFT and WPS features.