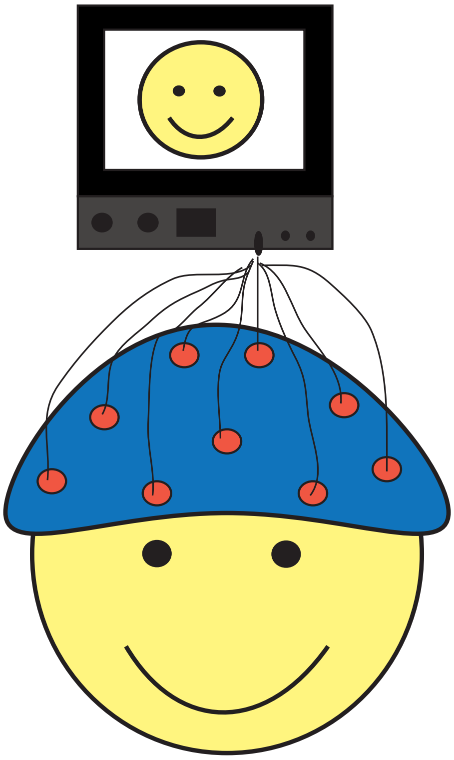
University of Twente
Faculty of Electrical Engineering Mathematics and Computer Science
Department of Human Media Interaction

Master of Science Thesis

Facial expressions in EEG/EMG recordings.



by

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Abstract

With focus on natural intuitive interaction of humans with their media, new ways of interacting are being studied. Brain computer interface (BCI), originally focussed on people with disabilities, is a relative new field for providing natural interactivity between a user and a computer. Using scalp EEG caps, healthy consumers can potentially use BCI applications for daily entertaining purposes, for example gaming.

Using facial expressions on the other hand is one of the most natural ways of non verbal communication. At the moment, there are several different techniques for a computer to read facial expressions. EEG recording is one of them that is hardly or not at all studied at the present, but would make an interesting addition for commercial BCI devices.

Because actual consumers are believed to be only interested in how well a device works, rather than how it works, it was decided to also look at EMG signals visible in recordings done with an EEG recording device. Thus the topic of this research is *facial expressions in recordings from a scalp EEG device*, rather than facial expressions in BCI. It was expected that EMG signals, visible in recorded EEG data, are bigger than the EEG signals them self.

The goals of this study were to gather EEG and EMG data, recorded with an EEG device, of voluntary facial expressions, and to analyze it. The hypothesis tested in this study was: *facial expression can be classified with an accuracy over 70% in an EEG recording*. Sub-hypotheses defined were: *EMG influence on the classification accuracy is significant larger that EEG influence*, *frontal electrodes will not yield significantly lower classification accuracies compared to using all 32 electrodes* and *using facial expressions with partially overlapping muscles will yield significantly lower classification accuracies.*

To gather the data, an experiment was carried out with 10 healthy subjects, who had to perform 4 different facial expressions, while data was recorded from 32 EEG electrodes and 8 EMG electrodes. Each subject was to sit through 8 blocks of 40 trials per block, with ten trials per expression. During a trial, subjects were shown a stimulus of one of the four expressions for 1 second. 1 second after the

disappearing of the stimulus, a new stimulus instructed them to perform that expression.

The recorded data was first analyzed by studying plots of the data in the temporal and spectral domain. Classification accuracies were then calculated for different preprocessing settings and compared. Calculation of the accuracies in component space was done using the CSP algorithm.

Results show that classification accuracies of four different facial expressions with the data recorded by the 32 EEG electrodes is significantly higher than 70%. Hemispherical asymmetry in the data was observed, varying per subject, making it necessary to use sensors on both sides of the head. Optimal frequency bands differed per subject, but all were observed to be above 20 Hz and all were smaller than 35 Hz on average. Combining the data of the EEG channels with the EMG channels, did not show significant higher classification accuracy compared to classification for only the EMG channels. This indicates that EEG channels are not useful in addition to EMG channels. The us of only frontal channels could not be shown to have a significantly lower classification accuracy in comparison to using all 32 channels. This is a contradiction of the results from the research of Chin et al. [11]. Expressions using overlapping muscles were observed to cause significantly lower classification accuracy.

It is shown that EEG caps can classify facial expressions, but that there is still much work to be done. Future studies can concentrate on improving the classification accuracies, adding more facial expressions and extend research to real life experiments. Or the can try to remove the EMG influence and concentrate on classifying facial expressions using purely brain signals, with possibilities for imaginary facial expressions.

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Chapter 1

Introduction

Human Media Interaction (HMI) is always looking for new ways for humans to interact with computers. With a future ahead that is likely to surround us with computers in all our daily routines, it is important that people can interact with them easily, without having to learn too much complicated controls for each and every single device they have to command. One of the goals of HMI is to make the interaction with computer devices more natural and intuitive. Speech and gesture commands are examples of natural interaction already used between humans and computers, mimicking the way humans would also interact with other humans.

Communicating by using our brains might not look as natural as speech and gestures, we do not communicate to anyone or anything with our brains after all. But our brain are used in every form of communicating and people are capable thinking about actions without actually performing them. Brain Computer Interface (BCI) is the field within HMI that studies communication by using your brain. 'Using your brain' could be anything from actively thinking about moving a body part to unconscious brain activity.

In the past, BCI research used to concentrate only at people with a disability and will most likely continue to focus mostly on that group [20]. The use of brain signals seems especially promising for paralyzed people or people with a prosthesis [47, 29]. But it can also help blind people [13], mute people [19] and people with other disabilities. Brain signals can command computers (or vice versa) both in and outside patients bodies and in that way improve their quality of life.

Lately however, BCI research also extends to the entertainment industry. While BCI research can help people with a disability through interaction of the brain and a device, it can also help to improve interaction of healthy people with a computer. Commands could be given with just a thought, and natural automatic responses could be read from the brain to make interaction better and more natural. With commercial 'brain signal reading' devices coming to the consumer market, the number of BCI researches with healthy subjects are also growing. While the commercial products are mainly concentrating on 'gaming with your brains' at this moment [20], there are also other useful applications being researched for healthy customers (e.g. [32]).

This thesis will focus on BCI for healthy people. But while the study will use methods and techniques from the field of BCI, it is not purely a BCI project. Where BCI research only focuses on signals from the brain, this study will also focus on signals from facial muscles (more on this in Section 1.2.4).

1.1 Motivation

The University of Twente takes part in the Dutch research consortium BrainGain, an initiative to support applied research on BCI, and concentrates on the subproject 'BCI research for healthy users', with games as the main focus. An example of research done is BrainBasher, a project which resulted in a game that can be used to collect BCI data from users playing it. This makes experiment more interesting for users and easier for researchers to acquire more data from them [4].

Interesting for the BCI field concerning games, but presently hardly researched in this field, are facial expressions. Facial expressions play an important part in natural interaction [6, 37, 23] and are known to convey emotional states [15]. With computer gaming becoming more and more interactive, and players interacting more and more with other players online, facial expressions could help to improve natural and emotional communication between players, and player and computer. Facial expression could also just provide an extra easy to use modality for users.

There are several known techniques for reading facial expressions digitally. Use of cameras (2D or 3D), motion capture and electromyography (EMG) sensors have all been evaluated in the past. Drawbacks of most methods for consumer market include annoyance of facial attachments and limited freedom in head movements and expressions. Consumer products also require very high recognition rates, and affordable hard and software before they will be used effectively in commercial products.

Using BCI techniques is an alternative way of recognize facial expressions, but also a relatively unknown technique in this area. However, due to upcoming releases of commercial hardware, providing end-users affordable BCI hardware, research focussed on recognizing facial expression using BCI gets relevant for the entertainment market. Facial expressions recognition can potentially easily be added to commercial BCI software, giving extra control possibilities to the game developers. Using BCI for facial expression recognition is also interesting when the underlying emotions are playing a role too, as additional emotional information can be read from the brain [34, 3].

So while there is plenty potential use for the recognition of facial expressions using BCI, there are still hardly any results accessible that evaluate this technique. This study will look into the potential of electroencephalogram (EEG) recordings for recognizing facial expression. As EEG recordings also contain EMG signals, which will be studied as well, instead of disregarding them as noise. Meaning that the study does not focus on just brain signals (BCI), but rather on EEG and EMG signals observed in an EEG recording.

1.2 Brain Computer Interface

BCI is the field of communication between the brain and a computer (external device). Communication can go both ways: From a computer to the brain (like in the vision restoring example [13]) or from the brain to the computer (like in the prosthetic example [29]). All existing applications used so far, use only one direction (1-way BCI), though an application could potentially use both directions at the same time (2-way BCI). Further writings will only consider 1-way brain-to-computer BCI communication, which is the focus of the described study.

Brain signals are produced by neural activity in the brain, which is involved in every single process in the brain. There are different type of brain signals a BCI could use. Brain waves with specific frequency bands for example, like alpha, mu or beta waves, caused by spontaneous activity, could be used to consciously control a computer (e.g. Brainball [22], BrainBasher [4]). Another example are event related potentials (ERP). ERPs are signals from activity evoked by specific events, and arise purely in response of stimuli. ERPs can be useful in a BCI for conscious and unconscious control of a computer (e.g. P300 steering [41], error recognition [9]). Brain waves can be observed up to about 100Hz (gamma waves), but signals usable with surface EEG lie in the 1 - 30 Hz bandwidth.

To use a BCI, the most important thing is to know the source of the signals. For some BCI, the source need not to be that exact, because the signal can be found in larger area's of the brain (e.g. alpha waves). For other purposes the source of the signal is precise so the BCI can interpret it. Activity associated with movement of limbs for example, can be measured in the motor cortex. As Figure 1.1 shows, specific area's of the motor cortex correspond to specific part of the body [40]. Signals originating from activity from such an area can tell if the corresponding body part was moved or not, or even if the subject thought about moving it.

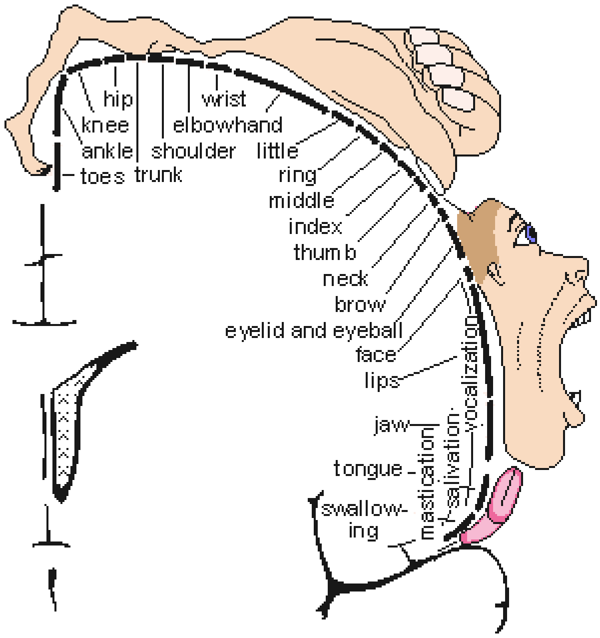


Figure 1.1: The division of the motor functions in the cerebral cortex of one brain half (the other half has the same distribution for the other side of the body). Image taken from Penfield and Rasmussen, 1950

1.2.1 Implementation of BCI

There are three ways to implement a BCI: Invasive, partially invasive and non-invasive. Invasive and partially invasive BCI produce good quality brain signals, but need surgery to implement the equipment. Healthy people would rather not care for a (potentially dangerous and costly) surgery to use an interface to their computer. This makes non-invasive BCI the most likely option for commercial BCI products targeting healthy consumers. The limited signal quality of non-invasive BCI is still good enough for multidimensional control [46] and the technique can be relatively cheap. In the rest of this thesis non-invasive BCI will be implied when mentioning BCI.

There are several non-invasive BCI techniques used for BCI applications: functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) and electroencephalography (EEG). While EEG has the worst spatial resolution of all, it has a good temporal resolution and is by far the easiest and cheapest way of measuring brain signals. Which makes it the most popular choice for research of healthy people, and the only sensible choice for the consumer market at the moment.

1.2.2 Electroencephalography

An EEG BCI measures electrical potential differences, associated with activity of the neurons in the brain. With non-invasive EEG, these small potentials (in the range of microvolts) are measured with several electrodes directly on the scalp and amplified. Each electrode measures the summation of the synchronous activity of thousands of neurons with the same spatial orientation (radiant to the skull). This way the source of signals can be determined. Currents from deep sources are less easy to measure than currents close to the skull, making EEG especially useful for measurements in the area's close to the skull.

EEG is presumably the most studied non-invasive technique due to the high temporal resolution, low costs, ease of use and portability. These advantages are also what makes EEG interesting for the consumer market. The most important drawbacks of EEG are the bad spatial resolution and susceptibility to noise.

1.2.3 EEG processing

Raw EEG recordings don't directly reveal much usable information for BCI when looking at them without processing. A montage (the resulting EEG channels of the electrodes, generated by a differential amplifier) shows many different brain signals with different sources mixed together. Often noise from non brain signals, like facial EMG and electrooculography (EOG) show up more clearly in the recordings than the brain signals.

Figure 1.2 shows a typical EEG montage of a frontal channel (FP1). The area marked with a circle shows a clear potential increase, but originated from an eye blink and not from an actual brain signal. Signals not originating from the brain are considered artifacts by most BCI researchers, though they contain useful information looking at it from a HMI point of view. By processing the data, unwanted artifacts can be erased or ignored and points of interest can be accentuated. Low frequency noise for example, can be avoided by using a high pass filter (allowing only data belonging to frequencies higher than the given value), while averaging the data over all trials of the same class can reveal ERP signals. Section 2.3 will discuss the processing techniques used this study.

For a deeper introduction to BCI, Kübler and Müller (2007) can be recommended [28]. For more reading about BCI signal processing, Dornhege et al. (2007) is recommended [14] and for a deeper reading into EEG, Niedermeyer and Lopes da Silva (2004) [35].

1.2.4 Pure brain-signals or 'contaminated' EEG recordings

As mentioned before, signals that are not originated from the brain, are seen as unwanted artifacts in the field of BCI. Some of these artifacts are external sources, such as power cables or moving electrodes. Other artifacts originate

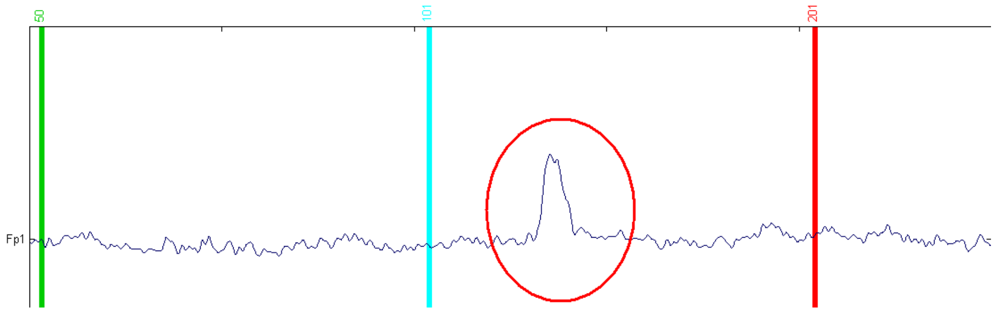


Figure 1.2: Sample of an EEG montage of channel FP1 showing an EEG signal contaminated with an eye blink artifact (marked with a circle). Sample was randomly taken from the experiment described in chapter 2 and was bandpass filtered for 0.3 - 30 Hz.

from other sources from the body, like facial muscles (EMG), eye movements (EOG) and heartbeat. This last category of artifacts is, unwanted as they are for BCI, actually pretty useful. Because of their relatively high amplitudes in the recordings, these artifacts can be used to help improve classifications on EEG recordings or even be the base of classifications done on EEG data. This is especially interesting for people who are not interested in pure brain signals, but rather in getting good performances, like the commercial oriented entertainment industry.

This thesis will not go in the dilemma whether it can still be considered BCI if 'artifacts' are used instead of only brain signals. Rather it is declared that EMG generated signals will be expected and allowed to play an important role in the classification of facial expressions in the data, recorded with and EEG device.

1.3 Facial expressions

Facial expressions occur from motions or positions of facial muscles and are known for some time to communicate emotions [12, 23]. Because most facial expressions are involuntary (though they can be learned) they often reveal how people feel. Facial expressions also form an important part of non-verbal communication between humans [33, 6]. Darwin concluded that facial expressions are the same for everyone, regardless of cultural differences. Thus that they are not learned, but rather of biological origin. A conclusion that is largely shared by researchers in the present [12, 23, 39].

There are many different facial expressions, some convey basic emotions (the term 'basic emotions' is actually undefined and argued about. Ekman even describes all emotions as basic [38]) like a smile, while other facial expressions are purely used for non-verbal communication (e.g. a wink) or are simply the result of an action (e.g. a yawn).

1.3.1 Facial Action Coding System

To describe and classify facial expressions, Ekman and Friesen developed a Facial Action Coding System (FACS) [16]. FACS can be used to describe (or code) any possible facial expressions and exist of Action Units (AU) that represent the smallest action segments in the building of a facial expression. AU are independent of interpretation and consist of actions that can not be described by smaller actions (though an AU can exist of multiple different muscles). FACS can describe (or code) a facial expression without the mentioning of emotion, making it ideal for research of facial expressions, as facial expressions based on described emotions can be more ambiguously interpreted by users. An overview of FACS can be found in Appendix G.

1.3.2 Facial expression recognition

There are multiple techniques for recognizing facial expressions. Image processing is a popular one and with very low costs, easy to use and feasible recognition rates, it can also easily be used for entertainment purposes [36, 7, 30].

Motion capture techniques allow for a good translation of facial movement to a computer and have a reasonably well recognition rate of facial expressions [8].

Facial electromyography (fEMG) records the electrical potential from the facial muscles, much like EEG, and has really good accuracy rates for facial expression recognition [1].

1.3.3 BCI and facial expression recognition

Recognizing voluntary facial expressions with the use of typical EEG equipment (head cap/band) can be done by either analyzing the EEG or EMG data recorded with it. For either way, hardly any literature was found at the start of the study. Most researches on the topic focussed on perception of facial expressions rather than on the production [26]. A reason for this could be the artifact problems common in EEG data accompanying facial expressions while consciously using the EMG in such data was not considered BCI and therefore undesired.

Korb et al. report a neural correlation between the motor preparation and early execution of voluntary 'fake' smiles. A late Bereitschaftspotential (BP) was found, similar to a BP preceding a finger movement. They reported differences however of the BP from the smile in comparison with the finger movement, such as a later onset, lower amplitude and a specific topography [27]. Korb et al. further look into the difference between spontaneous emotional facial expressions and voluntarily posed expressions in brain activations. The most consistent theory they find of such difference, is that the primary motor cortex (M1) is not necessary activated for emotional facial expression [26]. They also predict a more important role for cortical motor areas for separating spontaneous emotional facial expression activations from voluntary facial expression activations, as supported by Wild et al. [45].

Quite similar to the study in this thesis, Chin et al. published findings of a first study to classify 6 different facial expressions from combined EEG and EMG signals recorded by an 34 electrode head cap [11]. Surprisingly, they report a significant performance decrease when using only 6 frontal electrodes against all 34 electrodes. They suggest that signals from the premotor cortex and motor cortex are relevant in this, supported by [10, 24, 31], but alternative reasons are not discussed nor discarded.

1.3.4 Electromyogram

EMG signals are electrical potentials originating from muscle cells, measured over time. Like with EEG, they can be measured by electrodes, directly in the muscle or on the skin surface over the muscle. The latter method, surface EMG, will be referred to when mentioning EMG from here on. EMG recordings are done with electrode-pairs placed closed together on the target muscle to record the difference in electrical potential.

1.3.5 Facial electromyogram

Facial muscles are skeletal muscles, a striated type of muscle, and contract as a result of action potentials in the cellular base of a muscle. They are divided in motor units and generate action potentials after the motor units fires. The sum of these potentials in 1 motor unit, is called a motor unit action potential (MUAP). Since the cells of 1 motor unit are often distributed trough a larger part of the muscle, as opposed to concentration at one point, the firing of a motor unit and following MUAP can be observed as a wave from surface electrodes [44].

EMG montages are processed in the same manner as EEG montages. Fridlund and Cacioppo offer a good further reading for EMG research [18].

Figure 1.3 shows an overview of the different facial muscles. Using FACS, target muscles for facial expressions can be determined. To limit influence from motor units from non-target muscles, EMG placement needs to be done carefully. The EMG electrode placement guidelines from Fridlund and Cacioppo are still widely used for EMG research [18]. Figure 1.4 shows the suggested placement of facial EMG sensors.

Hayes shows that most primary energy in the surface EMG signal lies between 10 and 200 Hz [21]. Between 10 and 30 Hz this power is mainly due to the firing rates of the motor units, while at higher frequencies the shape of the MUAPs play a bigger role [18]. Van Boxtel suggest a high-pass filter frequency of 15-25 Hz (depending on the muscle) for facial EMG to get rid of low-frequency contamination without losing too much useful EMG signal [5].

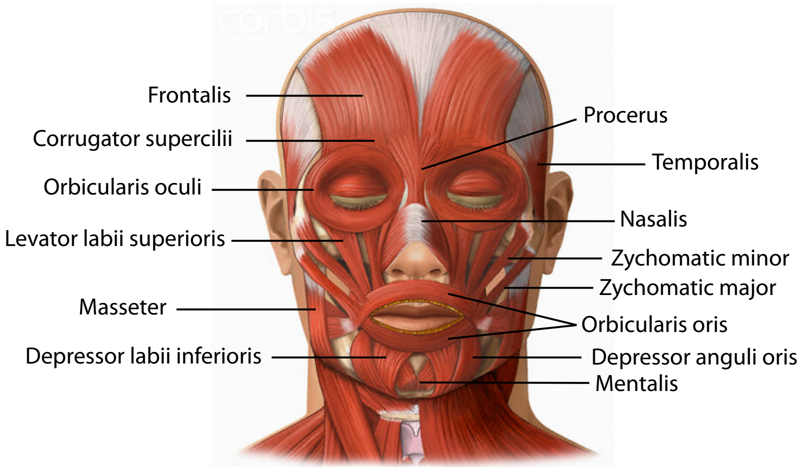


Figure 1.3: Overview of facial muscles.

1.4 Hypothesis

The hypothesis tested in this thesis is the following: **H1:** *It is possible to significantly classify facial expressions using EEG recordings*

As classification of 3 facial expressions showed promising results in a preliminary test, H1 was tested for 4 facial expressions, where the additional 4th expression was chosen to also test H1.1. As humans can differ between 6 facial expressions with an accuracy of 70-98% and other digital methods achieve an accuracy of 68-98% for 3-7 different facial expressions [36], significant in H1 is defined as an accuracy of at least 70%. The EEG recordings in H1 refer to recordings from a 32 electrode EEG head cap (BioSemi) using a subset of the extended 10-20 system.

Some expectations of the experiment are defined as sub-hypotheses for which the experiment is designed as well. Al sub-hypotheses refer to the EEG recording system described at H1.

- **H1.1:** *Using different facial expressions with partial overlapping AU, cause lower accuracies compared to using facial expressions without overlapping AU.*

- **H1.2:** *EMG influence on the classification accuracy is significant larger than EEG influence.*

- **H1.3:** *Using only frontal electrodes, will not yield significantly lower classification accuracies than using all 32 electrodes.*

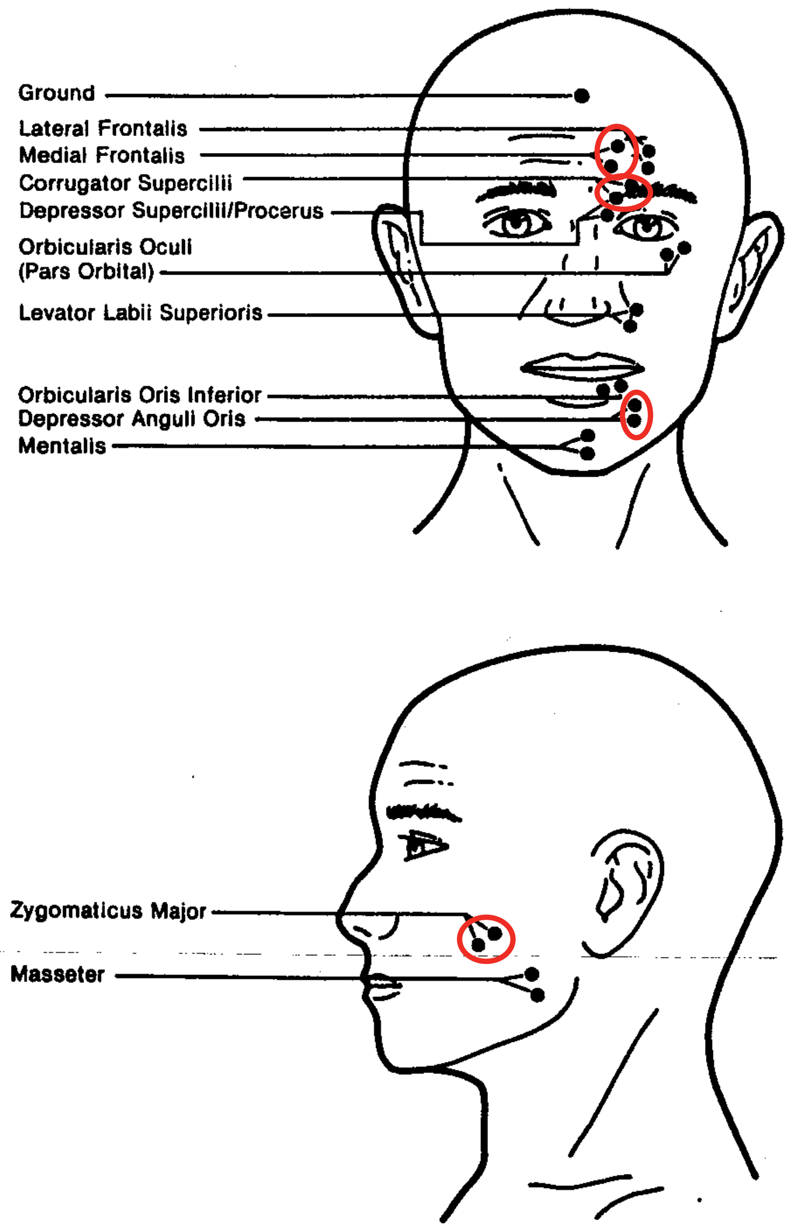


Figure 1.4: Placement of the facial EMG sensors, by Fridlund and Capaccio (1986) [18]. Electrodes circled are used during the experiment described in this thesis.

Chapter 2

Methodology

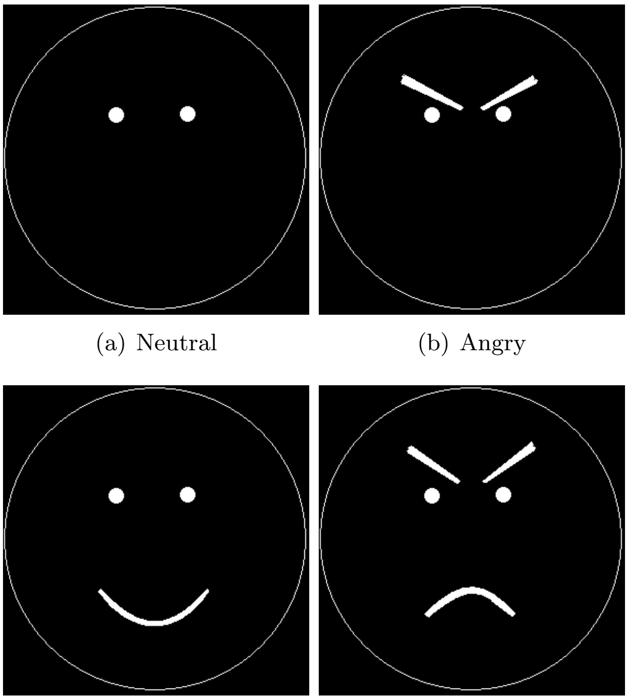
An experiment was conducted to gather data of voluntary facial expressions recorded with an EEG recording device. The data was analyzed with the focus on recognizing the facial expressions. This chapter describes the experiment design, the experiment procedure and the methodology of the analysis of the gathered data.

2.1 Experiment design

The goal of the experiment was to gather data for four classes of facial expressions: A neutral class, an angry class, a smile class and an angry-pout class. The first 3 classes were selected because each of them use different AU and all of them are easy to perform. The angry-pout class was selected for its overlapping AU with the angry class. Each class is described by a set of AU for performing the expression and a stimulus (an overview of FACS can be found in Appendix G). The angry pout class was selected specifically for the overlapping frown AU with the angry class.

1. **Neutral class.** Relaxing all facial muscles. AU: none. Stimulus: Figure 2.1(a).
2. **Angry class.** Lowering the brows. AU: 4. Stimulus: Figure 2.1(b)
3. **Smile class.** Raising lip corners. AU: 12. Stimulus: Figure 2.1(c)
4. **Angry-pout class.** Lowering brows, lowering lip corners and raising chin. AU: 4, 15 and 17. Stimulus: Figure 2.1(d)

An experiment session consisted of 1 or more training blocks and 8 experiment blocks. During all blocks, subjects needed to relax, look at the screen and perform



(a) Neutral (b) Angry (c) Smile (d) Angry-pout

Figure 2.1: Expression stimuli that show during SSP, belonging to the 4 facial expressions classes.

facial expressions after a cue. Appendix A contains a chronological test protocol for the entire session.

Training

The purpose of the training was to get the subject accustomed to the experiment (in particular the timing for performing the facial expression) and eliminating possible learning artifacts. A training sessions contained 1 block of 12 trials. This block was repeated until the learning curve of the subject stopped rising.

Experiment

The actual experiment consisted of 8 blocks of 40 trials each. Between each block, subjects could issue a small break if needed. After 4 blocks, a bigger break was issued by the researcher.

Blocks

A block contained 10 trials for each expression, meaning 40 trials in total per block. Expression stimuli were randomly shuffled among the 40 trials. Meaning, each block had the same amount of trials of each expression, but was unlikely to use a similar order as other blocks.

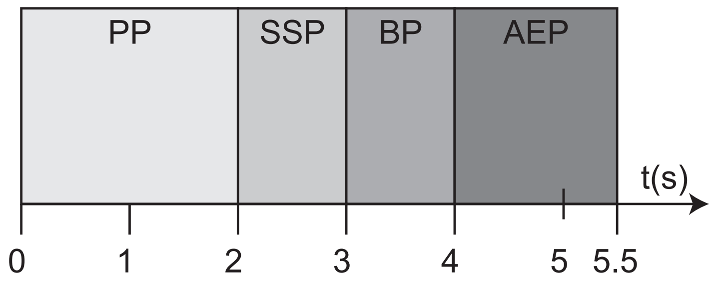


Figure 2.2: Schematic overview of the flow of a complete trial, showing all 4 phases: PP: preparation phase, SSP: stimulus showing phase, BP: building phase and AEP: actual expression phase.

Trial

Each trial consisted 4 phases, mentioned below and depicted in Figure 2.2. Additionally, Figure 2.3 shows the screen shots belonging each phase.

- Preparation phase (PP) [2 seconds]
- Stimulus showing phase (SSP) [1 second]
- Buildup phase (BP) [1 seconds]
- Actual expression phase (AEP) [1.5 seconds]

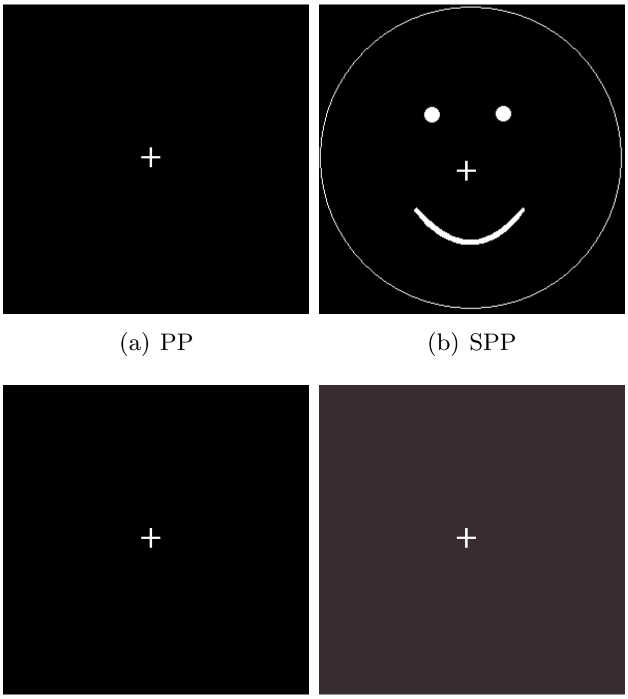
Preparation phase

The preparation phase starts 2 seconds before the expression stimulus shows. This phase was a necessary break between trials to regain concentration and relax. Artifacts in this period had no influence on the results, so any necessary movement, like excessive eye blinking or head movements, could be done in this period.

Screen: Black background with a white cross in the middle (Figure 2.3(a)).

Stimulus showing phase

One of the four expression stimuli, shown in Figure 2.1, was shown for 1 second, long enough for the subject to consciously differentiate between the four possible stimuli. Subjects did not perform any facial expression in this phase, and concentrated on the cross in the middle of the stimulus. Literature reports mimicking



(a) PP (b) SPP

(c) BP (d) AEP

Figure 2.3: Screens belonging to the 4 phases of one trial. Screen SSP is the only screen which variates, using 1 of the 4 stimuli shown in Figure 2.1. All screens are static during each phase. The only difference between the AEP screen and the BP/PP screen, is the background color.

of facial expression in static image within 1 second for healthy adults [2]. Making it likely for any possible mimicry to show up in the data in this phase.

Screen: Black background with a white stimulus and cross in the middle (Figure 2.3(b)).

Buildup phase

A period of 1 second between the disappearance of the stimulus and the performance of the expression. It is likely that any possible pre-potentials like the BP show up in this phase. This phase also ensures that the expressions done in the next phase are completely voluntary rather than emotional or mimicked expressions [2]. Subjects did not perform any facial expression in this phase and just concentrated on the cross.

Screen: Black background with a white cross in the middle (Figure 2.3(c)).

Actual expression phase

Subjects had 1.5 seconds to perform the correct facial expression. Subjects made sure not to strain the expressions too much as a preliminary experiment showed that too much strain was not necessary for good classification results, while the subject's facial muscles tired faster then necessary. The visual cue for this phase consists of a subtle change of the back ground color, so that eye movement or blinking due to the stimulus was minimized.

Screen: Light black background with a white cross in the middle (Figure 2.3(d)).

2.2 Procedure

2.2.1 Subjects

The experiment was conducted on 10 healthy subjects, 9 of them were right handed and 1 was left handed, 8 were male, and 2 female. The average age was 26, with a minimum of 21, a maximum of 32 and a standard deviation of 3.1. All subjects were university students, ranging from bachelor students (BSc) to PhD students. Only 2 of them used visual aids (glasses) and half of them consumed coffee before the experiment. None of the subjects used relevant medicine, or had known concentration problems. All subjects spend more than 6 hours a day working with a PC, except one, spending 4-6 hours a day with a PC.

2.2.2 Setup

Subjects were seated in a comfortable chair behind a desk containing a keyboard and a monitor in a room containing no direct light sources on to the screen. Subjects wore an EEG head cap with 32 electrodes and had 8 EMG sensors on their face. A webcam was placed under the monitor screen to record the subjects face during the experiment. Figure 2.4 shows a schematic overview of the entire set up and Figure 2.5 shows a screen shot from the webcam where the subject shows his left side of the face.

As described in the subject experiment protocol (Appendix A), subjects were presented a consent form (Appendix B) and user instructions before the experiment. During the setup, subjects filled out an experiment questionnaire (Appendix C). The used sampling rate was 512 Hz. Electrode offsets for all subjects were always < 25.

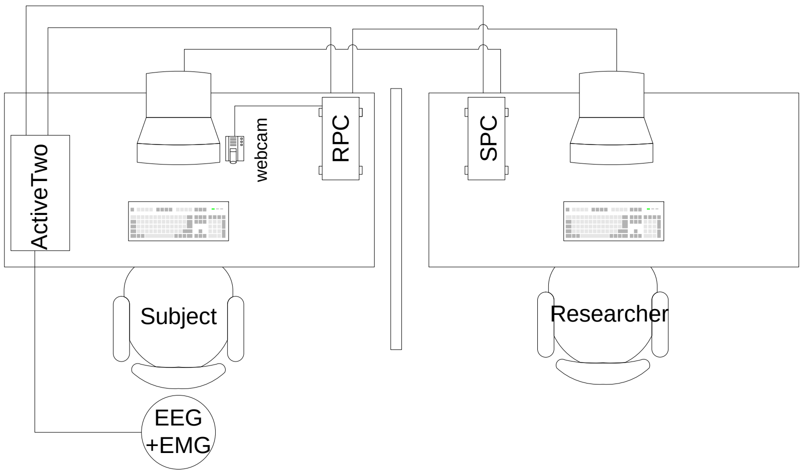


Figure 2.4: Schematic overview of the hardware setup during the experiment. The recording PC (RPC) is monitored by the researcher, while the stimulus PC (SPC) shows the user the stimuli.

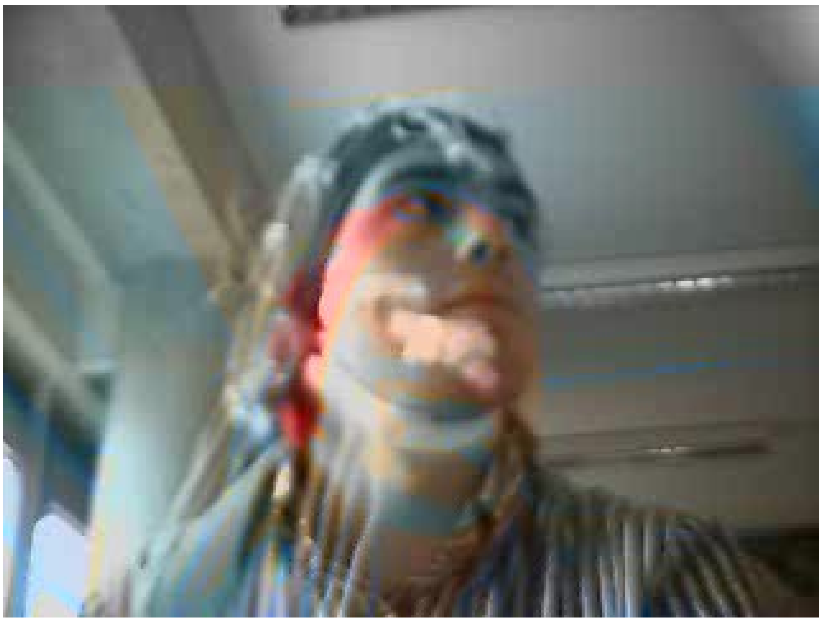


Figure 2.5: Screenshot of camera recordings, showing a subject's left side of the face.

2.2.3 Materials

Hardware

Hardware used are shown schematic in Figure 2.4.

- **Recording PC**: P4 3.2GHz 1GB RAM.
- **Stimulus PC**: P4 3.2GHz 1GB RAM.
- **Biosemi ActiveTwo**: With 32 active pin-type electrodes (Ag-AgCl) + 8 active flat-type electrodes (Ag-AgCl).
- **Biosemi Trigger cable**: parallel, from SPC to ActiveTwo.
- **Biosemi Headcap**: 32 electrode holes in the extended 10-20 system.
- **Camera**: Philips ToUcam fun camera.

Software

- **Actiview**: For recording EEG+EMG.
- **Presentation**: For showing stimuli (see http://www.neurobs.com/).
- **Windows moviemaker**: For recording camera images.

2.2.4 EMG sensor placement

EMG sensor placement was done using the guidelines from Fridlund and Ciopacci [18], also shown in Figure 1.4. 8 sensors were divided on the left side of the face (with the exception of the right frontalis). Sensors were kept in their place with special tape for skin use. The following muscle placements were used for EMG measurement:

Left Frontalis and Right Frontalis

Both frontalis placements are done by pairing 1 EMG sensor with the EEG sensor directly above them. They provide information about how each expression influences the frontal electrodes of the EEG cap on both sides of the head. The frontalis itself should not directly generate activity during any of the target AU, though the brow lowering is likely to move this sensor.

Left outer Corrugator Supercilii and Left inner Corrugator Supercilii

Measures the activity from AU 4, used in the angry class and the angry-pout class.

Left outer zychomatic major and Left inner zychomatic major

Measures AU 12, used in the smile class.

Left inner Depressor anguli and Left outer Depressor anguli

Measures AU 15, used in the angry-pout class.

2.2.5 Instructions

Subjects read a description of the experiment before participating and were instructed accordingly during the training.

Subjects were told to sit behind the screen, relax as much as possible and focus on the cross in the middle of the screen during the entire experiment (save the breaks). They could take a break between each block if desired for as long as necessary, in which they could drink, stretch or rest.

It was mentioned that each trial started with 2 seconds rest before the expression stimulus showed, in which movements, like eye blinking and head movement may occur if absolute necessary. It was shown to subjects what kind of influence different muscle movements had on the recordings, to make subjects of aware of them.

Subjects were instructed not to perform any muscle movement yet, when the expression stimulus showed, but wait until the stimulus for actually performing the expression (AEP) showed (2 seconds later), and then perform the expression. This was practiced in the training blocks until the timing and expression were correct.

It was carefully explained and practiced that subjects did not need to stress the expressions, so that they do not tire too fast or get muscle cramp (as was reported in a preliminary study).

2.3 Analysis

The analysis of the gathered data was divided in 2 parts. The first part, signal characteristics analysis, was conducted first and had the goal to get to know the data and describe common characteristics, in order to design the classification methodology. The second part, classification analysis, was conducted to generate comparable classification accuracies of different features of the data, with the goal to accept or reject the hypothesis and sub-hypotheses stated in Section 1.4.

Different methods used in both parts of the analysis are discussed below. Analysis for each method was always done by studying both individual subjects and grand averages over all subjects. The next subsection will first elaborate a bit on all EEG processing techniques that will be mentioned when describing the used methods.

2.3.1 EEG processing techniques

This subsection will shortly elaborate on the methods of the different EEG process techniques mentioned during the explanation of the analysis methodology. Readers familiar with EEG signal processing may skip this section.

Common Average Reference (CAR)

EEG channels are generally created from the potential difference of an electrode and a reference. When using CAR , this reference is calculated by averaging all the EEG channels. So activity for each channel is calculated by subtracting this average reference from the corresponding electrode.

Frequency filtering

When recorded, EEG channels contain data of the entire frequency spectrum allowed by the sampling rate. As data in certain frequency bands are more useful than in other bands, a bandpass filter can be applied on the data to leave only data within the target frequency band. In this study a finite impulse response filter with an order of 400 was used to filter the data.

Epoching

The average reference montage contains only continuous data. Since we often want to look at average characteristics of a class, or use specific classes for certain processes (such as classification), the data can be processed, so that different sets are made containing only epochs of that class. The word epoch is used instead of trial, because an epoch does not have to contain an entire trial and could even contain data outside a single trial. This processing, of creating data sets for each class, containing epochs of the same length per class, is called epoching. During classification epochs of only the AEP of each trial were created. During the study of characteristics other parts of the trial were included in the epochs as well.

Epochs will in this thesis be referred to as trials, to keep the reference to the original experiment trials. Each used epoch in this study always contained data from only 1 trial in the analysis. The process will however still be referred to as epoching.

Baseline removal

Trials often contain linear trends from the continuous data. A baseline correction is applied to detrend and position the trial relative to the used baseline. The baseline needs to be chosen outside of the influence of which is being studied. For example, in this study the SSP and BP period were used as the baseline during the characteristics analysis since the AEP was studied.

Common spatial patterns (CSP)

CSP is used to find spatial filters that maximize variance for one class, and at the same time minimizing variance for the other class. The filters found, called a weight matrix, are used to transform each channel to a component, resulting in components that maximize variance for one class in the first component and maximize variance for the other class in the last component. Because of using CAR, one component will contain the average reference of all other components and will be removed. The CSP algorithm used is based on Koles [25] and Ramoser [42].

Linear discriminant analysis (LDA) classification

The LDA classifier algorithm tries to find the linear combination of given features that separates the classes the best on the observations from the training set. The linear combination is used then to classify the observations from the test set. For more than 2 classes several methods exist to use the linear classification from LDA. In this study a pair wise classification was used for classifying more than 2 classes.

2.3.2 Signal characteristics analysis

For all analyses in this part, an average reference montage was used, constructed by applying CAR over the data recorded from the 32 EEG electrodes. The resulting data was epoched per class. Only EEG channels were studied in this part.

Analysis in this part can be divided in the temporal domain and the spectral domain. Both domains were studied one after another to find characteristics useful for classifying.

For the temporal domain, single trials were studied as well as the average over all trials, to look for possible common characteristics between trials of a class. Plots showing these averaged data per class are referred to as ERP plots, as they are meant to show ERP. It is important to realized however, that the data was generated by user induced movements rather than stimulus evoked potentials. This likely causes temporal shifts per trial for the induced potentials, as well as variating amplitudes of the potentials, making it hard to find significant ERP. Averaged data of the different classes were subtracted from each other to study potential differences between classes and topography plots were studied to find possible sources of the observed ERP.

Based on the findings in the temporal domain, the data was also studied in the frequency domain. Frequency plots, showing power differences over frequencies, were studied to find frequency ranges where differences between classes can be observed. Time frequency plots were created to show significant differences in frequency power between the classes in specific channels over time.

Considering the used sample rate of 512 Hz, frequencies until 256 HZ could be analyzed [43]. Preliminary results however showed no significant changes between 100 and 200 Hz, and literature described in Section 1.3.5 and 1.2 suggest that a low pass of 100 Hz will leave sufficient EEG and EMG signal for analysis, thus only spectral features of 100 Hz and below were observed to reduce the sample size.

2.3.3 Classification analysis

Using a linear classifier, a classification accuracy value (AC) could be given to each class for different preprocessing settings. By varying these settings, such as channel features or frequency bandpass, different AC were calculated and compared.

2.3.3.1 Classification pipeline

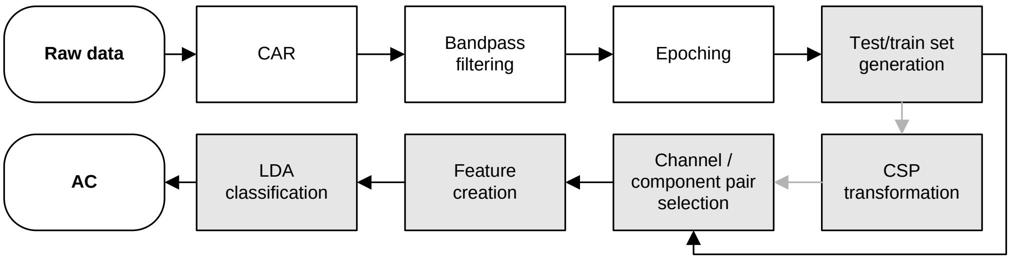


Figure 2.6: Schematic overview of the classification pipeline. Shaded steps are repeated 50 times to create an average AC over 50 runs. The CSP step is only taken when using component space instead of channel space.

All classification AC were created using the same basic pipeline shown in Figure 2.6. First, an average reference montage is created using CAR. A bandpass filter is now applied, using chosen high and low pass values. The resulting data is epoched for 4 classes (or 3, see Section 2.3.3.4). For each class a random training and test set is generated. The test set consists of 25% of the trials of each class, while the training set uses the remaining 75% of the trials of each class. When using component space instead of channels, CSP is used to transform the channels into components, this step is described in more detail below. Features are now created by selecting two channels (or components) and calculating the log variance of both channels for all trials (both for the training and test set), resulting in two 1-dimensional features for each observation (trial) given to the classifier. A log value was chosen to minimize the influence of outliers on the training of the linear classifier. The pairwise multivariate LDA classifier is trained on the training set and an AC is calculated using the result of the trained classifier on the test set.

Only 2 channels were used for feature creation for each classification for several reasons: First of all, preliminary classifications showed no real improvement when adding more channels as features. Secondly, channel selection comparison (discussed below) takes an enormous amount of time, considering all possible pairs, even with pruning methods. Thirdly, component space is more interesting when optimizing spatial features, due to more possibilities and faster automatic selection. And finally, considering the entertainment industry, two channel BCI are more likely to get released due to lower production cost, making 2-channel classification the most interesting for channel space observations.

When using component space instead of channel space, a transformation of the data from channels to components is used as an extra step in the pipeline. CSP is used for this transformation, because with CSP resulting components are based on maximizing difference of variance between the classes, which improves classifications based on difference in variance. A CSP weightmatrix is calculated on the training set and projected on both the training and test set, as an extra step directly after creating them. Component selection was fixed on the first and last component for all component space classification, as they contained the maximum difference of variance between the two classes of all components. This means that feature selection in component space happens automatically, as opposed in channel space where it needs to be selected manually. To extend the use of CSP to more than 2 classes, a pair-wise soft voting method is applied by using the probability estimates by the classifier on the test set. After creating the training and the test set, a classification run is done on those sets for each possible pair of classes, treating each run as a normal 2-class CSP problem. CSP transformations are applied like a normal 2-class problem on the training set, but are projected over the entire 4-class test set each time. The classifier estimates per observation the probability of each class being the source of that observation. The class with the highest sum of estimates on an observation after each pair is classified, is selected in the end.

To account for inter-trial variance, 50 runs with the same preprocessing but a different division of data among the training and test set were conducted for each specific preprocessing setting and feature selection. AC were averaged over those 50 trials, resulting in the output AC, accompanied by a standard deviation.

2.3.3.2 Channel selection

To find the optimal channel pair features for each subject, a selection method was used to calculate AC for classification using different channels during the channel selection step with a static bandpass of 20 - 40 Hz (based on a preliminary result).

AC were calculated for all possible channel pairs per subject and studied. This is referred to later as the channel selection method.

Note that AC were calculated for each pair on the test set, meaning that there is no automatic feature selection of the best channel pair, done on the training set during this method. While automatic channel selection using this method is possible, it is extremely time costly without good pruning and therefore not used. The goal of the method was to observe the results of channel pair classifications. This means however that the best resulting AC of this method cannot directly be compared to results in component space, as the CSP transformation creates components based up on the training set, and the first and last component are chosen without prior knowledge about the test set.

2.3.3.3 Frequency bandpass selection

Classification in both channel and component space could perform different for different bandpass values during preprocessing, different from each other or different per subject. Therefore it is necessary to view AC of multiple bandpass values. The same method used for the channel selection is used here to vary band pass values using each possible high pass and low pass pair. To save time, only frequencies Between 15 and 100 Hz were used. Results below 15 Hz repeatedly showed bad results in preliminary tests and results from the spectral analysis indicated low passes above 20 Hz to be useful. To save more time, only multiples of 5 Hz were used for the pairing, leaving the smallest window size at 5 and the largest 85. AC were calculated for bandpass values abiding those rules for both channel space and component space.

For channel space, the channels chosen for each classification in this method are the channels that had the highest AC on the channel selection method for that particular subject. This method is later referred as the frequency bandpass selection method.

Note that this method, like the channel selection method, is used on the test set to save time, meaning that there is no automated selection of the best frequency bandpass on the training set used during classification, and results are just observed.

2.3.3.4 The angy pout class

To see whether the angry pout class as an addition to the other 3 classes causes lower AC, the channel selection method and frequency bandpass selection method were repeated on only the neutral, angry and smile class, for both channel and component space. Results were compared to the results of the methods with 4 classes.

Results for 3 class classification were repeated, leaving out the other classes one by one, to see whether the difference between the 3 and 4 class classifications are due to the similarities in AU of the angry class and the angry pout class, or due to 3 classes having a better performance in general.

2.3.3.5 EMG influence

To see whether the EEG signals can show a significant difference in AC in addition to the EMG signals, classifications were made on the EMG channels first and then on the combination of EMG and EEG channels. Both AC were calculated in component space using the frequency bandpass selection method.

2.3.3.6 Frontal influence

A classification in component space using only frontal channels (FP1, FP2, AF3, AF4, F3, F4, F7, F8, FC1, FC2, FC6, see Appendix D for channel locations) was compared to the classification results in component space using all EEG channels. Results can indicate whether using more than just frontal electrodes yields significantly different AC. This was repeated by adding the two temporal channels (T7 and T8) to the frontal channels.

Chapter 3

Results

This chapter shows the results of the analysis conducted as described in Section 2.3. Results are shown in the two aforementioned parts: *Signal characteristics analysis* and *Classification analysis*.

For the signal characteristics analysis, the data was studied for common characteristics in the classes useful for classification. During the classification analysis, results of the classification methods were studied, with the goal to accept or reject the hypothesis and sub-hypotheses mentioned Section 1.4.

Findings in this chapter are discussed in the next chapter.

3.1 Signal characteristics analysis

The signal character analysis consisted of studying the recorded data in the temporal and the spectral domain with the goal to find characteristics common for each class. Results were used during the design of the classification methodology and serve as an introduction to the data in this thesis.

All plots shown in this chapter, are generated from an average reference montage of the data containing 32 EEG channels. Channels will be referred to by their name during the description of the results. Appendix D shows the spatial location of the channels on the scalp along with their name. The channels located most frontal (FP1 and FP2) and most temporal (T7 and T8) are mentioned often in the rest of the thesis and thus best remembered.

3.1.1 Temporal domain

Trials with distinct signals between classes were observed when studying the continuous data. Large, low frequency, potentials in the frontal channels (FP1, FP2, AF3 and AF4) were clearly visible for the non-neutral classes, demonstrated

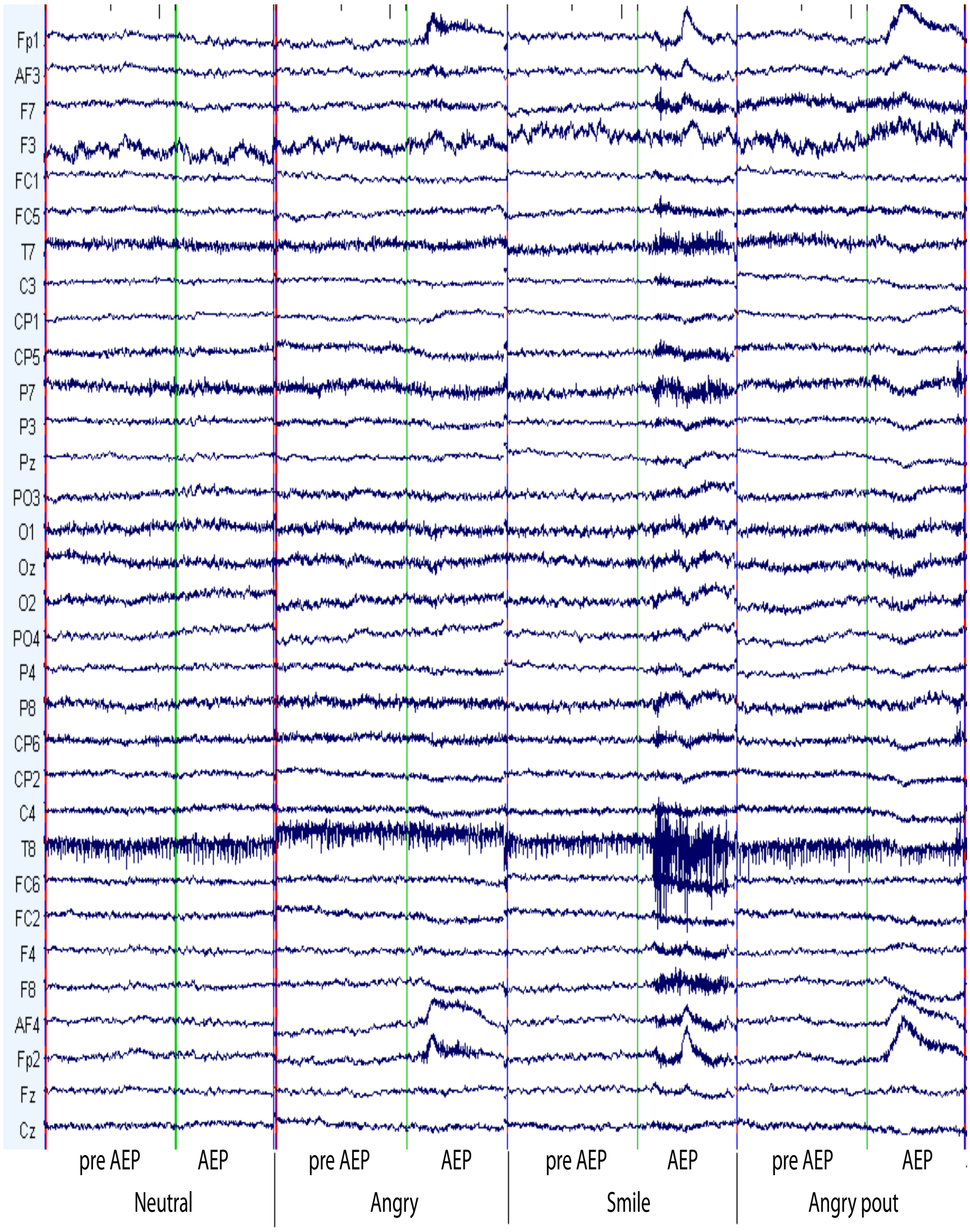


Figure 3.1: Samples of single trials, taken from the average reference montage of subject 4. Vertical axis shows potential for each channel. Horizontal axis show 2 seconds before AEP (SSP and BP) and the AEP for each trial. Frontal channel FP1, FP2 and AF4, as well as temporal channel T8, show high a high amplitude signal during AEP.

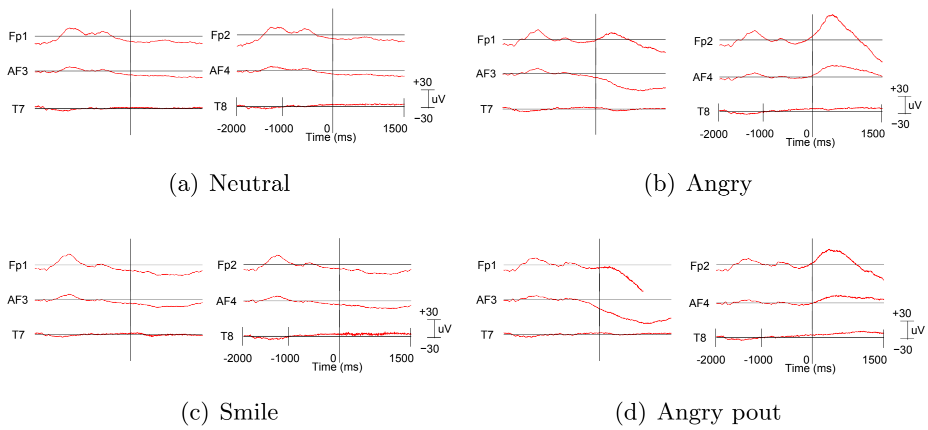
in Figure 3.1. Additionally, large, high frequency, potentials showed clearly in the temporal channels (T7 and T8) for the smile class. As the potentials in the continuous data were observed to show amplitudes over 100 μV, it can be assumed that the source of those potentials is EMG rather than EEG. It should be noted that the high potential signals observed in the continuous data had a high variance of amplitude between trials for all subjects.

As noted during the experiment, channel F3 was observed to show a constant low frequency signal during several parts of the experiments for certain subjects, also seen in the trials shown in Figure 3.1. This will be regarded as noise, because the signal was observed regardless of the experiment.

Also noted during the experiment was the moving of the cap of subject 1 during the expression. This has resulted in high potential artifacts, observed in the continuous data of subject 1. All results of subject 1 are still shown together with the other subjects.

ERP

To see whether the observations on the continuous data contain any significant evoked responses, ERP plots were studied. While reading the results from the ERP study, it is good to keep in mind that the actual expression, made during AEP, were user induced rather than evoked, meaning that a lot of variance is expected in the signal over all trials.

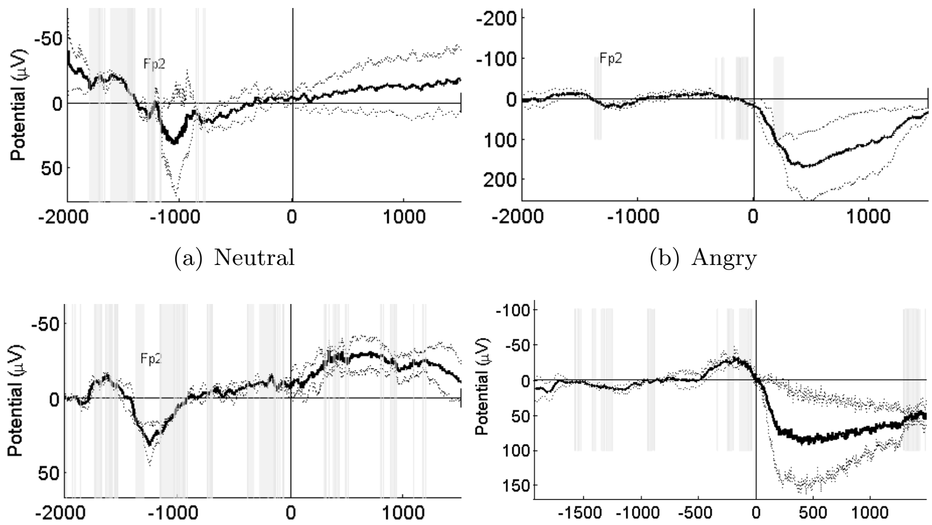


(a) Neutral (b) Angry

(c) Smile (d) Angry pout

Figure 3.2: Grand average ERP plot of all subjects, showing 2 seconds pre AEP (SSP and BP) and the AEP for, the most frontal and temporal channels for all classes. Pre-AEP (-2000 till 0) was taken as baseline. Appendix E.1 shows the same plot for all channels.

ERP plots studied for all 4 classes show the low frequency, high potential signals in the frontal channels also observed in the single trials, depicted in Figure 3.2 for the grand average. These ERP however show such high variance, that



(a) Neutral

(b) Angry

(c) Smile

(d) Angry pout

Figure 3.3: ERP plot of the right most frontal channel (FP2) of subject 9 with the standard deviation (grey plot lines) and significant time periods (vertical grey lines) shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$. Appendix E.2 also shows the ERP plots for the other channels of each class for subject 9.

they are not significant (compared against a zero mean dataset with the same variance), as demonstrated in Figure 3.3. As the source of these signals is located most frontal (which can be observed in Figure 3.4), the signals are likely to originate from facial muscle activity. It is interesting to notice that those observed signals are asymmetric over the scalp hemisphere.

ERP that did show significance, had small amplitude in comparison with the high potential ERP observed in the frontal channels, and were generally observed in central channels, as can be seen in Figure 3.5 and Figure 3.4.

Differences between the classes are difficult to find in the ERP plots and appear not significant as well, demonstrated in Figure 3.6. Differences between subjects observed, apart from the amplitude of the potential of the signals, are found in the spatial sources of the potentials. The form of the asymmetry of the spatial sources of the potentials on the scalp hemisphere differs per subject.

One other observation worth mentioning, is the significant potential increase in the parietal and occipital channels, about 300 ms after SSP onset (observed in Figure 3.7 and Figure 3.4), followed by an high variance potential increase in the frontal channels, 500 ms after SSP onset (observed in Figure 3.3 and Figure 3.4).

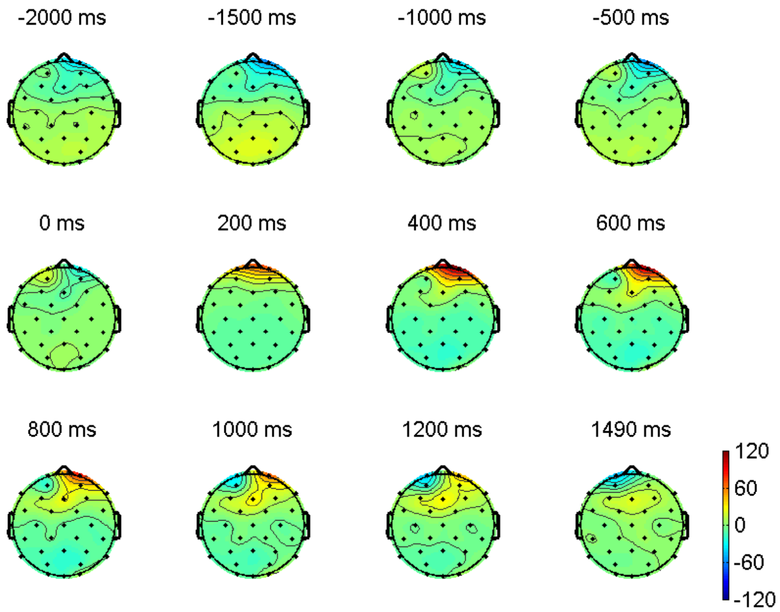
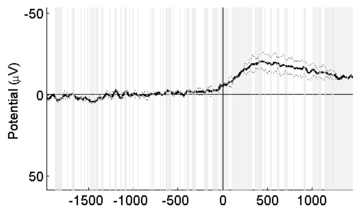
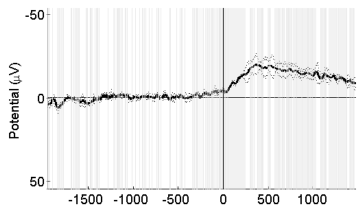


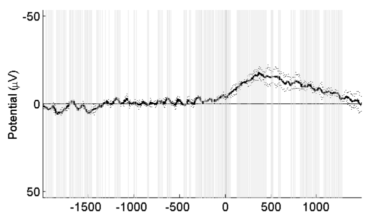
Figure 3.4: Topography plot of subject 9 for the angry class, showing potential changes in time over the scalp. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Apendix E.4 shows the same topo plots for all classes of subject 9.



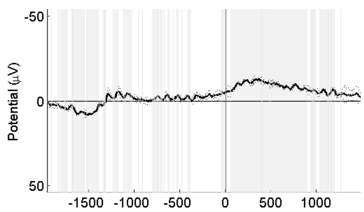
(a) C3



(b) C4

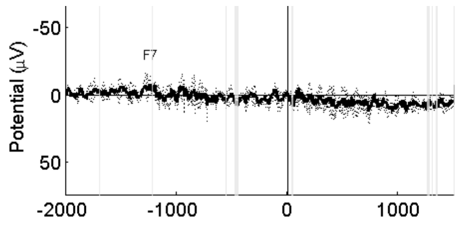


(c) Cz

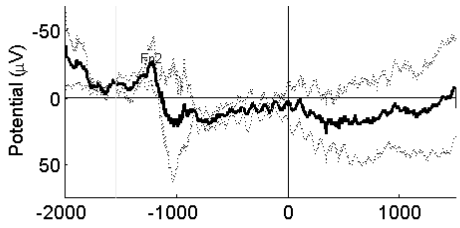


(d) CP1

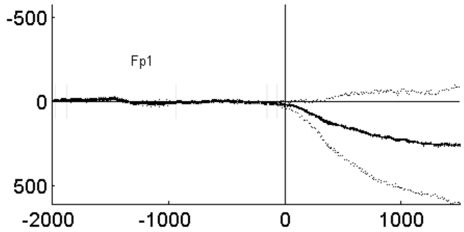
Figure 3.5: ERP plot of 4 central channels of the angry class of subject 9 with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$. Appendix E.2 shows the ERP plots for the other channels of each class for subject 9.



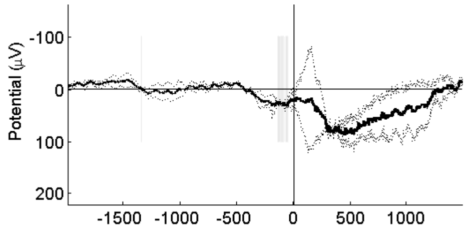
(a) Neutral - smile channel T7



(b) Neutral - smile channel FP2

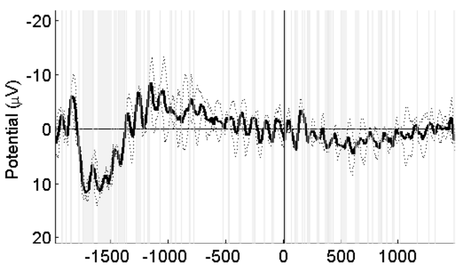


(c) Angry - angry pout channel FP1

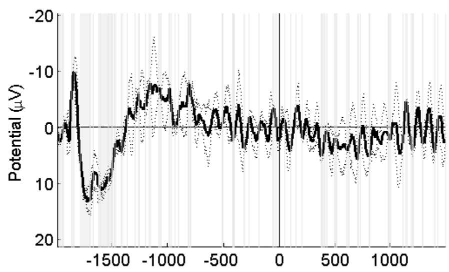


(d) Angry - angry pout channel FP2

Figure 3.6: ERP plot of 4 channels showing the difference between the neutral and smile class, and the angry and angry pout class of subject 9, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$. Appendix E.3 also shows significant difference ERP plots for all channels of both differences for subject 9.



(a) PO3



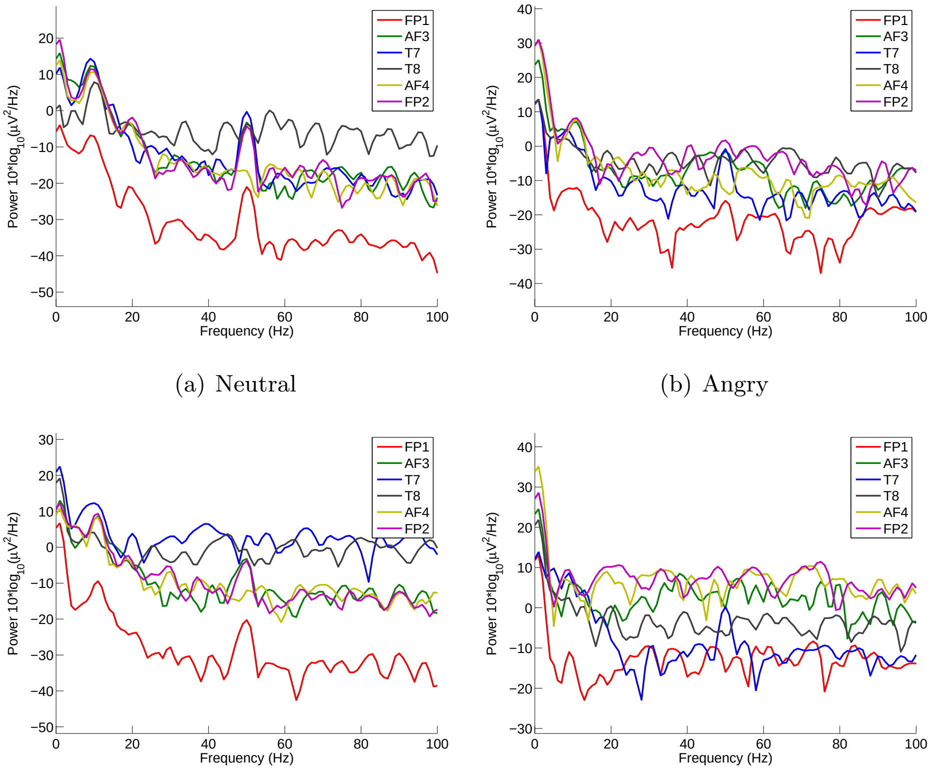
(b) PO4

Figure 3.7: ERP plot of two parietal channels of the neutral class of subject 9 with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$. Appendix E.2 also shows significant ERP plots for all channels of both differences for subject 9.

In conclusion, It is difficult to conclude anything about the ERP that is useful for classification, as there is too much variance in the big potentials observed over trials. Single trials show enough difference between the classes, but neither of them are significantly common over all trials. This result makes it interesting to study the spectral domain as well. The big potentials in the frontal channels showed low frequency, while high frequency potentials were observed in the temporal channels.

3.1.2 Spectral domain

When plotting the data as a signal in the frequency domain, periodical increases in power of the signal in the frequency spectrum of each channel can be observed (e.g. Figure 3.8). The signal is different for each channel, but consistent in the same channel of the same subject over all trials. Because the signals are different for different subjects, it is likely that frequency bands optimal for classification differ per subject.



(a) Neutral (b) Angry

(c) Smile class (d) Angry pout

Figure 3.8: Frequency plots of the AEP of all 4 classes of subject 9, using a log scale. All trials of the mentioned class were appended to 1 big trial for calculation of power spectra.

Due to the differences in power between the classes for certain channels over 20 Hz, a high pass of 20 Hz is expected to show most differences between the classes. The periodic power increases of the signal in the frequency domain are likely to be caused by muscle influence, and make it hard to see a more specific frequency bandpass that maximizes differences between the four classes. A smaller bandpass however is expected to have a higher probability to cause good results in general, since a bigger bandpass is more sensitive to the variance between trials. Increases in power observed for 10 Hz are due to alpha waves, while increases in power for 50 Hz are due to power line interference.

To see if there were specific significant bandpasses for each class that showed long enough during the AEP, time frequency plots were studied.

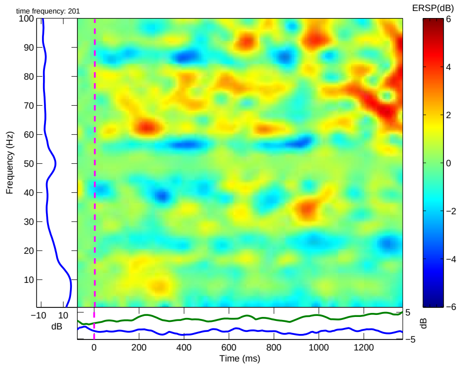
Time frequency analysis

The temporal channels, as well as the side frontal and side central channels, for the smile class, show significant power increase during the entire AEP for all frequencies above 25 Hz, in comparison with the other classes in time frequency plots (demonstrated in Figure 3.9 for subject 9). Only the Angry pout also shows a significant power increase (or decrease) in the temporal and other side channels on average, which could possibly be due to the muscle activity of the pout.

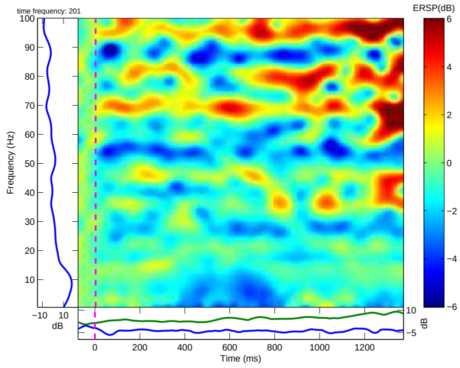
The most frontal channels were observed to show a strong increases in power in the angry and angry pout class, for the entire AEP on specific frequency bands, about 5 Hz to 20 in size. Implying that small specific frequency bands are in favor of bigger frequency bands. The frontal channels also show a strong increase and decrease in the frequency band from 0 Hz - 10 Hz, but this was observed for all classes on average and hold no significance when studying difference between classes.

Asymmetry over the scalp hemisphere was again observed in the spectral domain. Just like in the temporal domain, the form of the asymmetry differed between subjects.

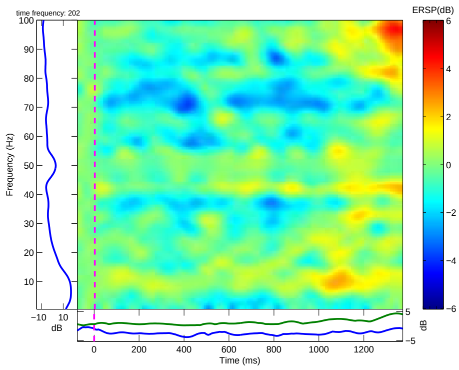
In conclusion, it is expected that a high pass of at least 20 Hz is needed to show differences between the classes for all subject. Specific frequency bandpasses, varying per subject are predicted to yield the best classification results with a small band size, not bigger than 20 Hz, on average.



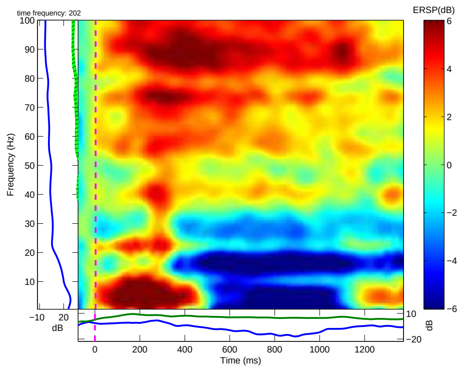
(a) Neutral channel T7



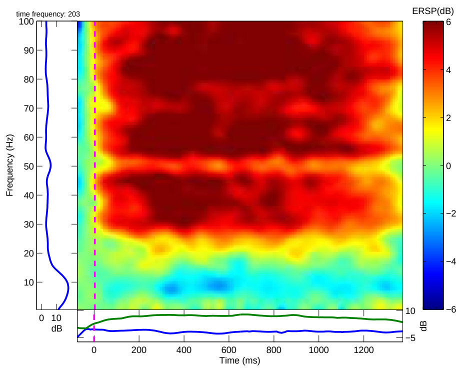
(b) Neutral channel FP2



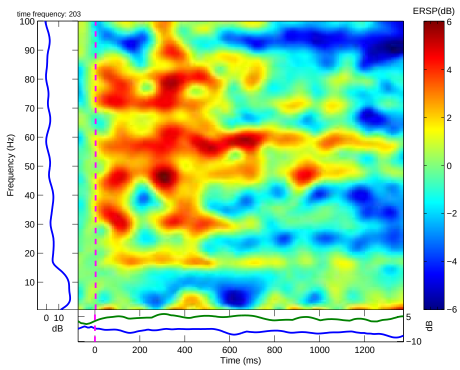
(c) Angry channel T7



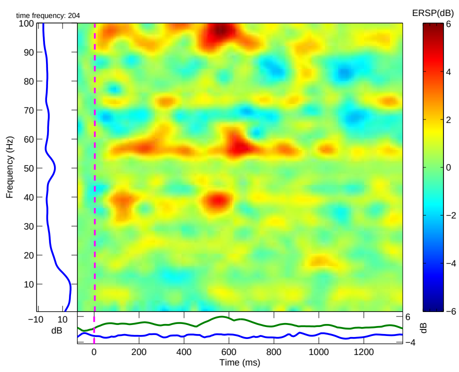
(d) Angry channel FP2



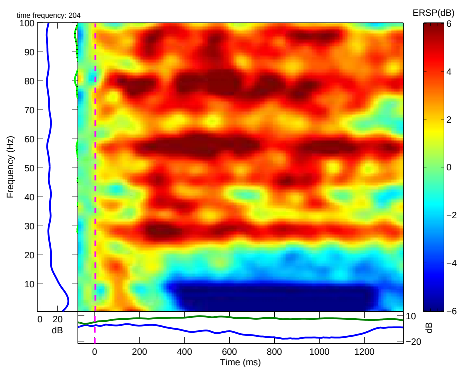
(e) Smile channel T7



(f) Smile channel FP2



(g) Angry pout channel T7



(h) Angry pout channel FP2

Figure 3.9: Time frequency plots of the left temporal (T7) and right most frontal (FP2) channels, for all 4 classes of subject 9, showing significant power changes compared to the spectral baseline (-700 to 0 ms) of the AEP, each point is calculated by a two-tailed t-test with a significance value α of 0.01.

3.2 Classification analysis

Classification analysis results were studied with the goal to accept or reject the hypotheses mentioned in Section 1.4. During the classification analysis, the classification accuracy (AC) was calculated for different preprocessing settings. The channel selection method was done for all possible EEG channel pairs, using a bandpass of 20 - 40 Hz. The best pair was used for the frequency bandpass selection method, varying frequencies from 15 to 100 Hz, with steps of 5 Hz. The frequency bandpass selection method was also done in component space, using CSP.

The results of the frequency bandpass selection method in both channel and component space (shown in Table 3.1) show that the AC for each subject is significantly higher than 70% for the classification of 4 classes (not counting subject 1 for earlier mentioned reasons).

It can be observed in Table 3.1 that all results are within the standard deviation from the mean of all subjects (again not counting subject 1), save two higher results, meaning that there are no particular bad results from individual subjects. There is however a clear difference between the AC of different subjects.

Results from Table 3.1, also imply a difference in optimal spatial selection and optimal frequency bandpass selection per subject which was studied in more detail, mentioned in the next two subsections.

	Channel space				Component space		
Subj.	**channels**	**frequency**	**AC**	**SD**	**frequency**	**AC**	**SD**
1	FP1- F7	70 -100 Hz	69.2%	5.5%	55 - 60 Hz	60.9%	4.2%
2	FP1-FC6	65 -100 Hz	75.7%*	2.5%	55 - 80 Hz	77.4%*	3.6%
3	F7 -FP2	75 - 95 Hz	88.8%*	2.5%	35 - 75 Hz	77.2%*	4.9%
4	FC6-FP2	55 - 75 Hz	82.8%*	3.9%	20 - 55 Hz	82.3%*	3.2%
5	T8 -FP2	70 -100 Hz	82.4%*	5.1%	45 - 65 Hz	79.3%*	5.9%
6	T7 -FP2	25 - 55 Hz	76.5%*	3.6%	85 -100 Hz	77.9%*	3.5%
7	FP1- F7	40 - 65 Hz	81.3%*	3.6%	35 - 75 Hz	77.2%*	3.9%
8	FC6-FP2	75 - 95 Hz	78.0%*	4.3%	50 - 80 Hz	79.4%*	4.0%
9	T7 -FP2	95 -100 Hz	85.6%*	3.5%	75 -100 Hz	86.6%*	3.1%
10	FP1- F7	40 - 65 Hz	84.3%*	3.3%	30 - 60 Hz	81.7%*	7.1%
Avg.			80.5%			78.0%	
SD			5.7%			6.7%	

Table 3.1: Classification results showing the best results for each subject for the frequency bandpass selection method for both channel and component space. For channel space, the shown channels are the result of the channel selection method. For component space (CSP), the first and last component are used for all subjects. A star means that the AC is significant higher than 70% with $p > 0.0001$ in 1 sample t-test.

3.2.1 Spatial selection

It was observed that for most subjects, 1 specific channel combination scored significantly higher than other channel combinations for the channel selection method (e.g. $p < 0.0001$ for an unpaired samples t-test between the pair with the highest and second highest AC of subject 9). This is however not necessarily true for every subject as subject 5 showed no difference between the pair with the first and second highest AC.

It was also observed that all specific channel combinations with an AC higher than 65%, included one of the most frontal channels (either FP1 or FP2, as can be observed in Figure 3.10) in combination with either a temporal channel or a side-frontal channel (T7/8, F7/8 or FC5/6, depicted in Figure 3.11).

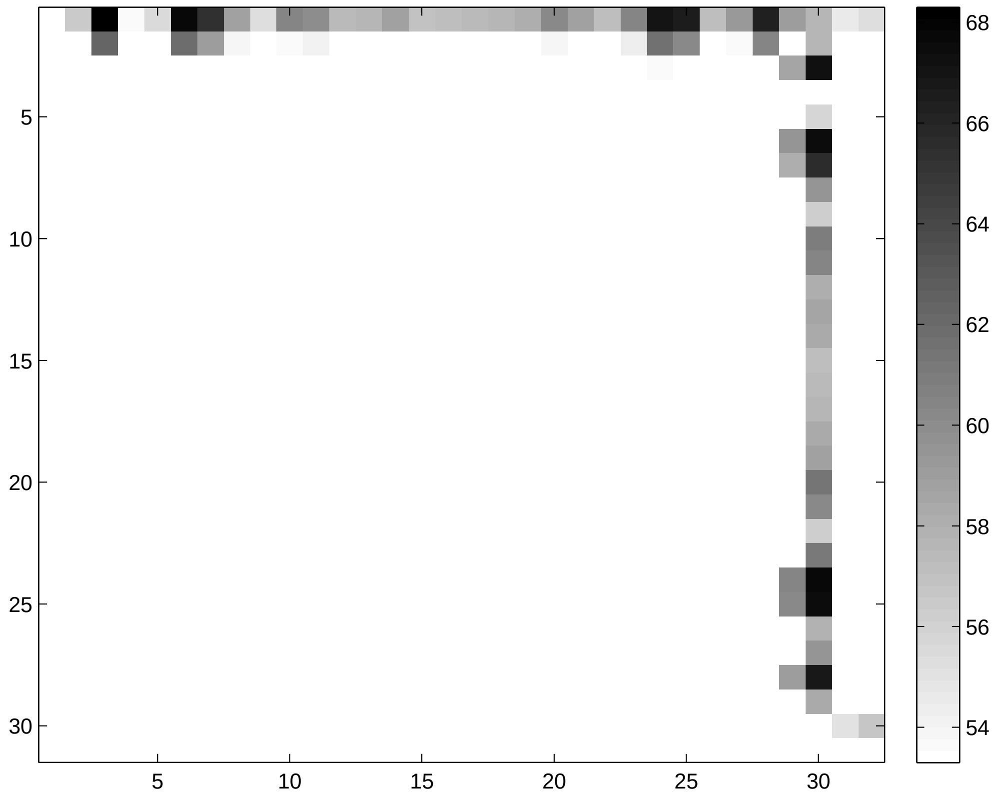


Figure 3.10: Grandaverage AC of the channel selection over of all subjects, shown per channel pair (each square is a pair). Channel FP1 and FP2 (1 and 30) show most high AC values. All channel locations corresponding to the channel numbers shown, can be found in appendix D.

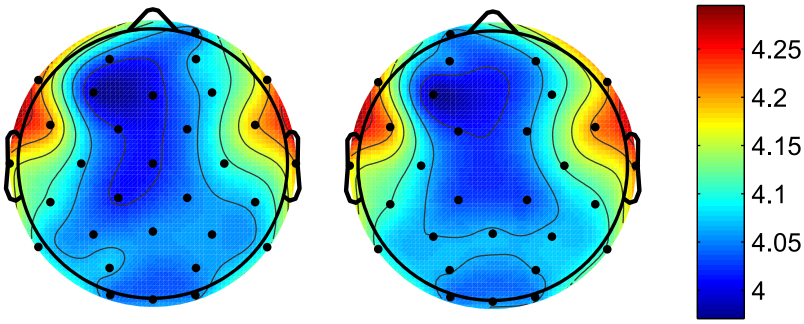
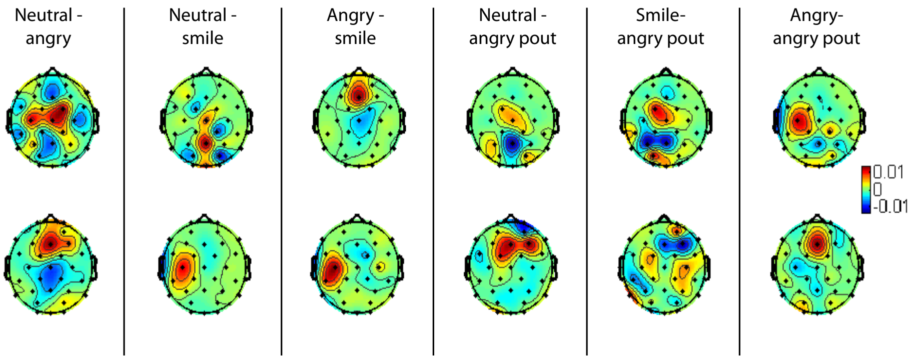
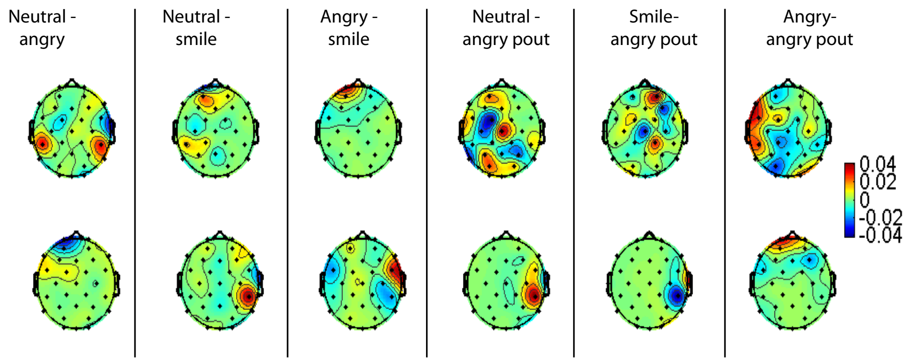


Figure 3.11: A scalp plot realization of Figure 3.10, showing the AC value of FP1 (left side frontal) and FP2 (right side frontal) in combination with the other electrodes. The score is the log of the AC of the shown electrodes paired with FP1 (in the left plot) or FP2 (in the right plot).



(a) subject9



(b) subject2

Figure 3.12: CSP weight matrix plot of subject 2 and 9. The first row is the first component and the second row is the last component. Each column is a pair of classes that produced the CSP weight matrix shown.

Component space

Spatial selection in component space, using CSP, also shows variating sources per subject (shown in Figure 3.12). It is, for example, interesting to observe the involvement of the middle frontal channel (Fz) in the classes containing frown muscle activity, rather than the most frontal channels for subject 9 (demonstrated in Figure 3.12), which was not expected considering earlier results and in comparison to the sources of, for example, subject 2 (shown in Figure 3.12).

3.2.2 Frequency bandpass selection

The frequency bandpass selection does not yield one bandpass that is significantly better than all other bands per subject (e.g. $p = 0.88$ for a unpaired samples t-test between the pair with the highest and second highest AC of subject 9). Instead there are multiple bandpasses that perform about the same, and even more bandpasses that produce only slightly lower AC (as can be seen in Figure 3.13).

On average, a high pass of 50 Hz and a band size of 35 Hz or less, show the highest AC over all subjects in channel space, as demonstrated in Figure 3.13. For component space a bandpass between 30 and 75 Hz show the highest AC, shown in Figure 3.14. Again the best band sizes are smaller than 35 Hz.

The observed high pass values imply that classifications with the highest AC, are done on EMG signals rather than EEG signals.

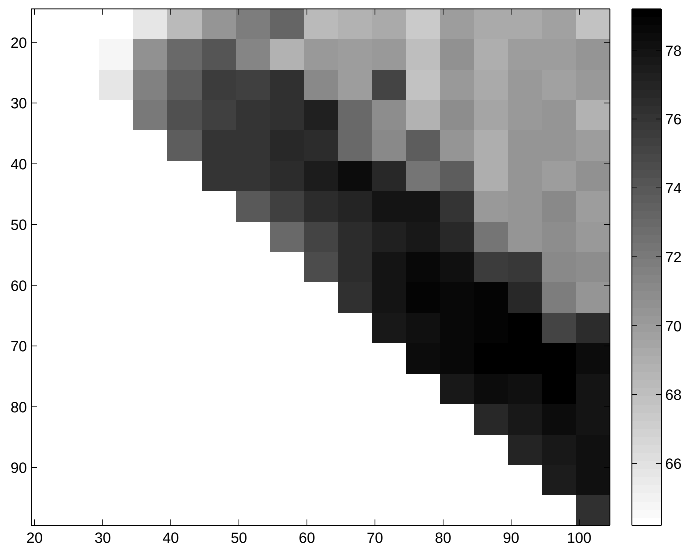


Figure 3.13: Grandaverage AC values of the frequency bandpass selection in channel space over of all subjects, shown per bandpass. Since the scale uses discrete steps of 5, each block is a bandpass read from the axis corresponding to the upper left corner of the block.

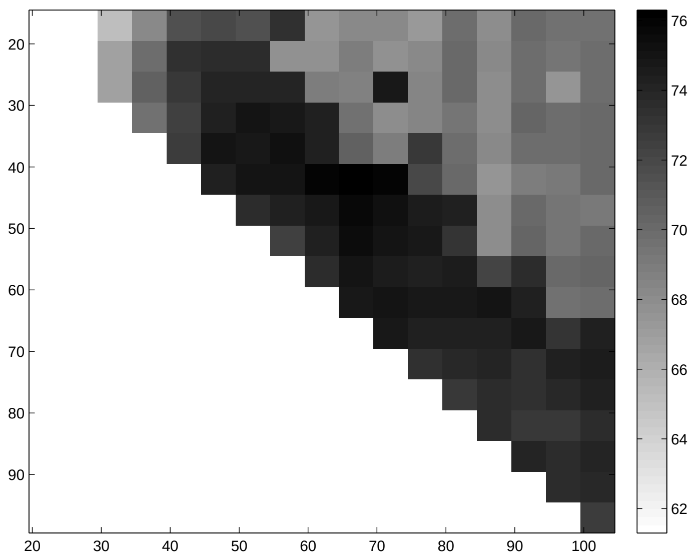


Figure 3.14: Grandaverage AC values of the frequency bandpass selection in component space over of all subjects, shown per bandpass. Since the scale uses discrete steps of 5, each block is a bandpass read from the axis corresponding to the upper left corner of the block.

(a) Subject 2 channel space: FP1 and FC6, 65 - 100 Hz

	neutral	angry	smile	angry pout
neutral	956	0	44	0
angry	0	831	0	169
smile	48	0	952	0
4	0	396	65	539

(b) Subject 2 component space: 55 - 80 Hz

	neutral	angry	smile	angry pout
neutral	914	16	69	1
angry	0	885	0	115
smile	51	0	946	3
angry pout	6	653	38	303

(c) Subject 9 channel space: T7 and FP2, 95 - 100 Hz

	neutral	angry	smile	angry pout
neutral	904	61	21	14
angry	15	889	2	94
smile	0	0	1000	0
angry pout	32	348	0	620

(d) Subject 9 component space: 75 - 100 Hz

	neutral	angry	smile	angry pout
neutral	934	38	24	4
angry	9	973	0	18
smile	0	0	1000	0
angry pout	18	381	6	595

Table 3.2: Confusion matrix of classification errors made in classifications in both channel space and component space (CSP), for subject 9 and subject 2. Confusion values were taken and summed for 50 runs. Rows show actual values, columns show classifier predictions.

3.2.3 Angry pout

Since the angry pout expression was suspected to reduce the AC of classification, due to partially overlapping muscles with the angry class and a more complicated execution, the influence of the angry pout on the classifications was studied in more detail.

As expected, the angry class and angry pout class show the most errors during classification, both in channel space and component space, as can be observed in Table 3.2. The current classification pipeline shows difficulty in linearly separable between the features of both classes given to the classifier, also demonstrated in Figure 3.15.

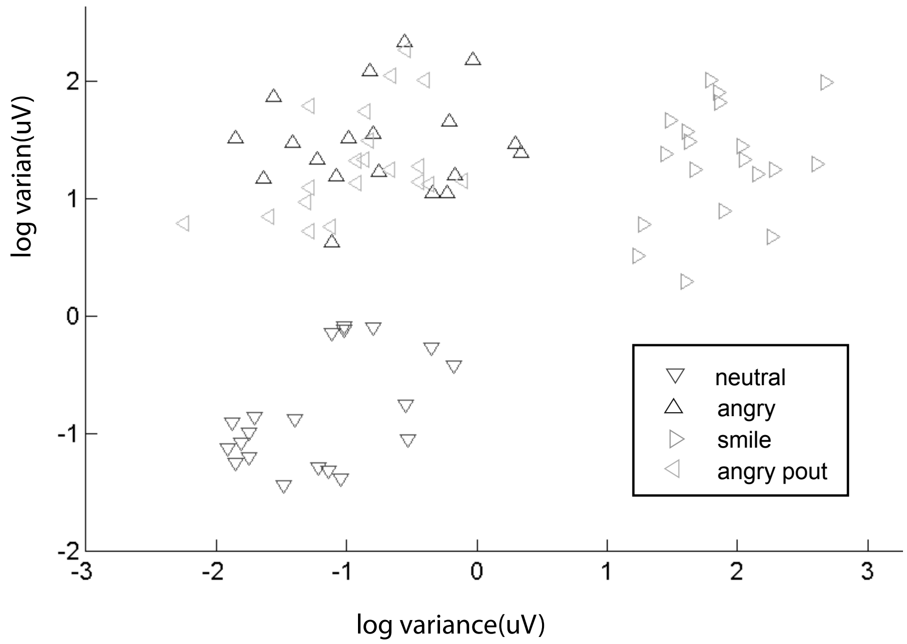


Figure 3.15: scatterplot of a test set, during classification of subject 9 with the variance of one channel feature as the y-axis and the variance of the other channel feature as the x-axis. Each triangle represents a class.

	channel space			component space		
Subj.	**channels**	**frequency**	**AC**	**frequency**	**AC**	**SD**
1	FC6-FP2	25 - 40 Hz	83.3%	25 - 35 Hz	78.8%	4.3%
2	FP1-FC6	65 - 100 Hz	96.8%	40 - 70 Hz	95.8%	2.5%
3	F7 -FP2	65 - 90 Hz	93.3%	95 - 100 Hz	85.8%	4.5%
4	FC6-FP2	90 - 95 Hz	99.8%	70 - 100 Hz	99.7%	0.6%
5	T8 -FP2	90 - 100 Hz	95.6%	60 - 85 Hz	96.3%	2.7%
6	T7 -FP2	30 - 40 Hz	91.3%	40 - 45 Hz	97.6%	1.6%
7	FP1- F7	20 - 40 Hz	95.3%	40 - 50 Hz	92.7%	6.4%
8	F8 -FP2	35 - 45 Hz	95.2%	30 - 40 Hz	95.2%	2.7%
9	T7 -FP2	90 - 100 Hz	95.4%	70 - 95 Hz	97.1%	2.7%
10	FP1- F7	40 - 70 Hz	94.2%	40 - 45 Hz	90.0%	5.2%
av.			93.1%		92.9%	
SD			4.4%		6.4%	

Table 3.3: Classification results of classification on 3 classes; without the angry pout class. showing the results with the highest AC for each subject for the frequency bandpass selection method for both channel and component space. For channel space, the shown channels are the result of the channel selection methods on the 3 classes.

As expected, removing the angry pout class yielded better classification AC in channel and component space (shown in Table 3.3). Removing the angry class instead, as shown in Table 3.4, also revealed a significant better AC, which is not significantly different from the AC from removing the angry pout class ($p = 0.11$ for a paired samples t-test). Removing either the neutral or smile class hoever, results in a lower AC compared to classifying four classes, which is significant for the neutral class, but not for the smile class ($p = 0.0023$ and 0.0844 respectively for a paired samples t-test.). Errors on the 3 class classifications were comparable to the 4 class classifications (see Figure F.1 in appendix F).

		no neutral		no angry		no smile	
Subj.	**Freq.**	**AC**	**SD**	**AC**	**SD**	**AC**	**SD**
1	25 - 35 Hz	62.4%	5.5%	59.8%	10.1%	65.8%	4.2%
2	40 - 70 Hz	73.3%	4.1%	94.4%	2.3%	72.4%	4.0%
3	95 - 100 Hz	75.9%	3.9%	78.8%	4.6%	80%	3.7%
4	70 - 100 Hz	67.4%	4.4%	99.2%	1.1%	65.6%	4.4%
5	60 - 85 Hz	72.2%	5.6%	97.4%	1.7%	70.8%	6.9%
6	40 - 45 Hz	69.1%	4.9%	97.3%	1.9%	69.6%	4.7%
7	40 - 50 Hz	70.8%	3.9%	97.4%	2.7%	70.9%	4.5%
8	30 - 40 Hz	71.7%	4.6%	84.5%	4.0%	83.7%	3.5%
9	70 - 95 Hz	81.9%	5.0%	90.1%	3.0%	83.4%	3.8%
10	40 - 45 Hz	76.4%	5.5%	90.9%	3.7%	76.7%	5.8%
av.		72.1%		89.0%		73.9%	
SD		5.4%		12.1%		6.7%	

Table 3.4: Classification results for all subjects for 3 classes in component space, leaving out either the neutral class, angry class or smile class. The frequency bandpass was fixed and taken from the best result for the according subjects from the frequency bandpass selection method on the 3 classes leaving out the angry pout class, shown in Table 3.3.

3.2.4 EEG versus EMG

Results up till now showed strong assumptions that EMG signals were responsible for all good classification AC. Classifications of the EMG channels were studied to see whether EEG channels can make a difference in the classification AC when combining them with the EMG channels.

Results show no significant difference between classification AC of only the EMG channels and classification AC of the EMG channels and EEG channels together in component space ($p = 0.29$ for paired samples t-test), shown in Table 3.5. Meaning that adding EEG channels to EMG channels, does not influence classification results. Leaving EMG channels out however yields significantly lower AC ($p = 0.0002$ for paired samples t-test).

An interesting observation is that the difference in frequency bands is less important for classifying data containing EMG channels, as shown in Figure 3.16.

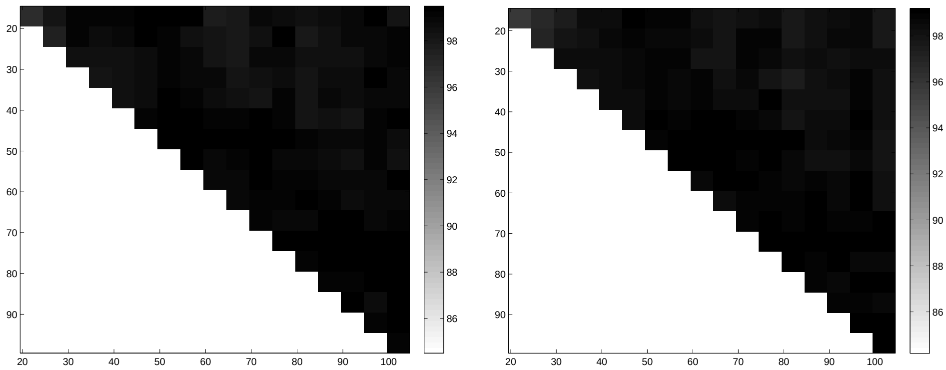
		EMG		EMG + EEG		EEG	
Subj.	**Freq.**	**AC**	**SD**	**AC**	**SD**	**AC**	**SD**
1	55 - 60 Hz	94.8%	2.5%	95.5%	2.7%	60.9%	4.2%
2	55 - 80 Hz	97.1%	1.8%	96.6%	1.7%	77.4%	3.6%
3	35 - 75 Hz	88.3%	3.0%	83.0%	3.1%	77.2%	4.9%
4	20 - 50 Hz	93.3%	2.4%	91.9%	2.6%	82.3%	3.2%
5	45 - 65 Hz	99.5%	0.6%	99.9%	0.4%	79.3%	5.9%
6	85 - 100 Hz	95.2%	2.1%	94.8%	2.3%	77.9%	3.5%
7	35 - 75 Hz	97.6%	1.7%	98.7%	0.9%	77.2%	3.9%
8	50 - 80 Hz	87.3%	2.9%	85.3%	3.2%	79.4%	4.0%
9	75 - 100 Hz	99.4%	0.8%	98.8%	1.1%	86.6%	3.1%
10	30 - 60 Hz	98.2%	1.5%	99.4%	0.9%	81.3%	7.1%
av.		95.1%		94.4%		79.0%	
SD.		4.3%		6.0%		6.7%	

Table 3.5: Results of classification (on 4 classes) in component space for 3 different data sets as input data: only EMG channels, both EMG and EEG channels and only EEG channels.

3.2.5 Frontal channels versus all channels

Results so far showed good classification AC when using the frontal and temporal channels, likely due to those channels being influenced the most by the stronger EMG signals. To study the influence that the frontal channels and temporal channels have on the classification AC, the results of using only frontal channels and using only frontal and temporal channels were compared in component space.

Results show, that using only frontal channels and using only frontal and



(a) channel (b) frequency bandpass

Figure 3.16: Results of the frequency bandpass selection method in channel space for subject 9 for both EMG input and EMG + EEG input, shown per bandpass. Since the scale of the frequency plot uses discrete steps of 5, each block is a bandpass read from the axis corresponding to the upper left corner of the block.

temporal channels, for classification in component space do not yield significant different AC compared to using all EEG channels, as can be seen in Table 3.6 ($p = 0.95$ and 0.87 respectively for paired samples t-test).

Interestingly, some single subject show significantly higher AC for classifying only frontal and temporal channels compared to classifying on all EEG channels in component space (e.g. subject 5 shows $p < 0.0001$ for an unpaired samples t-test).

		Frontal EEG		Front.+Temp. EEG		all EEG	
Subj.	**Freq.**	**AC**	**SD**	**AC**	**SD**	**AC**	**SD**
1	55 - 60 Hz	64.3%	5.3%	63.1%	4.8%	60.9%	4.2%
2	55 - 80 Hz	78.0%	4.5%	79.4%	3.0%	77.4%	3.6%
3	35 - 75 Hz	78.7%	3.9%	78.3%	5.4%	77.2%	4.9%
4	20 - 50 Hz	77.2%	2.9%	77.4%	3.3%	82.3%	3.2%
5	45 - 65 Hz	88.9%	3.9%	84.2%	4.9%	79.3%	5.9%
6	85 - 100 Hz	65.5%	5.0%	72.5%	7.0%	77.9%	3.5%
7	35 - 75 Hz	78.4%	3.0%	77.6%	2.9%	77.2%	3.9%
8	50 - 80 Hz	78.0%	4.3%	79.3%	3.6%	79.4%	4.0%
9	75 - 100 Hz	87.9%	2.7%	88.6%	3.0%	86.6%	3.1%
10	30 - 60 Hz	84.3%	3.3%	81.2%	7.2%	81.3%	7.1%
av.		78.1%		78.2%		79.0%	
SD.		8.8%		6.8%		6.7%	

Table 3.6: Results of the classification (on 4 clases) on only frontal channels, frontal and temporal channels and all EEG channels in component space.

Chapter 4

Discussion

This chapter discusses the findings from the previous chapter. The hypothesis and sub-hypotheses are reviewed and observations from the results that need interpretation are discussed. As last, possible future work following this study is discussed.

4.1 Classification of facial expressions

The hypothesis of study was: **H1:** *It is possible to significantly classify facial expressions with an EEG head cap.* It was determined in section 1.4 that H1 is accepted when AC > 70%, meaning that the accuracy is high enough to be meaningful.

The results found from the experiment, support the acceptance of H1. When looking at table 3.1, all subjects had AC significantly higher than 70% for classification on all 4 classes both in channel space and component space. Note the results from subject 1 are ignored here due to the artifacts caused by the moving cap. Considering that the AC were significantly higher without the angry pout class to classify, as shown in table 3.3, it can be concluded that different facial expression can indeed be classified with a significance over 70% using EEG recording equipment, when not ignoring the EMG signals in them. The results of Chin et al. also support this conclusion, yielding a test accuracy of 86% on 6 different facial expressions [11].

Note that this conclusion only addresses voluntary facial expressions. While involuntary expressions are expected to show differences in the brain compared to voluntary expression, like activity in the M1 [27, 26, 11], this is assumed to be not significant when EMG is classified as well as EEG due to the large difference in potential. There are however also differences in EMG signals between voluntary and involuntary expressions, regarding the asymmetry and the intensity of the expressions, that could have impact [17]. Whether or not spontaneous involuntary facial expressions can be classified in the same manner, should be studied.

The results confirming the hypothesis also showed some other important observations, discussed in the following subsections.

4.1.1 Performance difference between subjects

Because EMG is implied to be a major source for the classifications, it is unlikely that the classifications suffer much from so called 'BCI illiterate' problems, as often observed in BCI research. However, there were still differences observed in the optimal AC between subjects. At this point though, it is not sure whether these differences are due to inter-subject differences or due to difference in intensity of the performed expression, as subjects had a certain degree of freedom in performing the expression. Training subjects on performing the expressions to get the highest AC possible (using an online classifier with feedback), could possibly yield AC that are not significantly different over subjects, as well as AC higher than shown in the results in this thesis.

4.1.2 Differences between optimal spatial selection

One interesting finding, was the difference in the optimal spatial selection per subject. Asymmetry over the hemisphere was observed for all subjects, and significant differences between subjects for the optimal side were also observed. This means that sensors on both sides are always required for optimal results. These differences can be explained (when assuming EMG has indeed the strongest influence on the classifier) by the fact that facial expressions themselves are asymmetrical, especially with voluntary (non-emotional) expressions [17]. The theory however also suggest that the left side is often the stronger side for right handed people. This is something not observed in the results, but with results for only 8 right handed people (ignoring the results for subject 1) and no focus on asymmetry, it is not possible to conclude that the left side does not show stronger potentials. The absence of fEMG sensors on the right side of the face during the experiment also make it not possible to check the gathered data for differences between muscle potentials to each side of the face.

One critical note regarding the results from the channel selection method should be made. Because the channel selection method was done on a fixed bandpass, which proved to be not the optimal choice afterwards, the channel selection method does not necessarily have yielded the optimal channels to generate the highest possible AC for that subject. To demonstrate this, the method was repeated for subject 5, choosing a fixed frequency bandpass of 70 - 100 Hz this time. Performing the channel selection method now reveals an AC of 85.1% for channel 19 and 30. And performing the frequency bandpass selection method on that result yields an AC of 87.4% for 85 - 100 Hz, which is significant higher than the first result shown in 3.1 of 82.4% (with $p < 0.0001$ for samples t-test). It was however chosen not to run this test recursively on all subjects, because of time complexity of the algorithm and because choosing the best channel pair would be based on the results on the test set, meaning that repeating the process (again on the test set) would yield unrealistic results. Any difference in optimal channels observed, did not change any of the conclusions, because relative positions on the scalp hemisphere did not change. Finding the optimal AC was also no goal of this study.

4.1.3 Differences between optimal frequency band selection

Differences in optimal frequency band pass between subjects were hardly observed on average. The most consisting conclusion is that frequency below 20 Hz are not useful for classification. Most subjects had several optimal frequency bands that were not significantly different and almost all subjects shared those bands, making it likely to use certain frequency bands to classify all subjects for reasonable well AC for each subject. A method like filter bank CSP (FBCSP) could prove a good way to automatically take care of the frequency bands [11]. The difference between channel and component space in optimal frequency band could be explained partly due to the CSP algorithm using more different sources divided over the scalp in comparison to channel space where only 2 electrodes were used as source. The agreement of both channel and component space classifications on a band size between 5 and 35 Hz for optimal results however is the most remarkable observation from the frequency analysis. Big frequency bands were expected to perform worse, as they would contain more high variance data, due to EMG signals having more variance, and thus were less likely to show differences between the classes on average. This however does not explain why there is a big difference between frequency bands smaller than 35 Hz and frequency bands bigger than 35 Hz, especially not considering that there is not much difference between the different frequency bands smaller than 35 Hz.

4.2 Influence of the angry pout

One of the sub-hypotheses was: **H1.1:** *Using different facial expressions with partial overlapping AU, cause lower accuracies compared to using facial expressions without overlapping AU.*

Results regarding the angry class and the angry pout class show that this is indeed the case as removal of either one of them yielded significant higher AC, while removing either the neutral or the smile resulted in lower AC. The confusion matrices showed that this is caused because the classifier mistakes the angry pout class for the angry class.

It should be noted that these results could also mean that muscle influence from additional AU of the angry pout class (i.e. the pouting), in comparison to the angry class, did not help the classifier at all. Differences between the two classes could also be found due to difference in the intensity of the frown AU between the two classes.

It is likely that when a different AU than the frown AU is part of two expressions, no significant differences can be found compared to two expressions without similar AU. The frown muscles for example, lie close to the electrodes, and is more likely to have big influence on the recorded data, while the pouting muscles lie far away from the electrodes. Meaning that two expressions containing both the pout AU are likely to yield a significantly higher classification AC compared to the angry and angry pout expressions, which share the frown AU.

4.3 Influence of EMG

Another sub-hypothesis was: **H1.2:** *EMG influence on the classification accuracy is significant larger that EEG influence.*

Results showed that, using CSP, there were no significant differences in the resulting AC when classifying EMG channels compared to classifying EMG and EEG channels, while there was a big significant difference compared to using only EEG channels. This means that the EEG channels did not add useful signals for the classifier. However it should be noted that because of the significantly higher potentials of the EMG signals measured in the EMG channels, that possible EEG influence in the EEG channels might be over shadowed. This means that H1.2 can not be accepted with this result without completely removing the EMG influences from the EEG channels, for example using independent component analysis. This was however not the intend of this study and is therefore not mentioned in this thesis.

Other results however (like the high frequency bands for the highest AC, the preference of the classifier for channels closest to the used muscles, and the high amplitude signals in the channels that produce the highest AC) confirm that EMG has a big influence on the classification done on the EEG channels.

4.4 Influence of the frontal channels

The last sub-hypothesis was: **H1.3:** *Using only frontal electrodes, will not yield significantly lower classification accuracies than using all 32 electrodes.*

Result showed no significant differences between either using only frontal channels, using frontal and temporal channels and using all 32 EEG channels. Meaning that H1.3 can be accepted.

Chin et al. however had a different conclusion from their experiment, claiming that using only frontal electrodes yielded a significant lower AC [11]. They suggest this difference is due to the role of the motor cortex in voluntary facial expressions, though no evidence is given for this suggestion, nor found in the results described in this thesis. The differences in methods of both studies make it hard to compare the results. Possibly the use of 6 facial expressions make the use of more electrodes for CSP more important. Another explanation could lie in the used classification pipeline being different, or differences in the intensity of the expressions made by the subjects.

It should also be noted that when using only the frontal channels, the CSP algorithm has an unfair advantage constructing the weight matrix based on the training set, as it uses only channels which are known to yield a good performance. This could explain the observations that for some subjects classifications on only the frontal channels yielded a higher AC compared to classifying on all EEG channels.

4.5 Future work

4.5.1 Online classification and optimization

For commercial use, an online classifier would be needed, as well as better classification AC. Since this study did not look into optimization of the classification algorithm, it is expected that resulting AC can greatly improve. For online classification it is important that classification speed is optimal, meaning that the selection methods to study the data described in this thesis are not suited. A study could be done using the gathered data to find an optimal classification pipeline for online classification of facial expression using EEG electrodes.

4.5.2 Facial expressions recognition

One observation was that the angry class and the angry pout class were hard to separate from each other by the classifier. This is suspected to be because of the shared frown AU. It is interesting to know how certain combinations of AU would classify together with other combinations of AU. Certain AU might have a bigger impact on the signal by default, like the frown AU due to being closer to the electrodes. Some AU might also be controlled for different intensities of the expression and yield separable data for each level of intensity. A study focusing on the AU and how well they classify can reveal which facial expression could be used to optimized classification results, as well reveal how to perform the expressions to optimize the results.

4.5.3 Multi modality

Using facial expressions in applications for healthy consumers is most likely an addition to other modalities. Facial expressions could be detected while playing a game with you hands, or facial expression provide added control to an application where people already fully use their hands. In both applications hand movements are made, which could provide extra noise from the facial recognition point of view. A study should be done to test performance during the use of other modalities, to see whether facial expressions can still be recognized while using other input modalities apart from the facial expressions. Expectations are positive on this fact, since fEMG signals are less likely to be disturbed by arm movement than EEG signals, making facial expression recognition by EEG recordings a useful extra modality to existing applications.

Alternatively, a BCI application that measures, for example, alpha waves, could also use facial expressions as an extra modality. It should be studied how this affects recognition of both.

4.5.4 Real situation facial expressions

Applications for the consumer market are not likely to be used in experimental setups, meaning that a lot more noise will influence the classifier. A study to show the effects of 'real situation', using a setup to classify facial expressions should be carried out to gather data. Head movements, eye blinking, eye movements, body movements and talking should be among the interferences tested for. Involuntary facial expressions can be tested in those conditions as well. Results could be used to optimize the methods for real life situational use.

4.5.5 Role of the motor cortex

Considering the result from Chin et al. and the speculations made by Korb [11, 27, 26] it is worth focusing more on the motor cortex during facial expressions to see whether it will be an significant source in addition to the frontal channels, meaning that headsets with electrodes over the motor cortex could provide better results. Even when the motor cortex does not show significant influence compared to the EMG influences on the classifications, the results of such a study would be very interesting for the BCI community.

4.5.6 Pure EEG recognition

Also interesting for the BCI community would be to classify facial expressions without any help of EMG signals. While this is direct not helpful for commercial sector, it is interesting to classify facial expressions that are hardly or not carried out, especially for involuntary expressions, which is in return interesting for, for example, the games industry.

4.5.7 Imagined facial expressions

While imagined movements between both hands are already hard to classify, facial expressions are expected to be even harder. There are no results yet of research to imagined facial expressions at the moment. Area's in the motor cortex are close together and differences between expressions thus extremely subtle. With improving results in the imagined movements field the coming years, imagined facial expressions might become interesting enough to study. Because of the close link with emotion recognition, due to the underlying mechanism in the brain, the motor cortex might not be the only interesting area to study.

Chapter 5

Conclusions and recommendations

5.1 Conclusions

An experiment was carried out with the goal to gather data of four voluntary facial expressions using a 32 electrode EEG cap. The data was then studied with the goal to find out whether or not the classification would be feasible, in respect of using it for commercial entertaining purposes and thus to not care about the sources of the recorded signals.

Results showed that facial expressions could indeed be classified from data recorded by EEG sensors. With the four described classes (the neutral, angry, smile and angry pout class), an average classification accuracy of over 80% was observed. The results suggested that using facial expressions with overlapping muscles, like the angry class and the angry pout class, contribute to lower classification accuracies. Leaving out the angry pout class (or the angry class) improved accuracy over 90%, while leaving out the neutral or smile class resulted in reduced accuracy.

While 2 electrodes could be enough for good classification AC, variation in hemispherical asymmetry between trials and subjects show that electrodes to either side of the hemisphere are required to make it work for all persons. Using only frontal side channels on the other hand in a commercial EEG reading device, is suspected to be able to classify just as well as the 32 electrode cap used in the experiment, judging from the results.

Optimal frequency bands were all observed to be above 20 Hz and were smaller than 35 Hz on average, but no single band is shown to be optimal for all subjects. When using CSP components instead of channels, the optimal frequencies bands were found lower.

Combining the data of the EEG channels with the EMG channels, did not show significant higher classification accuracy compared to classification accuracy on only the EMG channels, indicating that EEG channels are not an useful in addition to EMG channels. However, this does not mean that EEG signals are not used during classification with only EEG channels. Other observations, like the high frequency bands for optimal classification accuracies, the high amplitude in channels with good accuracies and the topography of the signals used in classifications with good accuracies, do confirm that the influence of the EMG signals is the base of the classifications.

5.2 Recommendations

Future experiments in this field might do well to look into dry electrode testing, as this will likely be the future of entertainment BCI devices. Using dry electrodes would especially be useful for testing in more 'realistic' user environments where traditional wet electrode setups do not contribute to a 'realistic' user setup.

It is recommended to use EMG on both sides of the face when measuring the facial expressions due to asymmetry of the expressions. The on and offset of the EMG signals can be used to create epochs of the EEG data. This ways both voluntary and involuntary signals can be better studied. Additional EMG sensors could be placed over non target muscles to see whether they produce potential during the expressions or not, to make sure the measured potentials in the EEG sensors are only originated from target muscles and EEG signals.

Researchers and developers of facial expression, do well to make sure users and consumers do not need to stress the expressions too much. Applications using facial expressions would require users to be able to use it for some time without getting tired, painful or cramped muscles. Testing with minimal expression effort is also needed for involuntary expression recognition as users do not control the intensity of them.

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Appendices

Appendix A

Subject experiment protocol

Preparation:

- Filling out consent form and getting the experiment explained
- Filling out experiment questionnaire
- Putting on EEG cap and EMG sensors

Training:

- Free moving to see influences on EEG recording
- Training session (1 block of 12 trials)
- If subject not trained enough, repeat training session

Experiment:

- 4 blocks (40 trials per block)
- Session break
- 4 blocks (40 trials per block)

Finishing:

- Clean up subject

Appendix B

Consent form

Naam onderzoeker: .... Deelnemer ID: ....

Universiteit Twente
Faculteit Elektrotechniek, Wiskunde en Informatica (EWI)
Leerstoel: Human Media Interaction (HMI)
Postbus 217
7500 AE Enschede

Informed Consent (genformeerde toestemming)

Beste deelnemer,

Je hebt aangeboden om mee te doen met dit onderzoek. Dit document bevat wat informatie over je rechten en de procedure van het volgende experiment. Lees alsjeblieft de volgende paragrafen zorgvuldig door.

1) Het doel van het onderzoek

Het doel van het onderzoek is het verzamelen van EEG (hersenactiviteit) en EMG (spieractiviteit) data te verzamelen voor gezichtsuitdrukkingen. Deze data zal geanalyseerd worden met als hoofddoel het classificeren van de data per uitdrukking.

2) De procedure van het onderzoek

In het begin zul je een elektrodekap op krijgen. Je hoofd zal hiervoor worden opgemeten, je hoofdhuid kan wat schoongemaakt worden met alcohol, en een kap zal worden vastgemaakt. In deze cap zitten gaten waarin gel zal worden gespoten en elektrodes zullen worden geklikt. Verder zullen er 8 sensoren op je gezicht worden geplakt door middel van een stikker die op de huid blijft zitten. Om de sensoren en de snoeren die er aan zitten goed op hun plaats te houden zal er ook tape over heen geplakt worden op het gezicht. Dit hele proces duurt ongeveer 15 minuten.

Het daadwerkelijke experiment zal ongeveer een uur duren. De onderzoeker zal bij je in de ruimte blijven gedurende het experiment en kun je elk moment vragen stellen. Er zal steeds een stimulus laten zien worden, waarvan de bijbehorende gezichtsuitdrukking gedaan moet worden. Er zal eerst een korte training sessie gehouden om te oefenen, en vervolgens twee grote sessies die beide uit 4 blokken van 4 minuten bestaan. Tussen blokken en sessies is er altijd een pauze waarbij je zelf bepaald hoelang deze is.

Tijdens het experiment wordt je gezicht gefilmd met een camera. Deze beelden zullen niet gebruikt bij de verwerking van de resultaten en dienen slechts voor terug kijken bij vreemde resultaten om zo data te verwerpen. De beelden zullen nimmer uit handen worden gegeven of gebruikt bij publicatie en kunnen altijd op aanvraag verwijderd worden. Je hebt ook het recht om het filmen van te voren te weigeren, in dat geval zal er niets worden opgenomen. Voor en na het experiment worden een aantal vragen gesteld, je bent niet verplicht te antwoorden als je dat niet wilt.

3) Risico's en bijwerkingen

Dit onderzoek is gebaseerd op de huidige kennis van de hoofdonderzoeker en is veilig en pijnloos voor de deelnemers. Door deel te nemen aan dit onderzoek loop je geen specifieke risico's, en er zijn geen bijwerkingen bekend. Echter, omdat dit soort onderzoeken in het algemeen vrij nieuw is, kunnen onbekende bijwerkingen niet worden uitgesloten.

Belangrijk: laat het de onderzoeker zo snel mogelijk weten als je ziektes hebt of onder medische behandeling staat. Laat het ook meteen weten als je ooit een epileptische aanval hebt gehad of last hebt van oorsuizen. Vragen hierover kun je stellen aan de onderzoeker.

4) Stoppen van het experiment

Je hebt het recht om het experiment op elk moment te stoppen zonder te vertellen waarom. Deelname is volledig vrijwillig en zonder verplichtingen. Er zijn geen nadelen door het stoppen van het onderzoek.

Tijdens het experiment zijn er meerdere pauzemomenten, je kan dan eten drinken of naar het toilet. Als je op enig moment tijdens het experiment ongemak voelt, laat dat dan direct weten aan de onderzoeker.

5) Privacybescherming

Je privacy wordt gerespecteerd. Persoonlijke gegevens zullen niet worden doorgespeeld aan derden. De verzamelde data wordt anoniem gemaakt door ons en zal alleen in deze anonieme vorm worden gebruikt en gepubliceerd.

6) Verklaring

Door je handtekening onderaan dit formulier te zetten, ga je akkoord met het volgende:

"Ik verklaar hierbij dat de onderzoeker van dit experiment me heeft genformeerd over de bovenstaande punten. Ik heb het gelezen en begrepen. Ik ben in overeenstemming met elk van de punten. Hierbij geef ik toestemming dat de data die verkregen wordt met dit onderzoek wordt geanalyseerd voor wetenschappelijke doeleinden en anoniem wordt gebruikt voor publicatie. Ik ben genformeerd over mijn rechten als proefpersoon en over de vrijwillige deelname van dit onderzoek"

Plaats, datum Handtekening

....

Appendix C

Questionnaire

Informatie Proefpersoon

Algemene informatie experiment *in te vullen door onderzoeker*

Datum: ___ - ___ - _______ *Start:* ___ *:* ___ *Eind:* ___ *:* ___

Omschrijving: ____

____

____

Software: ____

Actiview settings: *Bandpass:* ____ Hz - ____ Hz *Sample frequency:* _____ Hz

Experiment definitie: ____

Onderzoeker(s): ____

Algemene informatie proefpersoon

in te vullen door proefpersoon

ID: ____________________________

Geslacht: m / v

Leeftijd: ____

Dominantie: linkshandig / rechtshandig

Opleiding: __________________________

Beroep: ____________________________

in te vullen door onderzoeker

Hoofd omtrek: ___ cm *Cap*: _____

Nasion-inion: ___ cm *Cz*: ___cm

Slaap-slaap: ___ cm *Cz*: ___cm

Haaromschrijving: ______________

Haarproducten: ________________

In te vullen door proefpersoon

Visuele hulpmiddelen: o contactlenzen o bril o geen

Alcoholconsumptie: o dagelijks o wekelijks o maandelijks
o minder dan maandelijks o nooit
Voor experiment: ___________________________

Koffieconsumptie: o 5+ kopjes per dag o 3-5 kopjes o 1-3 kopjes
o minder dan 1 kopje o nooit
Voor experiment: ___________________________

Zwarte/groene thee: consumptie o 5+ kopjes per dag o 3-5 kopjes o 1-3 kopjes
o minder dan 1 kopje o nooit
Voor experiment: ___________________________

Tabakconsumptie: o 2+ pakjes per dag o 1-2 per dag o 1 pakje per dag
o minder dan 1 pakje o af en toe o nooit
Voor experiment: ___________________________

Aantal uren slaap: per nacht: ___ voor experiment: ___

Mate van alertheid op dit moment:
niet alert o o o o o zeer alert

Medicijnen: ____

Aandachts-/neurologische/psychiatrische problemen:

Werken met de PC	o 6+ uur per dag	o 4-6 uur p.d.	o 2-4 uur p.d.
(niet per se voor beroep)	o dagelijks, <2 uur	o wekelijks	o maandelijks
	o minder dan maandelijks		o nooit

Handigheidstest:

Geef aan met welke hand je de volgende taken zou uitvoeren:

Schrijven	Links / Rechts
Tekenen	Links / Rechts
Bal gooien	Links / Rechts
Knippen	Links / Rechts
Tanden poetsen	Links / Rechts
Brood snijden met mes	Links / Rechts
Eten met een lepel	Links / Rechts
Een computermuis gebruiken	Links / Rechts
Een lucifer aansteken (de andere hand houdt het doosje vast)	Links / Rechts
Een pot openmaken (de andere hand houdt de pot vast)	Links / Rechts

Met welke hand schrijven:

Moeder	L / R / ?	*Zus*	L / R / ?	*Dochter*	L / R / ?
Vader	L / R / ?	*Broer*	L / R / ?	*Zoon*	L / R / ?

Eventuele extra broers/zussen/dochters/zonen:

L / R	L / R	L / R	L / R
L / R	L / R	L / R	L / R

Opmerkingen:

Appendix D

Channels

D.1 topography of the electrodes/channels

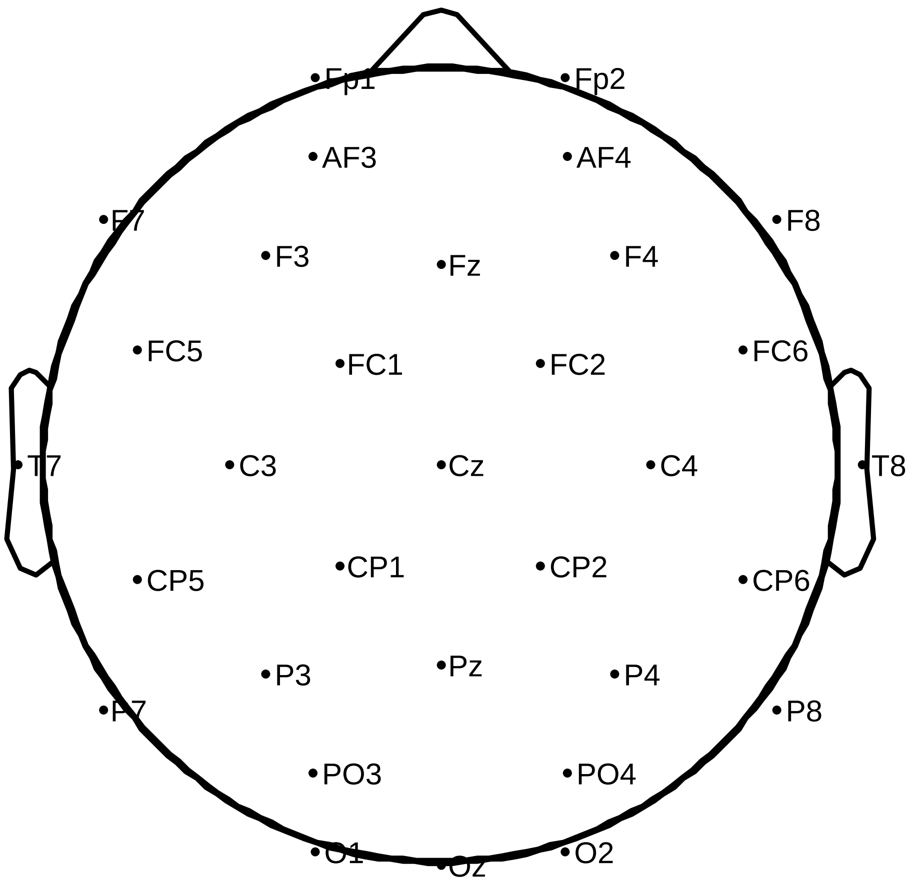


Figure D.1: Scalp topography plot showing the location of all electrodes by name.

D.2 topography of the electrodes in numbers

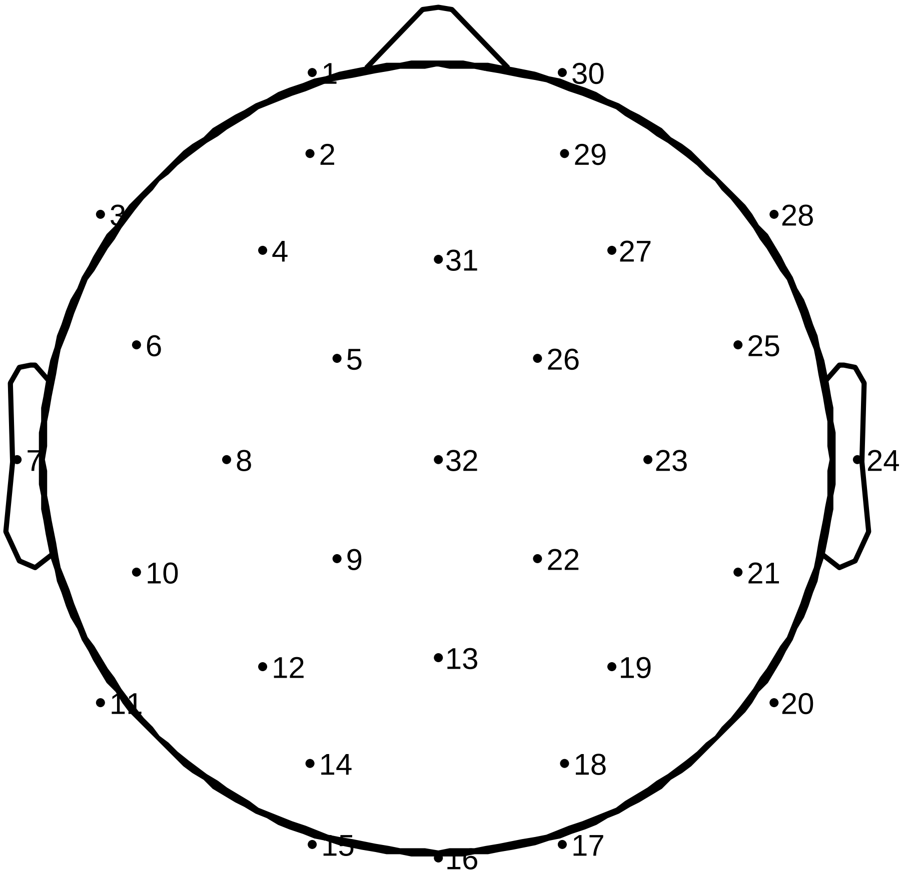
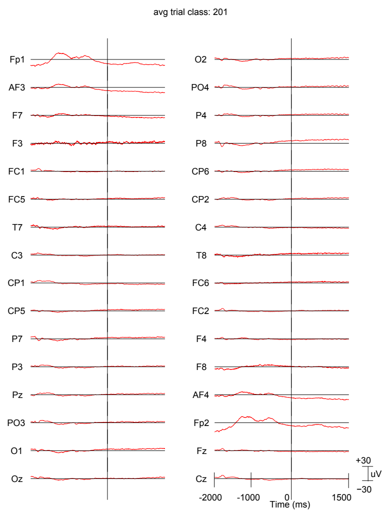


Figure D.2: Scalp topography plot showing the location of all electrodes by number.

Appendix E

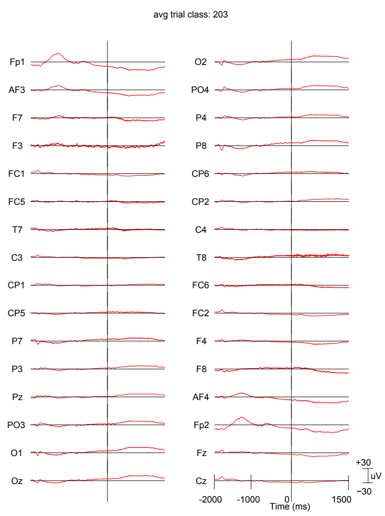
ERP plots

E.1 Grand average

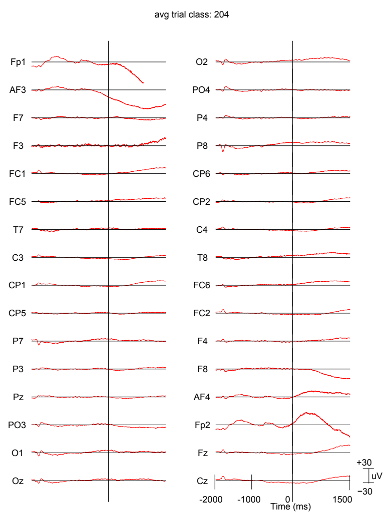


(a) Neutral

(b) Angry



(c) Smile



(d) Angry pout

Figure E.1: Grand average ERP of all subjects, showing 2 seconds pre AEP (SSP and BP) and the AEP for all 32 channels for all classes. Pre-AEP was taken as baseline. Appendix E.1 shows the same plot for all channels.

E.2 Significance

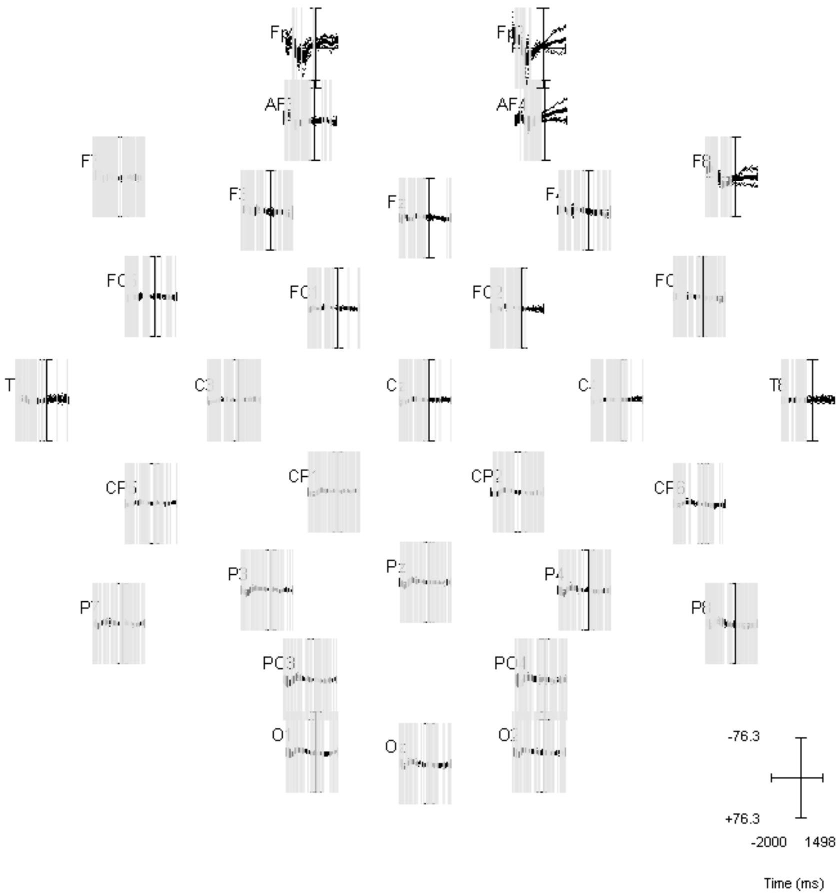


Figure E.2: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the neutral class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

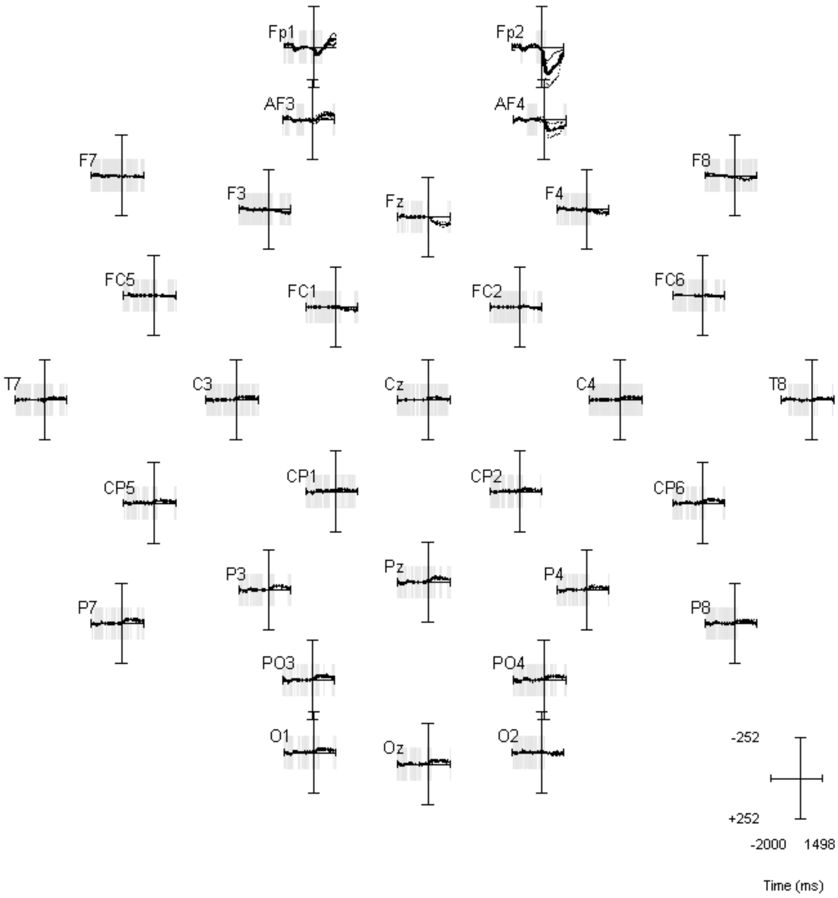


Figure E.3: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the angry class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

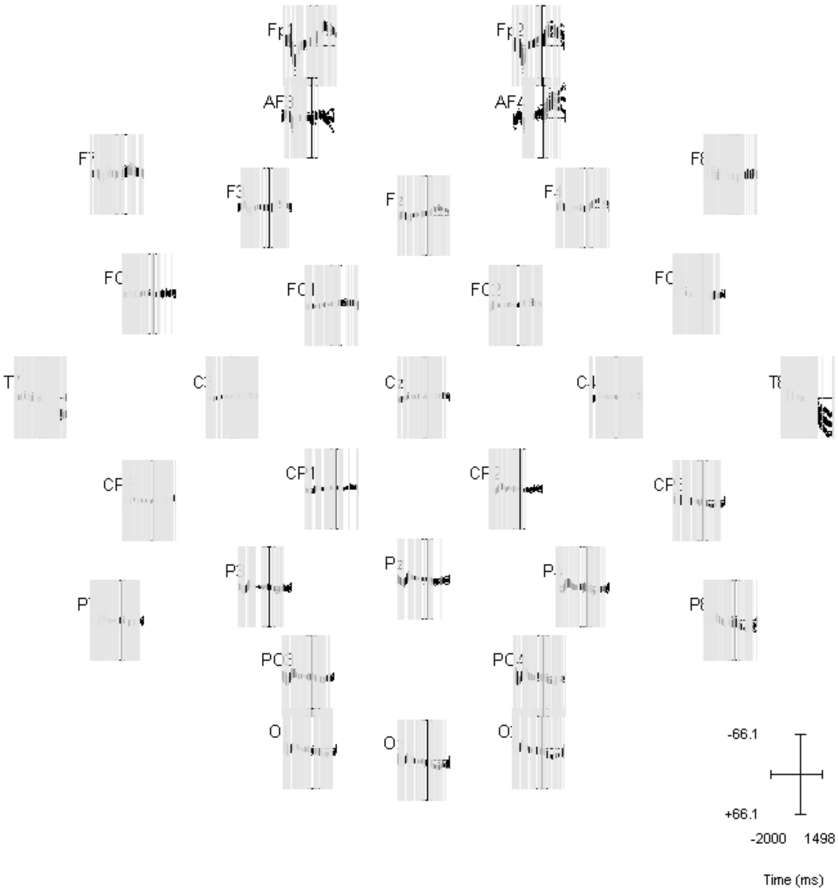


Figure E.4: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the smile class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

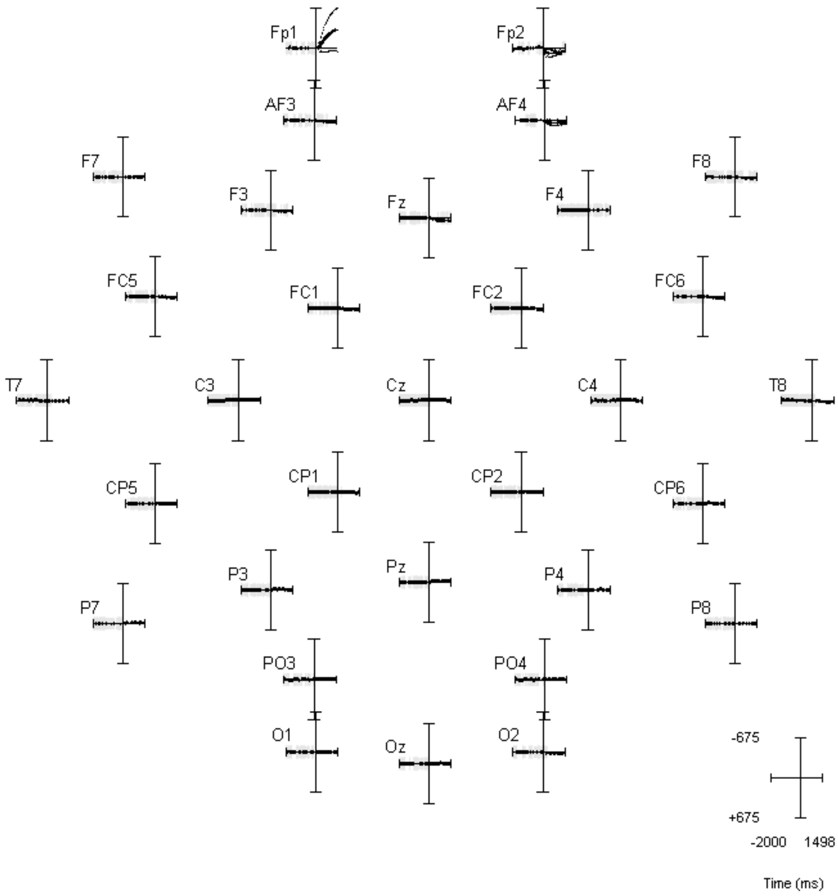


Figure E.5: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the angry pout class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

E.3 Significance difference

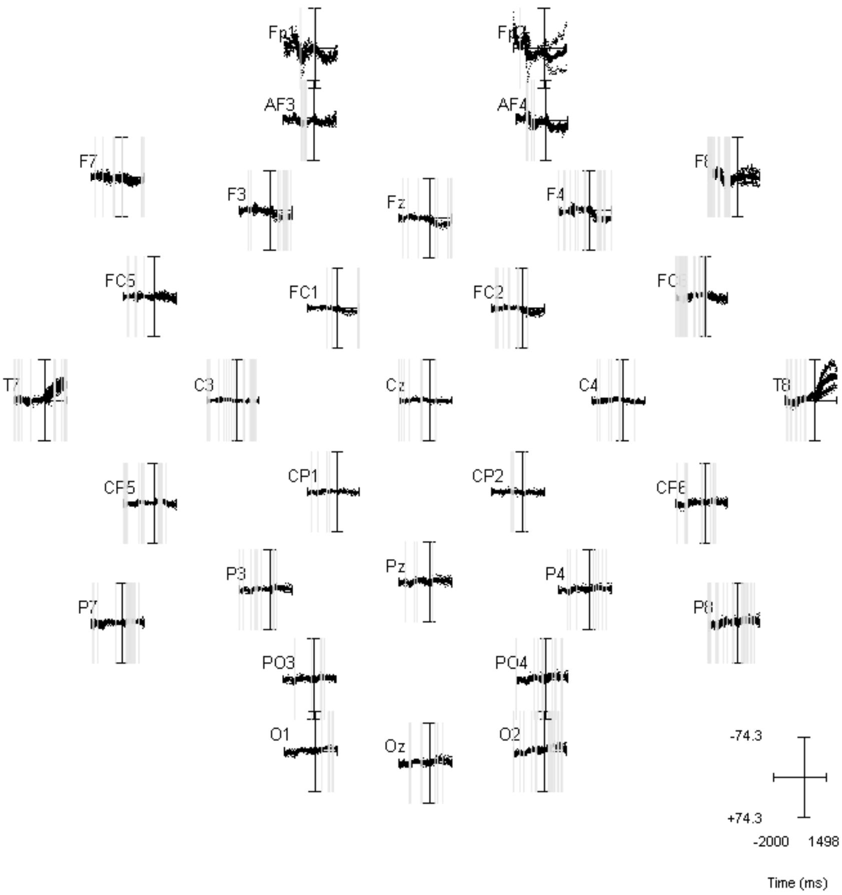


Figure E.6: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the difference of the neutral and smile class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

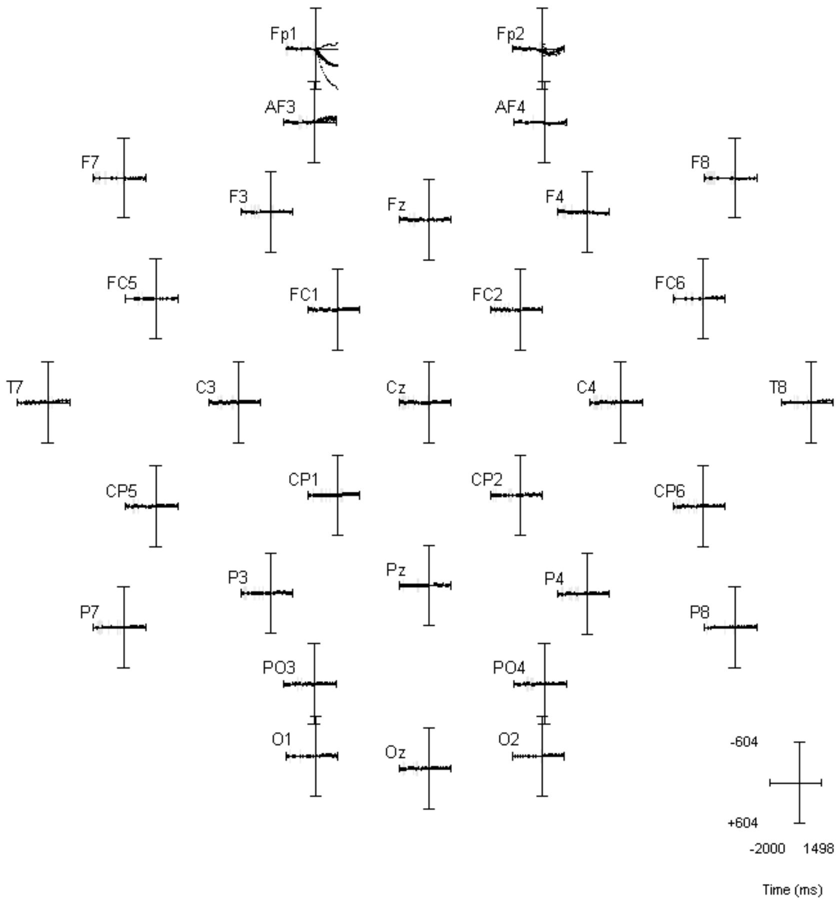


Figure E.7: ERP plot of all channels (arranged in spatial scalp location) of subject 9 for the diference of the angry and angry pout class, with the standard deviation and significant time periods shown. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline. Significant areas were calculated with a two-tailed t-test with $\alpha = 0.05$.

E.4 topo

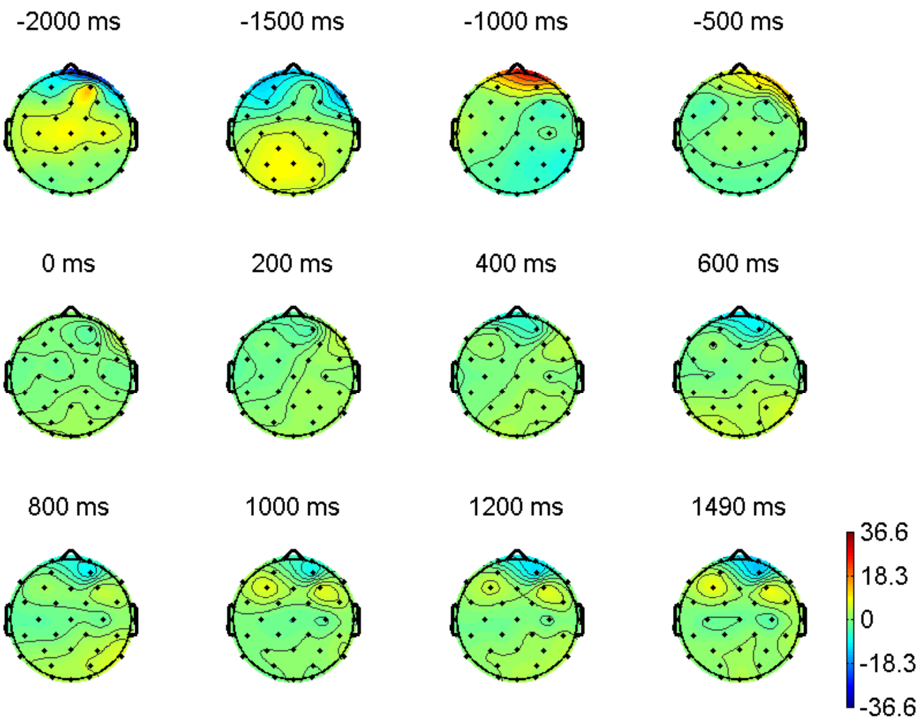


Figure E.8: Topography plot of subject 9 for the neutral class, showing potential changes in time over the scalp. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline.

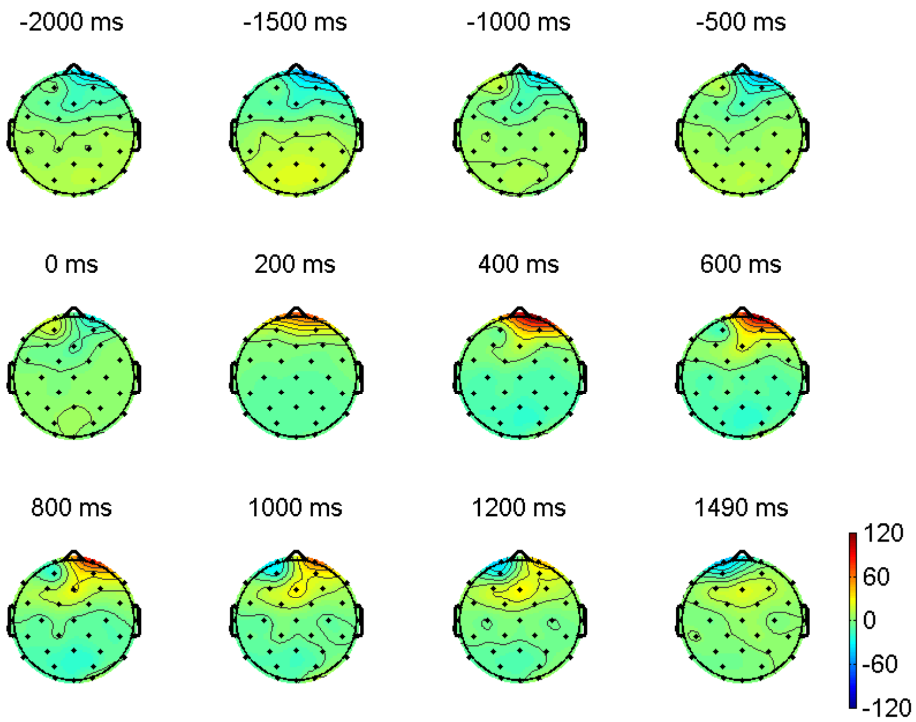


Figure E.9: Topography plot of subject 9 for the angry class, showing potential changes in time over the scalp. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline.

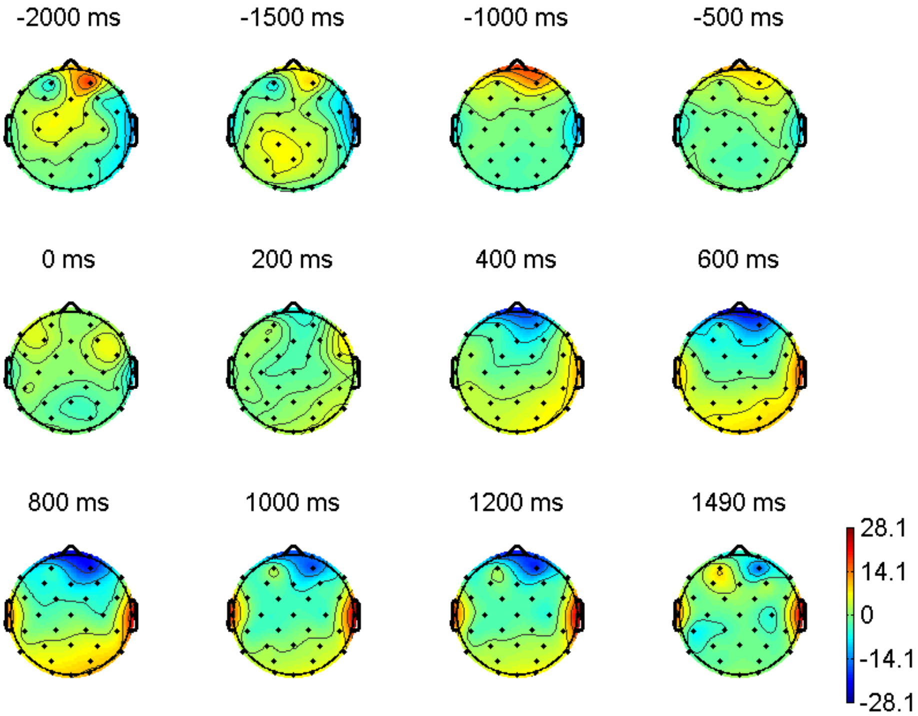


Figure E.10: Topography plot of subject 9 for the smile class, showing potential changes in time over the scalp. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline.

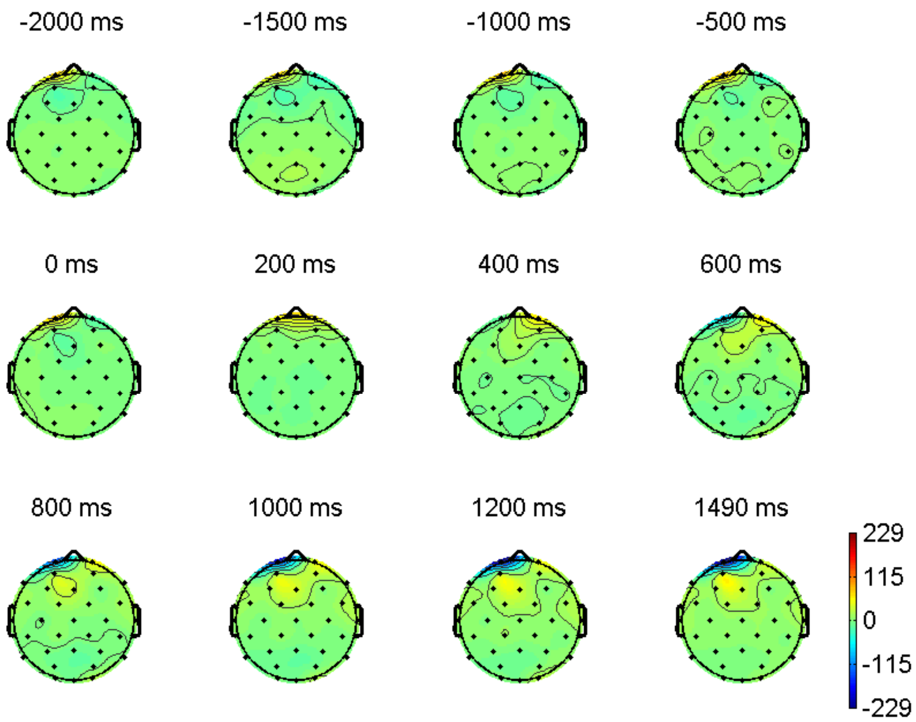


Figure E.11: Topography plot of subject 9 for the angry pout class, showing potential changes in time over the scalp. 2 seconds pre AEP (SSP and BP) and the AEP are shown with the pre-AEP taken as baseline.

Appendix F

3 class confusion matrix

(a) No neutral class

	angry	smile	angry pout
angry	892	0	108
smile	9	925	66
angry pout	357	4	639

(b) No angry class

	neutral	smile	angry pout
neutral	920	11	69
smile	0	1000	0
angry pout	215	1	784

(c) No smile class

	neutral	angry	angry pout
neutral	937	38	25
angry	9	925	66
angry pout	25	381	594

(d) no angry pout class

	neutral	angry	smile
neutral	923	58	19
angry	10	990	0
smile	0	0	1000

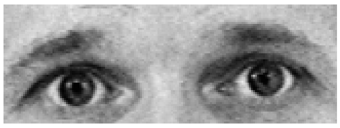
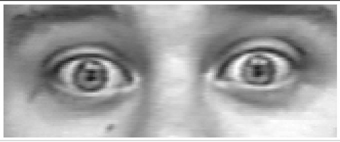
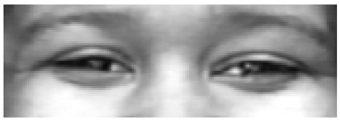
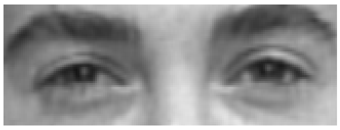
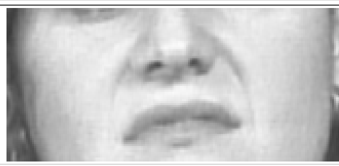
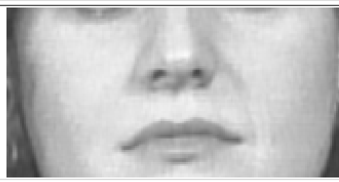
Table F.1: Confusion matrix of classification for 3 classes of subject 9 in component space filtered for 70 - 100 Hz. Confusion values were taken and summed for 50 runs. Horizontal values show actual observations, vertical values show classifier result.

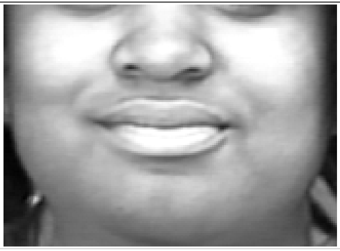
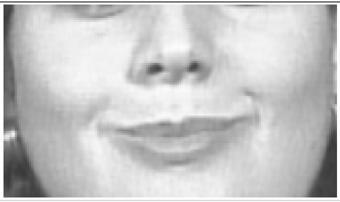
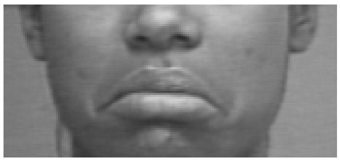
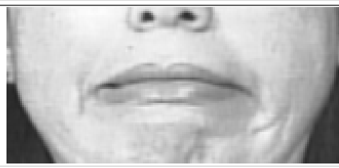
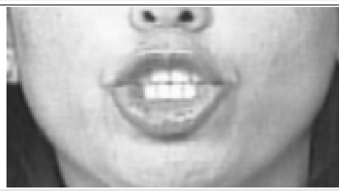
Appendix G

FACS

FACS - Facial Action Coding System
(2002 Revision is here)

(Ekman and Friesen 1978)

AU	Description	Facial muscle	Example image
1	Inner Brow Raiser	*Frontalis, pars medialis*	
2	Outer Brow Raiser	*Frontalis, pars lateralis*	
4	Brow Lowerer	*Corrugator supercilii, Depressor supercilii*	
5	Upper Lid Raiser	*Levator palpebrae superioris*	
6	Cheek Raiser	*Orbicularis oculi, pars orbitalis*	
7	Lid Tightener	*Orbicularis oculi, pars palpebralis*	
9	Nose Wrinkler	*Levator labii superioris alaquae nasi*	
10	Upper Lip Raiser	*Levator labii superioris*	
11	Nasolabial Deepener	*Zygomaticus minor*	

12	Lip Corner Puller	*Zygomaticus major*	
13	Cheek Puffer	*Levator anguli oris (a.k.a. Caninus)*	
14	Dimpler	*Buccinator*	
15	Lip Corner Depressor	*Depressor anguli oris (a.k.a. Triangularis)*	
16	Lower Lip Depressor	*Depressor labii inferioris*	
17	Chin Raiser	*Mentalis*	
18	Lip Puckerer	*Incisivii labii superioris and Incisivii labii inferioris*	
20	Lip stretcher	*Risorius w/ platysma*	
22	Lip Funneler	*Orbicularis oris*	

List of Symbols and Abbreviations

Abbreviation	Description	Definition
AC	classification accuracy	page 23
AEP	actual expression phase	page 15
AU	action units	page 9
BCI	brain computer interface	page 3
BP	buildup phase	page 15
CAR	common average reference	page 21
CSP	common spatial patterns	page 22
EEG	electroencephalography	page 6
EOG	electrooculography	page 7
EMG	electromyography	page 10
ERP	event related potential	page 5
FACS	facial action coding system	page 9
fEMG	facial electromyography	page 9
fMRI	functional magnetic resonance imaging	page 6
HMI	human media interaction	page 3
M1	primary motor cortex	page ??
MEG	magnetoencephalography	page 6
MUAP	motor unit action potential	page 10
PP	preparation phase	page 15
RPC	recording PC	page 18
SPC	stimulus PC	page 18
SSP	stimulus showing phase	page 15

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