EEG-based Emotion Recognition

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The Influence of Visual and Auditory Stimuli

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ABSTRACT

Making the computer more empathic to the user is one of the aspects of affective computing. With EEG-based emotion recognition, the computer can actually take a look inside the user's head to observe their mental state.

This paper describes a research project conducted to recognize emotion from brain signals measured with the BraInquiry EEG PET device. Firstly, literature research has been performed to establish a suitable approach and determine optimal placement of a limited number of electrodes for emotion recognition. The second step consisted of putting this information into practice with the BraInquiry apparel during the experimental phase, which finally was analyzed to see what results could be achieved.

Keywords

Brain-computer interaction, electroencephalogram, emotion, emotion recognition, valence-arousal model, affective computing.

1. INTRODUCTION

Affective computing is a rising topic within human-computer interaction that tries to satisfy other user needs, besides the need of the user to be as productive as possible. As the user is an affective human being, many needs are related to emotions and interaction. Picard and Klein state:

> "Recognising affect should greatly facilitate the ability of computers to heed the rules of human-human communication" [24].

The need for computer applications which can detect the current emotional state of the user is ever growing [24]. In an effort to copy human communication, research has already been done into recognizing emotion from face and voice. Humans can recognize emotions from these signals with a 70-98% accuracy, and computers are already pretty successful especially at classifying facial expressions (80-90%) [26]. Note that these high success rates are under very controlled circumstances, and will be lower in ordinary situations.

However, emotions are not just what is displayed. In psychology, an explicit separation is made between the physiological arousal, the behavioral expression (affect), and the conscious experience of an emotion (feeling).

Facial expression and voice concern the second aspect of emotion: the expression. This can be consciously adapted, and its interpretation is not objective. For this reason, research has been conducted to look at the physiological aspects like the user's heart rate, skin conductance, and pupil dilation [26, 23].

With the rising interest for brain-computer interaction (BCI), user's EEGs (electroencephalograms) have been analyzed as well. Whether the EEG just shows a physiological response, or also gives insight into the emotion as how it is experienced mentally, is still unclear.

Currently, correct EEG-based recognition of artifically evoked emotion is only about 60%, but much research shows the suitability of EEG for this kind of task [7, 6]. This field of research is still relatively new, and there is still much to be done to improve on existing elements in BCI, but also to discover new possibilities.

2. BACKGROUND

For practical use of BCI, the costs and hassle of placing many electrodes and getting the connection with the computer set up should be minimal. Hence, for any BCI, the accuracy of interpretation should be maximized for as few electrodes as possible.

The BraInquiry EEG PET (ElectroEncephaloGraphy Personal Efficiency Trainer) device has only five electrodes and is therefore a suitable candidate for this research [4, 5]. With only two channels (two dipole electrodes and one ground) for measuring brain activity, the exact placing of the electrodes becomes all the more important.

Psycho-physiological research shows there is a direct link between the amount of action in the left frontal lobe and the right frontal lobe and the resulting emotion. A more active left frontal region indicates a positive reaction, and a more active right anterior lobe negative affect [20].

This shows great potential for EEG-based emotion classification, but to only be able to distinct between happy and unhapy will often not provide sufficient granularity to be of much use for human-computer interaction. Therefore it is also necessary to derive a suitable method for representing and classifying emotions.

Another element that can have much influence on the classification success rate is the way the emotions are elicited in the test subjects. For this research visual, auditory, and audiovisual stimuli will be compared.

3. RELATED WORK

Much research has been done in the field of EEG-based emotion recognition, but few definite conclusions have been derived. In this section the research of Hoekstra and Janssen is mentioned for their experience with BraInquiry [14]. Choppin's master thesis provides valuable insights in methodology and important EEG features for emotion recognition [7]. The final article discussed in this section shows preliminary results for classifying emotions based on signals from three electrodes [26].

3.1 BraInquiry

Hoekstra and Janssen used the BraInquiry PET EEG device for analyzing biosignals during transfer of knowledge. The device has five electrodes of which two were used for meauring ECG activity, and the final three for acquiring brain signals using the 10-20 system, positioned at A1 (left ear), A2 (right ear), and Cz (centrally, at the top of the head). Only the Cz electrode measurements were used in this particular research [14].

3.2 Emotion Expression with Neural Networks

In 2000, Choppin analyzed EEG signals and used neural networks to classify them in six emotions based on emotional valence and arousal, with a 64% success rate.

Important for our case, because of the limited number of available electrodes, are the influential EEG features detected during various emotional stimuli [7]:

- Valence: positive, happy emotions result in a higher frontal coherence in alpha, and higher right parietal beta power, compared to negative emotion.
- Arousal: excitation presented a higher beta power and coherence in the parietal lobe, plus lower alpha activity.
- Dominance: strength of an emotion, which is generally expressed in the EEG as an increase in the beta / alpha activity ratio in the frontal lobe, plus an increase in beta activity at the parietal lobe.

More about alpha and beta frequencies can be read in section 8.1 about the nature of EEG signals.

3.3 Emotion Recognition with 3 Electrodes

Takahashi used a setup of three dry electrodes on a headband to classify five emotions based on multiple bio-potential signals (EEG, pulse, and skin conductance): joy, anger, sadness, fear, and relaxation. The succcss rate when classifying solely on the EEG using support vector machines was 41.7% [26].

4. RESEARCH QUESTIONS

Now there is an awareness of the current state of EEG-based emotion recognition, and its use within human media interaction, it is time to move on to the primary goals of this research.

The main questions addressed in this research are:

1. Is the modality of the stimulus (visual, auditory, or audiovisual) recognizable from the recorded brain signals?
2. To what extent are emotions recognizable from an EEG?
3. What is the influence of the modality of the stimulus on the recognition rate?

But first, to get an EEG-based emotion recognition system set up with the BraInquiry device, a few other questions need to be answered:

4. When using only five electrodes, what would be good positions to place them for emotion recognition?
5. What features are interesting to extract from the recorded EEG signals for emotion recognition?

5. HYPOTHESES

This section discusses expectations for the answers to the research questions posed previously. These predictions are based on the perparatory literature research. For some hypotheses, use of the BraInquiry apparel has a big influence, which will in such cases be noted in the final paragraphs of that subsection.

5.1 Modality Recognition

Stimuli of different modalities will activate different areas of the brain to process the stimuli cognitively. If the electrodes would be positioned over the areas that are responsible for visual and auditory processing, recognizing the stimuli modalities should be very feasible.

The ability for modality recognition highly depends on the electrode placement, which may not at all be suitable for this. As the main goal of this research is emotion recognition, the optimal electrode placement for the five electrodes is chosen to support this, not to support stimulus modality specifically.

5.2 Emotion Recognition

The recognizability of different emotions depends on how well the EEG features can be mapped onto chosen emotion representation. The emotion representation used is the two-dimensional mapping with valence and arousal axes, which were already mentioned shortly in section 3.2. A more detailed explanation of this representation is provided later on in section 7.

If valence will be hard to determine, it is still possible to have usable results on the arousal scale, and vice versa. Of course ideally, both dimensions will have a good spread, and any emotion that can be mapped onto the two axes can be recognized.

5.3 Influence of Modality

Recent research into auditory brain-computer interfacing concludes it is easier to learn to increase or decrease the sensorimotor rhythm amplitude with visual feedback than with auditory feedback. This is not related to emotion recognition, but in the discussion it is noted that healthy people with no eye problems may have a less developed sense of hearing [21].

As the visual sense is more developed, visual stimuli could be easier to recognize from brain signals than audio stimuli. Following this reasoning a combined effort from both visual and auditory stimuli to elicit an emotion should provide the best environment for emotion recognition.

In this situation where only five electrodes are available, the modality for which the electrodes are placed optimally could give the best classification results.

5.4 Electrode Positioning

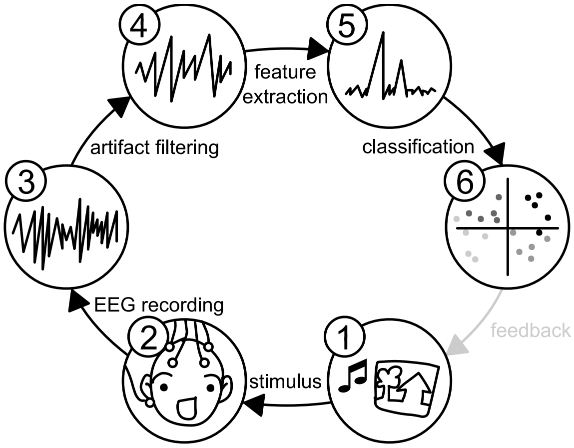


Figure 1: Brain-computer interface cycle.

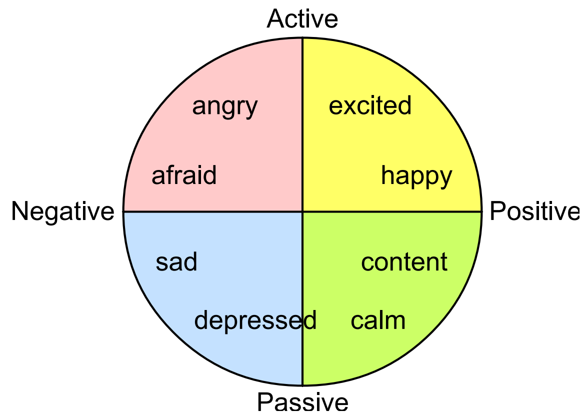


Figure 2: Arousal-valence model.

Suitable electrode positions are probably around the frontal and parietal lobes [7].

Based on the BraInquiry manual, one ground electrode is needed, leaving two options for the remaining four electrodes: two dipole, or two monopole signals (with the two other electrodes of the dipole pairs on neutral spots) [4].

Optimally, the EOG (electro-oculogram, eye movements) would also be measured for artifact removal in a later processing stage. In this case however, a preliminary low-pass and high-pass filtering can be done to remove part of the artifacts from the signal.

5.5 EEG Features

Many different features have been thought up to be extracted from EEG signals. The most frequent transformation used is Fourier analysis to be able to look at specific frequency bands [25].

6. BCI BASICS

EEG-based brain-computer interfaces consist of very typical components, each of which performs its own critical function. Figure 1 shows the process cycle. First of all (1) a stimulus set and test protocol is needed. During testing (2) the test subject will be exposed to the stimuli according to the test protocol. The resulting voltage changes in the brain are then recorded (3) as an electroencephalogram, from which noise and artifacts are removed (4). The resulting data will be analyzed (5) and relevant features (like power spectra) will be computed. Based on a test set from these features a classifier will be trained (6), and the rest of the data will be classified using this classifier. This step provides an interpretation of the original raw brain signals. The feedback step will not be used during this research, but is shown for completeness.

Multiple alternatives exist for realizing the many elements that make up an emotion recognition system. Because of the limited time available for this research, in some cases, a decision had to be made based on somewhat limited knowledge of the subject. Experimenting with and comparing alternatives could be very interesting for future work.

7. EMOTION REPRESENTATION

There are two perspectives towards emotions that are of interest for theoretical emotion representation:

1. *Darwin:* basic emotions have evolved through natural selection. Ekman, following Darwinian tradition, derived a number of universal basic emotions, which has now expanded to a list of 15 affects [10]. Plutchik proposed eight basic emotions: anger, fear, sadness, disgust, surprise, curiosity, acceptance, and joy[1].

2. *Cognition:* Lang proposes a two-dimensional scale, on which emotions are mapped according to their valence (positive/approach versus negative/withdrawal), and arousal (calm versus excited) [17].

Both methods are widely used, but for this research, the second representation is chosen because of its simplicity and suitability. Instead of absolute classification, regression can be used, which can possibly provide more insight.

This representation is shown in Figure 2. The general indication of the positions of certain emotions is based on the emotion labeling from the SAM evaluation and the indicators used in FeelTrace [2, 9].

8. EEG RECORDING

To determine the optimal positions for the few electrodes available, insight into what the EEG actually shows is invaluable. Based on this information and on what parts of the brain are involved in emotion processing, it is possible to provide a general indication of relevant areas. Related research also gave more insight. Also the expert opinion of Martijn Arns, biological psychologist specialized in psychophysiological monitoring systems and founding director of BraInquiry B.V., has been acquired. Putting all this information together, an informed decision for electrode placement has been made.

8.1 The Nature of EEG Signals

When a neuron fires, voltage changes occur. Generally, an incoming signal triggers some sodium ions to transport into the cell, which causes a voltage rise inside the cell (compared to the outside). When this voltage increase reaches a

[1]Reference: http://en.wikipedia.org/wiki/Robert_Plutchik

certain threshold, an action potential is triggered by the fast influx of sodium and the slower outflux of potassium ions. This action potential is a wave of electrical discharge that travels over the dendrite to neighbouring neurons. During this event, which only lasts for about two milliseconds, the voltage goes from the resting potential of about -60mV to +20mV.

The electrical activity measured by the surface electrodes represents the field potentials resulting from the combined activity of many neuronal cells. The activity that is seen most clearly on the EEG are those of the neurons in the cortex (nearest to the skull) closest to the electrodes. Deeper structures like the thalamus and brain stem cannot be seen directly.

The cortical activity as measured by the EEG is distorted by the tissue and bone inbetween the electrodes on the head and the cortex. Because of this, the amplitude of the EEG potentials is only microvolts, even though this represents the summated activity of many neurons (with voltage changes in millivolts).

Even though the EEG is obviously not a precise measurement, it still provides important insight into the electrical activity of the cortex. Frequency and amplitude are the characteristics of the recorded EEG patterns. The frequency range is normally from 1 to 80Hz (divided in alpha bands, beta bands, and more), with amplitudes of 10 to 100 microvolts [16].

The observed frequences have been divided into specific groups, as specific frequency ranges are more prominent in certain states of mind. The two that are most important for this research are the alpha (8–12Hz) and beta (12–30Hz) frequencies. Alpha waves are typical for an alert, but relaxed mental state, and are most visible over the parietal and occipital lobes. High alpha activity have also been correlated to brain inactivation. Beta activity is related to an active state of mind, most prominent in the frontal cortex and over other areas during intense focused mental activity [16]. Note: where the frequency bands end and begin sometimes varies a few Herz, depending on the source of information.

For more details, refer to the EEG processing sections.

Now there is insight into the general ideas that form the basis of EEG recording, let's have a look at the brain structures involved in emotion processing.

8.2 Emotion in the Brain

Stimuli enter the brain at the brain stem. The limbic system which is like a cortical ring around the brain stem is responsible for initial emotional interpretation of these signals from the autonomic nervous system. This part of the brain has also been found important for motivation and memory functions. Although motivation and memory also have their influence on the reaction to emotional stimuli, the rest of the text will focus on the limbic structures that are specificly relevant for emotional reactions.

The hypothalamus is responsible for processing the incoming signals and triggering the corresponding visceral physiological effects, like a raised heart rate or galvanic skin response [16].

From the hypothalamus the stimuli information is passed on to the amygdala, which is important for learning to connect stimuli to emotional reactions (reward / fear) and for evaluating new stimuli by comparing them to past experience.

The amygdala is considered vital for emotion processing. However, since it is an underlying structure like the rest of the limbic system, it cannot be detected directly in recordings from the scalp. The amygdala is connected to the temporal and prefrontal cortices, which is thought to be the way visceral sensations are interpreted cognitively, resulting in a consciously experienced feeling of an emotion [16].

The temporal lobe (the side areas covering T3–T6 in Figure 3) is essential for hearing, language and emotion, and also plays an important role in memory.

The prefrontal lobe (directly behind the forehead) is involved in the so-called highest level of functioning. It is responsible for cognitive, emotional and motivational processes. The prefrontal lobe is part of the frontal cortex (top half in Figure 3), which is said to be the emotional control center and to even determine personality . It is involved in, among others, judgement and social behavior. These functions are very much based on the experience of emotions [1].

8.3 The 10-20 System

To make replicable setups, there are standardized sets of locations for electrodes on the skull. One of these sets of electrode positions or *montages* is the 10/20 system. To make the results of this experiment reproducible, this system is taken as a vantage point for determining a suitable electrode placement.

The name of the system is derived from its method for finding the exact electrode positions. Head size is a variable measure. Therefore this system uses distances in percentages from a couple of fixed points on the head.

The starting points are the nasion, the dent at the top of the nose, and the inion which is the boney bump at the back of the skull. There is an imaginary vertical line from the nasion to the inion, and a horizontal line from the left ear lobe to the right.

From 10% above the nasion and anion, along the vertical line, a theoretical circle is drawn around the head, hence the *10* in the name. The other electrodes are positioned maintaining a 20% inter-electrode distance, as is indicated by the *20*. 20% up from the circle from the nasion is Fz, and another 20% further along is the top of head labeled Cz. Pz is positioned on the vertical line in a similar manner. C3, T3, C4 and T4 are positioned in the same way along the horizontal mark. The electrodes on the imaginary circle are also at a 20% distance from each other, while keeping T3 and T4 on the horizontal line. The remaining electrodes are placed equidistant between de vertical line and the circle, filling the horizontal lines of the frontal and parietal electrodes [15].

To make this textual explanation a little less abstract, refer to Figure 3 for a visual representation. Please note that this is *not* a normal top view of the head, in which the positions on the circle would be shown on the outer border and the temporal lobe would not be visible. The positions are stretched along the nasion-inion outer circle. A general indication of the cortical areas is also shown: the top half is the frontal lobe, parietal justbelow the frontal lobe, the temporal areas to the sides, and the occipital cortex at the bottom.

8.4 Arousal: Beta/Alpha Ratio

Brainball is a game based on brain activity in which the

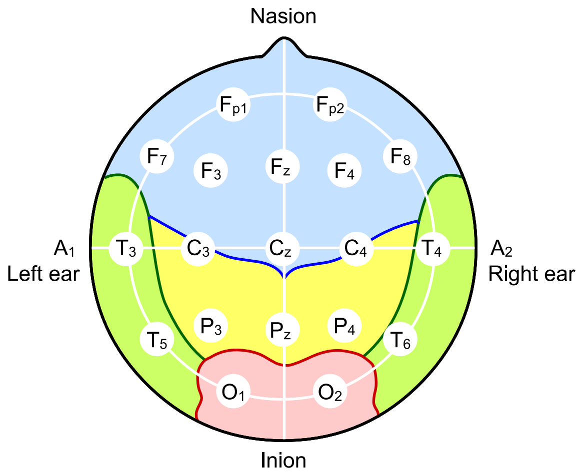


Figure 3: 10-20 system of electrode placement.

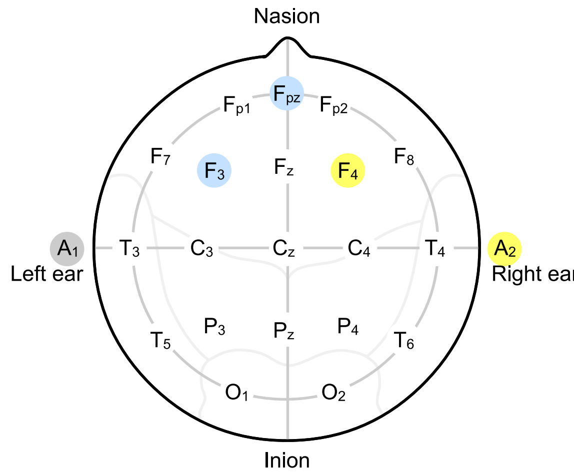


Figure 4: The montage used in this research.

person that stays the most relaxed will win. How relaxed a player is, is determined by the ratio of the beta and alpha brainwaves as recorded by the EEG. The EEG is measured by three electrodes mounted on the forehead (Figure 3: Fp1, Fp2, and Fpz - inbetween Fp1 and Fp2 on the vertical line). There is no mentioning of reference leads or whether the measurements are bipolar or monopolar [13]. However, as the application is to measure alpha and beta activity, not relative to other positions, monopole measurements can be assumed.

Beta waves are connected to an alert state of mind, whereas alpha waves are more dominant in a relaxed person. Research has also shown a link between alpha activity and brain inactivation, which also leads to the same conclusion. This beta/alpha ratio could therefore be an interesting indication of the state of arousal the subject is in.

8.5 Valence: Hemispherical Inactivation

Psychophysiological research has shown the importance of the difference in activation between the two cortical hemispheres in the reaction that test subjects show towards stimuli. Left frontal inactivation is an indicator of a withdrawal response, which is often linked to a negative emotion. On the other hand, right frontal inactivation is a sign of an approach response, or positive emotion.

High alpha activity (8-12Hz on the EEG frequency band) is shown to be an indication of low brain activity, and vice versa. So when mentioning cortical inactivation, in the EEG an increase in alpha activity is observed, joined with a decrease in beta waves [20].

F3 and F4 (Figure 3) are the most used positions for looking at this alpha activity, as they are located above the dorsolateral prefrontal cortex [communication with Martijn Arns] [20]. As mentioned in the previous section about emotion in the brain, the prefrontal lobe plays a crucial role in emotion regulation and conscious experience.

Harmon-Jones' research suggests that the hemispherical differences are not an indication of affective valence (feeling a positive or negative emotion), but of motivational direction (approach or withdrawal behavior to the stimulus). Affective valence does seem tightly linked to motivational direction, but one example can clearly show the difference: anger. Anger is experienced as a negative emotion, but generally results in an approach behavior with the intention to remove the stimulus. The author however does not provide a better alternative for detecting emotional valence [12]. Therefore, this method of comparing hemispherical activation does promise the best results for valence detection.

8.6 Monopoles and Dipoles

Montages may consist of monopolar or bipolar electrodes. In the monopolar case, each electrode records the potential difference, compared to a neutral electrode connected to an ear lobe or mastoid. Bipolar measurements show the potential difference between two paired electrodes [16, 19].

The device used in this research, BraInquiry PET 2.0 bipolar, is only suitable for bipolar measurements. Monopolar recording could still be simulated by attaching the two reference elctrodes on neutral places like the mastoids [communication with Martijn Arns].

Emotional valence research focuses on the difference in activity between both hemispheres. A bipolar montage provides this feature instantly [4]. However, to be able to compare the amount of alpha and beta waves for determining arousal, a monopolar measurement is necessary.

8.7 Conclusion for Experimental Montage

Most emotional valence recognition systems are based on the difference in hemispherical activity in the frontal cortex. This difference can be recorded using bipolar electrode measurements crossing the hemispheres. This means the ground electrode will be connected to a neutral site, the left mastoid, while two electrode pairs are available for recording bipolar signals. The most-used locations for EEG-based emotion recognition are F3 and F4, because of their positioning above the dorsolaterial prefrontal cortex.

For determining arousal, a monopolar recording is required. Interesting positions indicated by related research are Fp1, Fp2 and Fpz. Since there is only one pair of electrodes left of which one will need to be positioned in a neutral spot (right mastoid), only one of these positions can be measured. For this the most central position is chosen: Fpz.

The resulting montage can be seen in Figure 4: the dipole combinations are F3/F4 and Fpz/right mastoid, of which the second pair will result in a monopole recording of the Fpz position. The left mastoid is used as ground. Note that A1 and A2 are generally used to indicate the ears. The mastoids however are right behind the ears, and specified as suitable ground areas in the BraInquiry documentation [4].

One disadvantage of using mid-frontal electrode positions is that they are very sensitive to artifacts created by eye movement. This issue will be addressed in the section below about the organization of the experiment.

9. EXPERIMENT ORGANIZATION

This section handles all elements of the test procedure, from materials to the protocol.

9.1 Materials and Setup

For EEG recording the BraInquiry PET 2.0 EEG device was used, in combination with BioExplorer. The experiments were conducted in the test subject's own homes, using their own personal computers. Reusable electrodes for F3 and F4 attached with conductive glue, throw-away electrodes for Fpz and mastoids.

The electrode montage is depicted in Figure 4.

9.2 Stimuli Set Construction

For emotion elicitation there are generally two approaches:

- To let the test subject imagine the wanted emotion (e.g. by thinking of a past experience).
- To evoke the emotion in the test subject by using images, sounds, or a combination of the two.

To find an answer to the question whether it matters for the EEG whether an emotion is evoked visually or auditory, the first method is of no use, because memories cannot be called up in vision or sound only.

IAPS and IADS

There are two libraries with emotion-annotated images (IAPS) and sounds (IADS) available for non-profit research, which are very useful for emotion research [3, 18]. Figures 5 and 6 show the spread of the 956 visual and 167 auditory stimuli databases on the two-dimensional arousal/valence map. The valence and arousal ratings were obtained by research showing the stimuli to many test subjects and obtaining their affect with the self-assessment manikin [2].

Note: some stimuli in the IAPS database were used in multiple picture sets resulting in more than one set of arousal and valence values. In such cases the values were averaged over all instances of the same picture.

Stimuli Selection

For this experiment 36 emotion-eliciting stimuli were selected from these IADS and IAPS databases. 12 stimuli for each of the modalities, spread over the extremes on the emotion map: three positive/aroused, three positive/calm, three negative/calm, and three negative/aroused - based on the annotations provided by the stimuli databases.

The selected stimuli are to be as much on the extremes of the two-dimensional emotion map as possible. Also the emotion ratings need to be quite unanimous, as this experiment does not include self-reporting to determine any person-dependent deviations.

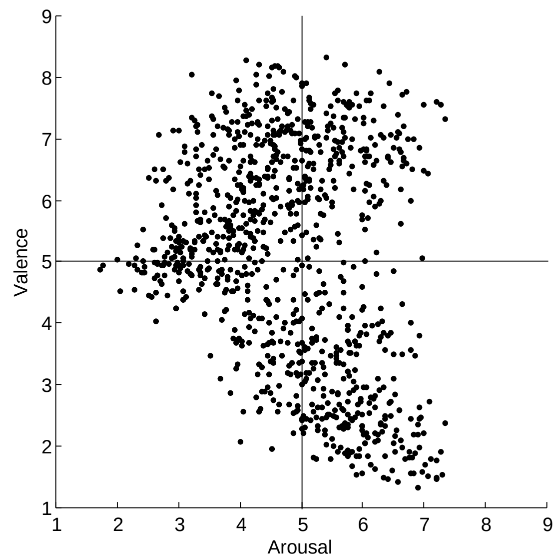


Figure 5: IAPS database mapped onto the arousal/valence dimensions.

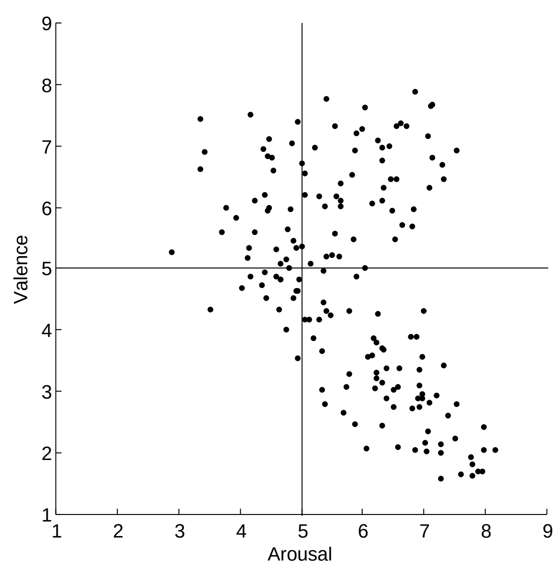


Figure 6: IADS database mapped onto the arousal/valence dimensions.

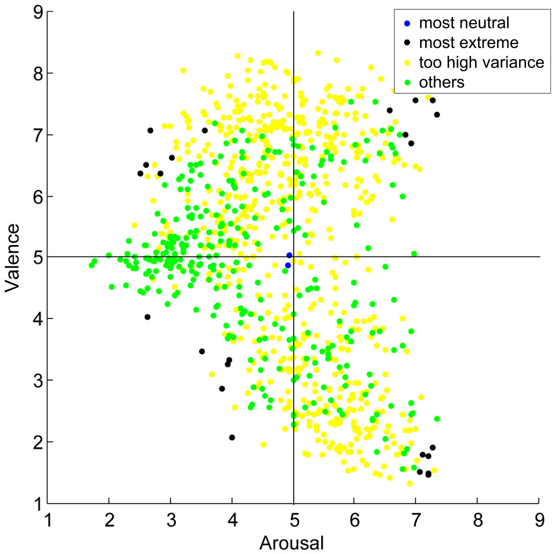


Figure 7: Selected picture stimuli.

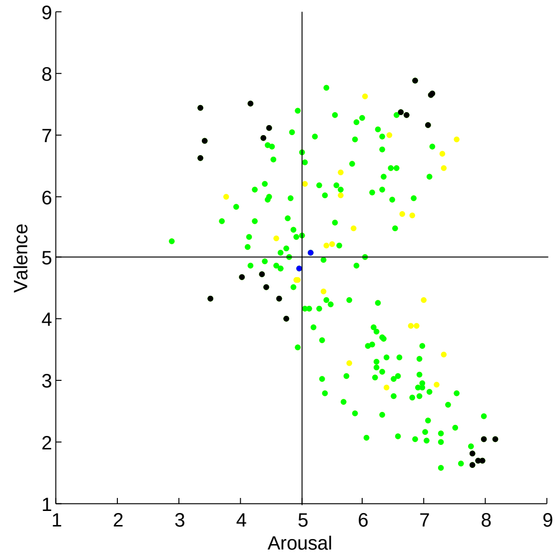


Figure 8: Selected audio stimuli.

The audio and image of audiovisual stimuli match in emotional value. For example, a positive/aroused sound is matched with a positive/aroused visual.

If the cooling down period works as intended, the order of the stimuli should not matter. Because of the limited number of test subjects, the influence of the order of specific stimuli cannot be taken examined for this research. At least, there should not be a recognizable ordering to the stimuli, to minimize user expectations, therefore order of the stimuli is randomly determined once, and the same for each test subject.

Also three neutral stimuli (audio, visual, audiovisual) have been selected in a similar manner. These stimuli were used for the initial test run, before the emotion-eliciting stimuli are shown. Read on for more details about this.

The Constructed Stimuli Set

A mapping of the selected stimuli can be seen in Figures 7 and 8. The ‘too high variance’ marks indicate stimuli that were discarded for their high standard deviations (over 2.1). The ‘other’ stimuli were discarded as they were not the most extreme stimuli in their quadrant. The extremity was calculated by multiplying arousal and valence difference with the center (5,5). Using this formula, stimuli that were closer to the axes that divide the quadrants were regarded as less optimal. The ‘most extreme’ dots are chosen stimuli for the tests. The neutral stimuli for the test run are indicated as ‘most neutral’.

The selected stimuli with descriptions and their ordering is listed in Appendix A.

9.3 Test Protocol

In advance, the subject will be instructed about what will happen and the do’s and don’ts during testing. The full text as presented to the test subject is listed in Appendix B.

The second step is a short test run of 45 seconds during which the user will be exposed to 3 neutral stimuli (one sound, one visual, and one audiovisual stimulus). This has two functions. The user will get to know what the actual test runs will be like, and it is a handy moment to record a neutral EEG which can be used for comparison or as a base line later on.

The actual experiment is set up as follows. During 9 minutes, 36 additional stimuli will be presented. Five seconds of stimuli exposure will be followed by ten seconds of cooling down. Ten minutes (in total) should be well within the attention span of average test subjects. This stimuli series will be shown as a whole automatically, so the timing is easy to match with the recorded brain signals.

9.4 Subjects

The number of test subjects will be limited to five people, with varying gender, age and background. Test subjects A, B, and E are in their twenties; C and D in their forties. All subjects practice or study for practicing varying jobs: journalism, art and technology, housekeeping, mechanics, informatics. A, B, C, and E are female; D is male.

9.5 Test Subject Instruction

In advance, the participating test subject will be informed about the procedure. The main goal of the latter is to avoid artifacts in the relevant EEG recordings [11]. The actual sheet shown to the subjects previous to the procedure is included in Appendix B.

The user is instructed to follow these guidelines during the stimulus presentation:

1. Try not to blink, move your eyes[2], or move any other part of your body (This will cause noise in the EEG measurements).

2. Try to stay relaxed and do not tense up (Artifact prevention).

[2]Subjects are allowed to use eye movement if necessary to obtain an image of the visual stimulus.

3. Keep your eyes open, also during the auditory stimuli (Closed eyes will cause a high alpha component in the EEG signals).

After each stimulus there will be a cooling down period during which the user can relax and is brought back to a neutral state. The test subject will be instructed to:

1. Use this moment to blink and move. Consciously relax your shoulders, neck, jaw, and face if necessary. Just be careful not to damage the equipment and to leave the electrodes in place while doing so.

2. During the final 5 seconds, count down mentally with the numbers presented on the screen (to let the user return to an emotionally neutral state).

3. During the final seconds, keep your gaze steady on the center cross, where the stimulus will be shown (to prevent eye movement from being necessary).

10. CLASSIFICATION PROCEDURE

To go from EEG recording to actual classification results, many intermitting steps have to be performed, as shown in Figure 1: artifact filtering, feature extraction, classifier training, and of course the actual classification itself.

10.1 Bandpass Filtering

In section 9, describing the basics of the test protocol (Experiment Organization), a couple of methods are already mentioned to avoid artifacts in the EEG recordings. However, avoiding those artifacts completely is impossible. Therefore also methods are needed to filter the recorded signals afterwards.

Filtering and feature extraction have some overlap. Automatic filtering of artifacts can be done, but only if those artifact frequencies are not important for the features interesting for emotion recognition. Also, by selecting specific features, artifacts in other areas are automatically avoided.

In the section explaining EEG Recording, the alpha (8–12Hz) and beta (12–30Hz) bands were highlighted as particular areas of interest for emotion recognition for both valence and arousal [13, 20]. The influence of EOG artifacts (eye movement/blinking) is most dominant below 4Hz, ECG (heart) artifacts around 1.2Hz, and EMG (muscle) artifacts above 30Hz. Nonphysiological artifacts caused by power lines are in the high 50Hz range (in the Netherlands) [8, 22, 11]. This means that by extracting only the alpha and beta frequencies, the influence of much noise has already been reduced much.

Bandpass filtering is the method by which specific frequency bands can be extracted. Using Fourier frequency analysis, the original signal is split up in frequencies. At this point specific frequencies can be removed, and the signal can be transformed back, now containing only the frequencies of interest [25]. For this research, the bandpass filter implementation provided by EEGLab for Matlab was used.

10.2 Feature Extraction

At this point alpha and beta bands are available from both recorded channels Fpz and F3/F4. In the EEG Recording section, beta / alpha ratios and power were also mentioned.

As it is unknown what combinations will provide the best classification results, all interesting possibilities are tested for both channels: alpha, beta, alpha and beta, beta / alpha, alpha power, beta power, alpha and beta power, beta / alpha power, and beta power / alpha power.

PCA (principal component analysis) was also applied to reduce the total number of features from 1000 (200Hz sampling rate, for 5 seconds), to 1 – 25. For each of the number of principle components within this reach, the classification procedure was applied, as the optimal number was unknown at this point.

10.3 Classification

Linear classifiers like naive Bayesian networks and Fisher's discriminant analysis have already been applied for classifying EEG signals into different classes of emotions [6].

For this research, binary linear FDA (Fisher's Discriminant Analysis) classifiers are used. For each category (modality, valence, arousal), a classifier was trained for each class (audio / visual / audiovisual, positive / negative, aroused / calm) to provide an indication of whether it does or does not belong to that specific class.

As only 39 samples were available from the experimental phase, the samples were split up in three sets. Three runs were performed, each time using a different set for testing, and the other two for training the classifier. By using this method, classification results for each stimulus could be obtained, without having to train on the stimulus to be classified itself.

The samples were only labeled with their explicit category classes. In this case, the arousal and valence data of the IAPS and IADS databases was not used during training.

Classification using FDA (Matlab, PRtools), results in a value between 0 and 1, where a value over .5 is interpreted as instance belonging to the class that was classified for.

Note that for each test subject, separate classifiers were used, because of the differences between EEGs from different individuals. Seeing what the results would be when using the same classifier for all test subjects, can be explored in future research.

11. RESULTS & EVALUATION

A visual inspection of the brain signals for each type of stimulus could not provide usable insights (see the plots in the Experiment Results Appendix). Therefore, for evaluation of the research questions, the classification results will be the main indicators.

11.1 Feature Selection

Literature research pointed specifically to the alpha and beta frequency bands for emotion recognitions. Various combinations of the two were tested for each of the two channels (Fpz and F3/F4): alpha band, beta band, both bands, alpha power, beta power, alpha and beta power, beta to alpha ratio, beta to alpha ratio power, and beta power to alpha power ratio.

For each of the different classifications (modality, arousal, valence), different features could give the best results. From literature research, the following is expected:

- Modality: Fpz, interesting frequencies unknown
- Arousal: Fpz beta/alpha power ratio
- Valence: F3/F4 alpha power, or beta/alpha power ratio

To test this, the obtained data was classified according to the following process. The data, already grouped per stimulus, was randomly divided in three sets, while maintaining class ratios. Since there was very little data, classification was done in three runs, once for each split up in training and test sets. Before the classification itself, first the number of features was reduced again using PCA. This number was varied from 1 to 25. The test data was also transformed using the same pca transformation matrix. The linear binary Fisher classifier was then trained on the training set of 26 samples, and tested on the 13 sample test set.

The plots in Figures 9, 10, and 11 show the performance rates (correctly classified / total classified) for each of the classification categories, averaged over the binary classification for each class, and averaged, minimized and maximized respectively over the results for each number of PCA.

Modality

As the mean performance stays around this same percentage for each of the channel features, to determine the best feature, the maximum performance will be the main criterium.

The best performance rates were obtained for Fpz alpha and beta power, and for Fpz beta band: an 82.1% classification rate. This preference for the Fpz channel was already predicted, as F3/F4 was mainly added for hemispheric difference for valence classification.

Compared to the results for arousal and valence classification, modality classification is apparently more difficult. This is to be expected, as the electrode positions were selected for emotion detection, not for modality classification.

Arousal

Looking at arousal performance plot, the average performance again stays quite level. The maximum performance is taken into account for selecting the best channel features.

There is no lower maximum performance than 92.3%, which is already a pretty acceptable performance with 3 errors on 39 classifications. The best obtained performance rate is that of 97.4% (1 error out of 39), with F3/F4 beta power and Fpz beta frequencies. Although a preference for the Fpz channel was expected, the results do not show this bias.

Valence

The plot of the valence performances also shows very high correct classification rates. As the mean is again quite stable, the deciding criterium for the best channel feature will be the maximum obtained performance.

The performance is relatively good for all channels (at least 92.3%). Surprisingly, the highest performance rates of 94.9% (2 errors on 39 classifications) were obtained for both Fpz and F3/F4. This is not supported by the advice from Martijn Arns, nor by literature research. Both indicated F3/F4 to be the most suitable electrode positions to detect emotional valence. The channel features that provided these best results were: F3/F4 alpha and beta band power, F3/F4 beta power, F3/F4 alpha band, and Fpz alpha and beta band power, Fpz beta band, and Fpz alpha band.

11.2 Modality Influence

For the influence of modality on classification performance, the minimum, mean, and maximum performances for each of the modalities have been plotted, which is shown in Fig-

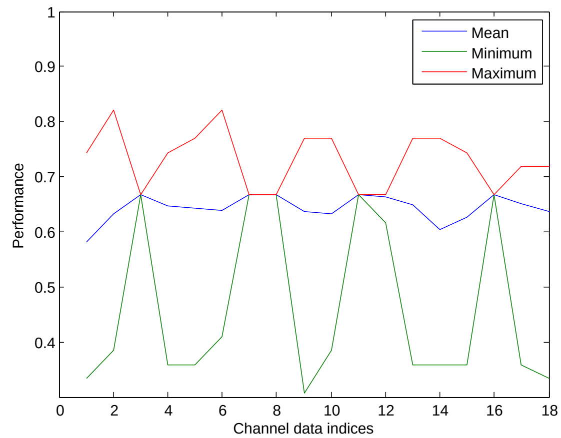


Figure 9: Performance of each channel feature, for modality classification.

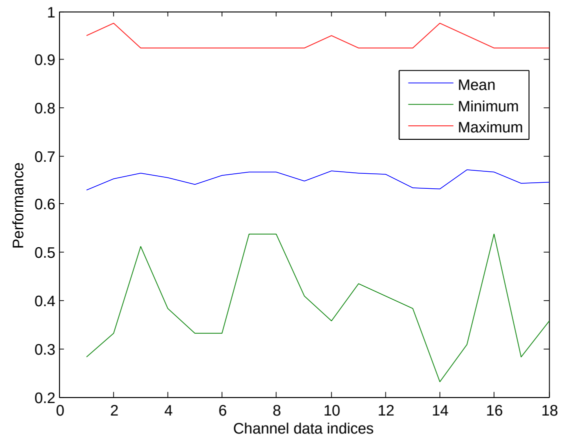


Figure 10: Performance of each channel feature, for arousal classification.

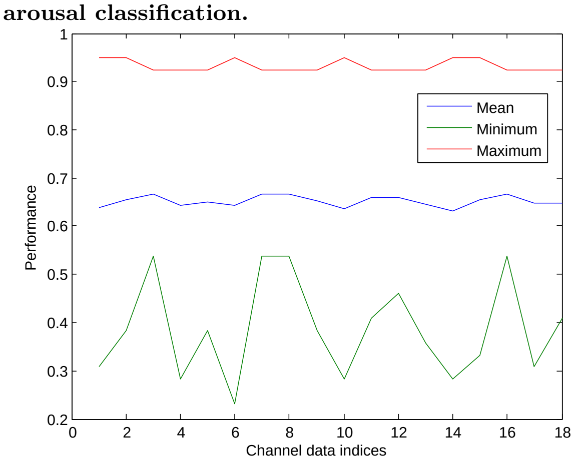


Figure 11: Performance of each channel feature, for valence classification.

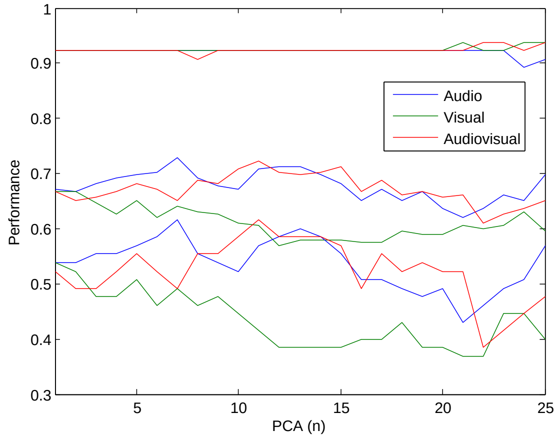


Figure 12: The minimum, mean, and maximum performances for each of the modalities.

ure 12. Even though the performances for audio and audiovisual stimuli stay together relatively speaking, the line showing the classification rate for visual stimuli stays clearly below the other two.

12. CONCLUSIONS

This section will list the answers to the research questions posed at the beginning of this paper. These answers are based on the results from the experiments, and on the conducted literature research. For a reflection on these results, refer to the section hereafter.

Is the modality of the stimulus recognizable from the recorded brain signals?

A binary modality classification rate (whether it does or does not belong to a specific modality) of over 80% seems attainable (for features: Fpz beta band, and Fpz alpha and beta power). Note that the highest noted performances are based on the optimal number of principal components, based on performance after classification.

Are emotions recognizable from an EEG?

The binary classification rates show maxima of over 90% for each of the tested features. Note that this is for the optimal number of principal components , based on performance after classification. For mapping of the binary classifications onto the four emotion quadrants, the results will be different, for two reasons.

First of all, for the opposite classes (like positive and negative for the valence category) the class with the highest classification rate for the stimulus actually belonging to that class will be chosen as the most likely class. This could improve or worsen the end result, depending on the 'surety' indicated by the classifier.

Secondly, arousal and valence classifications will be combined. This means even if there is an error just on the arousal or only on the valence dimension, the resulting classification will be wrong. In the worst case, where none of the erroneous classifications on the dimensions overlap, the maximum performance is already reduced to 80%.

What is the influence of the modality of the stimulus on the recognition rate?

Visual stimuli appear more difficult to classify than their audio and audiovisual counterparts.

When using only five electrodes, what would be a good montage for emotion recognition?

Based on literature research the following montage was chosen: Fpz/right mastoid for arousal recognition, F3/F4 for valence recognition, left mastoid as ground.

Initial experiments support the suitability of this setup for emotion recognition, but there seems no apparent preference for Fpz or F3/F4 for either classification category.

What features are interesting for emotion recognition?

During the experiment evaluation, for arousal the best performances were reported for F3/F4 beta power, and Fpz beta frequencies. The highest performances for valence classification were obtained while using Fpz alpha and beta band power, Fpz alpha band, Fpz beta band, F3/F4 alpha and beta band power, F3/F4 beta power, and F3/F4 alpha band.

13. DISCUSSION

This section provides some ideas behind some of the results, but also indicates some problem areas within the conducted research.

13.1 Modality Recognition

The chosen electrode positions are definitely not optimal for modality recognition. Positions above the auditory cortex in the temporal lobes and visual cortex in the occipital lobe would have probably provided better results.

Another possibility is that the chosen features, the alpha and beta bands, are not as suitable to recognize the modality of a stimulus.

13.2 Emotion Recognition

The arousal and valence labels were based on the IAPS and IADS database annotations, not on what the user experienced. This will most definitely have had its influence, based on the conversations with the test subject afterwards. The sexually loaded pictures showed a heterosexual preference, which was not as interesting for one of the test subjects who happens to be homosexual. Also many people had problems with interpreting the image of a man lying down with his head totally smashed. One subject even reported to see a pizza instead of a head, initially.

Because the test subjects also tried to minimize eye movement, determining the exact contents of a picture also became more difficult.

For both IAPS and IADS, the negative/calm quadrant was a little underdeveloped compared to the other sections. As a result the negative/calm stimuli were less extreme.

Harmon-Jones' research suggests that the hemispherical differences are not an indication of affective valence, but of motivational direction [12].

Even though the results were promising, the electrode positions, signal processing methods, and classification methodes may have not been the most suited.

No explicit artifact removal methods were applied. This is an important issue, as theoretically emotions could very well be classified based on EOG, EMG and ECG recordings.

13.3 Modality Influence

As mentioned in the Hypotheses section, a higher success rate for visual stimuli was expected, as vision is the most developed sense for most humans. Perhaps this is actually what causes the difficulty: a more personal emotional interpretation because it is more developed.

Another reason could be that the occipital lobe (in which vision is processed), is farthest away from the electrode positions chosen for emotion recognition.

13.4 Experimental Phase

Data was gathered from five different test subjects, on 39 stimuli. Considering there were three modalities, and four emotional quadrants to classify, and preferably this data should be split up in a training set, a test set, and a validation set, this is very little data.

This experiment stimuli sequence takes a little less than ten minutes to show. It is hard for subjects to remember to relax and blink during the cooling down periods, to avoid having to blink during the stimulus.

Another issue that probably influenced the test results: the tester should be focused on the stimulus movie, but thoughts tend to wander, especially during a ten minutes period.

14. FUTURE WORK

While working on this research, many issues that would be interesting to look into, or related questions that could not be targeted within this project, arose. The following subsections list these ideas for possible future work.

14.1 Electrode Montages

Experimentally determine optimal electrode positions for emotion recognition, perhaps using an electrode cap with 32 or 64 electrodes.

Try the experiment using Fp1 and Fp2 instead of F3 and F4. These positions are also above the prefrontal area, with as a large advantage that it is easy to apply, for there is no hair growth on the forehead. For this reason it would be very interesting to see whether these positions will also provide usable signals for emotion recognition.

For modality recognition, experimental runs with electrodes above the auditory cortex and visual cortex could be done, to see if better results can be obtained. The influence of attention could also be researched this way.

14.2 Experimentation

To be able to provide more solid conclusions, more data from more test subjects should be obtained.

If there were more data, research could be done into the personal differences between the test subjects.

Self-reporting is very important for emotion recognition. Because of differences in past experience, environment, and personality, emotions elicited by one stimulus will not be the same for all test subjects. To take this into account, the experiment should be rerun, but including self-reporting using for example FEELTRACE or the Self-Assessment Manikin [9, 2].

The 10-minute runs done for this research were too long for some of the test subjects. It is hard to stay focused during such long periods, and subjects also forgot to make sufficient use of the cooling down periods. More data obtained from shorter runs could be more 'clean'. To still increase the total amount of data gathered, there are two options. One is to increase the number of test subjects. The second is to run multiple sessions, on different days, with the same people.

Experimental runs with combined sound and visual of different emotional values could be valuable to research sensory dominance, or to look into the importance of attentional focus.

14.3 Classification

Different signal processing methods could be tried out, to determine the most suitable:

- Artifact removal methods
- Other features
- Other classifiers/regressors, especially nonlinear methods, as for this research linear FDA was used.

One general classifier for all test subjects could theoretically be possible, based on the theory provided by the literature research. The setup and performance of such a general classifier could be researched.

The samples were only labeled with their explicit category classes. In this case, the arousal and valence data of the IAPS and IADS databases was not used during training. By using the actual mean values provided by the databases, regression could be used to actually get a classification result on the two-dimensional emotion map.

Research the differences between VEPs (visually evoked potentials) and AEPs (auditory evoked potentials) could provide valuable insight for modality recognition.

For this research, there was a direct link between the emotion representation and the selected eeg features to be used. Other representations and features could also be interesting to look into.

14.4 Application

A direct feedback emotion recognition system. Possible uses for such an application could be: instant messaging, chatrooms, online games, and facially paralyzed patients who otherwise cannot directly express their emotions.

15. ACKNOWLEDGMENTS

I thank Zsofia Ruttkay, for getting me interested in EEG-based emotion recognition in the first place, for allowing me to use the BraInquiry equipment, and for being my advisor for this Capita Selecta project even though she was already on a very tight schedule.

Martijn Arns I thank for patiently answering my questions about the BraInquiry equipment, and Betsy van Dijk for providing feedback on the test protocol. I'd like to thank Mannes Poel for sending me literature related to this research subject, and Martijn Plass and Almer Tigelaar for proofreading my proposal. My thanks also goes out to the people who agreed to letting their brain signals being recorded.

Furthermore, this research would not have been possible without access to the IAPS and IADS databases. For making these stimuli available for non-profit research, thank you, Bradley and Lang.

16. REFERENCES

[1] A. Bergsma and K. van Petersen. *Het brein van A tot Z*. Hersenstichting Nederland / Het Spectrum B.V., 2003.

[2] M. M. Bradley and P. J. Lang. Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of Behavioral Therapy and Experimental Psychiatry*, 25(1):49–59, 1994.

[3] M. M. Bradley and P. J. Lang. *International Affective Digitized Sounds (IADS): Stimuli, Instruction Manual and Affective Ratings*. The Center for Research in Psychophysiology, University of Florida, Gainesville, FL, USA, 1999.

[4] BraInquiry. Pet eeg installation manual, 2005. Last visited: April 20, 2007.

[5] BraInquiry. Wireless biofeedback and neurofeedback equipment, 2007. Last visited: April 16, 2007.

[6] G. Chanel, J. Kronegg, D. Grandjean, and T. Pun. Emotion assessment: Arousal evaluation using eegs and peripheral physiological signals. In *MRCS*, pages 530–537, 2006.

[7] A. Choppin. Eeg-based human interface for disabled individuals: Emotion expression with neural networks. Master's thesis, Tokyo Institute of Technology, Yokohama, Japan, 2000.

[8] K. Coburn and M. Moreno. Facts and artifacts in brain electrical activity mapping. *Brain Topography*, 1(1):37–45, 1988.

[9] R. Cowie, E. Douglas-Cowie, S. Savvidou, E. McMahon, M. Sawey, and M. Schröder. FEELTRACE: An instrument for recording perceived emotion in real time, 2000.

[10] P. Ekman. Basic emotions. *Handbook of Cognition and Emotion*, pages 45–60, 1999.

[11] M. Fatourechi, A. Bashashati, R. K. Ward, and G. E. Birch. EMG and EOG artifacts in brain computer interface systems: A survey. *Clininical Neurophysiology*, (118):480–494, 2007.

[12] E. Harmon-Jones. Clarifying the emotive functions of asymmetrical frontal cortical activity. *Psychophysiology*, 40(6):838–848, 2003.

[13] S. I. Hjelm and C. Browall. Brainball–using brain activity for cool competition. *Demo at NordiCHI*, 2000.

[14] A. Hoekstra and J. Janssen. Linking bio-signals to transfer of knowledge: Towards mind-reading ecas? Capita Selecta, 2006.

[15] H. H. Jasper. Report of the committee on methods of clinical examination in electroencephalography. *Electroencephalography and Clinical Neurophysiology*, 10:370–375, 1958.

[16] E. R. Kandel, J. H. Schwartz, and T. M. Jessell. *Principles of Neural Science*. Mc Graw Hill, 2000.

[17] P. J. Lang. The Emotion Probe: Studies of Motivation and Attention. *American Psychologist*, 50(5):372–385, 1995.

[18] P. J. Lang, M. M. Bradley, and B. N. Cuthbert. *International Affective Picture System (IAPS): Affective Ratings of Pictures and Instruction Manual*. The Center for Research in Psychophysiology, University of Florida, Gainesville, FL, USA, 2005.

[19] J. Malmivuo and R. Plonsey. *Bioelectromagnetism : Principles and Applications of Bioelectric and Biomagnetic Fields*. Oxford University Press, USA, July 1995.

[20] C. P. Niemic. Studies of emotion: A theoretical and empirical review of psychophysiological studies of emotion. *Journal of Undergraduate Research*, 1:15–18, 2002.

[21] F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D. J. McFarland, N. Birbaumer, and A. Kübler. An auditory brain-computer-interface (bci). *Journal of Neuroscience Methods*, 2007. (In press).

[22] D. O. Olguín. Adaptive digital filtering algorithms for the elimination of power line interference in electroencephalographic signals. Master's thesis, Instituto Tecnológico y de Estudios Superiores de Monterrey, Monterrey, Mexico, 2005.

[23] T. Partala, M. Jokiniemi, and V. Surakka. Pupillary responses to emotionally provocative stimuli. In *ETRA '00: Proceedings of the 2000 Symposium on Eye Tracking Research & Applications*, pages 123–129, New York, NY, USA, 2000. ACM Press.

[24] R. W. Picard and J. Klein. Toward computers that recognize and respond to user emotion: Theoretical and practical implications. *Interacting with Computers*, 14(2):141–169, 2002.

[25] B. D. Storey. Computing fourier series and power spectrum with matlab, 2002. Lecture notes.

[26] K. Takahashi. Remarks on emotion recognition from bio-potential signals. *2nd International Conference on Autonomous Robots and Agents*, pages 186–191, 2004.

APPENDIX

A. STIMULI SEQUENCE

The following table describes the stimuli sequence in the order as applied during the tests to obtain data for this research. For the 39 stimuli (combinations), it lists the IDs of the used visual and auditory stimuli, with a short description and the corresponding emotion quadrant.

audio stimulus	visual stimulus	emotion
	2220 (MaleFace)	neutral
425 (Train)		neutral
722 (Walking)	8466 (Nudists)	neutral
382 (Shovel)		neg/calm
	5000 (Flower)	pos/calm
285 (Attack2)		neg/arou
424 (CarWreck)		neg/arou
	2722 (Jail)	neg/calm
353 (Baseball)		pos/arou
277 (FemScream3)	3060 (Mutilation)	neg/arou
275 (Scream)		neg/arou
817 (Bongos)	4660 (EroticCouple)	pos/arou
367 (Casino2)		pos/arou
815 (RockNRoll)		pos/arou
	7325 (Watermelon)	pos/calm
723 (Radio)	9331 (HomelessMan)	neg/calm
	3080 (Mutilation)	neg/arou
172 (Brook)	1450 (Gannet)	pos/calm
	3170 (BabyTumor)	neg/arou
	9220 (Cemetery)	neg/calm
311 (Crowd2)	5621 (SkyDivers)	pos/arou
279 (Attack1)	6350 (Attack)	neg/arou
150 (Seagull)		pos/calm
	4659 (EroticCouple)	pos/arou
	8185 (Skydivers)	pos/arou
700 (Toilet)		neg/calm
252 (MaleSnore)	2490 (Man)	neg/calm
286 (Victim)	3010 (Mutilation)	neg/arou
	5800 (Leaves)	pos/calm
	9410 (Soldier)	neg/arou
352 (SportsCrowd)	8186 (Skysurfer)	pos/arou
	8030 (Skier)	pos/arou
810 (Beethoven)	7900 (Violin)	pos/calm
708 (Clock)	2590 (ElderlyWoman)	neg/calm
728 (Paper1)		neg/calm
	9360 (EmptyPool)	neg/calm
812 (Choir)		pos/calm
809 (Harp)		pos/calm
151 (Robin)	5711 (Field)	pos/calm

B. INFORMATION FOR TEST SUBJECTS

This section contains the information document as the test subjects received it for reading in advance of the experiment. The following text is in Dutch, since this is the mother language of all the test subjects. A translation is available on request.

Modalities during EEG-based Emotion Recognition

Neem dit goed door, zodat u zeker weet dat u geen bezwaar hebt tegen de stappen die tijdens deze test en dit onderzoek zullen worden uitgevoerd met u en de met u opgenomen gegevens.

Dit onderzoek heeft als doel op basis van hersensignalen emoties te herkennen. Tijdens deze test zal er een filmpje worden afgespeeld waarin bepaalde plaatjes zullen worden laten zien en geluiden zullen worden afgespeeld. Dit filmpje heeft als doel bepaalde emoties bij u op te wekken. Gedurende dit filmpje zullen uw hersensignalen worden gemeten door middel van vijf elektrodes die op uw hoofd geplakt zullen worden. De gemeten hersensignalen zullen achteraf worden geanalyseerd op de verschillen en overeenkomsten kijkende naar de bijbehorende emoties. De gegevens kunnen ook gebruikt worden voor eventueel vervolgonderzoek.

Nadat u dit document heeft gelezen en uw goedkeuring heeft gegeven, zullen de 5 elektrodes op uw hoofd geplakt worden: 2 bij uw oren, 1 op uw voorhoofd en 2 in uw haar boven het voorhoofd. Hiervoor wordt geleidende gel gebruikt om ervoor te zorgen dat de signalen goed te meten zullen zijn. De elektrodes zijn na de test eenvoudig te verwijderen en de gel is uit te wassen met warm water. **NB** Zorgt u dat u helemaal klaar bent (WC?) voordat deze stap wordt uitgevoerd. Zodra u vast bent geplakt aan het systeem is uw bewegingsvrijheid beperkt.

Het experiment is opgebouwd als volgt:

1. Voor elk plaatje/geluid krijgt u eerst 5 seconden om te ontspannen.
2. De volgende 5 seconden worden afgeteld. Tel mentaal mee.
3. Daarna ziet u het plaatje, hoort u het geluid, of in sommige gevallen: allebei tegelijk. Probeer ontspannen te blijven, en uw ogen niet te bewegen[3].

In totaal zult u op deze manier blootgesteld worden aan 39 stimuli; inclusief de rustperiodes tussendoor duurt dit minder dan 10 minuten. Pauzeren tijdens het experiment is niet mogelijk.

Tijdens de rustperiode (voor elke stimulus):

- Gebruik dit moment om uw ogen te knipperen en te bewegen. Ontspan bewust uw schouders, nek, kaak en gezicht. Dit is belangrijk om storingen in de metingen te voorkomen. Pas wel op de apparatuur en de elektrodes.
- Tel gedurende de laatste vijf seconden mentaal mee met de getallen op het scherm, vanaf 5 naar beneden. Houd uw blik gericht op het kruis in het midden.

Tijdens het laten zien van de plaatjes en het afspelen van de geluiden:

- Probeer niet met de ogen te knipperen of ze te bewegen - houdt het kruis in het midden van het scherm aan als kijkpunt. Houd uw ogen open, ook als er slechts geluid wordt afgespeeld.
- Houd ook de rest van uw lichaam ontspannen en stil.

Tenslotte: U zult een aantal vrij shockerende plaatjes onder ogen krijgen. Indien u hier problemen mee heeft kunt u nu weigeren mee te doen aan dit experiment.

Als u akkoord bent met de hierboven beschreven procedure, onderteken dan dit document.

Datum:
Naam:
Plaats:
Handtekening:

C. EXPERIMENT RESULTS

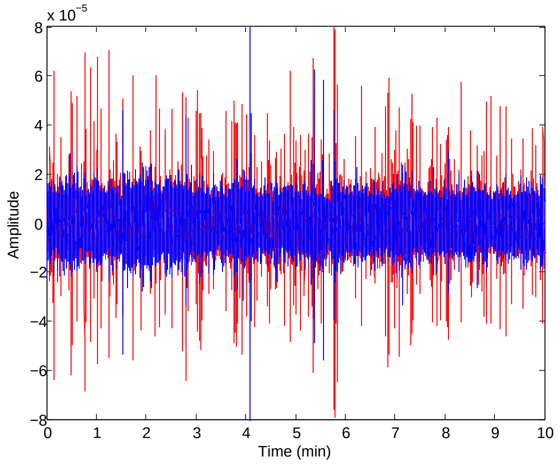
This section shows some extra information based on the experiments conducted for this research.

C.1 Individuality

[3]Mondeling werd toegevoegd dat in het begin oogbeweging mogelijk noodzakelijk is om een beeld te krijgen van wat wordt afgebeeld.

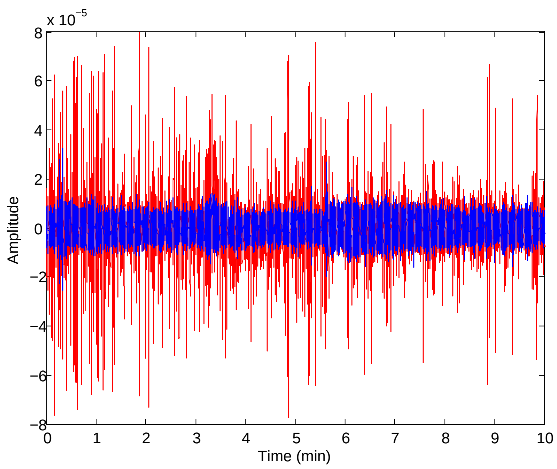
The raw recorded brain signals show big differences between each test subject. After bandpass filtering the EEG-data to limit it to alpha and beta frequencies, the differences are less apparent, but still there. The plots in Figures 13, 14, 15, 16 and 17 show the full length recordings of each of the test subjects, to illustrate this (red is Fpz, blue is F3/F4). These differences may have a lot of impact on the ease with which they are analyzed.

As mentioned before, test subjects A, B, and E are in their twenties; C and D in their forties. All subjects practice or study for practicing varying jobs: journalism, art and technology, housekeeping, mechanics, informatics. A, B, C, and E are female; D is male.



[ht]

Figure 13: Full length recording alphabeta band, test subject A.



[ht]

Figure 14: Full length recording alphabeta band, test subject B.

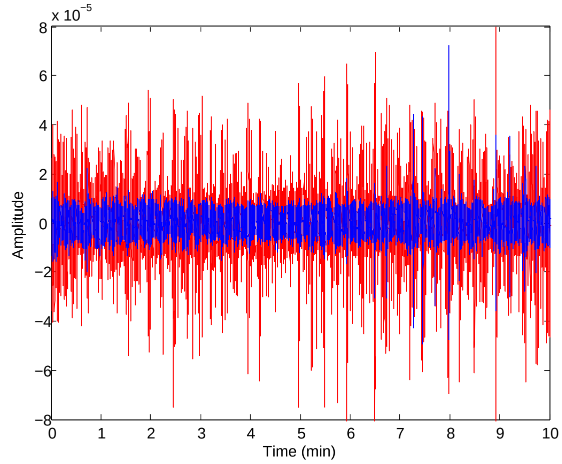


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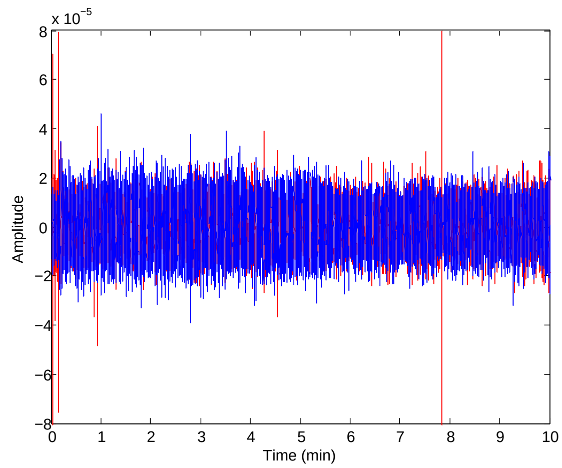
Figure 15: Full length recording alphabeta band, test subject C.



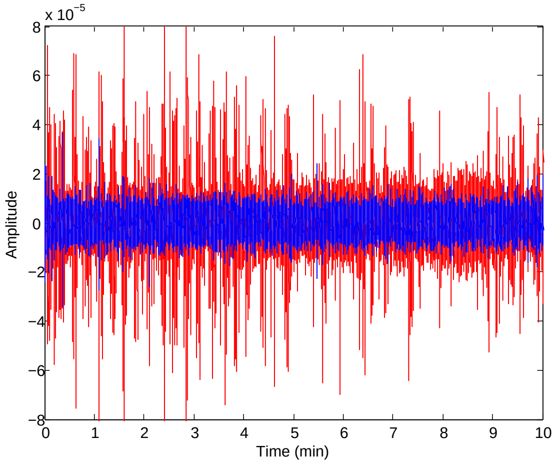
[ht]

Figure 16: Full length recording alphabeta band, test subject D.

C.2 Visual Analysis

One of the things mentioned in the research proposal was a visual analysis. Unfortunately, based on visual inspection, no conclusive interpretations could be made. However, for completeness, here are a few plots showing the alpha waves for the test subjects for the stimuli. The different colours indicate the different classes (audio / visual / audiovisual, positive / neutral / negative, calm / neutral / aroused) within the category (modality, valence, arousal). The x-axis shows the time duration (5 seconds in total.

- Modality: Figures 18, 19, 20, 21.
- Valence: Figures 22, 23, 24, 25.
- Arousal: Figures 26, 27, 28, 29.



[ht]

Figure 17: Full length recording alphabeta band, test subject E.

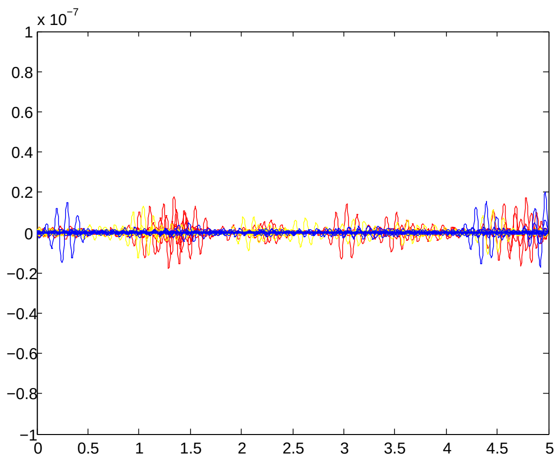


Figure 18: Subject A, alpha waves during stimuli, colour mapped for modality.

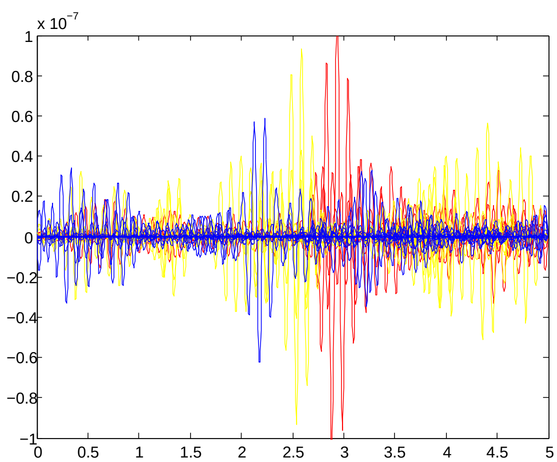


Figure 19: Subject B, alpha waves during stimuli, colour mapped for modality.

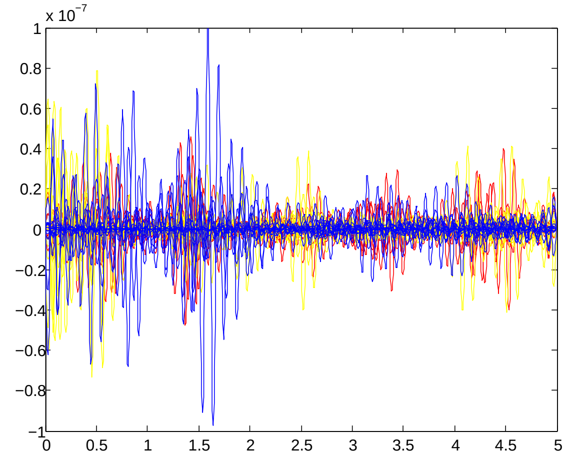


Figure 20: Subject C, alpha waves during stimuli, colour mapped for modality.

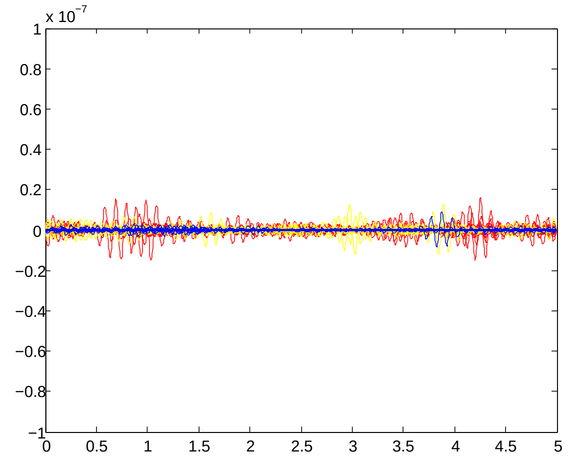


Figure 21: Subject E, alpha waves during stimuli, colour mapped for modality.

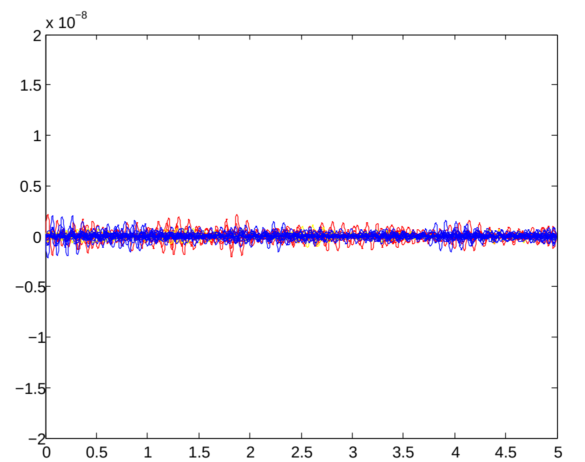


Figure 22: Subject A, alpha waves during stimuli, colour mapped for valence.

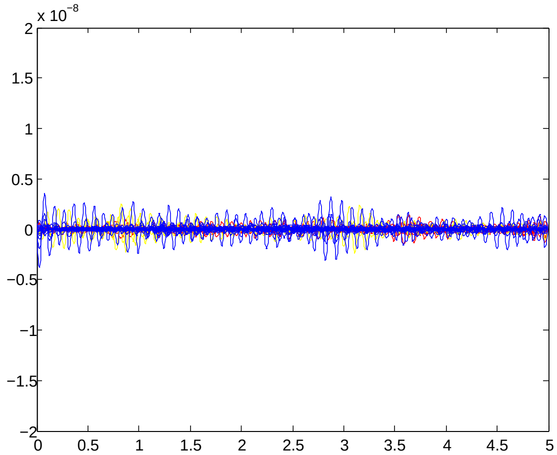


Figure 23: Subject B, alpha waves during stimuli, colour mapped for valence.

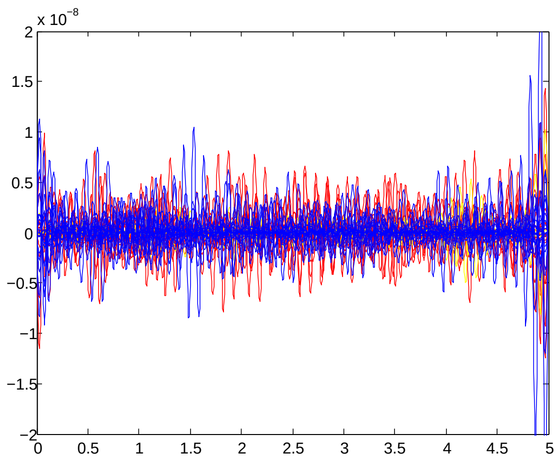


Figure 24: Subject C, alpha waves during stimuli, colour mapped for valence.

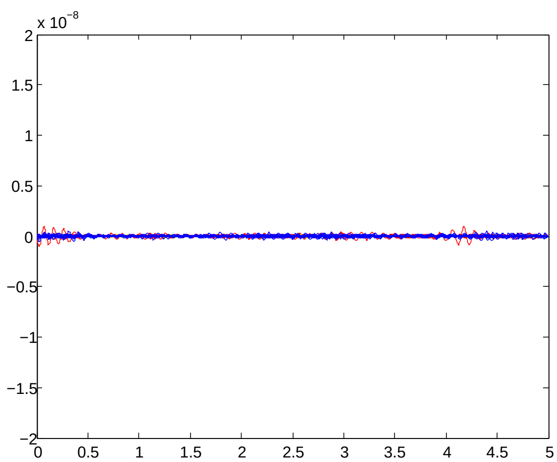


Figure 25: Subject E, alpha waves during stimuli, colour mapped for valence.

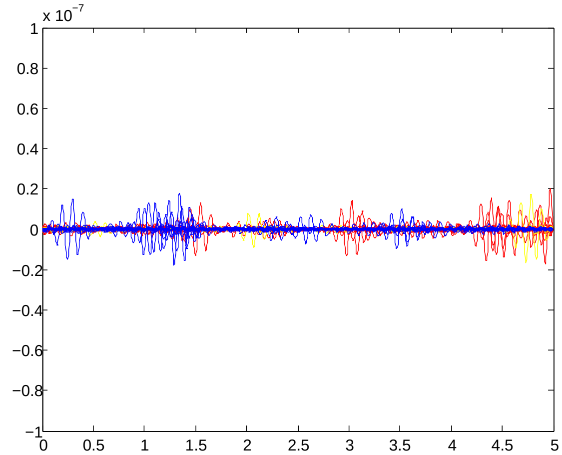


Figure 26: Subject A, alpha waves during stimuli, colour mapped for arousal.

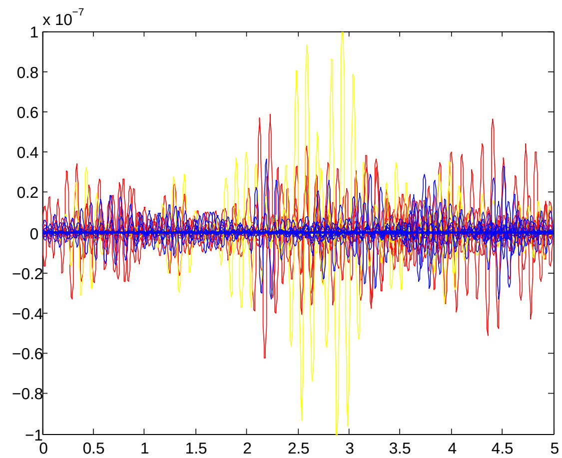


Figure 27: Subject B, alpha waves during stimuli, colour mapped for arousal.

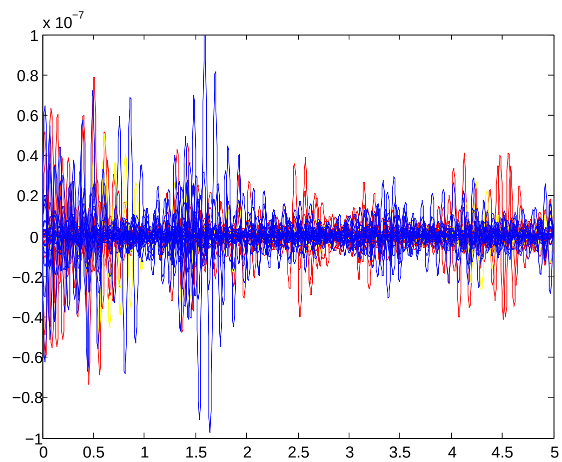


Figure 28: Subject C, alpha waves during stimuli, colour mapped for arousal.

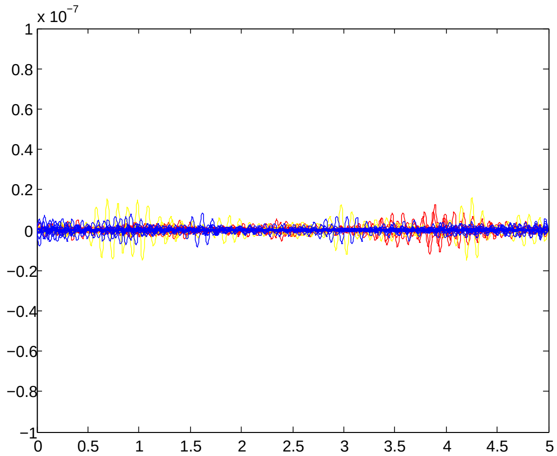


Figure 29: Subject E, alpha waves during stimuli, colour mapped for arousal.