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Towards a product design BCI

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Assoc. Prof. Dipl.-Ing. Dr.techn. Gernot R. Müller-Putz
Mag. Dr. Selina C. Wriessnegger

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Laboratory of Brain-Computer Interfaces

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Zusammenfassung

BCI Technologien, die nicht nur für Patientinnen und Patienten, sondern auch für gesunde Benutzerinnen und Benutzer ihre Anwendung finden, werden immer häufiger. Eines dieser neuen Felder, das sich diese Technologien zunutze macht, ist Neuromarketing. Diesen Trend greift auch die vorliegende Masterarbeit auf. Das Ziel dieser Arbeit ist es, anhand von evozierten Potentialen (konkret P300) festzustellen, ob den Teilnehmerinnen und Teilnehmern der Studie, bestimmte Designs gefallen oder nicht.

Um die Vorlieben der Teilnehmer feststellen zu können, wurde ein Paradigma sowie die Umgebung zur EEG Aufzeichnung und Analyse geplant und implementiert. Als Designobjekte, welche später analysiert werden sollten, wurde ein Set von 40 Graustufenbildern von Autos ausgewählt, wobei diese jeweils zur Hälfte Sport- und Normalwägen darstellten. Diese visuellen Stimuli wurden auf einem PC-Bildschirm präsentiert und zeitgleich das EEG der Teilnehmerinnen und Teilnehmer aufgezeichnet. Jedes Bild wurde für 100 ms mit einem Interstimulusintervall von 1 s angezeigt. Die präsentierten Bilder riefen ERPs hervor, welche eingeteilt in vier Fälle, mithilfe von shrinkage LDA analysiert wurden.

Die Ergebnisse zeigten, dass Unterschiede in den ERPs erkennbar sind, je nachdem ob dem Teilnehmer oder der Teilnehmerin der verwendete Stimulus gefallen hat oder nicht. Einige der Teilnehmerinnen und Teilnehmer konnten jedoch den Detailreichtum der Autodesigns in der kurzen Zeit von 100 ms nicht erfassen. Dies wird besonders deutlich, anhand der Ergebnisse des oddball Paradigmas, welches normalerweise zuverlässig gute Ergebnisse liefert, aber in dem vorliegenden Fall bei einigen Personen versagte. Somit war es leider auch nicht möglich, die Autos, welche den Teilnehmerinnen und Teilnehmern gefielen, von jenen die ihnen nicht gefielen, zu unterscheiden.

Abschließend bleibt zu sagen, dass für aussagekräftigere Ergebnisse, Verbesserungen bei der Stimulus Auswahl sowie den statistischen Voraussetzungen für die Klassifikation notwendig sind.

Stichwörter: Brain Computer Interface, P300 BCI, Neuromarketing, Produktdesign, Shrinkage LDA

Abstract

BCI technology, not only useful for disabled people, but also for healthy users is developed more and more often. One of the fields, which make use of this technology, is neuromarketing. This master thesis also seizes this emerging trend. The goal of this thesis was to determine if the participants were in favor of an item's design or not, just by analyzing the evoked potentials, especially P300.

To do so a paradigm, as well as the environment for EEG recording and analysis was planned and implemented. The design objects presented to the participants and analyzed subsequently, were a set of 40 greyscale pictures of cars. The set consisted of 20 sports cars, and 20 normal cars. Those visual stimuli were displayed on a PC screen and the EEG was recorded simultaneously. Every stimulus was presented for 100 ms with an inter-stimulus interval of 1 s. The images elicited ERPs, which were analyzed in four cases employing shrinkage LDA.

The results showed that there are differences in the ERPs depending on the stimulus design. Some participants possibly have had problems handling the richness of detail presented by the car's design within the short time of 100 ms. Especially the oddball paradigm unveiled this shortcoming, since usually it reliably delivers good results, but failed completely for some participants. Therefor it was not possible to distinguish the cars, the participants preferred, from the other ones.

It can be concluded that for more useful results, adjustments concerning the choice of stimuli as well as the statistical conditions for classification are required.

Keywords: Brain Computer Interface, P300 BCI, neuromarketing, product design, shrinkage LDA

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Abbreviations

BCI: Brain Computer Interface

EEG: Electroencephalogram

MEG: Magnetoencephalography

fMRI: functional Magnetic resonance imaging

NIRS: Near infrared spectroscopy

ERP: Event related potential

SCP: Slow cortical potentials

AEP: Auditory evoked potential

VEP: Visual evoked potential and

SEP: Somatosensory evoked potentials

SSEP: Steady-state evoked potentials

SSVEP: Steady-state visual evoked potentials

ERS: Event related synchronization

ERD: Event related desynchronization

EOG: Electrooculogram

LDA: Linear discriminant analysis

SLDA: Shrinkage-LDA

1.Introduction

This chapter will introduce some basic principles to gain an insight into the subject and help understand the statements which are made in this thesis. Starting with Brain Computer Interfaces (BCIs) in general, P300 BCIs, as well as passive BCIs are introduced before a short insight into neuromarketing is provided. At the end of this chapter the goal of the thesis is stated. Subsequently the methods and setups are explained, which were used for data acquisition and signal analysis, followed by the obtained results. Finally the outcomes are discussed, an outlook is provided, and improvements are suggested.

1.1. BCI

A Brain Computer Interface (BCI) is a communication system (Hardware and Software) that can enable humans to interact with their surroundings even if they are not able to control their nerves and muscles, for example because of severe motor disabilities. This provides an additional communication channel which is controlled by signals generated from brain activity and therefore highly improves the users quality of life. [28]

The term BCI describes a communication or control device that is capable of interpreting brain signals and therefore can be operated without motor command. It comprises four main parts: input, output, translator, and the operating protocol. BCIs record electrophysiological or hemodynamic changes in the brain. Those Signals can either be recorded from the scalp or invasively from the surface or the inside of the brain. After amplification and digitization, features are extracted from the acquired signals, which are converted into commands. This conversion from brain signals into commands is a very sophisticated task in BCI research. The estimated commands are used as the BCIs output in order to control the desired modality. [36]

Different technologies exist that are able to monitor brain activity and therefore can be used for BCIs. The most prominent non-invasive technologies are electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) and near infrared spectroscopy (NIRS). Because MEG and fMRI are bound to non portable and expensive equipment they are more often used to address questions of basic brain research. Actual NIRS and EEG devices are cheaper than MRI or MEG, are easier to handle and therefore mostly used for BCI applications. [35]

He et al. (2013) mentioned five kinds of applications that can be controlled by BCI outputs. Those five kinds are able to replace, restore, enhance, supplement or improve the natural output of the central nervous system. The first two kinds, replacement and restoration, are the focus of present-day BCI research while the other three types gather more and more attention. [14]

"Although BCIs are also developed for entertainment and thus potentially for healthy users, the main focus for BCI applications that are aiming at communication and control are people with severe motor impairment." [20]

Figure 1 shows the scheme of a BCI system like it is described above.

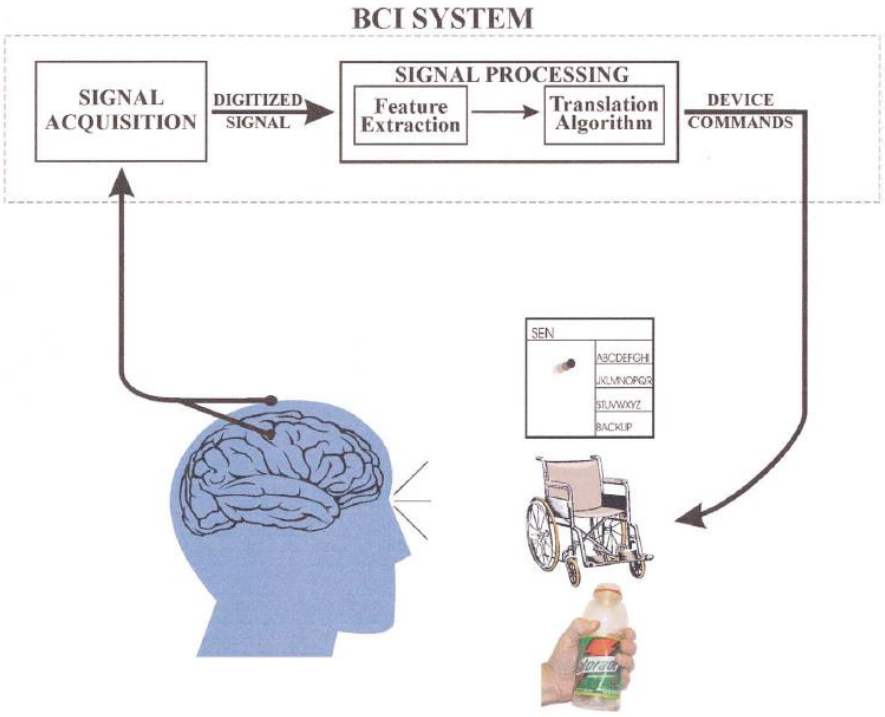

Figure 1: Main components of a BCI system (modified from [36])

The features necessary to operate a classic BCI can be modulated by the users mental activities and therefore his intentions get interpretable and can be used for control. [12]

Two different approaches to BCI control exist: the biofeedback approach and the machine learning approach. The biofeedback approach aims on training the user by giving visual, auditory or tactile information about her/his brain state. With the help of this feedback the user learns to control his brain activity and subsequently the BCI outputs. The machine learning approach uses exemplary datasets of which the algorithm is able to learn a certain statistical structure to apply within the control task. This approach needs no training of the user. In practice BCIs will neither rely only on biofeedback nor on machine learning but a combination of both. [21]

Because the BCI implemented for this thesis does not require any training of the user and only gains the information by statistical analysis of the recorded signals it utilizes the machine learning approach.

EEG-based BCIs can be divided according to the electrophysiological signals they make use of. The two main categories of brain signals measured non-invasively, event-related potentials (ERPs) and cortical oscillations are explained in the following.

- **Event-related potentials**

  The processing of a sensory stimulus can lead to a time-locked series of positive and negative deflections in the EEG [24]. These event-related potentials can be divided by scalp location and their latency with respect to the stimulus. Components with latencies shorter than 100 ms are mainly determined by the properties of the evoking stimulus. Components with latencies of 100 ms to 500 ms reflect ongoing brain processes. Finally, the longest latency ERPs, called slow cortical potentials (SCPs), with latencies of some seconds correspond to response-oriented brain activity. [35]

  Auditory, visual as well as somatosensory stimuli can be utilized and lead to auditory evoked potentials (AEPs), visual evoked potentials (VEPs) and somatosensory evoked potentials (SEPs).

  Steady-state evoked potentials (SSEPs) are elicited by repetitive auditory, visual or somatosensory stimulation at a certain frequency. The stimulation frequency and corresponding harmonics can be detected in the EEG.

  In the following VEPs and P300 are explained further because they are of interest for this thesis.

- **Visual evoked potentials (VEPs)**

  The VEPs typically start with a negative component, measureable at the primary visual cortex, 75 ms after a visual stimulus. This is followed by a positive component at about 100 ms and a final negative complex with a latency of approximately 145 ms. [35]

  Steady-state visual evoked potentials (SSVEPs) are triggered by a visual stimulus flashing on a certain rate. This triggers an oscillatory brain response in the visual cortex. When presenting a couple of commands flashing at different rates, the command the user intends to communicate elicits an oscillatory brain response specific for the stimulation frequency. After recording the EEG over the visual cortex, the SSVEPs are analyzed and the BCI is able to execute the corresponding command. [33]

- **P300**

  The P300 is a positive deflection in the EEG peaking about 300 ms after stimulus onset. Its occurrence is correlated to the neural processing of the stimulus. If an infrequent, desirable or in other ways significant stimulus (target) is interspersed with frequent or routine stimuli (non-target) a positive complex over the centroparietal cortex, about 300 ms after stimulus onset, is evoked. In practice the target stimuli appear with a probability of 0.2 and the frequent non-target stimuli with a probability of 0.8. P300 occurs with auditory, visual as well as somatosensory stimuli. The stimulation with frequent non-target and infrequent target stimuli is known as oddball-paradigm. For the oddball paradigm it is necessary that the users attention is focused on the target stimulus. [35]

  The P300 BCI enables the user to choose from commands arranged in a matrix just by concentrating on the desired command. Because P300 is a feature analyzed for this thesis and the P300 BCI is the most prominent P300 application it is further explained in chapter 1.2.

- **Slow cortical potentials (SCPs)**

  Slow cortical potential changes (0.5 to 10.0 s) on the scalp depend on potential changes in the cortex. They can be associated with cortical activation when they are negative and with reduced cortical activation when they are positive. This cortical activation can be learned by users in order to communicate. [1]

- **Spontaneous EEG - cortical oscillations**
  - **μ and β rhythms**

    In certain areas of the human brain frequency specific (μ: 8-12 Hz, β: 18-26 Hz) EEG activity can be found. Those rhythms are associated with the cortical areas most directly connected to the brain's normal neuromuscular outputs what makes them good signal features for EEG-based BCIs. The user is able to increase (event-related synchronization ERS) or decrease (event-related desynchronization ERD) those rhythms by movement. More precisely movement and preparation for movement decrease those rhythms. The rhythms increase after movement and with relaxation. Even motor imagery is sufficient for increasing or decreasing those rhythms in certain regions of the sensorimotor cortex what makes it also usable for e.g. paraplegic users. A categorization algorithm is fed with the power in the μ and β bands measured at central electrodes in order to control a device. [29]

For further information on brain signals see [1], [24], [29], [33] and [35].

As described before, BCIs translate brain signals into commands. The physiologic changes can be triggered in different ways. This is where another three categories for BCIs come into play, namely active, reactive, and passive BCIs. Those categories have been introduced in [38] and are only explained briefly in the following [38]:

- **Active BCI:** Uses brain activity, which is directly and consciously modulated by the user. There are no external events necessary to control. Examples of active BCIs are control via motor imagery and slow cortical potentials.
- **Reactive BCI:** Uses brain activity, which appears as a reaction on an external stimulus. The user is indirectly able to adapt this brain activity e.g. by concentration. An example for reactive BCIs is the P300 Speller.
- **Passive BCI:** Uses autonomous brain activity without any effort by the user. It delivers information on the affective user states.

While active and reactive BCIs represent the classical BCIs for direct and indirect control, passive BCIs stand for all others, mainly those for implicit control. To use active and reactive BCIs the user has to willingly control his brain activity, however for passive BCIs the user does not have to control his brain activity in a certain way. Because the BCI implemented for this study is of passive character, passive BCIs are further explained in 1.3.

In the following chapters the P300 BCI, passive BCIs and the utilization of BCIs in the field of neuromarketing, are explained.

1.2. P300 BCI

The P300 BCIs make use of the ERP with its positive peak at about 300ms post-stimulus. In practice P300 is elicited by infrequent visual stimuli combined with frequent one when the user pays her/his attention on the infrequent stimuli. This characteristic can be used to distinguish two classes. Because EEG also records lots of random brain activities, ERPs of single stimuli are not visible in the raw recordings. Removing the random noise by averaging over several repetitions, uncovers the ERPs. The ERPs elicited after target and non-target stimuli are depicted in Figure 2.

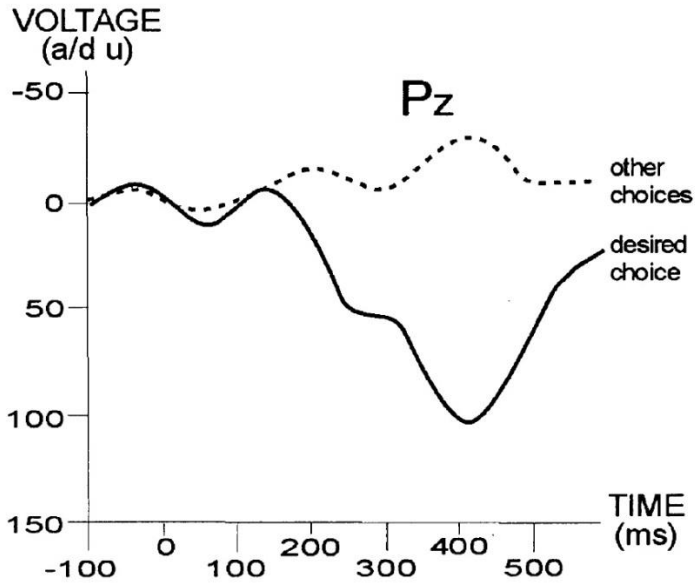

Figure 2: ERPs recorded after target (solid line) and non-target (dashed line) stimuli with the target evoking P300 [34]

The dashed line in Figure 2 shows the ERPs elicited by frequent (non-target) stimuli and the solid line shows the ERPs after infrequent (target) stimuli. The target stimuli cause a positive deflection of brain potential (P300) starting at about 300ms after the stimulus is presented (0ms). In contrast, the non-target stimuli do not show the P300 and therefore targets and non-targets are distinguishable. While the figure only shows ERPs at one electrode position P300 is most prominent over electrode positions C_z, P_z and O_z.

A P300 speller enables the user to choose commands arranged in a matrix (typically 6x6) on a screen in his field of sight. The commands can either be to write letters of the alphabet or other things the user might want to communicate. The stimuli to elicit ERPs are random intensifications of the rows and columns of the input matrix. By focusing on the command the user wants to choose P300 can be measured whenever the row or column containing the desired command is highlighted. The command can be determined as the intersection of the row and column evoking maximum P300. [8]

A major improvement for the P300 speller is the optimization of the stimulus to elicit ERPs like it was presented in [16]. Kaufmann and colleagues highlighted the characters of the speller by superimposed familiar faces and therefore achieved remarkably increased ERPs compared to simply flashing characters. These findings improved the speed and therefore the fluency of communication based on the P300 speller.

Another application of the P300 BCI is Brain Painting [19], where the commands of the control matrix are painting functions in order to produce abstract images. Brain Painting aims on improvement of mood, motivation and quality of life in patient users. It improves rehabilitation because of the positive emotions caused by creative and playful expression. [9]

1.3. Passive BCI

As explained in section 1.1 BCIs can be divided according to their type of user interaction. For this thesis a kind of passive BCI was used, therefore this type is explained more precisely in the following section.

In common (active, reactive) BCIs the user modulates her/his brain activity in a trained manner to control his surroundings. This is mostly used to improve disabled people's ability to communicate. In contrast to disabled users, whose quality of live is improved a lot, BCIs usually do not improve the lives of healthy people. But with the usage of passive BCIs new types of applications arise, which are also advantageous for healthy users. [37]

In contrast to active BCIs, passive BCIs are not controlled in an explicit voluntary way. They make use of cognitive states which occur as side effects of the primary human-machine interaction. Because of the implicit nature of the features used in passive BCIs they seem to be more robust in comparison to features used in active BCIs. This might be because features for passive BCIs are related to automatic processes of cognition which cannot be modulated that easy by conscious processes. [39]

When passive BCIs are used, additional features can be included in the signal processing. This channel offers valuable information about the users mental state like her/his intentions, situational interpretations or emotional states. The additional knowledge is gathered without any additional user effort. Therefore passive BCIs are defined by the key aspects complementarity, composability and controlled cost, which are explained shortly [37]:

- **Complementarity:** Passive BCIs do not interfere with other human-computer interactions.
- **Composability:** There is no maximum number of passive BCIs being applied at the same time. That is because no user effort is required which limits active and reactive BCIs.
- **Controlled cost:** Because there is no conscious input into passive BCIs the costs are calculated by their wrong indications. They can be designed in a cost-optimal way to improve outcome and leave it unchanged if no improvement is possible.

1.4. Neuromarketing

More and more applications for BCI technology emerge that are not restricted to communication or control like gaming, biofeedback, rehabilitation, diagnosis of disease, and so on [5]. This thesis also tries to address this trend in BCI research by interpreting subconscious reactions on visual stimuli and use the outcome for the purpose of neuromarketing.

Neuromarketing in general is defined as the application of neuroscientific methods to understand human behavior in the context of markets and marketing exchanges. [23]

In the field of neuromarketing brain imaging devices are used to determine consumer preferences, while excluding influences of normative expectations as well as social influences. This means that statements can be supported by measurements to understand consumer intentions. Even the most impartial participants in studies investigating consumer behavior cannot switch off subconscious or emotional decisions. A major challenge of neuromarketing is to present the proper stimuli in order to trigger useful brain responses. [11]

The presented study tries to disconnect the choice of favored items from the conscious level. This is done by utilizing a BCI to reflect the subconscious favors of the participants. Several studies targeting brain responses on marketing stimuli already exist (e.g. [4], [26], [3]), but most of them used the very costly and complex method fMRI with which the activation patterns of subcortical brain areas were studied. Only few studies so far used ERP analysis (e.g. [13, 25]). An advantage of analyzing marketing stimuli by ERPs recorded with EEG is the high temporal resolution which allows the examination of subliminal stimuli. This means the users brain state is recorded before she/he is able to react to the stimulus.

Because EEG devices are relatively inexpensive, robust and even wearable compared to other brain imaging techniques it is the technology utilized for analyzing marketing stimuli. [34]

In [34] a relation of pleasantness or unpleasantness regarding the presented marketing stimuli and the measured deflections in ERPs is suggested. Therefore brainimaging tools are able to provide useful information to marketers.

For example Ma and colleagues [25] can be quoted. In their study they used a S1-S2 paradigm to evaluate possible brand extensions. For that purpose a well-known brand was presented in the first stimulus followed by products of a certain category in stimulus two. The second stimulus elicited a P300 that was transferred into analysis. The P300 showed different amplitudes and spatial distributions for products of categories which are related to the previously presented brand compared to products without any relation.

Also the group of Handy and colleagues [13] used EEG recorded ERPs to evaluate marketing stimuli. Their study tried to find electrophysiological signs correlated to the perception of liking or disliking particular advertising logos. They recorded ERPs of visual stimuli in the context of a target identification task. By analyzing the ERPs elicited through each of the logos they found out that visuocortical processing shows an increase of the early ERP components at specific brain areas associated with the observation of disliked logos.

A first study towards product design based on EEG recorded ERPs was conducted by Freislederer in 2012 (see [10]). He tried to classify attractive and unattractive images after rapid serial visual presentation. His study did not come up with a statistically significant correlation between the ratings of the participants and the results of classification. The possible improvements stated at the end of his thesis mainly suggest improvement of the timing in the paradigm.

The study presented in this thesis also utilizes the sensitivity of ERPs to the emotional valence of visual stimuli. Therefore the study tries to make a step towards a product design BCI that might overcome the need to collect verbal preferences of consumers and find future use in marketing departments.

1.5. Goal

The aim of this thesis is to find out if it is possible to distinguish attractive designs from unattractive ones by means of ERP analysis. I assume that it is possible to find user preferences concerning car design because attractive cars would elicit higher P300 than unattractive. To investigate this, a BCI has to be implemented that records the ERPs elicited by stimuli with different designs. After ERP analysis a statement should be possible about the participants' design-favors. Because no particular activity is required and the participants' subconscious reaction is analyzed, a passive BCI is employed. In a broader sense this study should pave the way towards a "product design BCI" suitable for neuromarketing. It might help finding the users preferences, even when she/he is not able to define them her-/himself. The measurement setup, paradigm, data acquisition, and signal analysis should be developed.

2. Methods

In order to achieve the goal mentioned in section 1.5, measurement setup and methods for analysis should be prepared. The very best outcome would be to find an item within the set of design objects, that elicits significantly different ERPs compared to the rest after short visual presentation.

Electrodes, amplifier and other necessary hardware should fulfill ease of setup. Presentation of the designs, data acquisition, as well as the signal analysis, should be implemented in MATLAB® (The MathWorks, Inc., Natick, Massachusetts, USA) and SIMULINK® (The MathWorks, Inc., Natick, Massachusetts, USA).

This chapter introduces the key features of the procedure a participant has to undergo, as well as the hard- and software for presentation, signal recording, and analysis.

2.1. Procedure

The goal of the study was to obtain information, whether a participant prefers a certain design or not, just by analyzing her/his brainwaves. For this purpose the ERPs for every stimulus were analyzed and compared. The items used for stimulation were 40 greyscale images of two categories: 20 sports and 20 normal cars. Sports cars were distinguished as higher priced cars with big engines mainly from brands also well-known from motorsports. In contrast normal cars are reasonably priced cars where usability has high priority, and which can be seen on the road every day. Example pictures for both categories are shown in Figure 3.

For the measurement the participants were seated in a shielded and darkened measurement room, on a comfortable armchair. In order to minimize artifacts they were asked to leave their mobile phone outside the box and avoid movements throughout the whole measurement session. The computer screen for stimulus presentation was placed at a distance of about 1.5m to their face.

Figure 3: Example images for sports cars (left) and normal cars (right). All the used images can be found in 7.1

The measurement procedure was divided into eight runs. Those eight runs consisted of a control run (run0), six measurement runs (run1, run2, run3, run4, run6, run7) and one feedback run (run5). Before every run, the participant was introduced to the task by the investigator and a short break for relaxation was taken. The runs are explained in the following.

– **run0:** In order to show that only picture information was relevant and no other optical properties within this run blurred pictures were presented,. The blurred pictures were generated by randomly changing the pixel positions. Each of the 40 pictures was presented eight times with a rate of one picture per second (40 blurred pictures x 8 repetitions = 320 trials per run). Within one of those 40-picture sets the order was randomized. The timeline of one trial is depicted in Figure 4.

For preparation a white dot was presented in the center of the screen for 500 ms followed by the blurred picture for 100 ms. After the stimulus and before the next white dot showed up, the screen remained black for another 400 ms. This led to an inter-stimulus interval of 1s. In run0 the participant was advised to concentrate on the center of the screen and avoid artifacts.

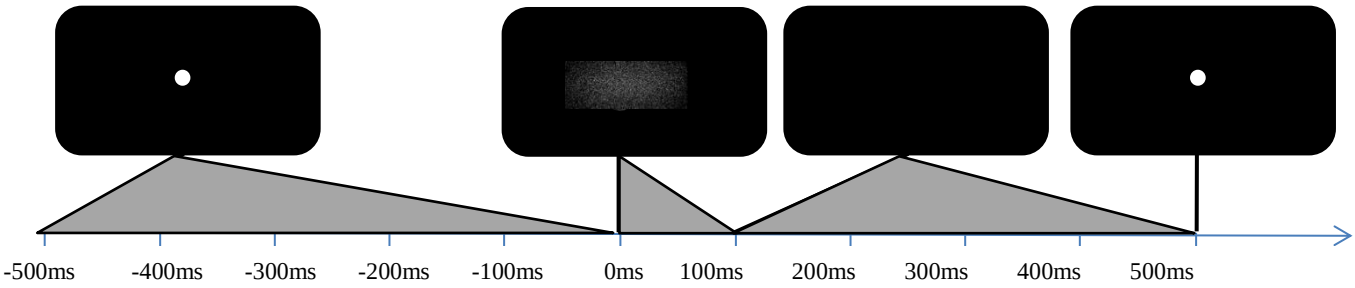

Figure 4: Timeline of run0

– **<u>run1, run2, run3, run4:</u>** Those four runs were equivalent to each other showing the greyscale pictures of cars on black background. The timing was the same as in run0. All 40 pictures were shown eight times in random order (40 cars x 8 repetitions = 320 trials per run) with a rate of one picture per second. For sake of completeness the timeline of these four runs is also shown in Figure 5.

For preparation a white dot was presented in the center of the screen for 500 ms followed by the picture of a car for 100 ms. After the stimulus and before the next white dot showed up, the screen remained black for another 400 ms. This led to an inter-stimulus interval of 1 s.

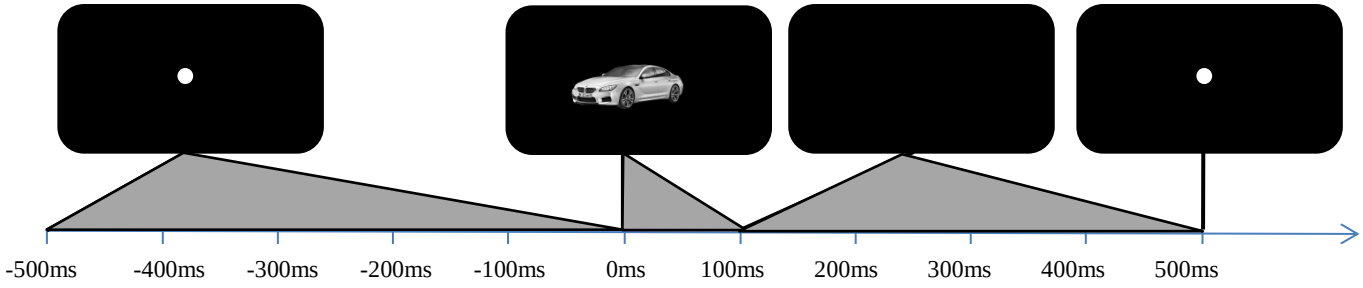

Figure 5: Timeline of run1, run2, run3, run4, run6 and run7

– **run5:** In run5 every of the 40 pictures was shown once, and the participant was asked to give feedback by pressing a button on the feedback box to express whether she/he likes the shown cars design or not (see Figure 6). The box was handed to the participant with the black button on the right side [7]. Both buttons were operated with the thumb (left thumb/red = dislike, right thumb/black = like). The timing of the presentation can be extracted from the timeline in Figure 7.

After all pictures have been rated, an overview of all the cars from both categories was presented, and the participant was asked to choose one favorite from every category and memorize it as good as possible.

Figure 6: Feedback-box. right button = like, left button = dislike

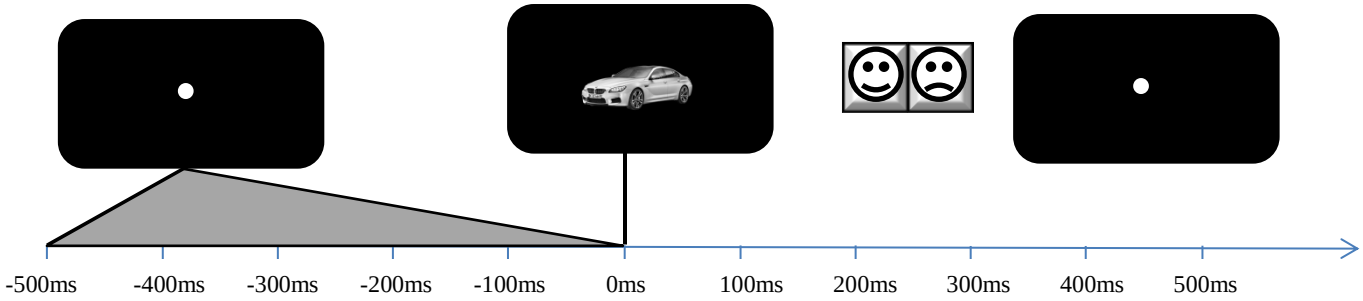

Figure 7: Timeline of run5

In order to be as similar to the other runs as possible, a white dot for preparation was shown for 500 ms in the center of the screen. Then the image was shown until a choice was expressed by pressing a button. After pressing a button the next white dot was presented.

– **run6, run7:** These two runs were equivalent to run1, run2, run3 and run4. Only the task was different. Instead of just concentrating on the center of the screen, the participants were asked to count the appearances of the two favorite cars, chosen after run5, at the back of her/his mind.

The whole procedure was executed like depicted in Figure 8. Expected time for the whole measurement was about 40 minutes. Together with the breaks and the time of about 10 minutes used to mount the electrodes, the overall time per participant was about one hour. This short time was possible, because mounting of the active dry electrodes used less time than traditional passive gel-based electrodes.

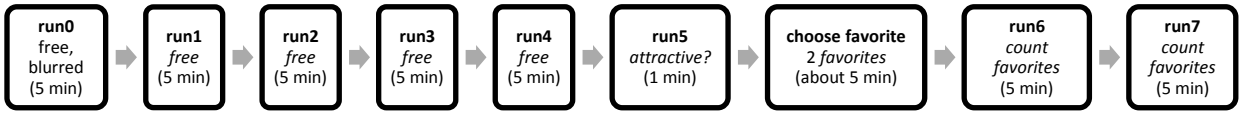

Figure 8: Wrap up of the procedure

2.2. Participants

Twelve participants were consulted for the measurements. All of them were right handed and had normal or corrected to normal vision. Their age ranged from 22 years to 29 years with a mean of 24.75 years, and standard deviation 1.53 years. The gender distribution was 42% female and 58% male. Each cooperated voluntarily and signed a consent form prior to the measurements.

For every participant a measurement protocol was completed to guarantee the same procedure (explained in section 2.1) for all of them. This protocol also included a short set of questions to get an idea of the participants' opinions on cars.

The three questions (translated from German into English) were:

1. Do you own a car?
2. What aspect is more important concerning cars, usability or appearance?
3. Why did you choose the cars you chose in run5?

In order to keep the participants anonymity, each of them got assigned a three digit code like it is used in the chapter Results.

2.3. Data Acquisition

This subchapter describes the hardware and the software used to record the EEG as well as the preprocessing methods to reduce artifacts.

2.3.1. Hardware

In order to record the EEG, six dry electrodes were mounted on the electrode caps (g.GAMMAcap, g.tec medical engineering GmbH, Austria) positions F_z, C_z, P_z, O_z, PO_7 and PO_8 according to the international 10-20 system [15] as well as three perpendicular electrooculogram (EOG) electrodes [30]. The EOG has been recorded to eliminate EOG artifacts more effectively. Ground and reference were obtained with adhesive electrodes mounted on the left and right mastoid. The electrode positions and the corresponding channels of the signal amplifier can be found in the schematics in Figure 9.

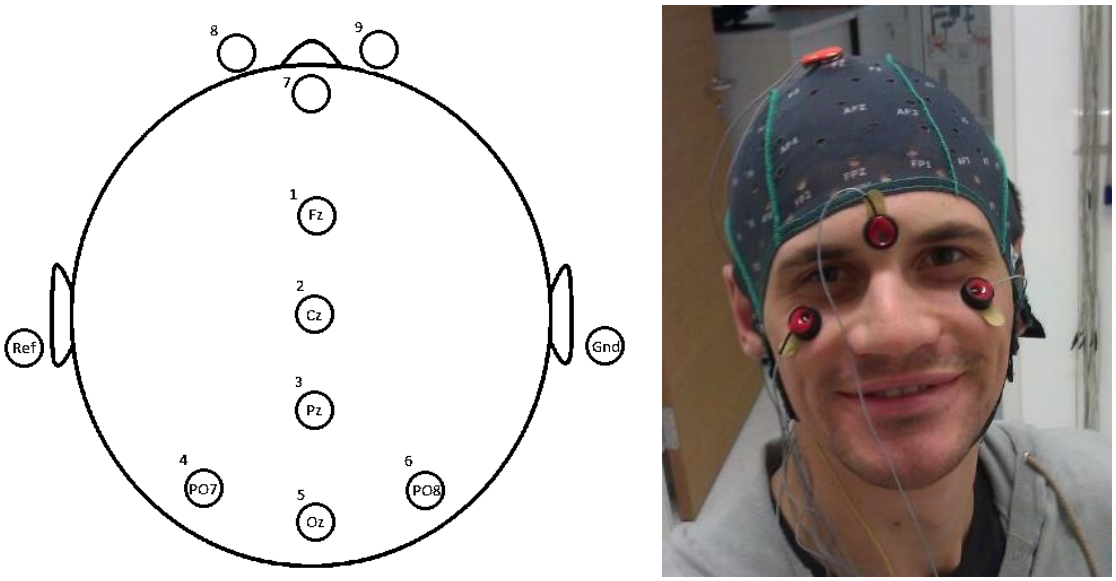

Figure 9: Electrode positions and corresponding channels

The Hardware used for signal acquisition was composed of six g.SAHARA electrodes (g.tec medical engineering GmbH, Austria) for EEG recording, three g.Ladybird electrodes (g.tec medical engineering GmbH, Austria) for EOG recording, two adhesive electrodes for ground and reference, a wristband connected to building ground for noise suppression, g.SAHARAbox (g.tec medical engineering GmbH, Austria), g.USBamp (g.tec medical engineering GmbH, Austria), and a personal computer. (see Figure 10).

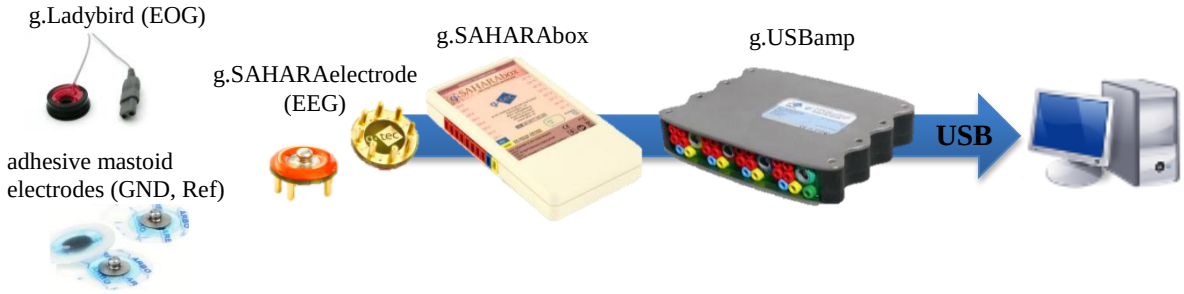

Figure 10: Recording equipment comprising the electrodes and signal acquisition modalities through to the recording Personal Computer [www.gtec.at/Products]

The used biosignal amplifier recorded the EEG as well as the EOG at a sampling rate of 256 Hz. A band pass filter, incorporated into the amplifier (8^{th} order Chebyshev with pass-band at 0.5 Hz and stop-band at 100 Hz) and a notch filter at 50 Hz were applied on the incoming EEG signal before it was digitized and sent to the PC via USB.

2.3.2. Software

A SIMULINK® model was used for presentation of the paradigm as well as the recording of the signals. The functions necessary for recording and saving were obtained from the tools4BCI project [http://tools4bci.sourceforge.net/].

2.3.3. Preprocessing

In order to prepare the recorded data for analysis, certain steps of preprocessing were beneficial. To do so the MATLAB® function *filtfilt* was utilized as well as manual artifact tagging in the time series of the EEG recordings.

Artifact tagging was done using the software SigViewer (http://sigviewer.sourceforge.net). Electromyogram and movement artifacts were tagged because they could be separated best from the EEG by visual examination and are limited in time. Muscle artifacts were tagged as such, according to the properties: duration, morphology and frequency [31]. Trials containing an artifact were excluded and not used for further processing.

The *filfilt* function was used with the parameters of a 4^{th} order Butterworth filter with pass-band between 0.5 Hz and 5 Hz. It was applied to all channels.

Finally every trial was baseline corrected. This basically means that the mean signal value of the 200 ms pre-stimulus interval was subtracted from every sample point in the interval 200 ms pre- to 800 ms post-stimulus.

To obtain the ERPs the average brain signals to every picture from every run were calculated. The EEG from 100 ms pre-stimulus to 800 ms post-stimulus was cut out of the recording and averaged over all appearances of a picture within one run.

2.4. Data analysis

The algorithm for offline analysis was implemented in MATLAB® and was supported with functions that are part of the BCI Toolbox. This chapter explains the statistics as well as the used features for the classification problem.

2.4.1. Statistics

For analysis four cases were conceived to analyze the gained data. Categorization of stimuli was necessary in order to use it as input for a classification algorithm. For comprehension purposes those cases are explained in the following.

- **case1:** This case checked, if there is a significant difference in the EEG response on the cars the participant has chosen as his favorites after run5 compared to all other cars in run1, run2, run3 and run4. This means the first category contained two, and the second category 38 cars leading to eight (2 cars x 4 runs) trials for class one and 152 (38 cars x 4 runs) trials for class two.
- **case2:** The classical oddball paradigm [32] was exemplary for the analysis of run6 and run7. The two chosen favorites after run5 were the targets, the participant had to concentrate on. This means, the two favorite cars made up the first category (2 cars x 2 runs = 4 trials) and the 38 others the second category (38 cars x 2 runs = 76 trials).
- **case3:** This case considered the feedback given in run5. The first category was composed of all cars the participant liked and the second category contained all cars she/he disliked. On average this led to 20 cars in category one (20 cars x 4 runs = 80 trials) and 20 cars in category two (20 cars x 4 runs = 80 trials).
- **case4:** The last case compared the elicited brain signals after presentation of 20 sports cars in category one (20 cars x 4 runs = 80 trials) with 20 normal cars in category two (20 cars x 4 runs = 80 trials).

Table 1 summarizes the analyzed cases with their categories and runs.

Table 1: Overview of categories and corresponding runs

case	category 1	category 2	runs
case1	two favorites after run5	38 non-favorites	run1, run2, run3, run4
case2	two favorites after run5	38 non-favorites	run6, run7
case3	cars liked in run5	cars not liked in run5	run1, run2, run3, run4
case4	sports cars	normal cars	run1, run2, run3, run4

In order to analyze the four cases in terms of their discriminability of categories, shrinkage-LDA [2] in combination with a leave-one-out cross validation [18] was used. The leave one-out cross validation is equivalent to a k-fold cross validation with k being the total number of trials. The algorithm executing this analysis was set up by built-in MATLAB® functions as well as functions from the BCI Toolbox.

Shrinkage-LDA (SLDA) was used to calculate the linear classifiers because according to [2], SLDA outperforms LDA and stepwise LDA in ERP classification tasks. Especially it performs better when the number of features is considerably larger than the number of training samples per class. The superior performance is achieved with regularization of the covariance matrix. Find more details on SLDA and its utilization for ERP classification in [2].

In words the algorithm took the entire trials of both categories and separated them into test-set and train-set. According to the leave-one-out cross-validation, one trial was used for testing where all others were used for training. The train-set was used to obtain the classifiers by shrinkage-LDA. Those classifiers were finally applied on the test set and the outcome was evaluated. This procedure was repeated, since every trial was used once for the test-set. By averaging over all results, the result for the classification problem was calculated.

The input used to feed the shrinkage LDA contained the features the algorithm should base its decision on. Because we recorded visual evoked potentials and wanted to distinguish the designs by means of P300, the feature vector for each trial was composed by the potentials recorded at the three electrode positions C_z, P_z, O_z (see also **Fehler! Verweisquelle konnte nicht gefunden werden.**) from 200 ms post-stimulus to 600ms post-stimulus (see also 2.4.2). Additionally, the extracted time series was downsampled by a factor of ten, in order to improve the trial to feature ratio. To justify this feature decision, they are explained roughly in the following.

2.4.2. Temporal features

The temporal feature vector was built up of the EEG potentials at the three central electrodes over time. This means every sample point was treated as a feature. Because discrimination by means of P300 was intended, the brain potentials over time were extracted from 200 ms post-stimulus to 600 ms post-stimulus resulting in 102 sample points per channel. After down sampling by a factor of ten, ten features per channel were left. Downsampling was done with the with the MATLAB® function *resample.* This made a feature vector with 30 elements, which was fed into the shrinkage LDA for every trial. Figure 11 depicts the evoked potentials over time with respect to the stimulus.

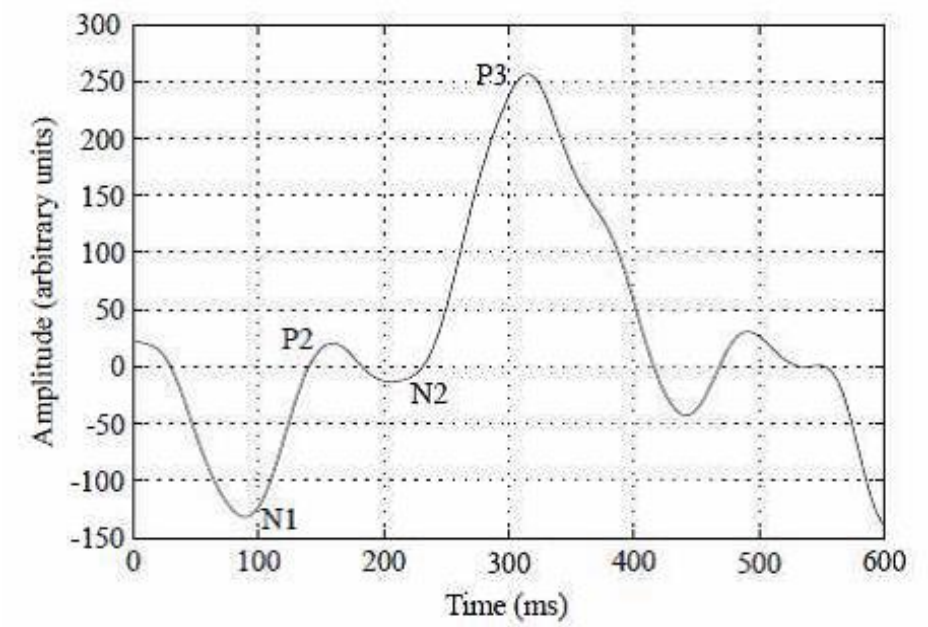

Figure 11: Definition of the evoked potentials and their temporal appearance with respect to the stimulus onset at 0ms [http://www.intechopen.com/source/html/6798/media/image32.png]

In order to increase the amount of information that can be fed into the classification algorithm, the information of three electrodes was used. These electrodes were C_z, P_z and O_z, because P300 is most prominent on the central positions, and O_z helps improving the outcome of classification like it is explained in [2].

The features of the three chosen electrodes were put together to obtain the feature vectors.

3. Results

In this section the obtained results are presented. The four cases (see Table 1) that are of particular interest were processed with the algorithm explained beforehand. Results are shown in tables containing statistical numbers about the classification for every case. In addition figures show the grand average of all participants ERPs. In the figures a red dotted line at 0ms represents picture onset. The blue and the red line represent the two classes mentioned in the legend and described in Table 1.

run0 was conducted in order to show that only the picture information is relevant for eliciting P300, and no other optical parameters. In the recordings of run0 no ERPs were noticeable.

Also a paired sample t-test comprising all participants was conducted for every case. This test was done in order to find out if the maximum values of P300 for the analyzed classes were significantly different. The t-test was executed with the MATLAB® function *ttest2* assuming unknown and unequal class variance. This assumption was necessary because the values fed into the t-test were derived from classes of different size. The maximum of each class within the interval 200 ms to 500 ms post-stimulus were used as input, in order to use the P300 amplitude. Twelve samples were taken, one for every participant.

As explained in section 2.4.1, the data was separated into training and test set. The training-set was used to calculate the classifier, which was then applied on the test-set. Because of the leave-one-out cross validation, 40 cases per run were gathered and their results were analyzed. For the purpose of analysis, the result of the classification was confronted with the known class of the test-trial and fed into a contingency table.

The accuracy of the classification was determined with the following formula.

$$acc = \frac{T1+T2}{n} \tag{1}$$

acc stands for the obtained accuracy, *T1* for the number of correct classifications in class 1, *T2* for the number of correct classifications in class 2, and *n* for the total number of classification attempts.

The better-than-random accuracy [27] is necessary to rate the accuracies calculated for each subject. It is obtained with the MATLAB® function *check_classifier* from the BCI Toolbox comprising an alpha value of 0.05.

Because accuracy is not a meaningful measure for the performance when the classes are not balanced, Cohen's Kappa is utilized.

The values as listed in the columns of the result tables termed *Kappa*, relate to Cohen's Kappa introduced in [6]. It is an index for the quality of the classification problem. A Kappa-value of zero relates to an accuracy equivalent to the chance level. For interpretation of the Kappa-value Table 2 is provided.

Table 2: Guidelines to interpret Kappa [22]

Value of κ	Strength of agreement
<0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

Cohen's Kappa κ is calculated with the following formula

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{2}$$

p_0 stands for the observed agreement of frequencies and p_e for the expected agreement of frequencies by chance. [6]

3.1. case1

The aim of analyzing case1 was to show, whether it is possible to distinguish the two favored cars (Figure 12: blue line) from the 38 others (Figure 12: red line) by ERP analysis. The interclass ratio of 2 to 38 led to a prevalence of 0.95.

A paired-samples t-test was conducted to compare the P300 amplitudes of the two favorite cars and the 38 others. There was no significant difference concerning the maximum of the two classes.

Table 3 lists the results of case1 analysis with SLDA and leave-one-out cross validation, namely obtained accuracies, better-than-random accuracies as well as Cohen's Kappa. It shows that classification with SLDA is only slightly better than random classification.

Table 3: Results of case1 analysis

ID	case1		
	accuracy	better-than-random accuracy	Kappa
CL8	0.95	0.93	0.00
CN1	0.95	0.93	0.00
CO5	0.94	0.93	-0.02
CQ6	0.95	0.93	0.00
CU5	0.94	0.93	-0.02
CU6	0.94	0.93	-0.01
CU7	0.93	0.93	-0.03
CU8	0.94	0.93	-0.01
CU9	0.95	0.93	0.00
CV1	0.94	0.93	-0.01
CV2	0.94	0.93	-0.01
CV3	0.95	0.93	0.18
grand average	**0.94**	**0.93**	**0.01**

In Figure 12 grand averages of the brain potentials at the three recorded electrode positions from 100ms pre-stimulus to 800ms post-stimulus are plotted.

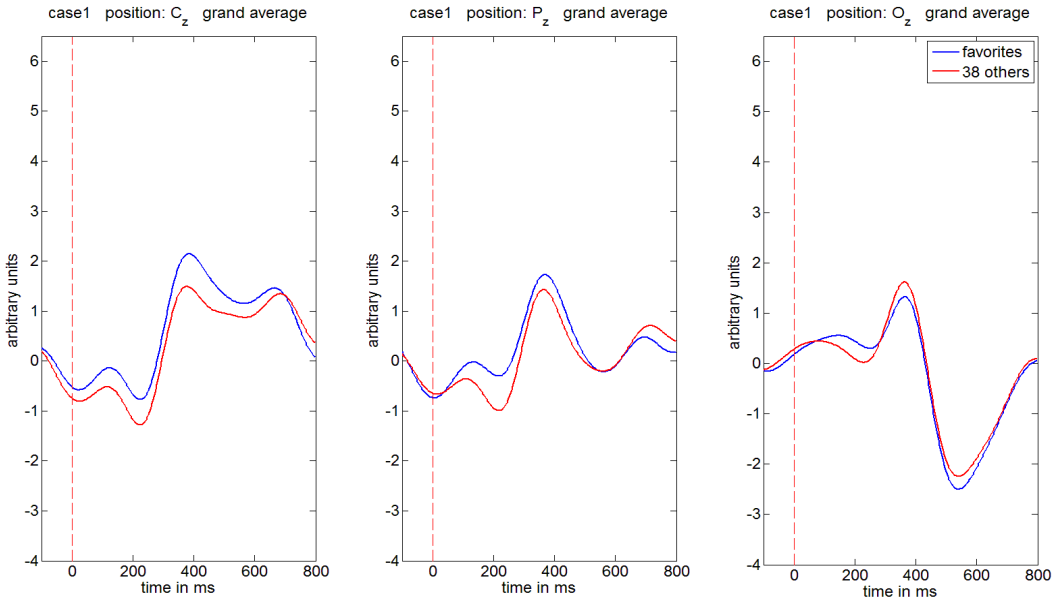

Figure 12: Grand averages of the recorded signals in case1 on the three electrode positions C_z, P_z, O_z

3.2. case2

The aim of analyzing case2 was to realize a classic oddball paradigm, and therefore to show the correctness of the experimental setup. Like already explained the target stimuli (Figure 13: blue line) were the chosen favorites after run5.

Here, a paired-samples t-test was conducted as well, in order to compare the favorite cars with the 38 others in run6 and run7. Significantly higher amplitudes of P300 were found for the target stimuli at channel P_z ($t_{20.3} = 2.493,\ p = 0.0213$) with a significance level of 0.05, but no difference could be stated for channels C_z and O_z.

Table 4 lists the results of case2 with SLDA and leave-one-out cross validation, namely obtained accuracies, better-than-random accuracies as well as Cohen's Kappa. It shows that classification with SLDA is only slightly better than random classification.

Table 4: Results of case2 analysis

ID	case2		
	accuracy	better-than-random accuracy	Kappa
CL8	0.95	0.94	0.00
CN1	0.94	0.94	0.25
CO5	0.94	0.94	-0.02
CQ6	0.95	0.94	0.00
CU5	0.95	0.94	0.00
CU6	0.94	0.94	-0.02
CU7	0.94	0.94	-0.02
CU8	0.93	0.94	-0.03
CU9	0.94	0.94	-0.02
CV1	0.95	0.94	0.00
CV2	0.95	0.94	0.31
CV3	0.99	0.94	0.85
grand average	**0.95**	**0.94**	**0.11**

In Figure 13 the grand averages of the brain potentials at the three recorded electrode positions from 100 ms pre-stimulus to 800 ms post-stimulus over all twelve participants are plotted.

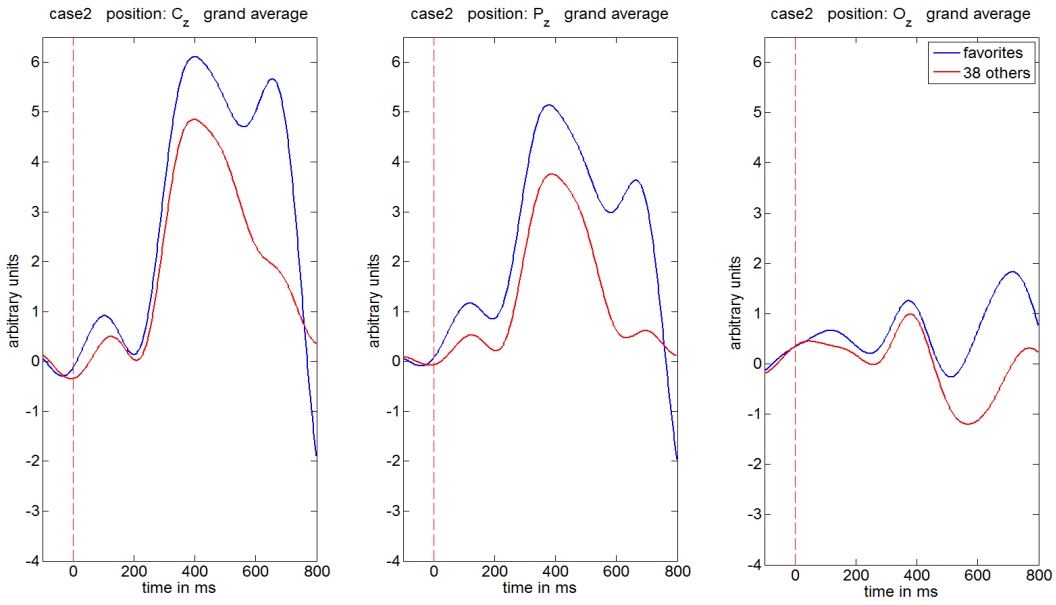

Figure 13: Grand averages of the recorded signals in case2 on the three electrode positions C_z, P_z, O_z

3.3. case3

The aim of analyzing case3 was to find out, if it is possible to categorize the images according to the users feedback on every car in run5. The ratio between the classes of liked (Figure 14: blue line) and disliked cars (Figure 14: red line) showed a grand average of 0.5.

The paired-samples t-test was conducted to compare the cars with positive feedback to the cars with negative feedback. No significant difference was found.

Table 5 lists the results of case3 analysis, namely obtained accuracies, better-than-random accuracies, Cohen's Kappa as well as the prevalence after run5. It shows that classification with SLDA is not better than random classification. But if considering only the participants performing better than random (gray shaded) the grand average accuracy would be increased to 0.616 with a better-than-random accuracy of 0.582 and a Kappa of 0.18.

Table 5: Results of case3 analysis

ID	case3			
	accuracy	better-than-random accuracy	Kappa	prevalence
CL8	0.62	0.57	0.24	0.53
CN1	0.56	0.57	0.11	0.48
CO5	0.46	0.57	-0.12	0.45
CQ6	0.55	0.57	0.08	0.45
CU5	0.60	0.61	-0.02	0.35
CU6	0.53	0.57	0.04	0.45
CU7	0.61	0.58	0.15	0.60
CU8	0.58	0.58	0.10	0.43
CU9	0.54	0.58	0.04	0.58
CV1	0.43	0.57	-0.15	0.48
CV2	0.58	0.57	0.13	0.55
CV3	0.69	0.61	0.27	0.65
grand average	**0.56**	**0.58**	**0.07**	**0.50**

In Figure 14 the grand averages of the brain potentials at the three recorded electrode positions from 100 ms pre-stimulus to 800 ms post-stimulus over all twelve participants is plotted.

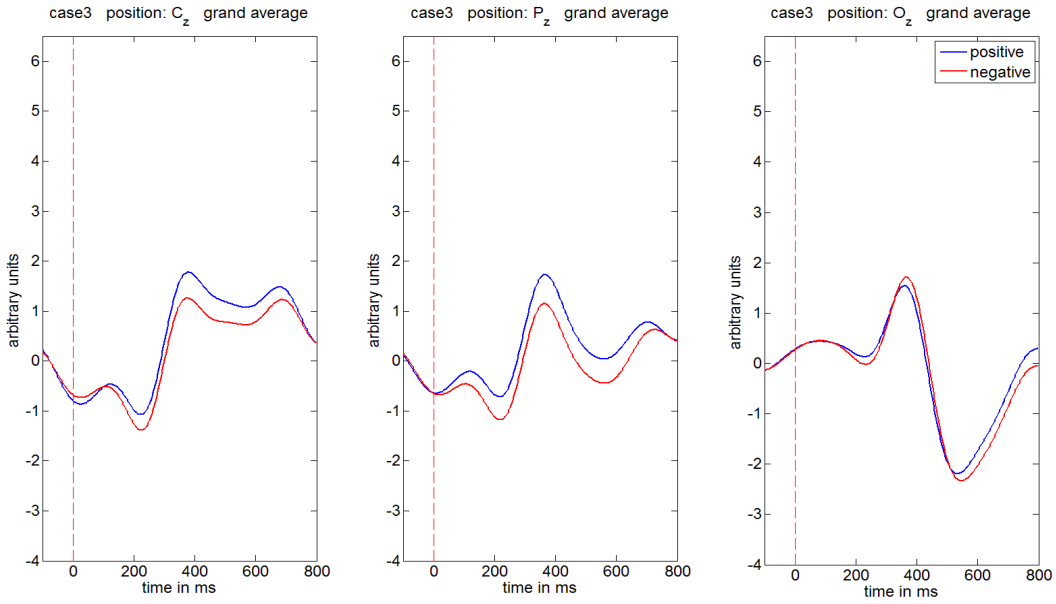

Figure 14: Grand averages of the recorded signals in case3 on the three electrode positions C_z, P_z, O_z

3.4. case4

The aim of analyzing case4 was to investigate if there is a difference in the brain potentials when sports cars (Figure 15: blue line), in contrast to normal cars (Figure 15: red line), were presented. The ratio of sports cars and normal cars was 0.5.

The paired-samples t-test was conducted to compare the sports cars with normal cars. But no significant difference was found.

Table 6 lists the results of case4 analysis, namely obtained accuracies, better-than-random accuracies, and Cohen's Kappa. It shows that classification with SLDA is slightly better than random classification. But if considering only the participants performing better than random (gray shaded) the grand average accuracy would be increased to 0.616 with a Kappa of 0.23.

Table 6: Results of case4 analysis

ID	case4		
	accuracy	better-than-random accuracy	Kappa
CL8	0.65	0.56	0.30
CN1	0.54	0.56	0.09
CO5	0.63	0.56	0.25
CQ6	0.59	0.56	0.19
CU5	0.62	0.56	0.24
CU6	0.59	0.56	0.18
CU7	0.60	0.56	0.20
CU8	0.58	0.56	0.16
CU9	0.53	0.56	0.06
CV1	0.50	0.56	0.00
CV2	0.57	0.56	0.14
CV3	0.71	0.56	0.41
grand average	**0.59**	**0.56**	**0.18**

Figure 15 shows grand averages of the brain potential at the three recorded electrode positions from 100 ms pre-stimulus to 800 ms post-stimulus over all twelve participants.

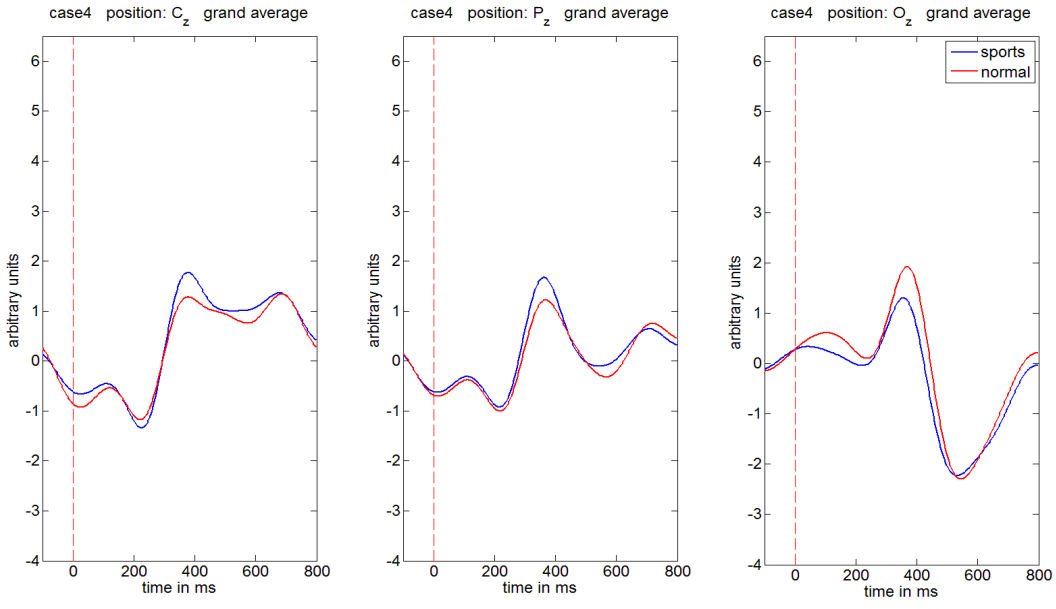

Figure 15: Grand averages of the recorded signals in case4 on the three electrode positions C_z, P_z, O_z

3.5. Results questionnaire

The three questions (translated from German into English) were:

1. Do you own a car?
2. What aspect is more important concerning cars, usability or appearance?
3. Why did you choose the cars you chose in run5?

In Table 7 the answers, as well as the total amount of each answer given by the twelve participants on the three questions, are listed. The answers to question 3 were translated from German into English.

Table 7: Answers on the questions

	question 1		question 2		question 3
ID	yes	no	usability	appearence	
CL8		x	x		different than others
CN1		x		x	appearence
CO5	x			x	design, brand
CQ6		x	x		design
CU5		x		x	positive emotions, high recognition
CU6		x	x		appearence, emotion
CU7		x		x	sporty
CU8		x		x	design
CU9		x		x	appearence
CV1		x	x		appearence, emotion
CV2		x		x	appearence, emotion
CV3		x		x	appearence, emotion
total	**1**	**11**	**4**	**8**	

4. Discussion

The goal of this thesis was to utilize BCI technology to interpret the users ERPs elicited by different car designs. The BCI used for interpretation should be able to determine if the user is in favor of the presented design or not. Therefore four cases of analysis in combination with the explained procedure and paradigm were introduced. A desirable outcome would have been good severability of the ERPs caused by designs the user likes/dislikes.

In the following, the results obtained with the presented methods are reviewed, interpreted and discussed. Also the limitations are mentioned and possible improvements for further investigations are proposed.

4.1. case1

The aim of case1 was to investigate the discriminability of the two cars the participants found more attractive compared to the 38 others. The results presented in 3.1 did not allow any statement concerning this case. They showed that classification with SLDA was only slightly better than random classification and therefore did not allow the detection of the participants' favorite cars. One reason is the unfavorable target to non-target ratio of 2 to 38 (8 trials first category, 152 trials second category), leading to a prevalence of 0.95, for classification. 8 trials of one category with 30 features per trial are too few to train the classifier in order to get proper classification.

The absence of a significant difference among the maxima of the two investigated classes within 200ms to 500ms post-stimulus like it was revealed with the t-test, could also be assessed in the grand average plots.

4.2. case2

case2 was established to prove the setup and timing of the experiment. Unfortunately it shows the biggest lack of this study, since the oddball-paradigm usually reliably delivers good values for Cohen's Kappa.

The analysis performed for this case yielded to very different results within the twelve participants. While nine participants nearly showed no agreement, and therefore Kappa values were around zero, the other three (CN1, CV2, CV3) participants showed 'fair' up to 'very good' (see Table 2) agreement with SLDA and leave-one-out cross validation. The obtained results allowed affirming the viability of the study with limitations. Apparently only three out of twelve participants achieved at least fair results. This might indicate difficulties for the majority, but not all, to accomplish the task. A lot of the participants reported problems to recognize their targets within the short time of 100ms. Of course this is a reason for the weak accuracy obtained by the oddball paradigm. Also the ERP plot for case2 in the Results section does not show a perfect P300 in the grand average. Nevertheless the plots for case2 show about double the amplitude around 400 ms post-stimulus at electrode positions C_z and P_z compared to the other cases. This increased activity of the brain might arise from increased attention the participants paid compared to the free runs.

The mean kappa-value for the participants that achieved a kappa-value greater than zero is 0.47, what refers to 'moderate' agreement. This shows that it is possible to accomplish the task but it was only achieved by few.

Another unfavorable circumstance for categorization is the target to non-target ratio of 2 to 38 (4 target trials, 76 non-target trials) like mentioned in 4.1. The four target trials recorded are too few in order to train the classifier for the target class.

The t-test conducted, showed that the peak amplitude for the target stimuli was significantly higher than for the non-target stimuli at the channel P_z across the participants while the channels C_z and O_z missed the significance level of 0.05.

The significantly higher amplitude for the target stimuli over all participants, supports the assumption of increased brain activity after a target stimulus, was presented.

4.3. case3

case3 analyzed the participants ERPs in run1, run2, run3 and run4 considering her/his feedback in run5. Because the participants were allowed to rate each car either positive or negative, the prevalence varied among them. But on average it turned out to be 0.5, as it was desired.

Only the ERPs of two participants were classifiable ‘fair’ by SLDA and therefore showed kappa-values larger than 0.21 but smaller than 0.4. All others kappa-values were distributed around zero, and therefore stated poor to no distinguishability. This means the classification algorithm is not able to separate the ‘liked’ cars from the ‘unliked’ cars.

Although the results of the t-test do not state significant difference in the amplitudes the maxima of the liked items are higher than those of the disliked items in the plots of the channels C_z and P_z. Similar to the discussion of case2 the higher amplitudes can be referred to increased brain activation after a car was presented the participant classified positive. But in contrast to case2 where the increased activity after certain stimuli was willingly induced the increased activation observable in case3 was elicited without any effort of the user. Therefore the subconscious reactions on the liked items result in higher deflections of the ERPs.

Similar findings were mentioned in [12] where ERPs are able to represent the users emotional intentions. They reported higher P300 amplitudes after stimuli with positive attitude. This statement underlines the analysis of case3 where the items with positive feedback, and therefore positive emotions, evoked significantly higher amplitudes compared to the items with negative feedback.

4.4. case4

The final case, case4, was introduced to check if there might be an observable difference in the ERPs elicited by normal cars and sports cars. Three participants delivered ‘fair’ and one participant delivered ‘moderate’ classifiable ERPs. Additionally three other participants obtained kappa-values close to ‘fair’ (CQ6, CU6 and CU7). These results allow assuming that there is a difference in the ERPs evoked by sport cars and normal cars. But adjustments in the paradigm are necessary in order to verify this.

The t-test determined no significant difference in the maximum amplitude of P300. By inspection of the plots one can see higher deflections for normal cars in the ERPs at position O_z. A possible explanation for the normal cars causing higher P300 amplitudes at electrode position O_z might be the less detailed designs of normal cars compared to sports cars. The missing uniqueness maybe makes it harder to distinguish them and therefore causes more mental activation. Related results were reported in [4], where sport cars triggered different brain responses than normal cars in male brains.

4.5. Limitations and possible improvements

In [34] the lack of comparable paradigms to verify the outcome of studies utilizing brain imaging tools for marketing purposes is mentioned already. Also the presented thesis revealed the need of standardized paradigms and routines to check the obtained results. Most of the participants struggled when they were asked what car they liked the most. Maybe they did not really care about the items design, or they did not want to show their true favorite that might be less socially accepted. Even when the participants came up with a favorite, mostly they were not able to name the reasons why they selected a particular design. This problem might be overcome by reducing the number of different stimuli and avoid similar designs, maybe by reduction to one car per brand. Also the presentation in front of the original background might increase the distinguishability of the items, but attention has to be paid not to distract the participants focus.

A participant specific aspect that could be relevant for this study is that not only visual aspects were taken into account for the choosing of the favorites. Especially price and brand of the shown cars were of great importance for some participants. Therefore it was hard for them to choose a favorite out of a set of cars only because of the design aspect, like it was requested. Getting a better idea of the honest design-preferences might be a future improvement in order to enhance and validate the process. Another point that might be addressed in this context is run5, the feedback run. In addition to the feedback that is asked to be as fast as possible a questionnaire might be completed where every item is rated on a scale.

Unfortunately the biggest lack of the study presented in this thesis, is the unfavorable ratio of class sizes in case1 and case2. Because the target to non-target ratio was 0.05, the number of target trials (case1: 8 trials, case2: 4 trials) was way too small to enable good training of the classifier and therefore obtain good classification accuracies. In order to get better results, the number of target trials has to be increased. Better balanced class sizes, resulting in more trials for training of each class, will lead to better kappa-values, and therefore stronger categorization statements might be obtained.

Another possible improvement is the utilization of objects with less complex design, and therefore easier to discriminate at first glance. Especially the utilization of objects, which are not only discriminable for experts, should be considered. This might also increase motivation of the participants. Participant motivation is an important point to address because a lack of motivation subsequently decreases the efficiency in BCI usage [17].

Also the analysis of earlier ERP components like N100 and N200 like it was realized by Handy and colleagues in [13] can give an insight into the subliminal reactions. If N100 and N200 are analyzed the filter has to be adjusted in order to allow higher frequencies.

As reported in [9], the repeated presentation of stimuli over and over can lead to a decrease of the P300 amplitude. During the whole procedure each of the 40 items is presented 48 times what makes a total of 1920 stimulations. By reducing the number of investigated items this potential limitation might be overcome without increasing the time of the whole procedure.

5. Conclusion

In conclusion, significantly higher ERP amplitudes were found for cars the participants liked compared to cars they disliked. Unfortunately classification by SLDA could not be achieved because of the limitations discussed in 4.5. However with the gained knowledge it is possible to improve the study in order to get better results to work with. The two main points to consider for future studies are the images used as stimuli and the number of trials used to train the classifier.

The used images should be easier to recognize and also should be easier to distinguish from each other. According to [2], SLDA gives better results than stepwise linear discriminant analysis when the number of trials for one class is larger than the number of features used for classification. When the experiment is tuned in order to get better classification results more reliable statements concerning the participants design preferences will be possible and another step towards a ‘product design BCI’ will be done.

6. References

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7. Appendix

7.1. Used Stimuli

In Figure 16 the sports cars used as visual stimuli are shown.

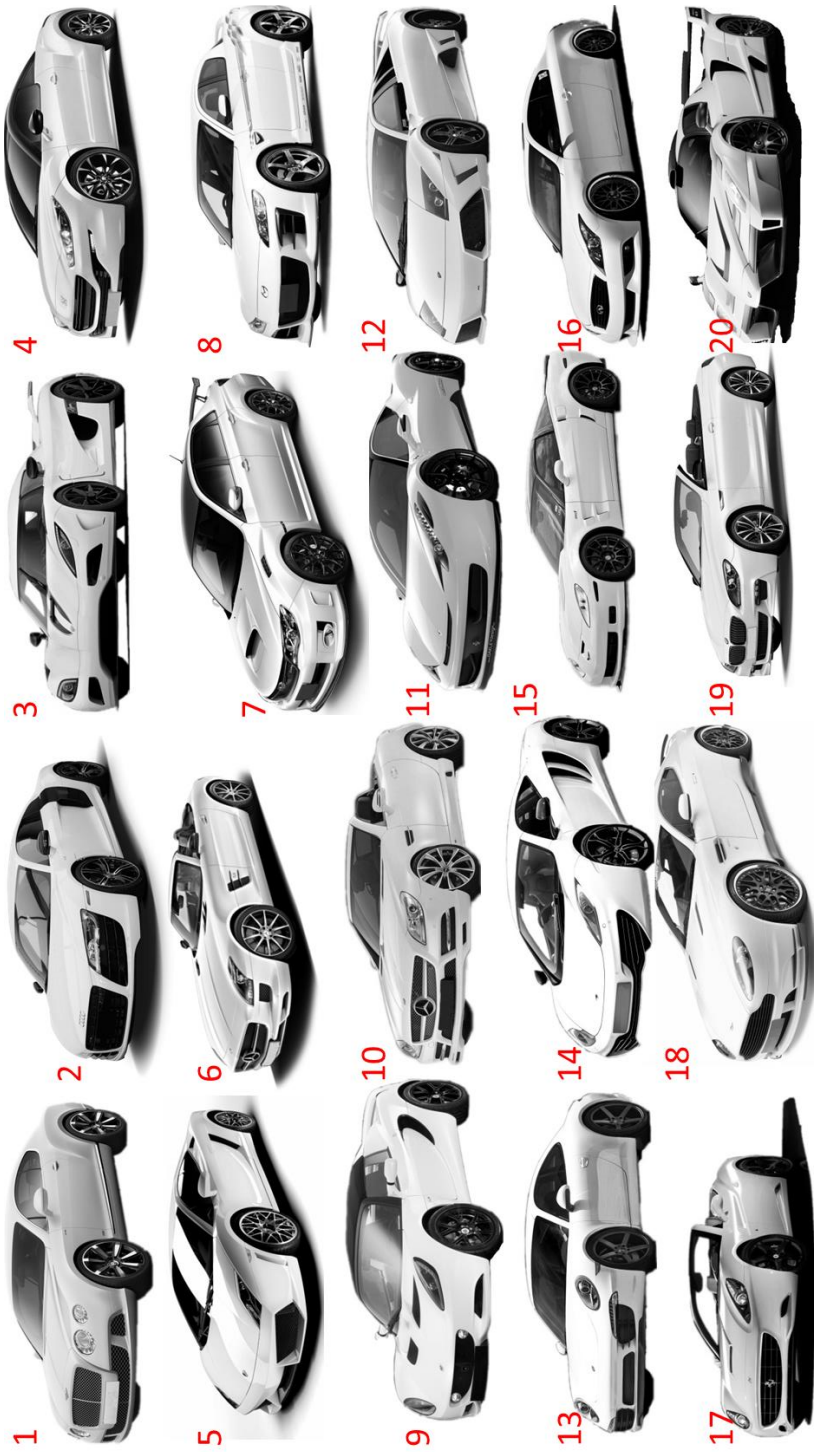

Figure 16: sports cars used as stimuli

Figure 17 shows the normal cars used for the paradigm.

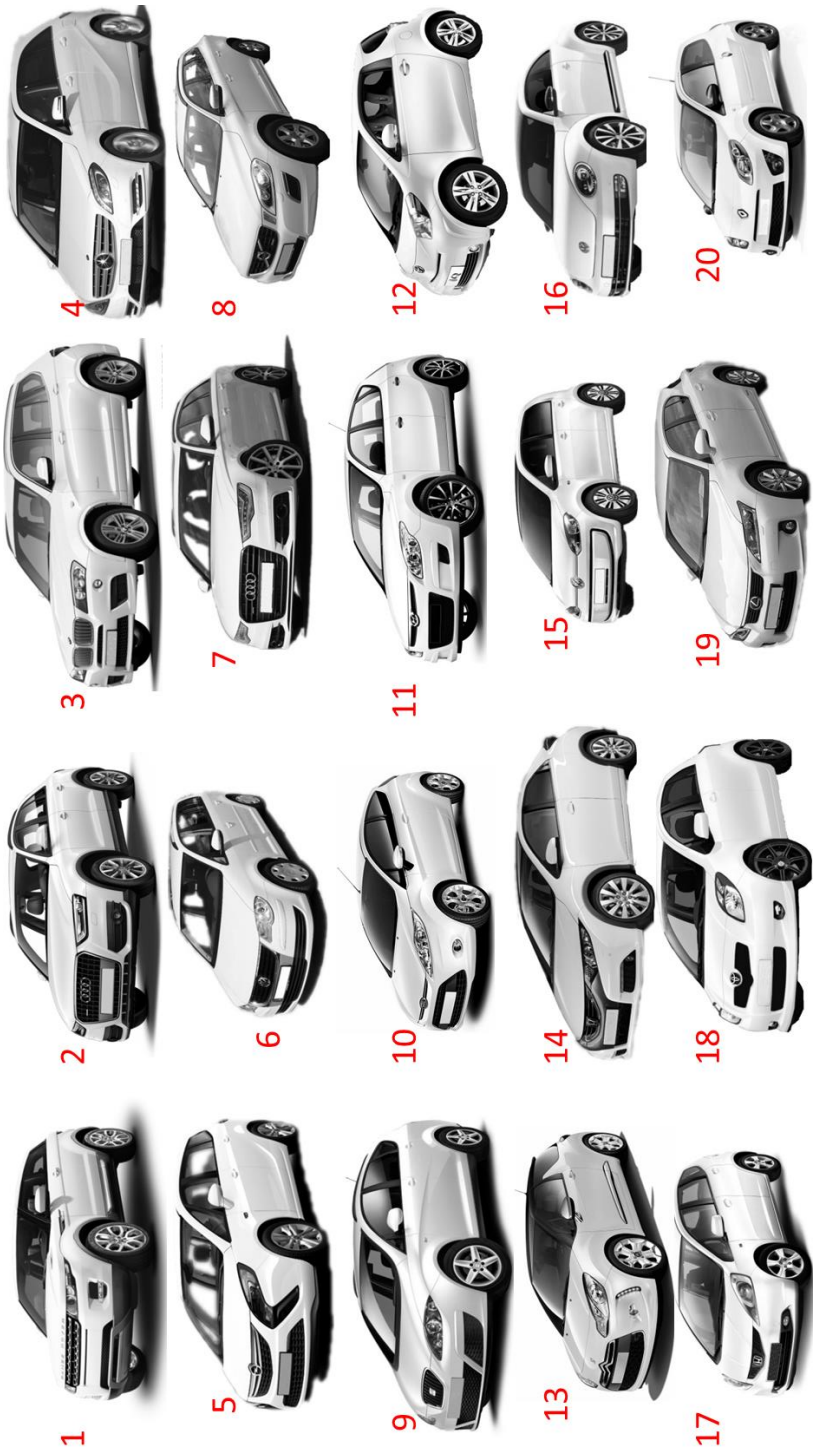

Figure 17: normal cars used as stimuli

7.2. Remaining figures

The figures depicted in the following show the recorded brain potentials at the three recorded electrode positions for every case and every participant.

case1:

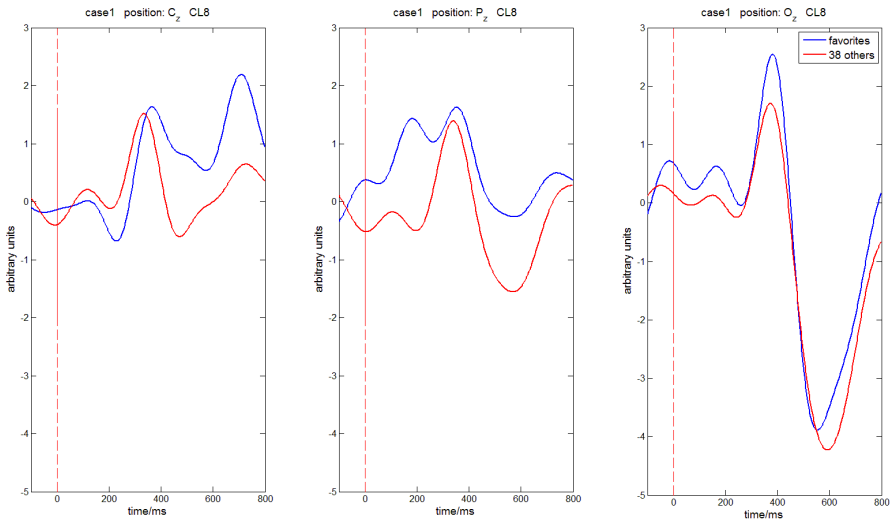

Figure 18: Recorded signals in case1 on three electrode positions of participant CL8

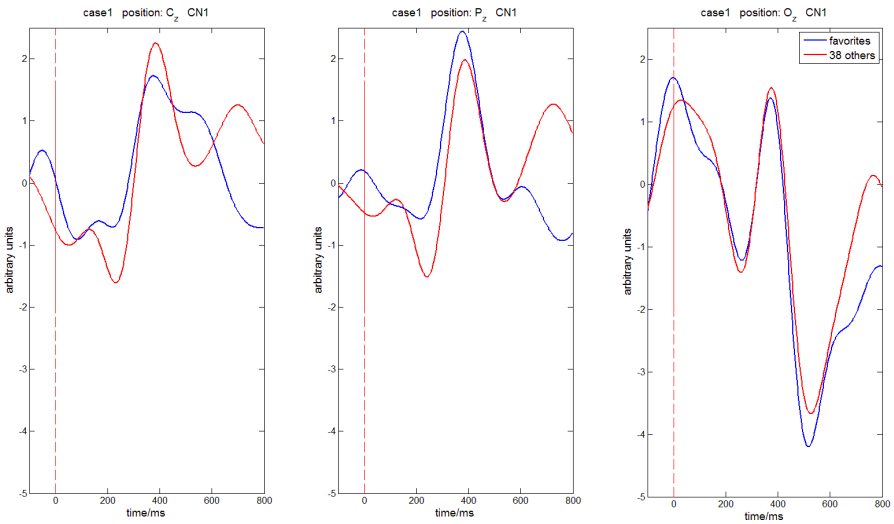

Figure 19: Recorded signals in case1 on three electrode positions of participant CN1

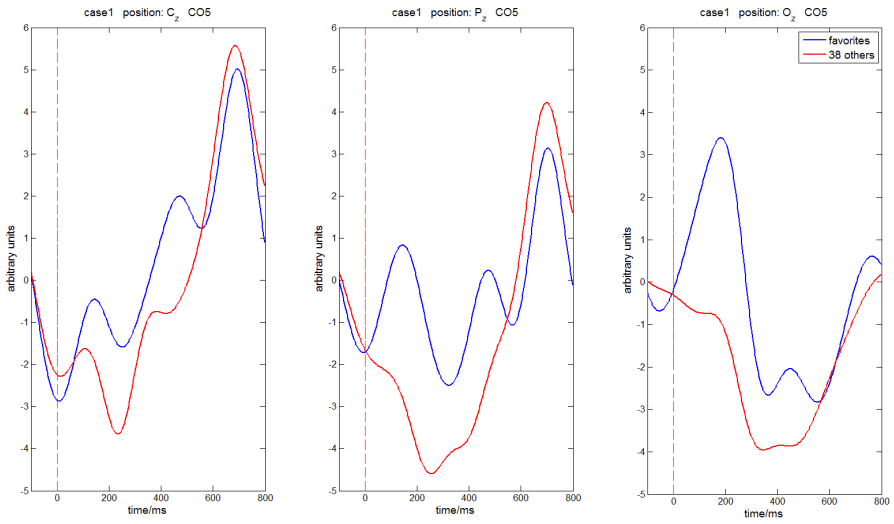

Figure 20: Recorded signals in case1 on three electrode positions of participant CO5

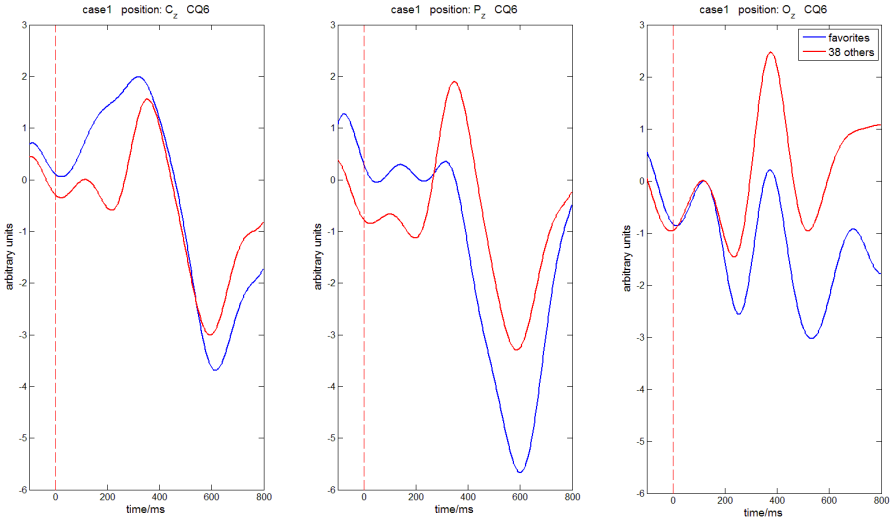

Figure 21: Recorded signals in case1 on three electrode positions of participant CQ6

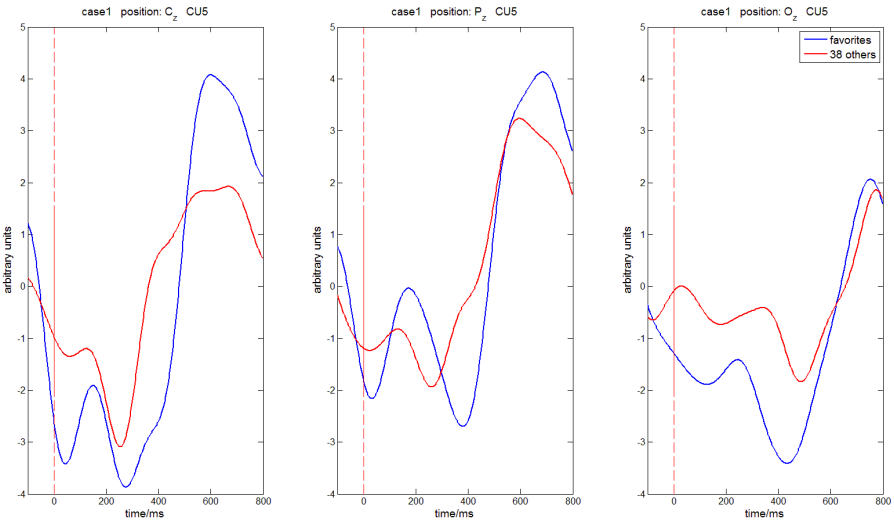

Figure 22: Recorded signals in case1 on three electrode positions of participant CU5

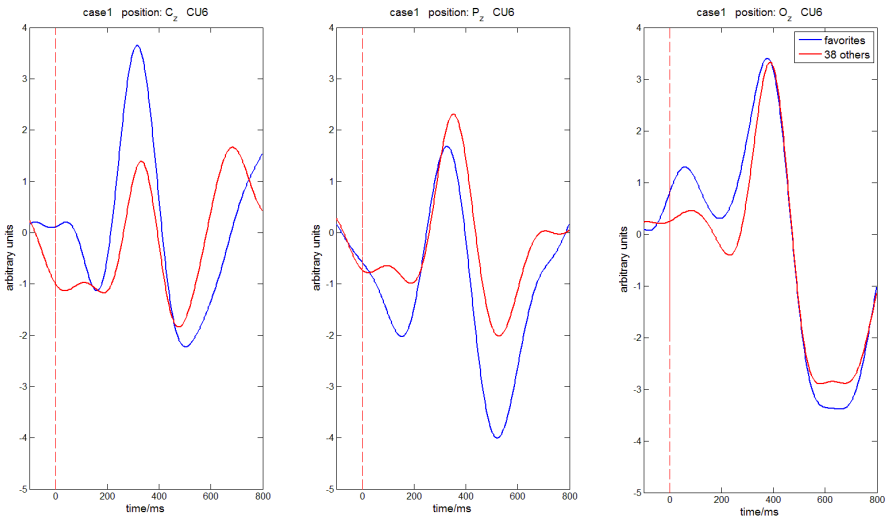

Figure 23: Recorded signals in case1 on three electrode positions of participant CU6

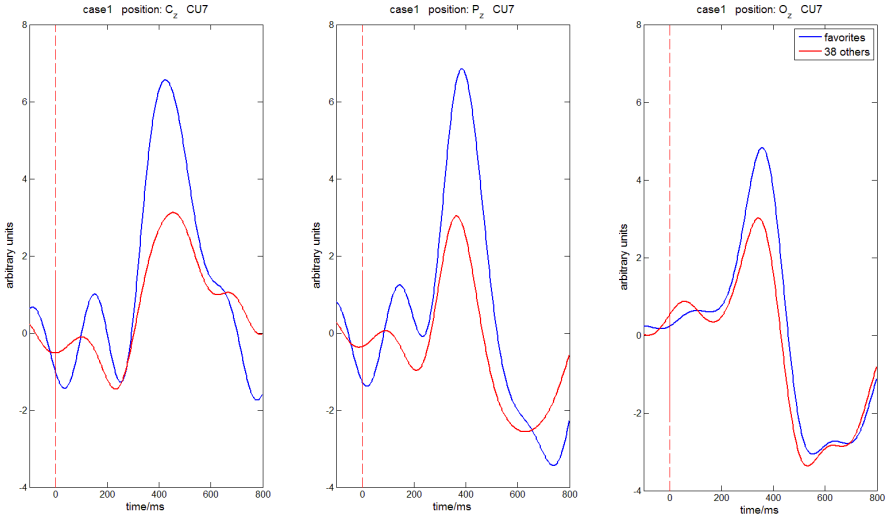

Figure 24: Recorded signals in case1 on three electrode positions of participant CU7

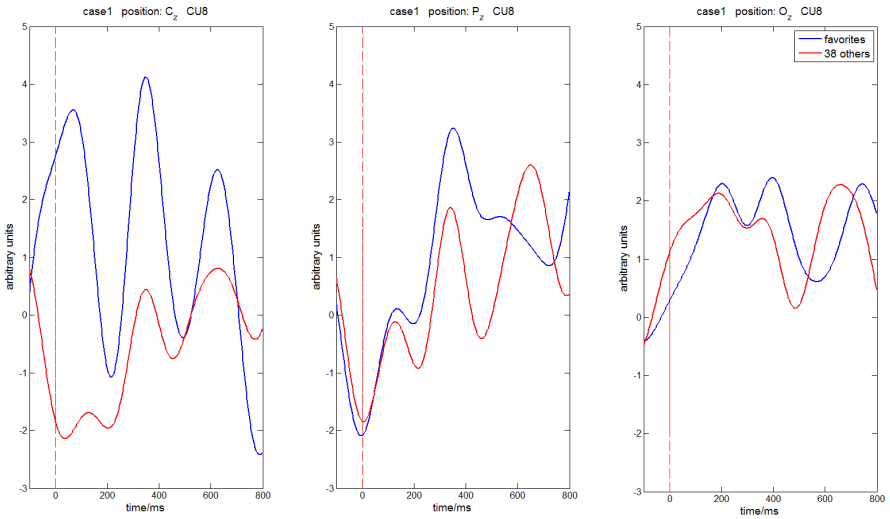

Figure 25: Recorded signals in case1 on three electrode positions of participant CU8

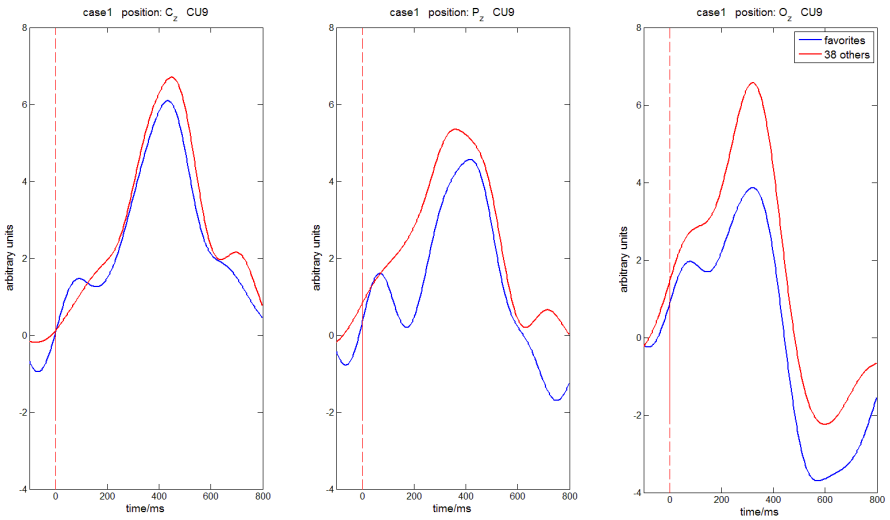

Figure 26: Recorded signals in case1 on three electrode positions of participant CU9

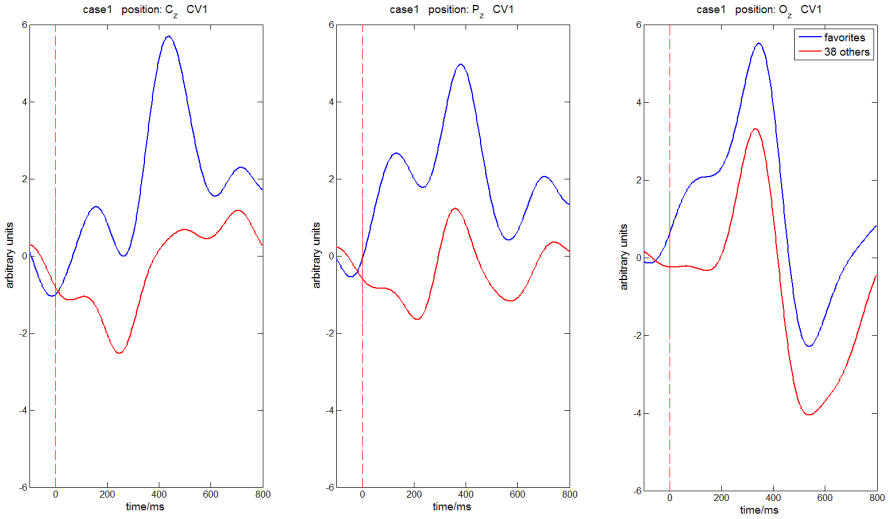

Figure 27: Recorded signals in case1 on three electrode positions of participant CV1

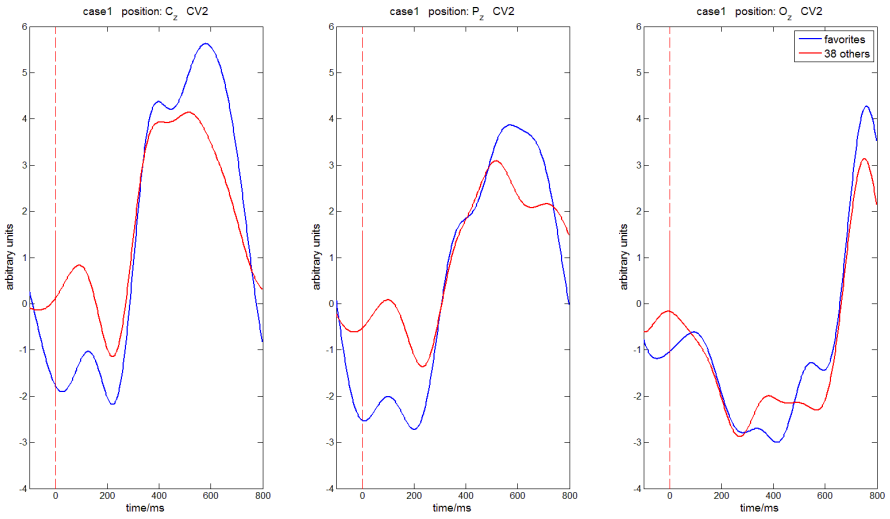

Figure 28: Recorded signals in case1 on three electrode positions of participant CV2

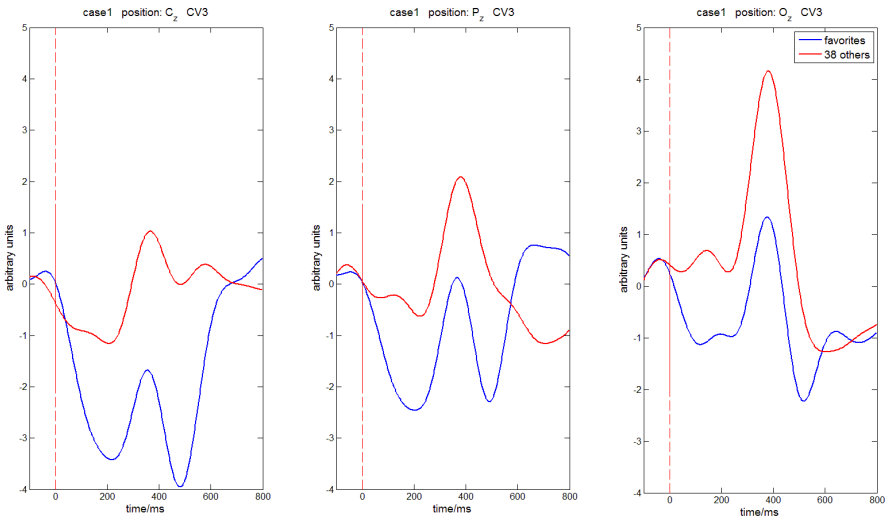

Figure 29: Recorded signals in case1 on three electrode positions of participant CV3

case2:

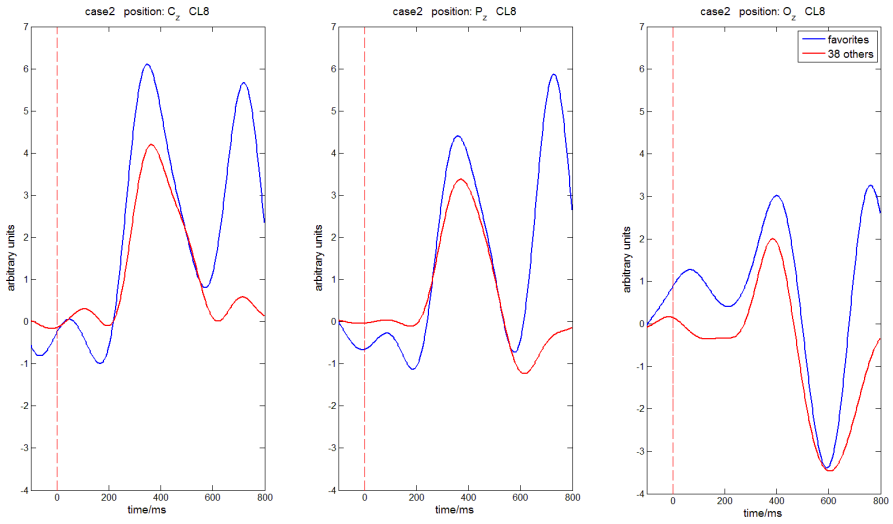

Figure 30: Recorded signals in case2 on three electrode positions of participant CL8

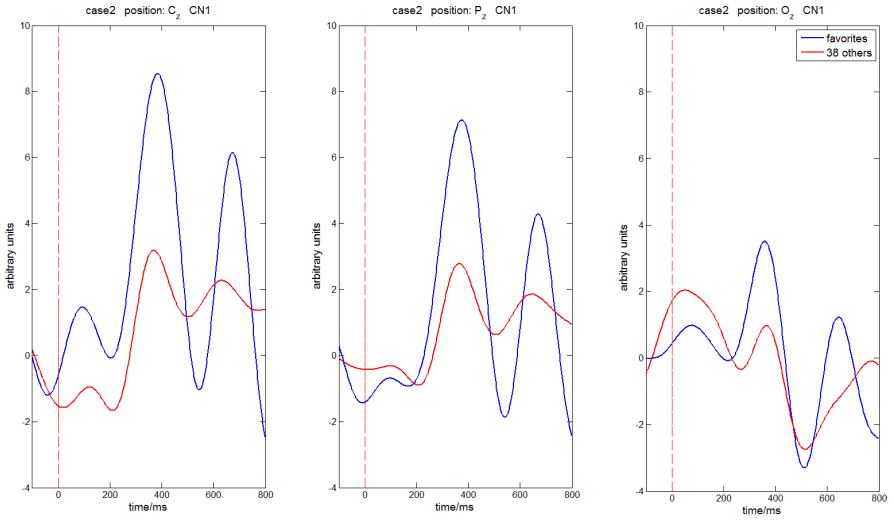

Figure 31: Recorded signals in case2 on three electrode positions of participant CN1

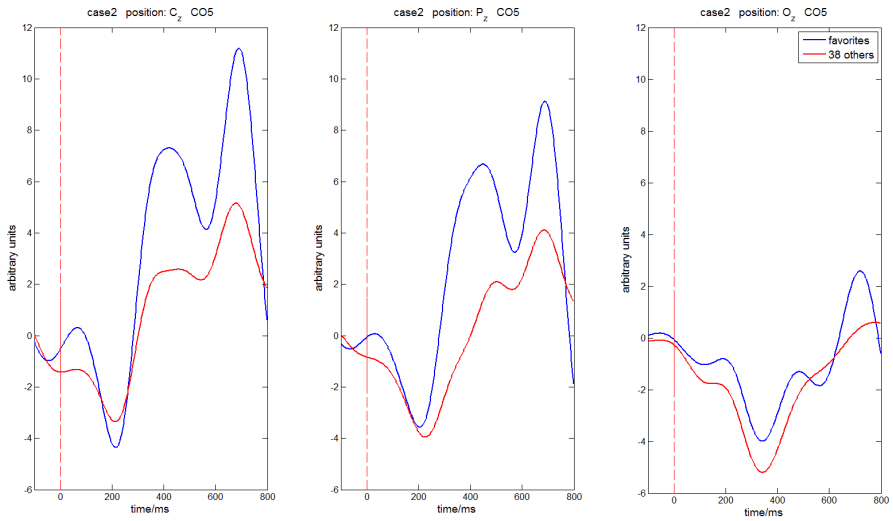

Figure 32: Recorded signals in case2 on three electrode positions of participant CO5

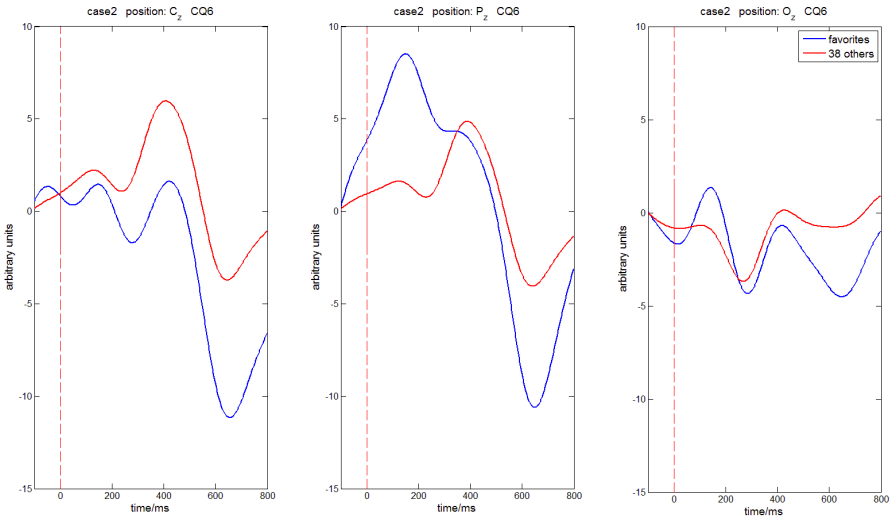

Figure 33: Recorded signals in case2 on three electrode positions of participant CQ6

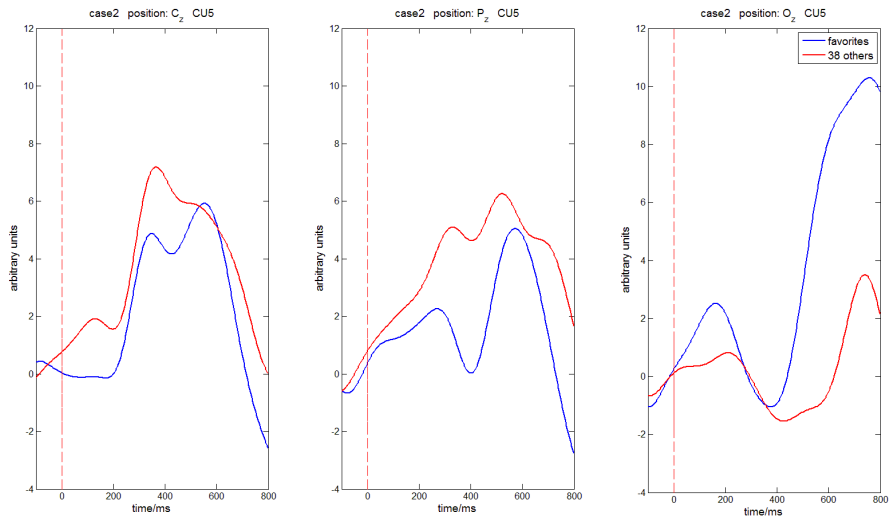

Figure 34: Recorded signals in case2 on three electrode positions of participant CU5

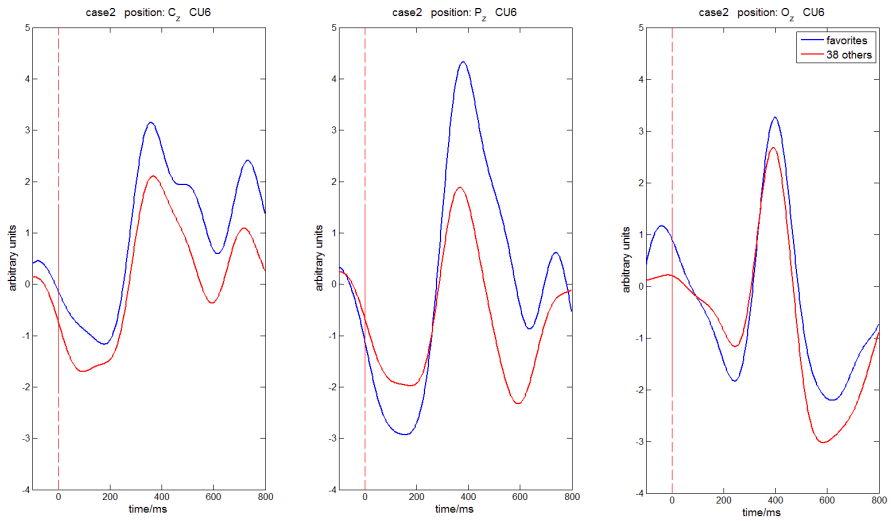

Figure 35: Recorded signals in case2 on three electrode positions of participant CU6

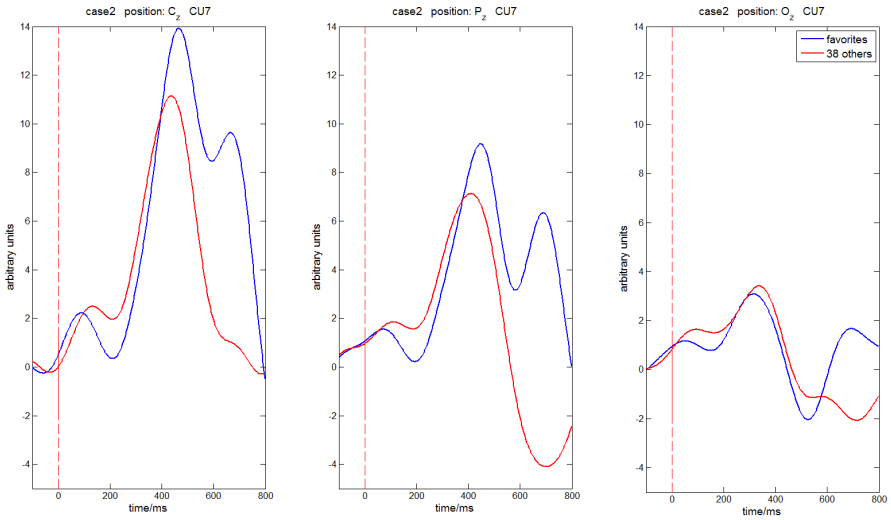

Figure 36: Recorded signals in case2 on three electrode positions of participant CU7

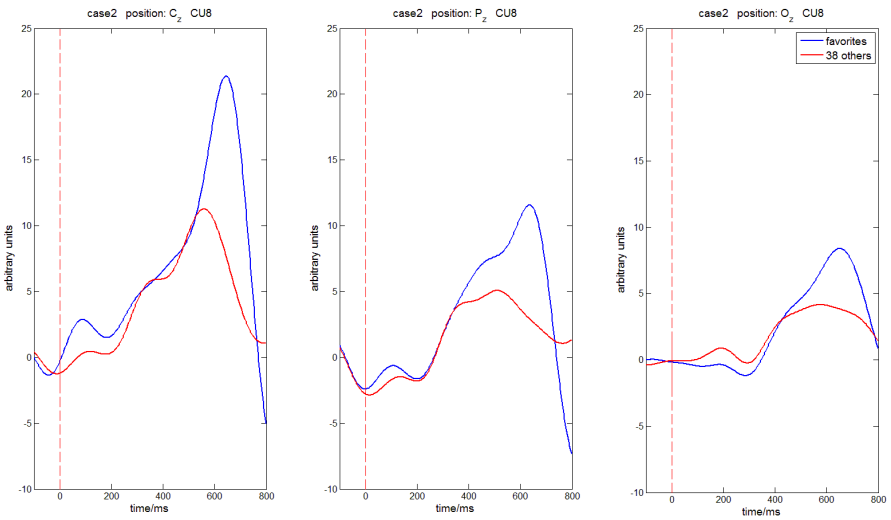

Figure 37: Recorded signals in case2 on three electrode positions of participant CU8

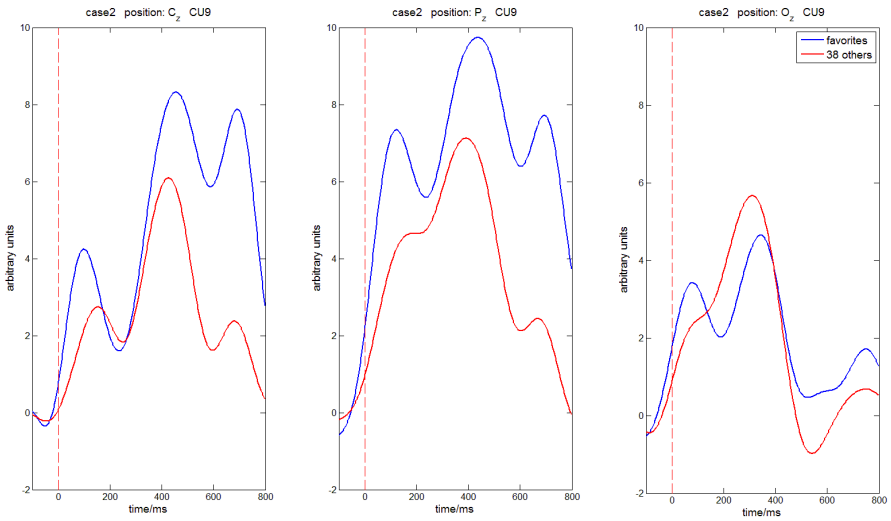

Figure 38: Recorded signals in case2 on three electrode positions of participant CU9

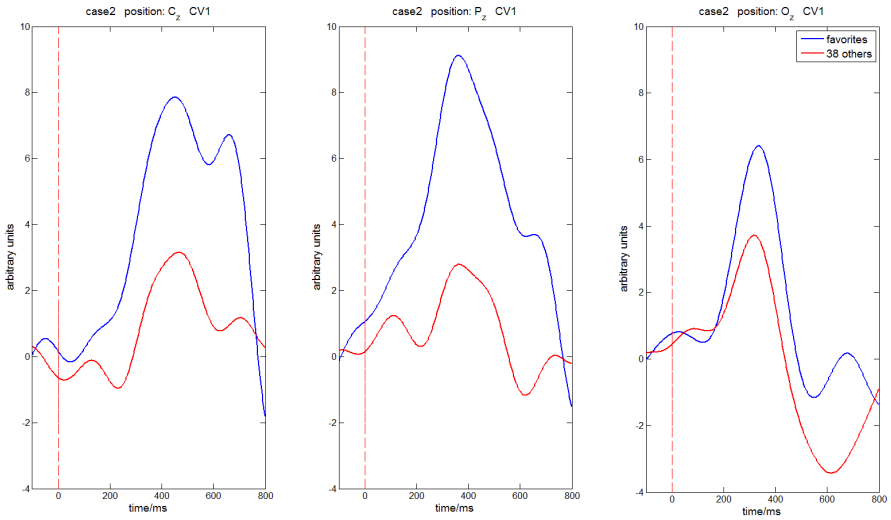

Figure 39: Recorded signals in case2 on three electrode positions of participant CV1

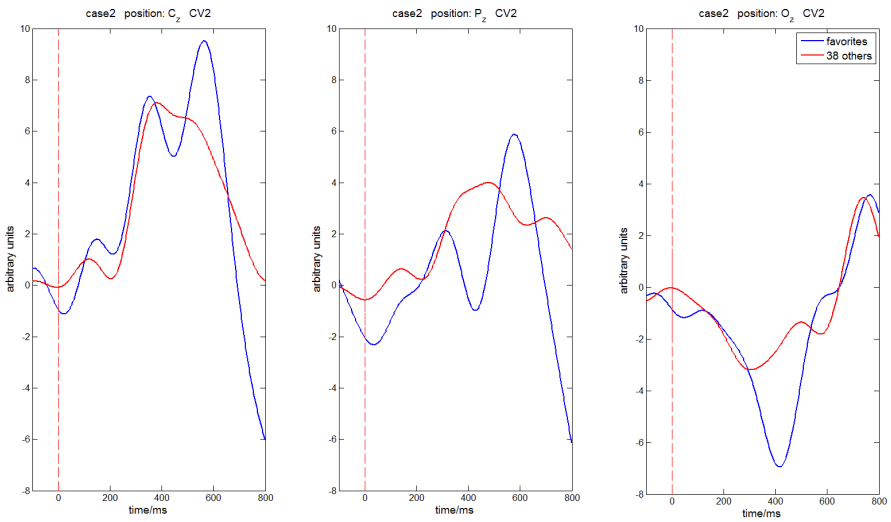

Figure 40: Recorded signals in case2 on three electrode positions of participant CV2

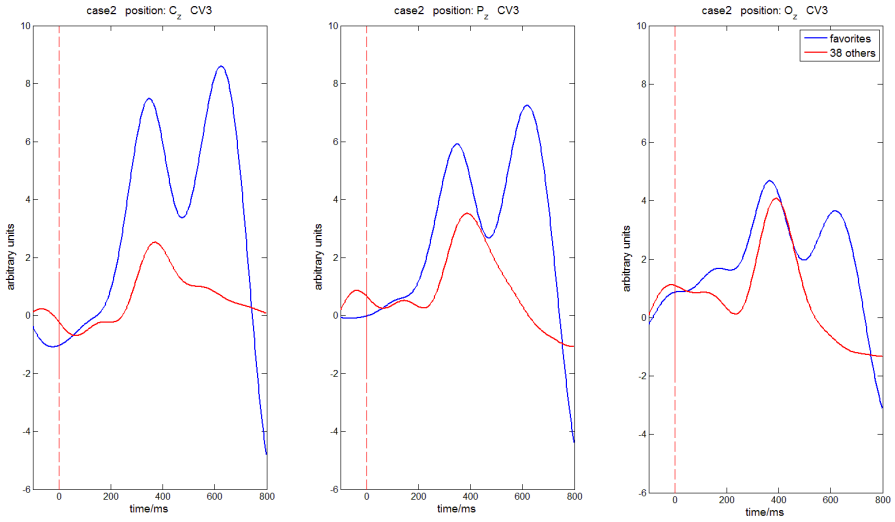

Figure 41: Recorded signals in case2 on three electrode positions of participant CV3

case3:

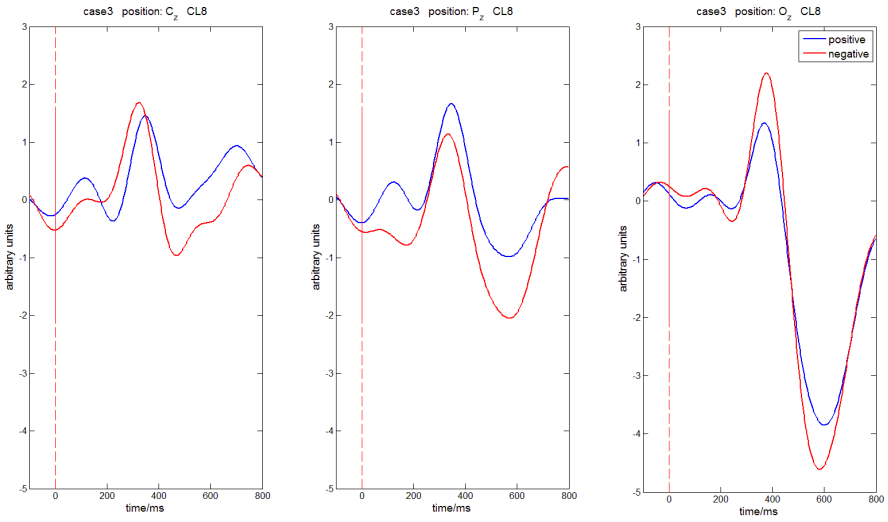

Figure 42: Recorded signals in case3 on three electrode positions of participant CL8

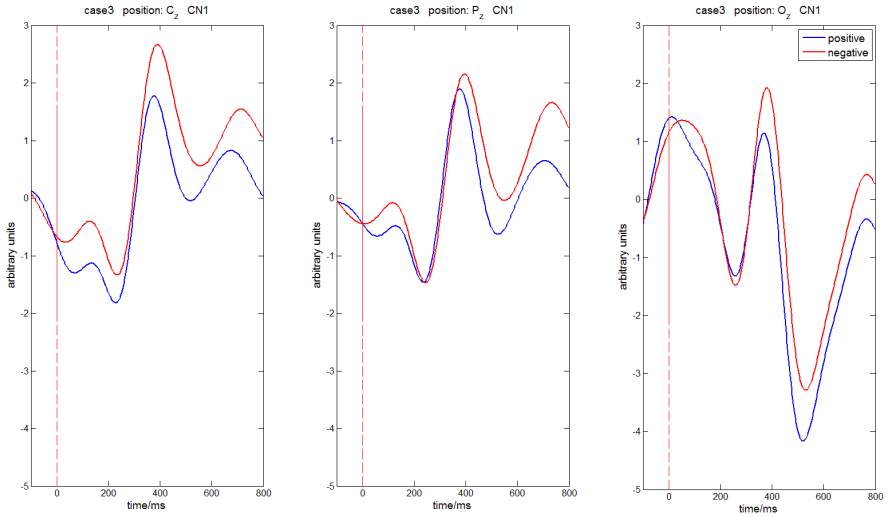

Figure 43: Recorded signals in case3 on three electrode positions of participant CN1

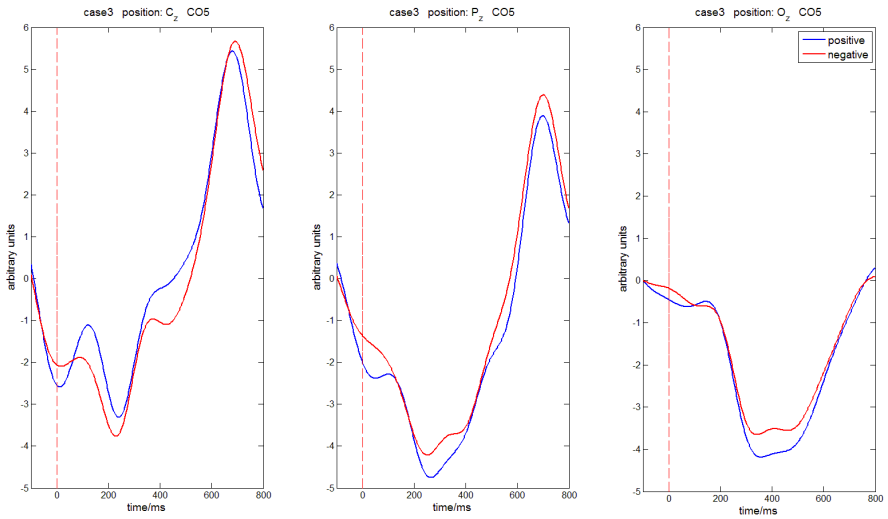

Figure 44: Recorded signals in case3 on three electrode positions of participant CO5

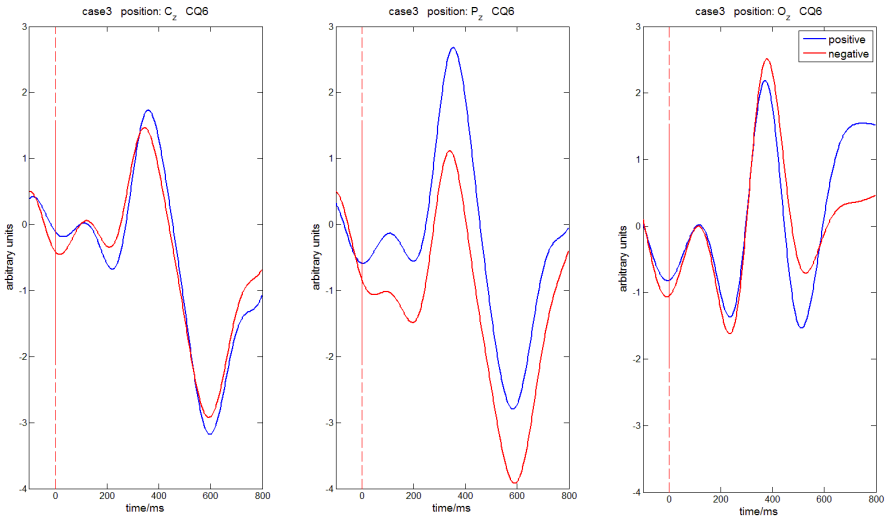

Figure 45: Recorded signals in case3 on three electrode positions of participant CQ6

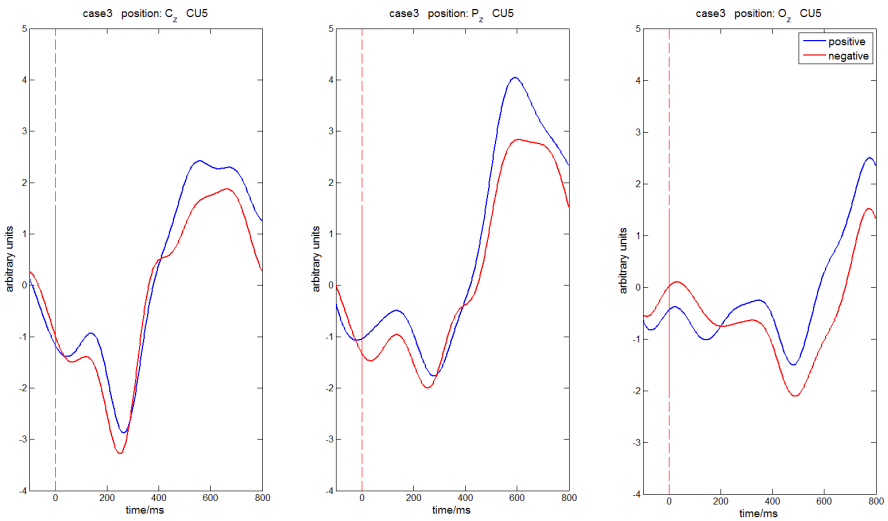

Figure 46: Recorded signals in case3 on three electrode positions of participant CU5

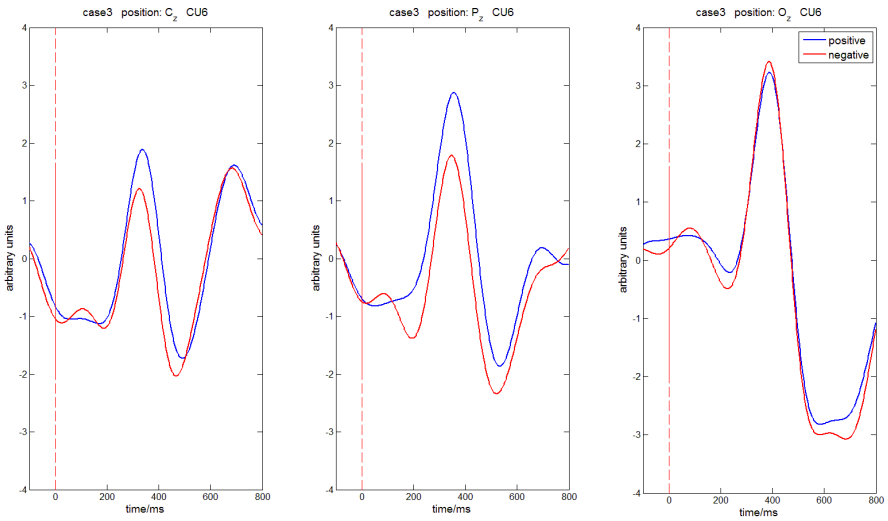

Figure 47: Recorded signals in case3 on three electrode positions of participant CU6

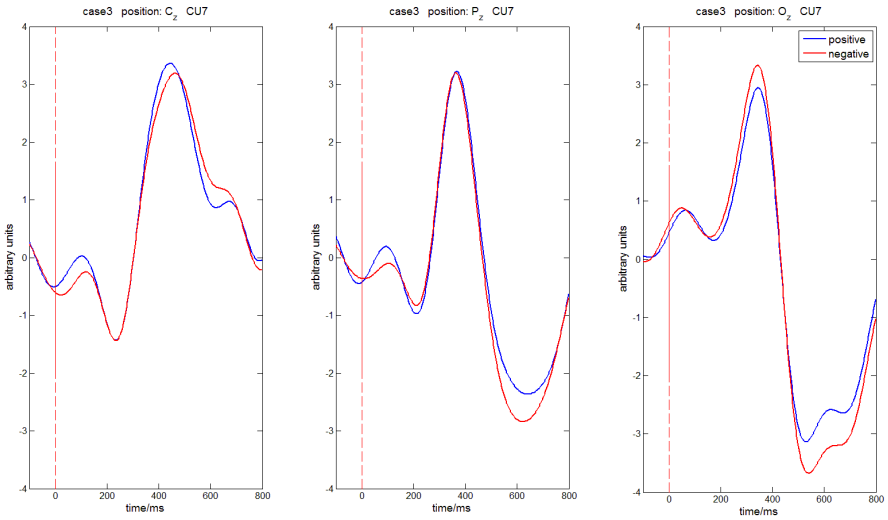

Figure 48: Recorded signals in case3 on three electrode positions of participant CU7

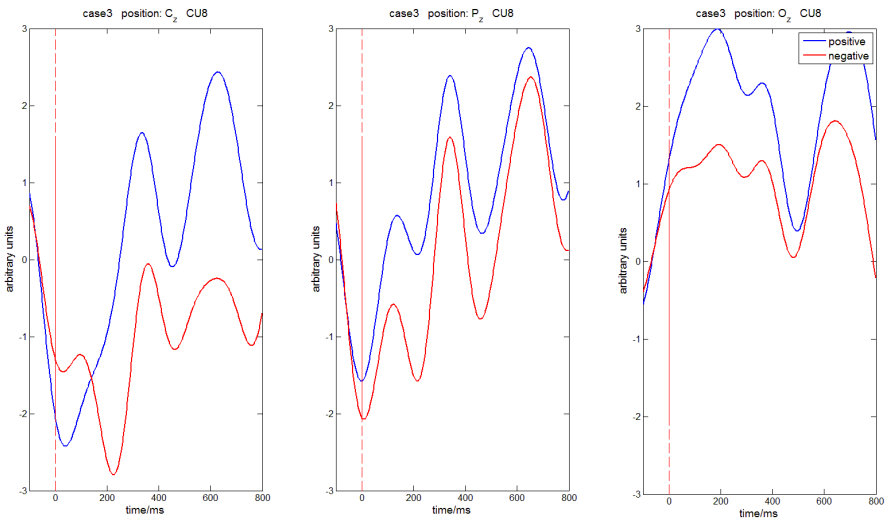

Figure 49: Recorded signals in case3 on three electrode positions of participant CU8

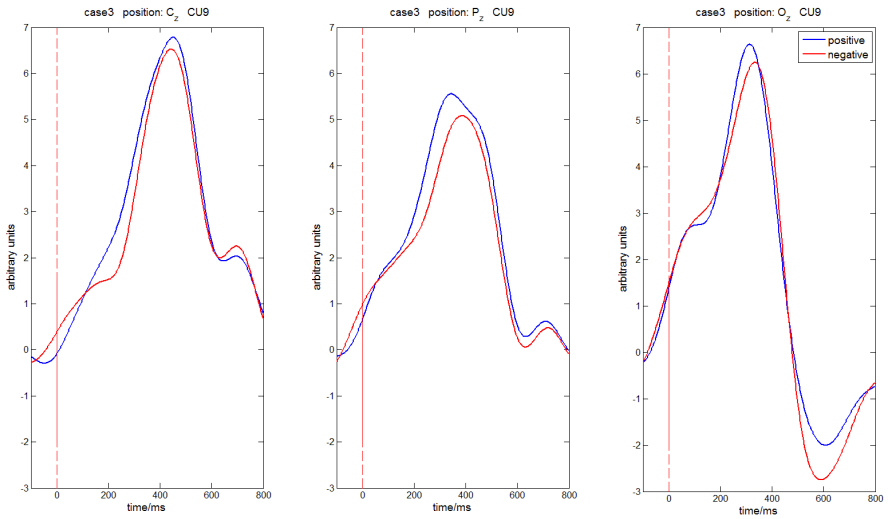

Figure 50: Recorded signals in case3 on three electrode positions of participant CU9

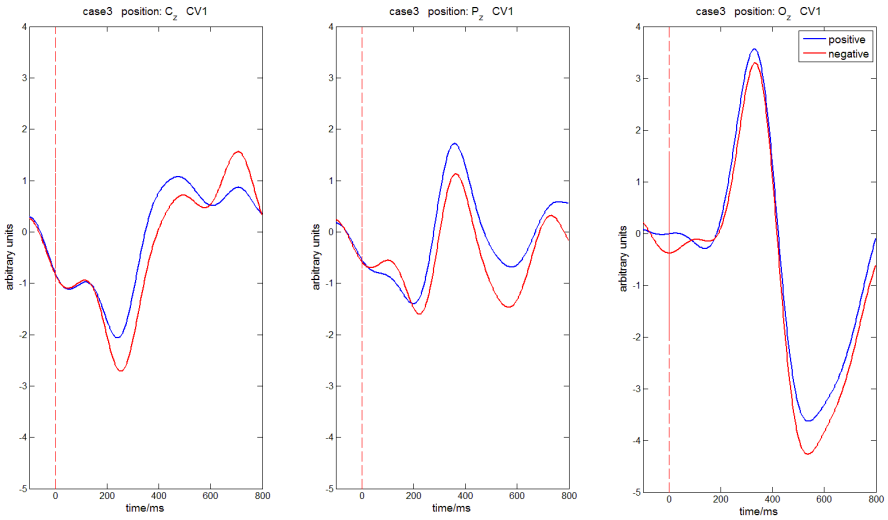

Figure 51: Recorded signals in case3 on three electrode positions of participant CV1

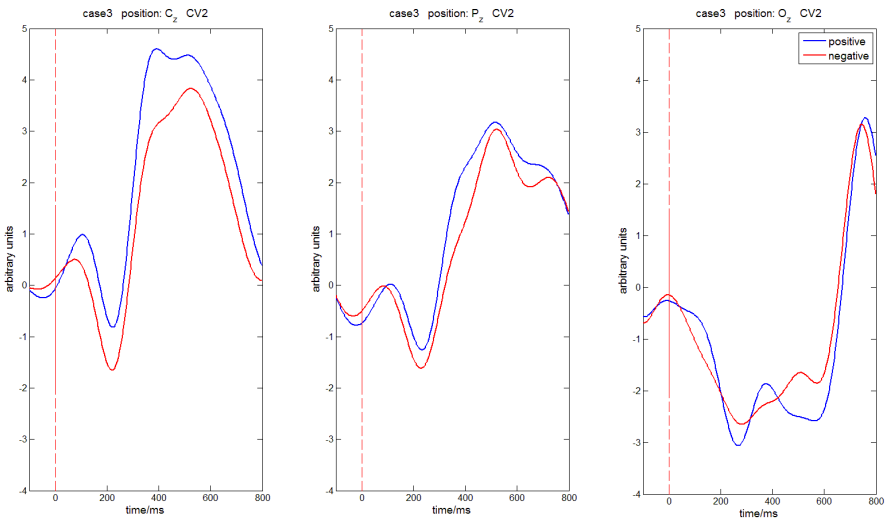

Figure 52: Recorded signals in case3 on three electrode positions of participant CV2

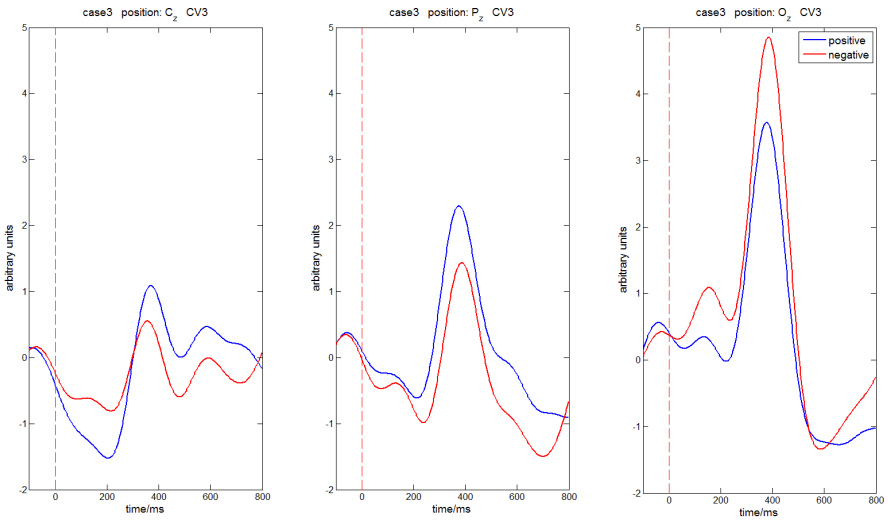

Figure 53: Recorded signals in case3 on three electrode positions of participant CV3

case4:

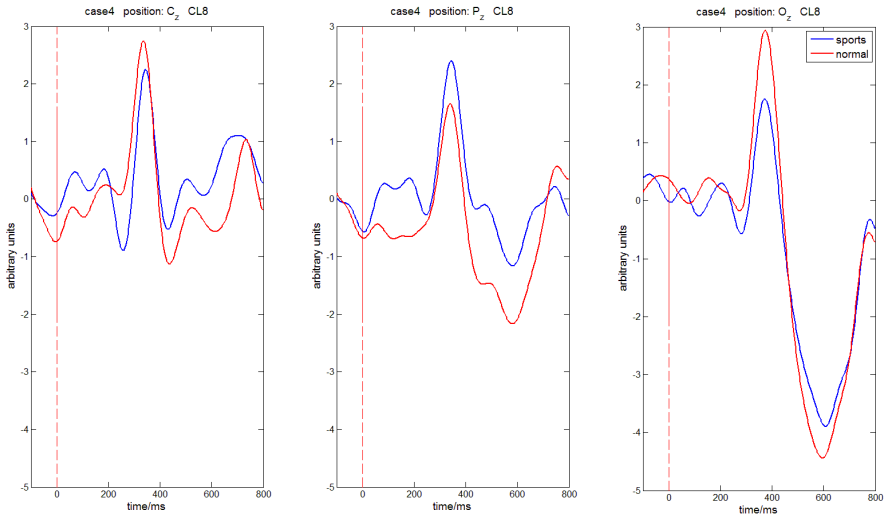

Figure 54: Recorded signals in case4 on three electrode positions of participant CL8

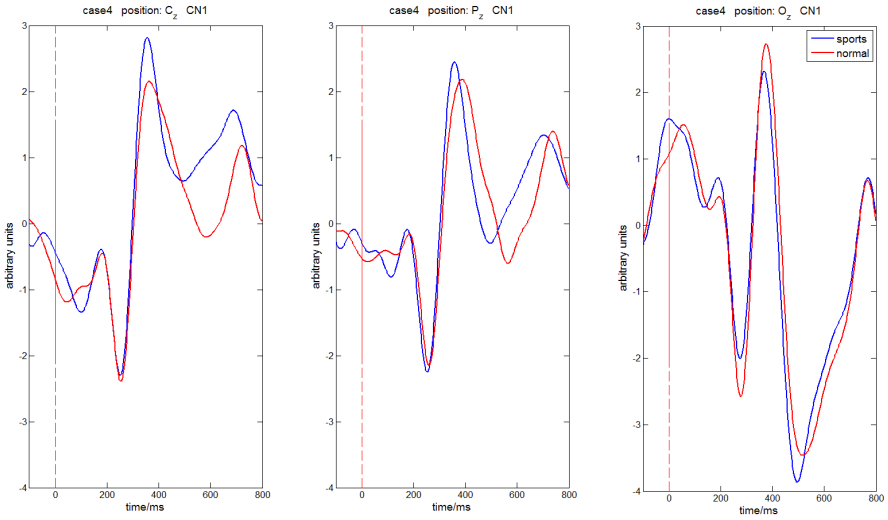

Figure 55: Recorded signals in case4 on three electrode positions of participant CN1

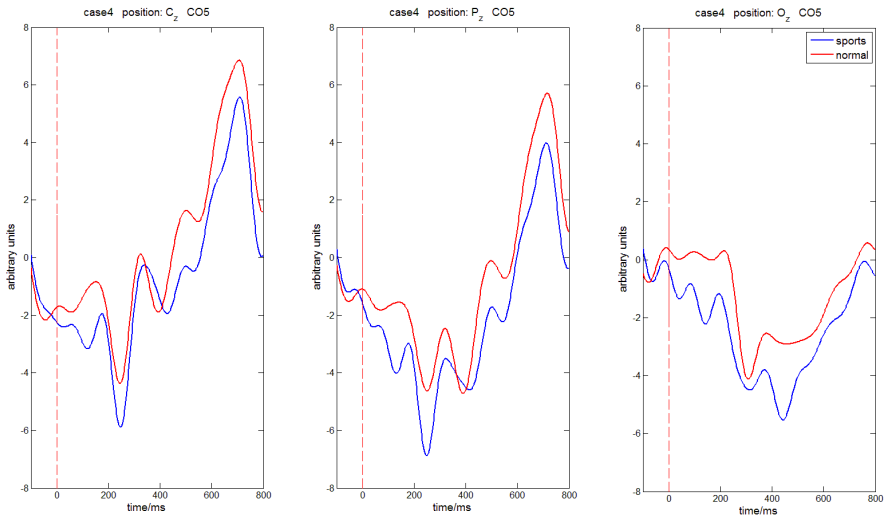

Figure 56: Recorded signals in case4 on three electrode positions of participant CO5

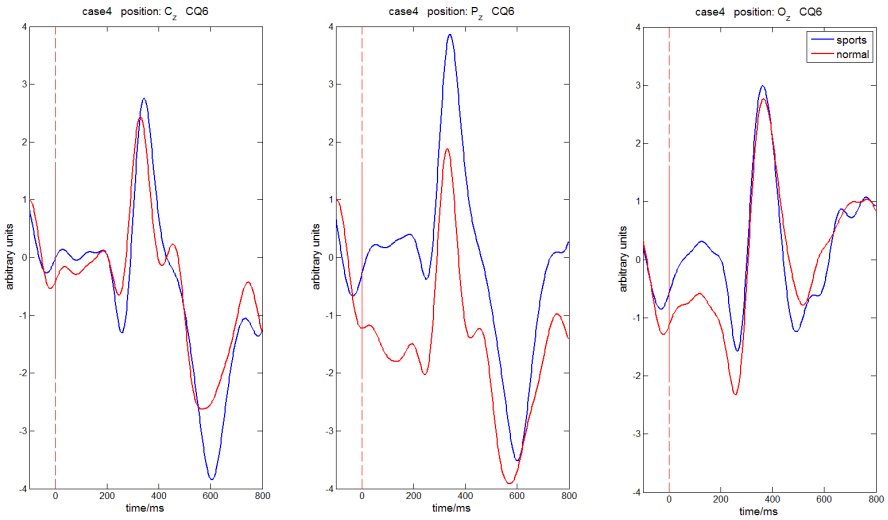

Figure 57: Recorded signals in case4 on three electrode positions of participant CQ6

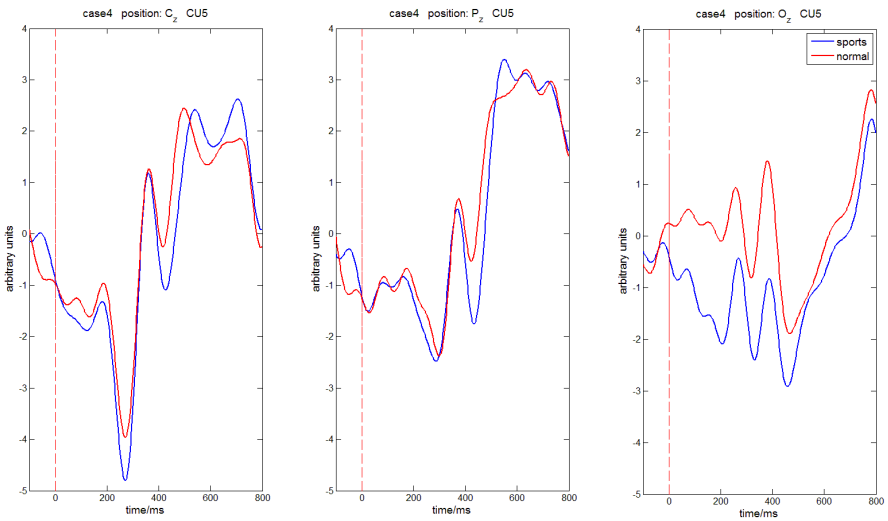

Figure 58: Recorded signals in case4 on three electrode positions of participant CU5

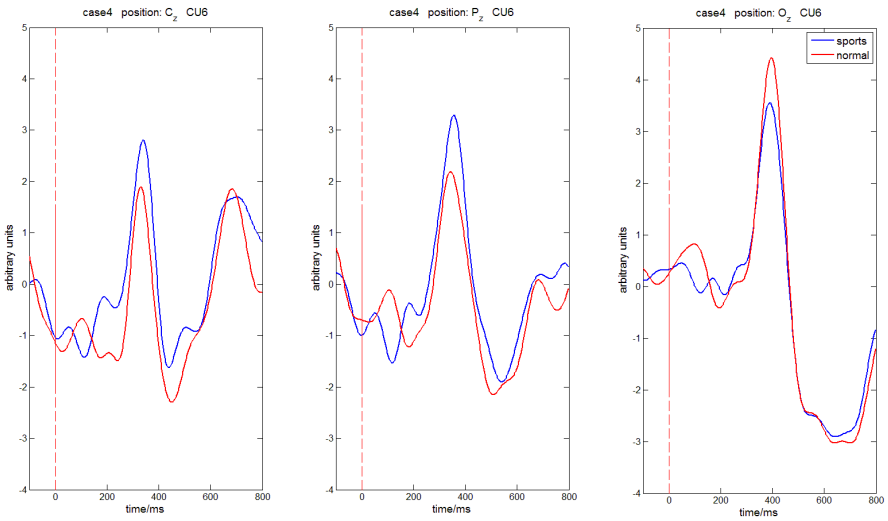

Figure 59: Recorded signals in case4 on three electrode positions of participant CU6

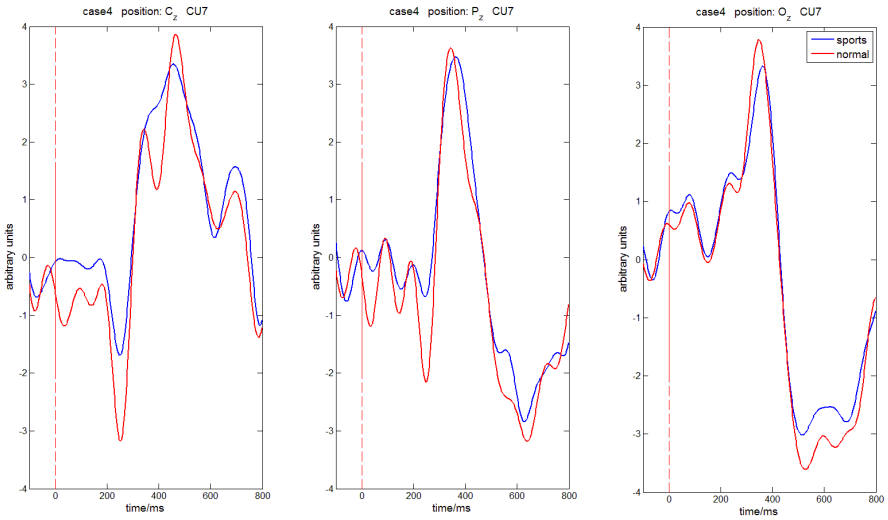

Figure 60: Recorded signals in case4 on three electrode positions of participant CU7

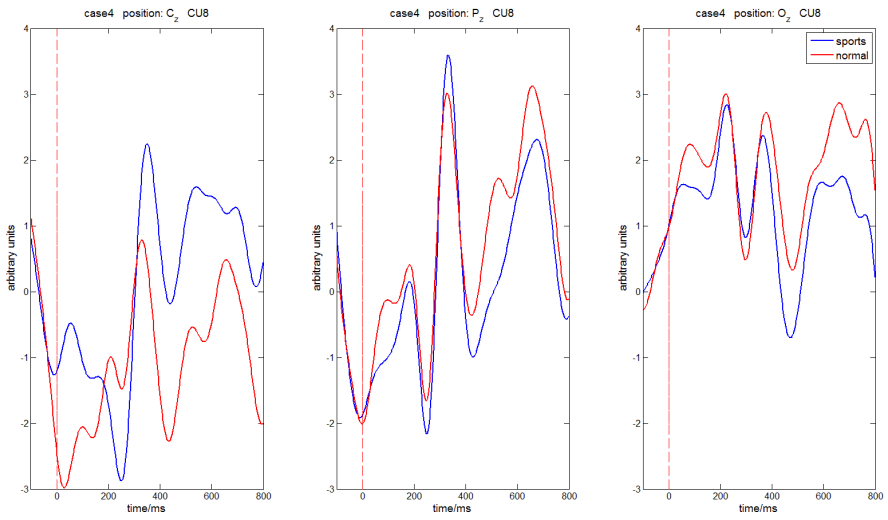

Figure 61: Recorded signals in case4 on three electrode positions of participant CU8

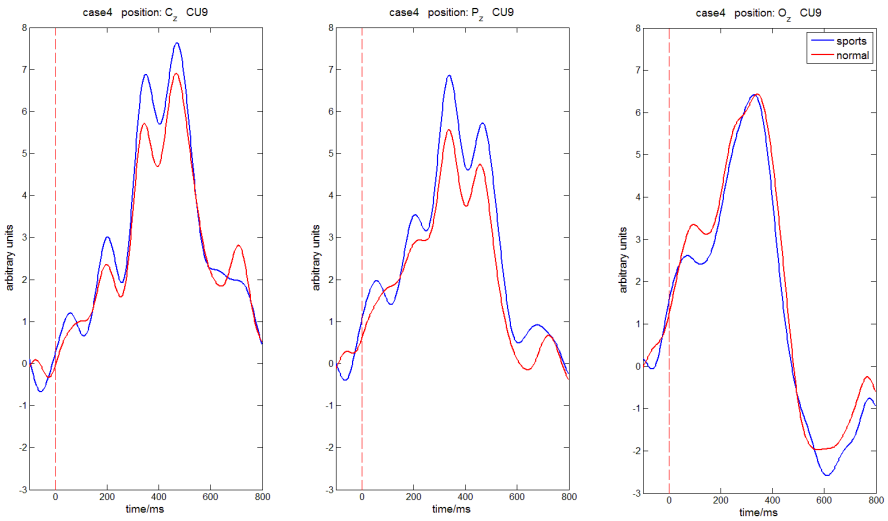

Figure 62: Recorded signals in case4 on three electrode positions of participant CU9

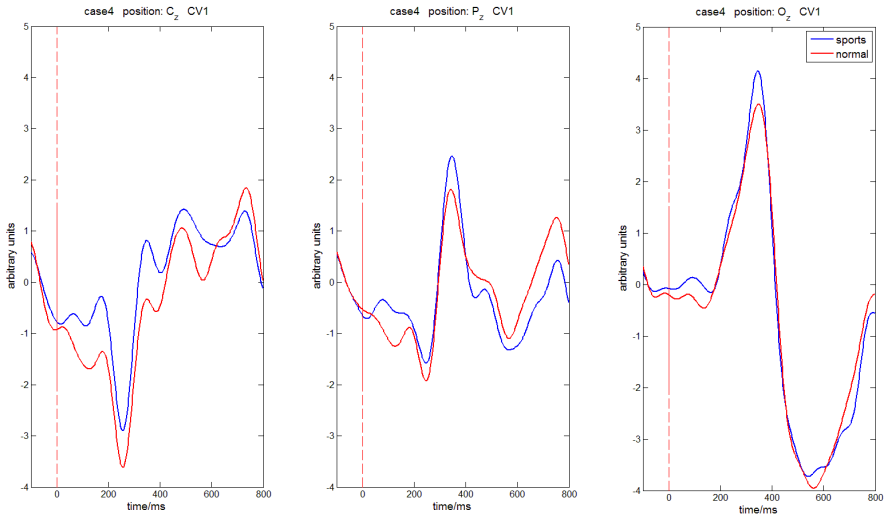

Figure 63: Recorded signals in case4 on three electrode positions of participant CV1

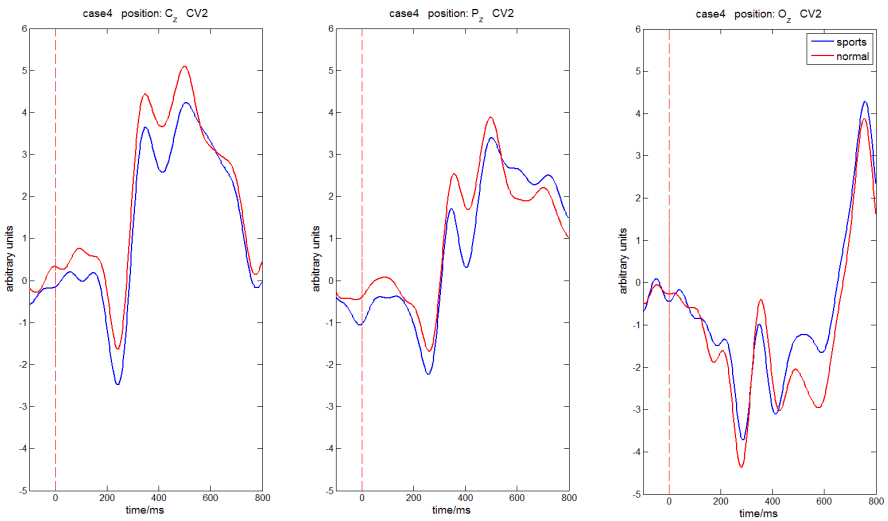

Figure 64: Recorded signals in case4 on three electrode positions of participant CV2

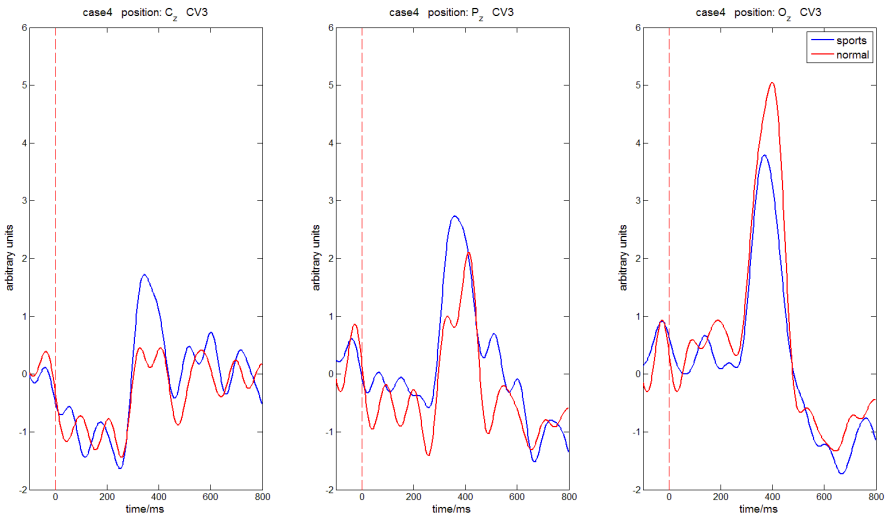

Figure 65: Recorded signals in case4 on three electrode positions of participant CV3