COMENIUS UNIVERSITY IN BRATISLAVA
FACULTY OF MATHEMATICS, PHYSICS AND INFORMATICS

A STUDY OF NEURAL MEASURES AND BEHAVIORAL PERFORMANCE OF CHANGE DETECTION TASK

DIPLOMA THESIS

2022 **ING. VIERA ŠTECKOVÁ**

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DIPLOMA THESIS

Study Programme: Cognitive Science
Field of Study: Computer Science
Department: Department of Applied Informatics
Supervisor: Ing. Mgr. Roman Rosipal, PhD.

Bratislava 2022 Ing. Viera Štecková

Univerzita Komenského v Bratislave
Fakulta matematiky, fyziky a informatiky

ZADANIE ZÁVEREČNEJ PRÁCE

Meno a priezvisko študenta:	Ing. Viera Štecková
Študijný program:	kognitívna veda (Jednoodborové štúdium, magisterský II. st., denná forma)
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Názov: Štúdium neurálnych mier a behaviorálnej výkonnosti spojených s CDT

Anotácia: Úloha detekcie zmien (CDT, angl. change detection task) sa často používa na preskúmanie procesov vizuálnej pracovnej pamäte. CDT umožňuje zamerať sa na kognitívne evokované potenciály (ERP, angl. event-related potentials) spojené s rýchlymi senzorickými reakciami mozgu na vizuálny stimul, ako aj na pomalšie kognitívne reakcie predstavujúce spracovanie a ukladanie obsahu stimulov do vizuálnej pracovnej pamäte.

Cieľ:

1. Štúdium princípov merania a spracovania ERP komponentov.
2. Identifikácia a popis ERP komponentov súvisiacich s CDT v MATLABe.
3. Štúdium variability ERP komponentov a hodnotenia úspešnosti správania v dôsledku zmien v prístupoch spracovania záznamov EEG a zmien v protokole CDT.

Literatúra:

Luck SJ. (2014). An introduction to the event-related potential technique. The MIT Press, London.
Vogel EK & Machizawa MG. (2004). Neural activity predicts individual differences in visual working memory capacity. Nature, 428(6984):748-51.

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Dátum schválenia:	prof. Ing. Igor Farkaš, Dr. garant študijného programu

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študent vedúci práce

Univerzita Komenského v Bratislave
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ZADANIE ZÁVEREČNEJ PRÁCE

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Study programme:	Cognitive Science (Single degree study, master II. deg., full time form)
Field of Study:	Computer Science
Type of Thesis:	Diploma Thesis
Language of Thesis:	English
Secondary language:	Slovak

Title: A Study of Neural Measures and Behavioral Performance of CDT

Annotation: The change detection task (CDT) is often used to examine visual working memory processes. The CDT allows focusing on event-related potentials (ERPs) associated with rapid sensory responses of the brain to a visual stimulus, as well as slower cognitive responses representing the processing and storing the contents of stimuli in the visual working memory.

Aim:

1. Study of principles of measurement and processing of ERP components.
2. Identification and description of CDT related ERP components in MATLAB.
3. Study of variability in ERP components and behavioral success due to changes in the EEG recordings processing and changes in the CDT protocol.

Literature:

Luck SJ. (2014). An introduction to the event-related potential technique. The MIT Press, London.
Vogel EK & Machizawa MG. (2004). Neural activity predicts individual differences in visual working memory capacity. Nature, 428(6984):748-51.

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Declaration

I hereby declare that I elaborated this master thesis independently using the cited literature that is referenced at the end of the thesis.

Bratislava, 2022

Acknowledgement

I would like to thank my supervisor Dr. Roman Rosipal for the guidance through the development of this thesis, for shared knowledge, patience, willingness to help in overcoming the problems that arose and encouragements to finish the thesis.

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Abstrakt

Protokol kontralaterálnej oneskorenej aktivity (CDA) študuje kognitívne evokované potenciály (ERP), ktoré predstavujú rýchle senzorické reakcie mozgu na vizuálne stimuly počas úlohy detekcie zmien (CDT). Okrem toho analyzuje aj kognitívne reakcie, ktoré stoja za spracovaním a ukladaním vizuálnych podnetov do vizuálnej pracovnej pamäte (VWM). Diplomová práca je zameraná na metódy predspracovania neurónového signálu naprogramované v softvéri MATLAB za účelom analýzy elektroencefalografu (EEG) zaznamenaného počas CDA protokolu, študujúceho účinky tréningu vo virtuálnej realite na VWM. Cieľom práce je analýza vplyvov rôznych metód spracovania EEG signálu na ERP a behaviorálnu výkonnosť v CDT. Okrem toho sme skúmali vplyv manipulácie so žmurknutím a zmenou pohľadu v protokole CDT na komponenty ERP a behaviorálny výkon. Ťažkosti pri rozlišovaní medzi žmurknutím a sakádou počas žmurknutia v EEG signále viedli k uskutočneniu pilotnej štúdii zaoberajúcej sa vplyvom zmeny pohľadu počas CDT na behaviorálny výkon.

Výber dolno-priepustného filtru ovplyvňuje latenciu skorých ERP komponentov. Preto postup spracovania EEG dát za účelom analýza CDA nie je možné použiť bezo zmeny pre analýzu skorých ERP komponentov.

Behaviorálne výsledky naznačujú, že žmurknutia počas zobrazenia testovacieho poľa v CDT nemajú vplyv na korektnosť odpovedí. Naproti tomu, zmena smeru pohladu v tejto fáze by mohla ovplvniť presnosť výsledku. Obe pozorovania je potrebné potvrdiť vykonaním experimentov s väčším počtom subjektov.

Kľúčové slová: CDT, ERP, MATLAB, spracovanie EEG

Abstract

Contralateral delayed activity (CDA) protocol studies an event related potentials (ERPs) representing rapid sensory responses of the brain to the visual stimuli during a change detection task (CDT). Additionally, it analyses cognitive responses that are behind the processing and storing of the visual stimuli in the visual working memory (VWM). The diploma thesis is focused on electroencephalograph (EEG) preprocessing methods programed in MATLAB software with the purpose to analyze the EEG recorded during CDA protocol that studies the effects of the training in virtual reality on VWM. The aim is to study the influence of different processing methods on ERPs and behavioral performance in CDT. Moreover, we manipulated blinks and eye movements in the CDT protocol and analyzed its influence on the ERP components and behavioral performance. The difficulty in differentiating between eye blink and horizontal saccade performed during blink in EEG signal led to a pilot study about the impact of a change of gaze during CDT on behavioral performance.

The selection of a low-pass filter affects the latency of the early ERP components. Therefore, the EEG data processing procedure suitable for the CDA analysis cannot be used without modifications for the analysis of early ERP components.

The behavioral results suggest that blinks occurred during the display of the test array in the CDT do not affect the correctness of the responses. On the other hand, a change in the direction of the view at this stage could affect the accuracy of the result. Both observations need to be confirmed by performing experiments on a larger number of subjects.

Key words: CDT, ERP, MATLAB, EEG data processing

Contents

Introduction

The task of the distinguishing an important visual information (target) from the non-relevant (distractor) and deciding how to react accordingly is an everyday task. Oftentimes, it is necessary to evaluate the visual stimuli in a time range of several seconds. Apart from the professionals that have to make quick decision on daily basis (air traffic controller, professional racing drivers or pilots, athletes of collective sports), the driving, video games playing, watching out for children, crossing road, it all requires to pay attention to targets and filter out the distractors. We not even have to look on those targets and distractors directly to be able to evaluate them. This information processing uses a working memory, a combination of storage and executive procedures (Baddeley, 2010). This storage has two limits; the capacity and the time range during whose it can hold the items in the memory. The storing of an item in working memory last only several seconds (Baddeley, 2010). It was researched that in the case of identifying differences between two sets of similar visual information with targets and distractors (detection task) the visual working memory capacity (VWMC) is between 1.5-5 item (Vogel & Machizawa, 2004). This number vary across population and depends on age (Brockmole & Logie,2013; Xie et al., 2019), mood or sleep quality (Xie et al., 2019). Similarly, the working memory accuracy depends on various factors such as the motivation (Grogan et al., 2022), affective states (level of arousal and valence in Gabana et al. (2017), stress hormone cortisol in Yeh et al. (2015)), nicotine (Ernst et al., 2001), alcohol (Saults et al., 2007). The results in (Katahira et al., 2018) suggest that the flow state (a mental state in which a person is fully immerse in the task (Nakamura & Csikszentmihalyi, 2009)) is correlated with "a high level of the cognitive control and immersion in a task" while the working memory has "relatively low load" (Katahira et al. 2018, p. 8).

The VWMC is highly correlated with cognitive capacity and can be reliably determined with a simple detection task, and so with the contralateral delay activity (CDA) analysis (Luck & Vogel, 2013). The VWMC's differences lead to a question if a cognitive training can increase the storage capacity, improve the filtering ability or behavioral performance and influence the neural activity connected to visual working memory (VWM).

"Virtual reality (VR) is an advanced, human-computer interface that simulates a realistic environment" (Zheng, Chan & Gibson,1998, p. 20). VR was applied in cognitive

rehabilitation with improvements in executive and visual-spatial abilities such as speech, attention and memory (Maggio et al., 2019).

This thesis research is part of a national funded project ECoReMiR conducted at FMFI UK, IMS SAS, and TUKE. One of the ECoReMiR research objective was to investigate whether a cognitive training using appropriately designed mixed reality environment will enhance perceptual and cognitive performance in healthy subjects, especially to improve their filtering abilities. A special mixed reality environment was developed in Košice to study this research question. It is LIRKIS CAVE, the virtual reality (VR) environment with a game-like-training. The game was created for the purpose of improving VWM by enhancing the ability to filter the relevant visual stimuli from irrelevant (Korečko et al., 2019).

Evaluation of the CDA during the visual tasks that engages VWM requires electroencephalograph (EEG) recordings. And while the experimental design is important, without proper analysis, the result may be misleading or even completely incorrect. Therefore, the preprocessing methods of the EEG data is a crucial step in an experimental paradigm (Luck, 2014).

One of the common problems during EEG preprocessing is a trial rejection caused by eye movement artifacts recorded in EEG. Their electromyographic (EMG) activity is interwind with the brain's neuronal electrical activity may lead to a rejection of a large number of trials. In specific experiment settings, only the saccades can be problematic, while the eye blinks are not. The CDA evoked by a first set of visual stimuli is not corrupted by eye movements occurred after the interval of interest (e.g., until the retention period). However, eye blinks may influence the visual input or saccades can influence the performance when they happen during the second, testing set of visual stimuli. When eye-tracker is not used to record eye movements, it is complicated to distinguish between eye blink and saccades during blink (Luck, 2014). If all trials with any of those artifacts are rejected it can lead to insufficient number of trials for statistical significance. A question arises, how the performance can change when the second set of visual stimuli is seen directly and not laterally.

In the first chapter we describe main theoretical attributes and experimental design of the problem. We introduce the VWM, take a look through the ERPs and CDA experimental designs, and we familiarize with EEG data preprocessing from artifacts up to the CDA wave creation. In the second chapter we will present the aims of this thesis. All the methods of the thesis, meaning the methods of the ECoReMiR experiment, methods of the preprocessing and analysis of the EEG data recorded during this experiment and methods of the CDT experiment that studies the influence of the gaze change on behavioral performance, will be

explained in the third chapter. The results are contained in the chapter number four which is followed by a discussion in the fifth chapter. The thesis is finished by a conclusion and the list of references is provided.

1 State-of-the-Art

1.1 Visual Working Memory

Baddeley's model of working memory presented by Alan Baddeley and Graham Hitch (Baddeley & Hitch, 1974) in 1974 contained three components: central executive, the visuo-spatial sketchpad, and the phonological loop. It was a dynamic representation (by organizing component) of primary memory, also known as short-term memory. In contrast to Atkinson & Shiffrin's (1968) multi-store memory model, in which the memory is divided into long term memory, short term memory (or working memory), and sensory memory, Baddeley's model distinguishes between short term memory being a storage and working memory playing a role of a multicomponent dynamic system. Furthermore, it included visual and auditory information from long term memory. A quart century later, the fourth component, episodic buffer, was added to the original model (Baddeley, 2010).

Central executive being a supervisory (supreme) system controls and regulates the flow of information from and to its slave systems and therefore regulates cognitive processes. It connects long-term memory with working memory. It updates and code incoming information, replaces old information, coordinates slave systems, binds information from multiple sources into episodes, shifts between tasks and retrieval strategies, inhibits automatic response, play role in selective attention. Phonological (or articulatory) look stores auditory information in short-term phonological store and articulatory rehearsal component (or articulatory loop). The second can retrieve auditory memory traces which are held in the first one while rapidly decaying. While auditory verbal information directly enters in phonological loop, language presented visually can enter by silent articulation. The visual information is encoded by the phonological process "inner voice" as auditory information into the phonological store or "inner ear". Visuospatial sketchpad stores visual and spatial information for manipulation. It subdivides into spatial short-term memory ("where" an object is) and object memory ("what" an object is). There are two different pathways in the

brain – where – a dorsal stream, what – a ventral stream, that can process information independently. The less intense tasks are handled in the occipital lobe, more complex ones are processed in the parietal lobe. The episodic buffer is a limited capacity store, that holds and connects information across domains. It links a long-term memory, semantic meaning and perception during a working memory task. It arranges a conscious access to phonological loop and visuospatial sketchpad. (Baddeley, 2010)

This research is interested mainly in the visuospatial sketchpad and central executive.

Visual working memory (VWM) can hold only 3 up to 4 items simultaneously, while it may vary among populations between 1.5 up to 5 items (Vogel & Machizawa, 2004). Those items can be colors regardless of the resolution of representation (Ye et al.,2014), orientations, shape, and even their binding (Luria et al., 2016). However, the VWM is flexible about which features of the objects are encoded, so the binding is not always present. In the experiment with colored polygons, the amplitude of CDA was lower when the color was relevant compared to the case of focusing only on the shape (Luria et al., 2010).

The divergence in the VWM capacity led to an interesting question of whether it is possible to increase the VWM by specific training with long time lasting results.

1.2 ERP Components

Event-Related potentials (ERP) are electrical potentials elicited by the event to which they are evoked at a stable time. Their dependency on provoking factors divides them into exogenous and endogenous components. The early sensory responses are exogenous, so they are dependent on external factors such as stimulus parameters. Endogenous components are slower cognitive responses depending on the internal factors (the task performed by the subject).

Recorded brain electrical activity arises most likely in pyramidal neurons which are aligned perpendicularly to the surface of the scalp, action potential short (a millisecond), postsynaptic potentials longer (tens of hundreds of milliseconds) – discrete voltage spikes – excitatory neurotransmitter, flowing current from extracellular space via apical dendrites and out of body cell and basal dendrites. This creates a dipole from positivity at cell body and negativity at the apical dendrites. The summation of spatially aligned dipoles from millions of neurons when discharge happen at the same time results at measurable voltage at the scalp. ERPs are therefore measured postsynaptic potentials.

This brain activity can be measured by electrodes attached to the scalp, as was discovered by Berger (Berger, 1929). Waveforms with specific amplitudes and frequencies represent this recorded activity called electroencephalogram (EEG). It contains various neural communications, including responses to specific sensory, cognitive, or motor events. Those responses, or ERPs, are extracted from EEG by averaging the segments of EEG corresponding to the same stimulus. This is more detail described and discussed in section 1.4. The averaged ERP waveform contains several ERP components under a form of voltage deflections represented as peaks or waves. They represent the information flow in the brain from early sensory detections to cognitive processing. ERPs are defined by their polarity - positive (P) or negative (N) and their amplitude. Their ordinal position in the waveform usually gives them labels, for example P1, N1, P2, N2 etc. Several ERPs are named according their latency, e.g., P300 signifying the positive peak at 300 ms after the stimulus onset.

Position of brain origin of ERP is not easy to determine from scalp voltages. Mathematically, it is an inverse problem; an infinite number of dipole configurations can lead to identical voltage distributions (Helmholtz, 1853).

The ERPs differ also by sensory stimuli that evoked them; therefore, we can find ERPs with same labels that are not related. They have only the same polarity and order.

Following the focus of the thesis, next visual sensory responses associated with the VWM are described:

The first ERP component C1 can vary in polarity; it is positive for stimuli in lower visual field, and negative for stimuli in upper visual field. C1 is generated in V1 – primary visual cortex, while onsets 40 ms up to 60 ms with peak at 80 ms up to 100 ms after stimuli onset (Luck, 2014).

The first positive ERP component is P1. It is largest at lateral occipital electrode; it has onset at 60 ms up to 90 ms with peak 100 ms up to 130 ms and usually it overlaps with C1. Latency can be influenced by contrast, direction of spatial attention, and state of arousal (Luck, 2014)

The first negative ERP component N1 contains multiple subcomponents. The peak is reached at 100 ms up to 150 ms at anterior electrodes, at least two posterior subcomponents achieved peaks at 150 ms up to 200 ms from parietal and lateral occipital cortexes electric signals. Those potentials are influenced by spatial attention. N170 can have higher negative amplitude when it is elicited by faces, while inverted faces can evoke even larger potential (Luck, 2014).

The P2 component can be detected at anterior and central scalp. When stimulus contains targets with simple features (only occurrence), infrequent targets result into larger components (Luck, 2014).

The N2 family contains multiple negative ERP responses (Luck, 2014). Basic N2 is elicited by a repetitive non-target stimulus. Larger amplitude was reported when deviants (other stimuli) are presented in a repetitive stimuli pattern. In the case of task-irrelevant deviants, we are talking about N2a or mismatched negativity. On the other side, when the deviants are task-relevant and therefore categorization process takes place, N2b is elicited with larger amplitude when targets are less frequent. When looking on the N2 family via spatial deviance, we can differentiate three subcomponents. Bilateral anterior N2 is elicited even when deviant is not target but participant must be looking for deviant. The presence of the other two N2 ERPs is conditioned by deviant being target. Posterior bilateral N2b is probability sensitive, so it is larger for less frequent targets (Luck, 2014).

As the name suggest, the posterior contralateral N2pc is observed at the posterior side contralateral to the target location and it represents a focus of the spatial attention onto the target location (Luck, 2014). N2pc is connected to the VWM task reflecting working memory maintenance in which case it is located more in parietal sites (Vogel & Machizawa, 2004). N2pc is observed at posterior occipital sites with maximum voltage at PO7 and PO8 electrodes at 200-300 ms stimulus onset. It is more negative at electrode contralateral to attended object than when attended item and electrode are at the same side. While N2Pc can be influenced by suppressed object (distractor), it represents processing of the attended object (target) (Luck, 2014).

Surprisingly, eccentricity as a degree between the inner edge of stimuli and midline of visual field does not have effect on the amplitude of the N2pc ERP component in the case of small degrees (up to 4°), not even when the edge is at the midline (0°). However, the N2pc amplitude is reduced by 50% when the eccentricity is 8° (Papaioannou & Luck, 2020). Therefore, the stimuli near midline doesn't reduce the effect of laterality.

Suppressing or inhibition of distractor is reflected by distractor positivity (Pd) with more positive voltage at contralateral sites to the distractor. It has similar scalp distribution to the distribution of N2pc and it is not present when the attention task contains only targets (Luck, 2014). It followed the N2pc component and in the case of large eccentricity, its amplitude increases (Papaioannou & Luck, 2020).

1.3 CDA Experiments

Change detection task (CDT) is experimental visual task for testing the VWM by detecting changes on rapid (hundreds of milliseconds) succession of images. Standard protocol consists of 6 steps. In the center of the visual field the cross is placed. By sustained gaze on this point, visual field is divided at the left hemifield processed by the right hemisphere and the right hemifield processed by the left hemisphere. At the start of each trial, a cue arrow is shown (e.g., 300 - 400 ms) to instruct the participant about the hemifield of the interest, or by other words, which hemifield should be remembered. Next, the memory array (MA) is shown for a short period of time (e.g., 100 ms). The array contains targets and/or distractors that can be in different shapes, colors, rotations or numbers according to the experimental paradigm. After the retention period (RP) (e.g., 900 ms) during nothing beside the center cross is displayed, the test array (TA) (e.g., 2000 ms) is revealed and the participant should report whether the targets at the cued hemifield changed.

A sustained higher negative activity at contralateral sites after N2pc component is another ERP component called contralateral delay activity (CDA). It is sensitive to the number of targets and connected to the VWMC. The amplitude increases with more items held in the memory (Vogel & Machizawa, 2014). CDA waveform is obtained as a difference of contralateral and ipsilateral waveforms while arising from posterior parietal cortex. CDA amplitude differs among population and becomes asymptotic when the VWMC is reached. By other words, it increases its amplitude with more targets until the maximum number of different targets that the individual is able to process is reached. It persists through the retention interval during which the items are held in the working memory (Luck, 2014; Luria et al., 2016). Furthermore, it is negatively corelated to the fluid intelligence,

The protocol of CDA studies rapid sensory responses and slower cognitive responses. Vogel and Mazichawa (2004) performed several experiments with the aim to find electrophysiological confirmation of lateralized activity of encoding and maintenance of items in the VWM. The MA presented in their first CDT consisted of 4 colored squares in each hemifield while in 50% trials one of the squares had different color in TA. The negative voltage approximately 200 ms after the onset of the MA was higher over the contralateral hemisphere at the lateral occipital and posterior parietal sites. For next experiments, they compared the neural activity elicited by different number of items in MA, while numbers of items at the left and right hemifield were same in one trial. Specifically, their three subsequent experiments tested 1 to 4 items, 2, 4 and 6 items and 2, 4, 8 and 10 items. Their

overcome the problem of multiple processes connected to the CDT contained in EEG waveform by computing difference between contralateral and ipsilateral activity for each set size. The 'difference waves' were free of any bilateral activity such as anticipation to the cue, executive processes, increased effort, arousal, focus on non-blinking (Luck, 2014; Vogel & Machizawa, 2004). The results shown that the averaged CDA waveforms significantly differed only up to 4 items while the bilateral activities increased significantly with the number of items in the MA even with 6, 8 and 10 items in each hemifield. Therefore, the ipsilateral and contralateral activities represented the general effort of performing task supported by reduction in accuracy. The averaged CDA waveforms reflected the maintenance of the items held in the visual memory and predicts the individual's memory capacity by calculating the amplitude increase between different set sizes (Vogel & Machizawa, 2004).

In the CDT, the visual memory capacity is usually computed as Cowan's K (Vogel & Machizawa, 2004; Luck & Vogel, 2013; Železníková, 2021). It represents the measure of behavioral performance and depends on the number of correct and incorrect responses (Cowan, 2001)).

1.4 Preprocessing of EEG Data

Recorded signal form the ERP experiment contains not only the neural response in the form of EEG but also the non-neural noise. The origin of the noise can be endogenous or exogenous. The later one is induced electric signal from the environment, for example from computer or lights. It is usually constant noise with small amplitude and can be reduced by preprocessing methods such as filtering or averaging. The noise of endogenous origin represents the interferences of the other biological signals such as muscle activity, eye blinks, eye movements or mental activity not connected to the ERP response. Biological signal causes artifacts which are transient noises with large amplitude and generally trials are discarded because of their presence (Luck, 2014).

Artifacts may cause three types of the problem in processing and evaluating data from the experiment. Firstly, they might reduce the signal-to-noise ratio (SNR) of the averaged ERP waveform. With lower SNR it can be harder to obtain significant differences between groups or conditions. According to the square root law (chapter 5 in Luck, 2014), 20% rejected trials cause 11% reduction in the SNR. Secondly, systematic artifacts are appearing at

approximately same times with respect to the stimulus and therefore are not removed by averaging. In the case that they are present in a higher amount in some conditions they cause difference in averaged ERP waveforms. That can be wrongly interpreted as difference in brain activity instead of real difference e.g., in motor behavior represented by more blinks elicited by specific stimuli. Thirdly, blinks and eye movement may change the sensory input or completely miss it when they happen at the start of the trial, what results in different input for different conditions.

According Hansen's axiom, which states that "There is no substitute for good data," (Luck, 2014) and the best practice is to minimize or better prevent occurrence of artifacts during recording the neural signal. Unfortunately, there are cases when one received recorded data and has to do processing and analysis. There are two approaches to dealing with artifacts. Either, trials with detected large artifacts are excluded from the final processing what is call artifact rejection. Or artifact corrections can be performed by estimating the influence of the artifact on the neural signal and subsequently subtracted.

1.4.1 Filtering and Slow Drifts

Filtering is based on the Fourier transform analysis (Luck, 2014). The Fourier transform calculates amplitudes, frequencies and phases of sinusoidal waveforms whose combination represent analyzed EEG waveform. It transforms the time-domain data into frequency domain. Usually, the term power is used instead of amplitude and it is equal to amplitude squared. By summing the found goniometric functions to reconstruct the original EEG waveform, the inverse Fourier transform is executed and the frequency domain is transformed back into time domain. This is only a mathematical representation of the data and doesn't mean that all found frequencies were really elicited by brain and therefore represent physiological oscillations. However, a neural oscillation at certain frequency represents one of the sin waveforms found in the Fourier transform.

The Nyquist theorem says "a continuous analogue signal can be converted into the set of discrete samples without losing any information while the rate of digitization is at least twice as high as higher frequency in signal" (Luck, 2014). In other words, filter out anything that is higher than half of the sampling rate (e.g., sampling rate of 250 Hz – filter anything beyond 125 Hz).

Filtering removes noise that occurs in the data, but also it can filter specific frequencies that correspond to a on activity or oscillation (alpha, beta, gamma, delta waves). A low-pass filter

leaves only smaller frequencies in data, while a high-pass filter removes lower frequencies. The subsequent use of those two filters is equivalent to a band-pass filter. Notch filter reduces specific frequency.

The filter's gain is a multiplication factor for change of frequency and in EEG/ERP it is between 0 and 1. Gain equal to 0.2 represents reduction of amplitude by 80%. The filter can cut off all frequencies beyond the limit or by other words remove all sinusoidal functions with those frequencies. This may lead to unwanted side effects therefore, usually, the gain is represented by smooth frequency response function and can be set for each filter separately. The steps for any filtering are, firstly, the Fourier transform, secondly, multiplication of the amplitude of each frequency function by corresponding gain, thirdly, the inverse Fourier transform. Filtering by two filters is equivalent to filtering with frequency response function created as a product of frequency response functions of those two filters. This applies to the software filters (offline analysis), the hardware (online or anti-aliasing) filters, and even their combination (Luck, 2014).

Skin potential and slow voltage shifts

Slow waves of drifts in EEG data can be caused by a sweat in sweat glands resulting into the change of impedance of the skin and change in electrical potential of the skin or by a change of electrode position, usually caused by a participant's movement. The drifts can sustain in the data for many seconds. Skin potential can be filtered out by be high-pass filter of 0.01 or 0.1 (selected according the experimental parameters) (Luck, 2014), or by a polynomial function (de Cheveigné & Arzounian, 2018). The change of EEG to the new level can be detected by a moving window with the peak-to-peak amplitude or step function. Low-pass filter above 100 Hz removes activity elicited by a muscle movement (Luck, 2014).

Alpha waves

Oscillations in EEG at the range of approximately 8 to 12 Hz are alpha waves. They are largest at posterior electrode sites and can be elicited by tiredness of participants or by closing their eyes. Alpha activity reflects recurrent connection between thalamus and the cortex. Since they are present among longer period of time, they influence a higher number of trials and therefore it is not recommended to reject them because the SNR worsens. They are usually not removed by averaging process and the typical approach is filtering. However, one should be aware that the filtering also removes other processes represented by oscillation around the filtered one (Luck, 2014).

1.4.2 Artifacts

Detecting an artifact is a signal detection problem, where an artifact is a signal that we want to detect (Luck, 2014). The detected artifact can be removed by a complete rejection of the whole trial, or it can be estimated and the signal can be corrected accordingly. Artifact rejection is used when the cause of artifact can influence not only the EEG signal but also the physiological response itself, e.g., eye movement representing the change of gaze which changes the lateral response plus and causes step artifact in EEG data.

Artifact rejection

Artifact rejection process results into fewer trials included in average ERP waveform therefore reduces the SNR of the estimated ERP response. Furthermore, experimental conditions may have unequal number of trials, consequences of which will be explained later.

The basic algorithmic approach to detect artifacts uses threshold value for detecting noise; anything above threshold is an artifact. This leads to four possible outcomes that are hit – artifact is present and signal is above threshold, correct rejection – artifact is missing and signal is beyond threshold, miss – artifact is present but signal is beyond threshold, false alarm – there is no artifact but signal exceeds threshold. First two are correct answers and last two are errors in detections. By increasing the threshold, we obtain more hits but also more false alarms. A higher number of rejected trials because of more false alarms causes lower SNR of the averaged ERP. On the other side, lowering the threshold produces more accepted trials but less hits what can lead to non-detected systematic artifacts in one or more but not all conditions which can also subsequently cause an invalid conclusion. Hence the necessity of the maximizing the statistical power while avoiding confounds means that not all artifacts are eliminated only problematic ones what can be specifically different for each experiment (Luck, 2014).

EEG is typically recorded on more than one electrode; therefore, a detected artifact causes rejection of not only the corrupted channel but the rejection at all channels. The artifact signal can spread across scalp with changing amplitude and while on one channel artifact is detected, the threshold may cause miss at other channels. The blink artifact at prefrontal electrodes Fp1 and Fp2 with amplitude 100 μV has at the frontal electrode F2 amplitude

approximately 36 μV, at the Cz electrode approximately 16 μV and at the Pz electrode approximately 10 μV. Blink artifacts at Cz and Pz would not be detected but their amplitudes will impact the experimental effect. Other problem which arises when rejecting trials on channels with detected artifacts, are different numbers of trials in averages. Additionally, different trials on different electrodes are averaged, so the scalp distribution may be untrusted. Therefore, rejecting only trials on corrupted electrodes is not generally recommended (Luck, 2014).

Artifact detection can be done visually by personally checking of each trial for artifacts. While trustworthy, the process is long and hard to verify. Other possibility is to apply a computer algorithm, which would be faster, more effective, bias-free and easy to verify. The threshold is known and can be easily changed to compare artifact-free data preprocessed by different thresholds even by different algorithms.

One way to detect artifact is using a fixed threshold for all subjects that is compared with absolute value of maximum voltage in trial. If artifact's amplitude exceeds the threshold, the trial is rejected. This approach is suitable for artifacts with large amplitude such as eye blinks but it also requests to do baseline correction before artifact detection. Also, drifts in signal can cause miss of an artifact too (Luck, 2014).

The algorithms for artifacts detection can be suitable for more types of artifacts. Next, we list several algorithms presented by Luck (Luck, 2014).

More suitable approach for blink detection is algorithm developed by Javier Lopez Calderon for the ERPLAB toolbox (Lopez-Calderon & Luck, 2014) called moving window peak-to-peak amplitude. A window with settable size (e.g,. 200 ms) is overlap with the signal waveform at the start of the trial and looks for difference in amplitude between the most positive and the most negative peaks (peak-to-peak). The window is shifted in time by a specified time step (e.g., 50 ms) and again, peak-to-peak amplitude is found. After the whole trial (or its specified part) is tested, biggest peak-to-peak amplitude is compared to the threshold and if above threshold, the trial is rejected. This algorithm does not need baseline correction prior the artifact detection because it works with amplitude differences instead of maximal absolute amplitude. It can correctly detect artifacts even when a drift is present in the data.

Sudden changes in amplitude level can be reliably detect by a step function. Similarly, as a previous algorithm, the step function works with moving window (e.g., 200ms) in which a difference of the mean amplitudes of both halves of the window (first 100 ms vs second 100 ms) representing a step in the data is calculated. The window is moved by a time step which

the user specifies (e.g., 50 ms). If maximal difference of mean amplitudes exceeds the threshold, the trial is rejected (Luck, 2014).

In all cases, the threshold can be set specifically for each subject (physiological differences) in the case of within-subject conditions. To avoid bias in the case of between-subject manipulations, the thresholds and other artifact rejection parameters (e.g., moving window) should be determined by a person blind to group membership. The initial threshold can be set according to the previous experience or similar studies. After the first artifact free trails are selected, visual inspection with comparison to raw data can verify whether the threshold removed all artifacts or it is necessary to increase its value. Similarly, if it rejects a lot of trials without visually confirmed artifacts on raw data, the threshold should be decreased. General Luck's advice is to exclude any participant with more than 25% rejected trials (Luck, 2014).

Artifact correction

Artifact rejection may lead to unrepresentative sample of trials, e.g., in the case of eye blinks removing specific group of participants (e.g., kids, neurological patients), using only trials with a high alert state of participants, experimental paradigm connected to eye movement and eyeblinks (Luck, 2014).

The problem is any specific instruction what participant should do (posture) or don't (blinking) is unwillingly added to the tested hypothesis; participant is focused not only on the task but also on the instructions and it is problematic to distinguish those two mental activities from EEG waveforms. Ochoa and Polich (2000) presented this drawback with non-blinking instruction during oddball test and tested it with contrast to the same test with no instruction about blinking among college students. The P3 ERP component has a smaller amplitude and longer latency in the case of non-blinking instruction.

Luck (2014) presented three approaches in correcting data and therefore preserving the SNR. Regression-based procedure designed by Gratton, Coles & Donchin (1983) estimates artifactual potentials generated by blinks and eye movement in electrooculogram (EOG). Subsequently, it is subtracted from the EEG data. However, EOG data contains also brain activity and by subtracting this activity is removed from EEG data. Dipole localization represent a dipole modeling method (Berg & Scherg, 1991). The method models how artifact's signal propagate via scalp. But for the correct results, the signal for the calculation should be recorded from at least seven electrodes for each participant and it assumes that vertical eye movement and blinks are the same. Statistical component analysis such as

principal component analysis (PCA) or independent component analysis (ICA), finds components of EEG with a characteristic scalp distribution, and then specifies which components represent artifacts and subtract their voltages from the waveforms. These methods can be used for correction artifacts with fixed scalp distribution (e.g., ocular or EKG artifacts) (Luck, 2014).

However, visual input changed by blink remain unfixed even if the ocular artifacts are corrected by these methods. So, the solution should be considered from case to case, e.g., reject all trials with blink prior to stimulus onset, remove the participant, or if the presence of the blink does not change the experimental paradigm, subject is hard to replace, and it is within-subject experiment with unwanted blinks in almost all trials than include it.

1.4.3 Corneal-retinal potential

Corneal-retinal potential is the constant electrical potential between the cornea (positive dipole) and retina (negative dipole) of the eye. This potential is present across the head while decreasing the amplitude with the increasing distance from the eye and causes offset in EEG and electrooculogram (EOG) raw waveforms. It is easy to diminish its presence in signal by baseline correction (Luck, 2014).

1.4.4 Blinks

Movement of the eyelids across eyeball creates voltage deflection because the eyelids work as a resistor. This change in potential can be detected at most electrodes with decreasing amplitude as was already explained. Movement of eyelids, or eyeblink, response recorded as a difference between two electrodes (active and reference) under and above the eyes is noted as VEOG (vertical EOG), with 50 - 100 μV deflection lasting 200 – 400 ms and has opposite polarity for the sites on head above and below the level of the eyes. In contrast, the true EEG deflection does not change polarity, so it is straightforward to distinguish it from the blink. Interestingly, voluntarily performed blinks have higher amplitude than spontaneous blinks so it may be problematic to use the same detection threshold for the control of blinks during the recordings. Besides moving window peak-to-peak amplitude and absolute maximum amplitude, which are suitable for the blink detection, also the step function work with eyeblinks detection (Luck, 2014).

1.4.5 Saccades

Eye movement also changes voltage in at half of the scalp if the eyes are turned toward. In other words, when turning the eye at left, the positive voltage deflection is at the left part of the scalp and negative on the right one. The horizontal EOG (HEOG) recording is done by two electrodes attached to the temples laterally to the eyes where one electrode is the active electrode and the other serves as a reference. Recordings of the vertical eye movement are same as those of blinks. In the case that an eye-movement is not strictly vertical or strictly horizontal, artifact will show on both, VEOG and HEOG, recordings. Saccades are quick shifts in the eye position represented as a step in the voltage that remain until next saccade is perform. In this case a boxcar-shaped voltage is present in the data. Its length is proportional to the time between two saccades (Luck, 2014).

The size of the voltage deflection is linear to the size of the eye movement. Large saccades are easy to detect by *absolute value of maximum voltage* but the threshold (e.g., 100 μV) set for their detection may not be sufficient to reveal the small eye movements (e.g., 10°). Therefore, using a step function that can detect even an eye-movement of 2° (1° under optimal conditions) is a more suitable approach (Luck, 2014).

Horizontal eye movement influences lateral neurological responses on visual input, specifically, it produces a negative voltage at the contralateral hemisphere, so it impacts N2pc and CDA components. Furthermore, as was already mentioned an eye movement may change the visual input, in this case by changing the location of the stimulus. With regards of good SNR of EOG, detecting smaller saccades then 1° can increase number of false alarms. What can be done is to divide EOG waveforms into groups of the conditions that may cause unidirectional movement of the eyes. The averages of the grouped EOGs will show consistent small eye-movements. So, the process is as follows: firstly, detect saccades larger than 1° and reject trials. Secondly, check if the averaged EOGs exceed the threshold for smaller saccades (e.g., 1.6 μV ~ 0.1°) (Luck, 2014).

On the other side, slow eye-shifts can be reliably detected only by the eye-tracking devices. Same applies for determining the position of the eye. Their neurological representation is not easily recognizable in recorded waveforms and mentioned algorithm don’t work adequately for their detection. However, for detection of the slow eye-movements there already exist complex algorithms developed for sleep analysis and evaluation (Magosso, 2007) and neural network for fatigue detection study (Jiao & Jiang, 2022).

Amplifier/adc saturation/blocking

Slow voltage shifts (e.g., or skin potential origin) causes the amplifier or analog to digital converter (ADC) to saturate. This results into flat EEG. During recording, the frequent occurrence can be solved by lowering a gain on amplifier. The way to detect this type of artifact is either to check large number of points with relatively same voltages or use the X-within-Y-of-peak developed by Jon Hansen at UCSD (Luck, 2014). The second method is based on finding the maximum and to count the number of points that are in the Y distance (e.g.,0.1 μV) of that maximum. If more points are found than the defined threshold X (e.g. 30), the trial is rejected. This process has to be performed for positive and negative voltages separately. Likewise, described method is a good tool for detecting electrodes that intermittently disconnected what it represented also by flat line (Luck, 2014).

Muscle and heart activity

Electromyogram (EMG) – electrical potential formed during muscle contraction. Rapid voltage fluctuations. It can be eliminated by a low-pass filter with a half-amplitude cut-off between 30 and 100 Hz. The electrode sites T7 and T8 can contain a recorded signal from jaws contractions, Fp1 and Fp2 detect a furrowing brow or cap pulling at forehead. The neck muscles movements and contractions influence the electric signal recorded by all electrodes if a mastoid reference was used.

Electrocardiogram (EKG) represents a heart beating; it propagates to head via carotid arteries – mastoid electrodes. Occurs once per second, so it is not possible to reject trials, therefore artifact correction is suitable approach. (Luck, 2014)

Any signal or artifact, that is picked up by reference electrode, occurs at all channels (Luck, 2014).

Speech related artifacts are beyond the scope of this thesis and are mentioned only for the consistency. Shortly, they are called *glossokinetic artifacts* and are caused by voltage created by moving tongue because of the electrical gradient between tip of the tongue and its base. More can be found in (Luck, 2014) and their possible application to man-machine interface in Nam et al (2016). Other non-usual artifacts can be found in Sazgar & Young (2019).

1.5 Building CDA

EEG signal is standardly recorded as a continuous signal of all trials in one block including event codes. Therefore, the first step consists of extracting trials and group them according to the trial parameters. From those trials are used segments time-locked to specific event, e.g., the MA onset, with the length depending on the type of components that will be analyzed (e.g., 500 ms). Each segment requires also the presence of the pre-stimulus EEG data referenced as baseline (typically 100 up to 200 ms) (Luck, 2014).

1.5.1 Baseline Correction

Baseline correction minimize offset voltage caused by slow fluctuations of skin hydration, skin potentials, and static electrical charges. The averaged activity before the stimulus onset is subtracted from the activity after the stimulus onset (Luck, 2014).

1.5.2 Averaging

We assume that the neural activity during a task differs only in noise and is time-locked to the events (e.g., the MA onset) in every trial (Luck, 2014). Noise, according to definition, has a random distribution (Luck, 2014), so it differs from trial to trial. Averaging is the sum of all trials divided by their number; therefore, the more trials are included, the greater the decrease in noise, and the SNR increases. The size of noise in an average of the N trials equals to $1/\sqrt{N}$ R, where R represents the size of noise in a single trial (Luck, 2014).

In the case of averaging, one should consider the number of trials in each condition. An unequal number can lead to a non-representative average, e.g., when averaging 40 and 20 trials. In those cases, a weighted average is a possible solution. Another approach requires equaling the number of trials in each condition, for example, by a random selection or doing more averages by random permutations. In the case the difference between the number of trials is small (e.g., 40 and 41), one may decide not to distinguish between them. However, those cases should always be reported (Luck, 2014). The CDA is calculated as a difference between ipsilateral activity and contralateral activity that were averaged over the conditions (Vogel & Machizawa, 2004; Luck, 2014).

1.6 Meaning of Blink

There are three types of blinks, voluntary, reflexive (in order to protect the eye) and spontaneous or endogenous (Wascher, 2015). The physiological role of the last type of blink is to maintain the tear film on the eyes. However, blinks occur more often than each 27 second what is an average tear-break-up-time (Sweeney, Millar & Raju, 2013).

Blink rate is affected by fatigue, task engagement or cognitive demand. Blinks are inhibited while the stimulus is expected, presented and processed. Wascher at al. (2015) carried out a set of experiments where they studied the blinking behavior in three experiments: spatial stimulus-response correspondence, change detection and continuous performance test. According to the obtained results, blink occurred at the same time frame after stimulus onset in go (manual response) and no-go trials, while in go trials they followed the manual response (button press). This indicated that the blinks were connected to the stimulus processing rather than to the motor-behavior itself.

Saccades could occur during a blink. (Rottach, 1998). The CDA protocol requires lateralized view, so the difference in neural activities can be observed between hemispheres. Therefore, it is necessary to reject any trials where the gaze changed, or by other words, where were detected horizontal eye movements during the MA. Also, response time (RT) should be free of eye movement. The CDA lasts during the whole retention period so any horizontal eye movement which creates negative voltage at the contralateral hemisphere will corrupt the ERP waveform, including N2pc and CDA. The eye movement during the TA doesn't influences CDA but they can affect the behavioral response of CDT.

The question is how performance of CDT is changed when the subject changes the gaze and he or she does not see the TA laterally as saw the MA, but directly. We decided to run a pilot experiment with gaze change during TA of CDT in addition to comparing the performance from the CDA experiment with and without including trial with blinks during the TA.

2 The Aims of the Thesis

The main aim of the thesis was an analysis of the neural measures and behavioral performance of the change detection task (CDT). To reach this goal, it was necessary to fulfill the following partial aims.

1. Study of principles of measurement and processing of ERP components
2. Identification and description of CDT related ERP components in MATLAB.
3. Study of variability in ERP components and behavioral success due to changes in the EEG recordings processing and changes in the CDT protocol.

The diploma thesis was a part of an ongoing research "Enhancing cognition and motor rehabilitation using mixed reality" supported by the Slovak Research and Development Agency (Korečko et al., 2019).

3 Methods

3.1 CDA Protocol

The objective of the CDA protocol was to investigate the influence of training in VR on perceptual and cognitive performance of the VWM especially on the changes in filtering abilities with the aim to improve them. The CDA protocol was designed with two conditions, therefore treatment group and control group were formed. Only the treatment group underwent the VR training. This experiment was a part of the project APVV-16-0202, "Enhancing cognition and motor rehabilitation using mixed reality" (ECoReMiR) supported by the Slovak Research and Development Agency (Korečko et al., 2019).

3.1.1 Procedure

Each session of training or data recording started and ended with questionnaires. There were three types of sessions, CDT, CDA and CAVE, while CAVE was exclusively for treatment group. Order of sessions for treatment group in Kosice (KE) was CDT (CDT2), CDA1, five CAVE sessions, CDA2, five CAVE sessions followed by and CDA3. The CAVE session was directly preceded by CDA1 or CDA2 session and between CAVE sessions was at least one free day. The control group had same order, only without CAVE sessions; CDT (CDT2), CDA1, one week pause, CDA2, one week pause, CDA3.

Questionnaire was divided into three sections, first section concerned general questions about participant, second was T-MENSTAT before each session (CDT, CDA or CAVE) and third was also T-MENSTAT after each session. They also contained questions about possible influences of mental states and cognitive performance (caffeine/alcohol intake, length of sleeping).

3.1.2 Change Detection Task

The same format of CDT with different parameters took place during the CDT and CDA sessions. CDT was performed on computer using script written in PsychoPy (Peirce & MacAskill, 2018). The objective was to memorize the orientation of the red rectangles (targets) and ignore blue and green rectangles (distractors). The rectangles were randomly placed on screen vertically, horizontally, or diagonally while their size was constant (0.5 cm x 1.5 cm). Their orientations were generated randomly and their counts on both hemifields were identical. The number of targets and distractors differed by a session type and are specified in the next two sub subchapters. The cue arrow was displayed for 200ms. After that, the span of attention (SOA) was randomly set from the interval 300 ms up to 500 ms. The memory array (MA) was present on the screen for 300 ms. The retention interval of 900 ms was followed by a test array (TA) that stayed at the screen for the 3 seconds.

3.1.3 CDT session

Firstly, skin of participants was prepared with abrasive paste. Then, EOG electrodes were attached to above and below left eye for vertical eye movement - blinks detection, and next to outer canthi of both eyes for horizontal eye movement – saccades detection. Reference electrode was attached on left earlobe and ground electrode was attached on the neck at the left side. Next, signal test using the script in PsychoPy was performed to check EOG recording. Electrodes were connected to computer using g.TRIGbox of g.tec company (gtec.at).

Secondly, participants subdue a practice of CDT containing instructions.

Finally, CDT1 with EOG recording took place. Participants were seated 70 cm before the screen. CDT consisted of combinations of 2, 3 or 4 targets and 0 or 2 distractors. So, six combinations, with focus on the left or right hemifield (x2), under changed or same condition (x2), in 5 blocks with 2 repetitions in each. This sums up to 240 (6x2x2x5x2) trials.

The whole session started and ended with a questionnaire.

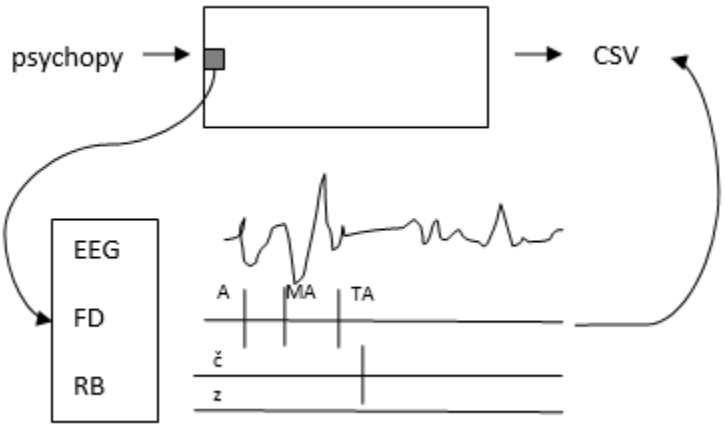

Fig. 1 Schematic representation of procedural setting for CDA and CDT recordings. RB – response button, A – cue arrow, MA – memory array, TA – test array. The rectangle at the top of the figure represent screen, FD – photodiode attached to the gray square at the screen records the changes on the screen event and synchronizes EEG recordings and RB responses. The input is the PsychoPy script, the output is a CSV file with the CDT parameters and responses.

3.1.4 CDA session

The CDA session contained CDT in PsychoPy, EEG ad EOG recordings. Settings for EOG were same as in the CDT case without ground electrode on neck. The 4 pairs of electrodes (P3-P4, PO7-PO8, P7-P8 a O1-O2), Fz, Cz, Pz and two earlobe electrodes were placed according to the 10 -20 international system using the EEG cap available in two sizes.

CDT for the CDA session consisted of 2 or 4 targets, and 0 or 2 distractors (therefore 4 combinations: 2,0; 2,2; 4,0; 4,2), 40 blocks and no repetitions. With two possible hemifield and two change conditions it sums up to 640 trials.

3.1.5 CAVE session

The objective of the CAVE session was to train in visual stimuli filtering by using the game proprietary constructed in the VR environment represented by LIRKIS CAVE at the Technical University in Kosice. The later was built by twenty LCD panels with total size of 2.5 m x 2.5 m x 3 m. The game was perceived three-dimensionally thanks to the 3D projection and 3D glasses.

The training game Tower Defense was designed in Kosice as the gaming analogy for CDT with corresponding cognitive load. The aim is to shoot down the enemy red drones

representing the target while ignoring the friendly blue and green drones playing the role of distractors (Korečko et al., 2019).

3.1.6 Participants

The two non-randomized groups of 15 participants in each were created. The group in Kosice (KE) represented treatment condition with training in VR and the group in Bratislava (BA) represented control condition. In both groups, participants had to meet the same criteria. All participants subscribed the consent and were informed about the experimental procedure. Participants were right-handed between the ages of 19 and 24 (BA: mean = 21.8, SD =1.21; KE: mean = 21.1, SD = 1.1) with 3 women in BA group and 4 women in KE group. They had no known neurological issues and normal or corrected to normal vision.

3.2 Preprocessing Methods for EEG

Preprocessing was done in MATLAB (The MathWorks, Inc. 2021) and consisted of several necessary steps. The original script was provided and then edited by myself or by my supervisor. My colleague then generated the results for each participant according to this script. Together we evaluated results and selected the final preprocessing steps.

The raw EEG data contained the noise from exogenous – interferences from electric devices and endogenous sources – muscle movement, or brain activity not connected to the task. Before analyzing the data, we had to filter out the relevant waveforms. The data visualization was done in MATLAB (The MathWorks, Inc. 2021), EDFBrowser (van Beelen, 2022) and AcqKnowledge (Biopac Systems, 2010).

3.2.1 Noise Problem

Even with detrending methods and filtering, the slow drifts were still present in the first few trials of each block of trials. This was caused by “flying” data during the pauses between blocks of trials, where the participant was moving, or electrodes were controlled/reattached. The recording often started before the drifting calmed. This caused that the detrending removed primarily the biggest drifts of pauses and since we used polynomial functions it couldn’t accommodate to lower drifting. Therefore, we decided to remove recorded data between blocks and only after that to start with preprocessing. Grace of this step, the

problematic detrending at the start of each block diminished. Consecutive detrending and filtering completely removed the slow drifts while preserving the CDA data above 0.01Hz.
The cutting was performed on the raw data by the MATLAB script when the time difference between two blocks of trials was greater than 10 seconds. The start of cutting was 5 s after the TA onset of the last trial of the previous block and end of cutting was 5 s before the first event onset of the following block. The responses were valid only until 3 sec after the TA onset, therefore any later response events were considered missed.
After the data was cut, the endpoints on both sites were joined and smoothed by 5-point moving average method using the interval of four points prior and four points after the joint. This procedure created new data that were preprocessed in the main MATLAB processing chain.

3.2.2 Removal of Slow Drifts

Standardly, a high pass filter of 0.1 Hz cut-off is used for removal of slow drifts, but there is a possibility that a slow-frequency part of CDA is lost due to this filtering. The way how to minimize the loss of this slow frequency is by using a polynomial function for detrending. We compared five different ways: high pass filter 0.1Hz, 0.01 Hz, 0.01 Hz and spline (de Cheveigné, & Arzounian, 2018), 0.01 Hz and spline with central step, 0.01 Hz with Savitzky-Golay filter (Press & Teukolsky, 1990).
Nodes (ss) for a spline used in (de Cheveigné, & Arzounian, 2018) were set at the time matching the beginning of each window from which the mean was computed:

```
ss(ch,j) = mean(data(chanArray(ch), win(j):win(j)+winpnts-1))
```

We defined the spline with the central step as a spline made from nodes that sit in the middle of the window from which the mean is computed:

```
ss(ch,j)=mean(data(chanArray(ch),win(j)-(winpnts/2):win(j)+(winpnts/2)-1))
```

The fitted spline was calculated using the MATLAB spline function performing cubic spline interpolation:

```
spline_fit = spline(1:nwin, ss(ch,:),xf);
```

Then, the fitted data were subtracted from original ones.

The moving window length was set to 1500 points being approximately 6 seconds (sampling rate 256 Hz) with the step of 500 points representing approximately two seconds.

```
okno winpoints =2000, 1000, prekryv winstep = 500
frequency - 256Hz; 1000:256 = 3.206s -> slow wave – 5s
5s ~ 5*256 = 1280 winpoints
6s ~ 6*256 = 1536
```

We utilized the first-order Savitzky-Golay (SG) filter (Press & Teukolsky, 1990) with the same window length of approximately 6 sec. After applying this filter, we further smoothed the filtered EEG traces with the moving average method using the span of the half of the used window, that is approximately 3 sec. The moving average method is a form of the SG filtering, so by other words we applied two SG filters.

```
filtered=sgolayfilt(data(chanArray,:)', 1, winpnts-1)';
for ch=1:numchan
      filtered (ch)=smooth(filtered (ch),winpnts/2);
end
data(chanArray,:)=data(chanArray,:)- filtered;
```

3.2.3 Filtration

The low pass filter with the cut-off frequency of 22 Hz was firstly used to validate the effect of the best preprocessing methods together with a notch filtering of alpha oscillations of [8 12] Hz. As a results of this validation and several methods testing, for the final processing of CDA, the low-pass filter with the 8 Hz cut-off frequency was applied.

3.2.4 EOG – Blinks and Saccades Rejection

The EOG data was used to reject the trials with eye movements or blinks before and during the MA. Initially, the filters were applied at EOG; high-pass at 0.01 Hz and low-pass at 25 Hz with stop at 30 Hz. The EOG artifact should not be present between 300 ms before MA onset and 700 ms after it.

There were programmed two ways of dealing with EOG artifacts: detecting blinks and saccade trials or only detecting trials with a saccade.

The artifact rejection was searching for blinks at VEOG using the peak-to-peak method with the moving window of 200 ms, the time step of 50 ms, and the peak-to-peak threshold at 100 μV. The HEOG was filtered for saccades by a step function method where the moving window lasts 400 ms, the time step had 10 ms, and the step threshold was set at 30 μV.

3.2.5 Artifacts

We programmed several artifacts detectors in MATLAB. Also, we proof-compared the detected artifacts with those obtained by automatic BVA artifact detection.
Foremost, baseline correction was done on copy of each trial and then the artifacts detection took place. The original trials still contained baseline.

Peak-to-peak

The minimum and maximum peaks in the window were computed and their difference in absolute value was compared to the threshold. The moving window was 15 ms wide, with 15 ms time step, and 80μV peak-to-peak threshold. Therefore, there was no overlap among moving windows.

Step function

We computed the mean amplitudes prior and after pointer index as a middle of the 200 ms moving window, and compared their difference to the threshold of 50μV. The window was then moved by 10 ms and the process was repeated.

Amplitude-beyond limits – set individually

The initial threshold amplitude was set at 75 μV, but at the end we decided to manually set threshold for each subject and each CDA specifically. The maximal absolute amplitude during trial was compared to the threshold.

Low activity

The low-activity was considered as an activity in the range of ±0.5 μV during 250 ms window, so it was detected by a moving window of 250 ms with time step of 50 ms.
Difference of the highest and lowest amplitude in the window was compared to the 0.5 μV threshold.

We created a matrix containing information about every detected artifact. In next step, it was possible to either reject all channels if an artifact was detected at least at one channel or reject only the pair of channels. Computerizing these steps allows easy switch between these approaches. The second approach required a weighting of electrodes.

3.2.6 Weighting of Electrodes

Each electrode contributed into ipsilateral and contralateral waves. Rejecting only pair of trial channels in the case that an artifact is at one of them causes unequal number of trials for each condition. Therefore, it might influence the final CDA by adding more strength into data from those conditions that had less trials (**Error! Reference source not found.**). Because of that, it was necessary to determine number of trials separately for each condition and each channel and then propagate this information via the whole process of estimating CDA waveforms. The weighted average formula is

$$\overline{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \quad \{w_i\}_{i=1,\dots,n} \geq 0,$$

and in case of the normalized weights

$$\overline{x} = \sum_{i=1}^{n} w_i' x_i \ , \qquad w_i' = \frac{w_i}{\sum_{i=1}^{n} w_i} .$$

Furthermore, the programmed algorithm allowed to decide about which pair of electrodes were included in the final processing.

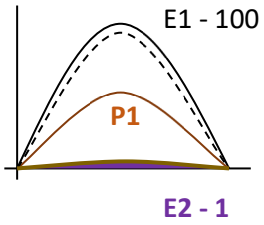

Fig. 2 The schematic explanation of the difference between average and weighted average. The average of E1 containing 100 samples and E2 containing 1 sample is P1, what is practically an average of two samples. But the weighted average P2 is an average of 101 samples. So, each sample has equal weight in contrast to P1 where E2 has a bigger weight than any of the samples in E1.

3.2.7 Order of Baseline Setting on Data

As was explained in 1.4.2, baseline correction should be done before detecting artifact by using the absolute value of voltage. However, we used the peak-to-peak detection and step function for treating artifacts. Both of those are able to overcome the effect of the baseline. Therefore, the baseline correction was done after filtering and artifact rejection during the CDA estimation.

200 ms before stimulus onset.

3.2.8 CDA estimation

The electrodes pair are O1/O2, P3/P4, PO7/PO8, P7/P8.

The cue arrow at the left hemifield includes 8 conditions, same for the right hemifield. We had four set sizes (2-0, 2-2, 4-0, 4-2), with or without distractor, and with the same or changed TA, that is 16 combinations for 8 electrode channels.

At the start, the algorithm takes values from each trial of a given set size, given channel and given time position and averaged them. It means it averaged the trials separately at each electrode for a given condition and given set size

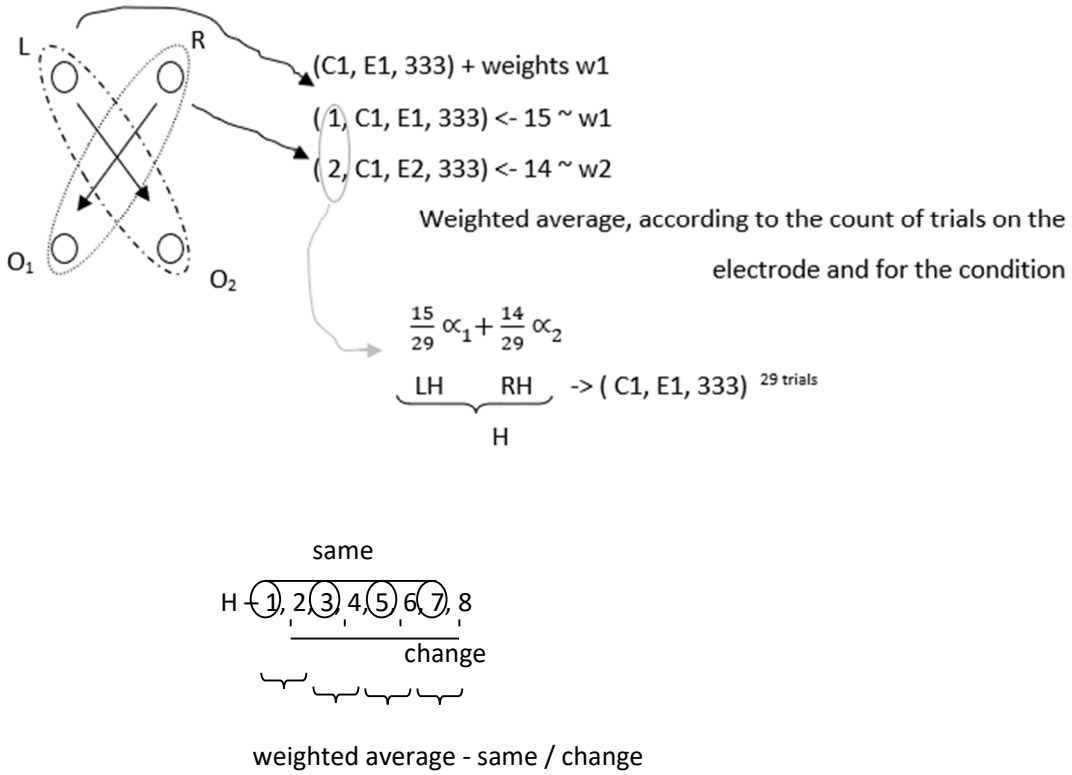

Fig. 3 Schema of contralateral waveforms averaging

Next, the pair electrodes are combined by the weighted average for the ipsilateral and contralateral waveforms. The contralateral waveforms required counting trials with cue on the left hemifield and recording at channels from the right hemisphere and vice versa. The ipsilateral waveforms included recordings from same sites as the cued hemifield, for the right-right and left-left combinations. We obtained ipsilateral and contralateral matrixes, and by computing their difference also a difference matrix.

The third (weighted) average covered change and no-change condition and was calculated separately for every matrix from the previous step. We compared two approaches, firstly we averaged the difference matrix and we called it D matrix. Secondly, we made a difference (aD matrix) from averaged ipsilateral and averaged contralateral matrices for the change/no-change condition. Mathematically, the average of differences and difference of averages is equal. It was confirmed by computing the norm difference between D and aD, which converged to zero ($7.3940e^{-31}$).

Finally, we obtained three waveforms (ipsilateral, contralateral and their difference) for each of set sizes.
This process was performed on every participant. Furthermore, the average by day over all participants from one recording site (KE or BA) and average of all days was performed.

3.3 Creation of Final ERP

The insensitive zone for the area under curve (AUC) was set as epsilon value equal to -0.5 μV. The detection area for the N2pc was adjusted after visual scan of CDAs according to the interval of 230 ms to 350 ms after the MA onset. The area for CDA was determined to be from 450 ms up to 850 ms after the MA was presented. The AUC was computed as a sum of values on the CDA curve. The negative sign corresponds to the physiologic properties of the CDA.

3.4 Performance and CDA

The CDA measure is the AUC with the insensitive area set in interval [-0.5 μV, 0.5 μV]. We compared the difference between CDA created from correct trials and CDA built from the incorrect trials only.

3.5 Effect of Eye Blinks on Performance

As was already said, the original design was not capable to distinguish the case of blink when saccadic eye movement was present. The CDA protocol was designed to obtain lateral differences in response to seeing and memorizing the MA, therefore any eye movements

were prohibited. Since we couldn't distinguish the saccades from blinks, we assumed that every blink contained saccade. Several participants were blinking extensively during specific periods around the TA what caused to reject many trials for performance as well as for CDA waves. We wanted to research under which conditions those trials could be permitted into the final analysis and how they can influence results.

Therefore, we manipulated task conditions by admitted which trial could, or could not, to be marked as valid. Firstly, we used the original data from the main experiment and compared the performances in case that any eye movement were excluded with the performances of trials included blinks and saccades from the onset of TA until 500 ms after. This corresponded to possibility that the participant looked on cued hemifield when the TA was shown.

Secondly, we decided to research the change in performance when the participant is instructed to look on the TA. In this case, three different results were possible: performance will be better indicating that looking on the TA make recall of the MA easier, performance will be same, or performance will be worse suggesting recall of the MA is harder when the point of gaze is changed. The experiment was designed with an eye-tracker as the tool to evaluate whether participant fulfilled the instructions with changing or fixing the point of gaze. However, after the preparatory work (research, scripts) was done, it was discovered the license for available eye-tracker was nonexistent and the manufacturer refused to provide one because the available eye tracker was obsolete. The alternatives suggested by manufacturers were beyond the financial limit of the project. Later in the time, another eye-tracker was available but because of logistics of that time (healthy issues and COVID restrictions) it was not possible to use it. Therefore, the original design was simplified, and it represented the pilot research instead of fully autonomous research. Since there was not the possibility to scientifically evaluate the precision of fulfilling gaze instruction, we decide to add the subjective evaluation into the post-questionnaire. In this way, the participants had the possibility to review and evaluate their performance, how they fulfilled the instructions and compare the two conditions they underwent.

3.5.1 Eye Blinks during TA in CDA session

Computing performance and testing significance of differences was done in MATLAB.

We regrouped data from both groups – treatment and control – into to two conditions – blinks and no-blinks.

Firstly, we detected blinks and eye movements in trials in the whole interval until the TA event. These trials were excluded, and the rest defined Set 1.
Secondly, we detected blinks and eye movements within Set 1 from TA until 500 ms after TA (TA + 500 ms), even though the blinks and/or eye movements started at the end of the interval. Trials containing these artifacts were referenced as Set 2.
Thirdly, we evaluated Set 2 by two conditions; the number of trials in Set 2 shall be higher than 20 and at the same time lower than 90% of Set 1. Trials fulfilled the conditions stayed in Set 2 and were compared with corresponding subject, set size, day, etc. The value of 90% was heuristically set as an expected change between blink and no-blink conditions.
Finally, we tested the percentual difference of performance and Cowan K (a measure of memory capacity) between the combinations of day and set size using the unpaired two-sample t-test.

3.5.2 Pilot CDT Experiment

The CDT procedure of the main experiment was modified to test the difference in performance between blink and no blink conditions by evaluating the role of saccadic eye movement in performance.
Two conditions within subject experiment used the original CDT with one set of original (FF) and one set of modified instructions (ZZ). In the case of modified instructions, the participants were asked to look at the cued hemifield after the TA onset without blinking.
The questionnaire of the original experiment was enriched by questions about eye conditions and subjective evaluation of the performance.

Stimuli

The three scripts in PsychoPy2 from the original experiment were reused. One script was edited for training with the instruction about the gaze change (ZZ), and one was for the fixed gaze (FF) training with instructions, and one for data acquisition were identical to the original ones. The scripts updated to the higher version PsychoPy3 for an offline distribution were not used because the correct behavior on the different platforms, hardware architectures and with the software dependencies were not guaranteed by PsychoPy developers and the online distribution did not support the programmed PsychoPy experiments, only those created by a Builder interface (psychopy.org).

Targets were red rectangles and distractors were blue or green rectangles with height of 1.5 cm and width of 0.5 cm. The field in which the rectangles were shown on each hemifield was 7.6 cm tall and 4.8 cm wide. The minimal distance from vertical centerline to the closest possible rectangle was 1.5 cm.

The CDT for both conditions consisted of 2, 3, or 4 targets and any or 2 distractors with 2 repetitions and 5 blocks, therefore 240 trials. They were randomly grouped into blocks, with short pauses (max 2 min, decided by participant) between them. One CDA took approximately 25 min.

Participants

For the pilot experiment, the participants were the only ones accessible during the COVID-19 restrictions. The 4 participants (2 women; ages 24, 58, 29,58), were right-handed, college educated with normal or corrected to normal vision without any previous brain injury.

Data acquisition

The experiment ran on notebook with refresh rate 60 Hz, screen width 34.5 cm, and resolution 1366x768.

Procedure

Participant signed informed consent after being introduced to the procedure of the experiment. Subsequently, they were pseudo-randomly assigned the order of conditions; one participant had a random order while the next one had the inverse order of the conditions to the previous participant. The order of participant was randomized. Then, they filled the first part of the questionnaire.

Participants were seated 70 cm in front of the screen and asked to not lean forward. They answered using a computer mouse where a right button represented the change of the TA and left button no change. Depending on what was easier to them, they either used one hand or both hands to control the mouse button. By this way, we diminished the mental effort connected with focus on remembering which button is controlled by which finger or hand.

Firstly, practice session was held with instructions of the first type of gaze (change or fixed gaze) with 1 or 3 targets and any or 2 distractors, and it took approximately 5 minutes. Secondly, CDT A took place. Thirdly, this was followed by a pause of 15 minutes for refreshing and eye relaxation. Fourthly, after pause a practice session with instructions of the second type of gaze (fixed or change gaze) with the same parameters was held. Again, it

lasted about 25 minutes. At the end, they answered to the second part of the questionnaire including their subjective opinion about their experience.
The total time of measurement per participant was one and half hour.

Methods of Analyses

We analyzed a subjective evaluation of the participants with regards to the difficulties of both gaze conditions.
The accuracy and memory capacity were calculated for each set size and gaze condition. The accuracy determined as a percentage of correct trials in a given set size. The memory capacity was computed as a Cowan's K that is a number of items stored in visual working memory (Vogel & Machizawa, 2004). The hit rate was corrected by a false alarm rate and multiplied by a set size (2, 3 or 4). Subsequently, the descriptive statistics and the parametric paired sample t-test was performed after the normal distribution of the data was confirmed by the Saphiro-Wilks test for both accuracy and memory capacity. The JASP (JASP Team, 2022) software was used for statistical analyses. However, we are aware that the low number of participants is not sufficient.

4 Results

4.1 Preprocessing methods for EEG

The CDA waveforms were built only from a subset of correct and incorrect trials, therefore aby trial without response or with response after the specified time frame of 3 seconds were not included into suitable trials.

4.1.1 Cutting

The cutting removed EEG data recorded during pauses from which the excessive drifting propagated into the subsequent trials. Data were cut individually for each subject. For example, ones' original data contained 1 104 128 samples what represent 71min 53 sec, cut data had 964 352 samples corresponding to 62 min 47 sec.

Original data

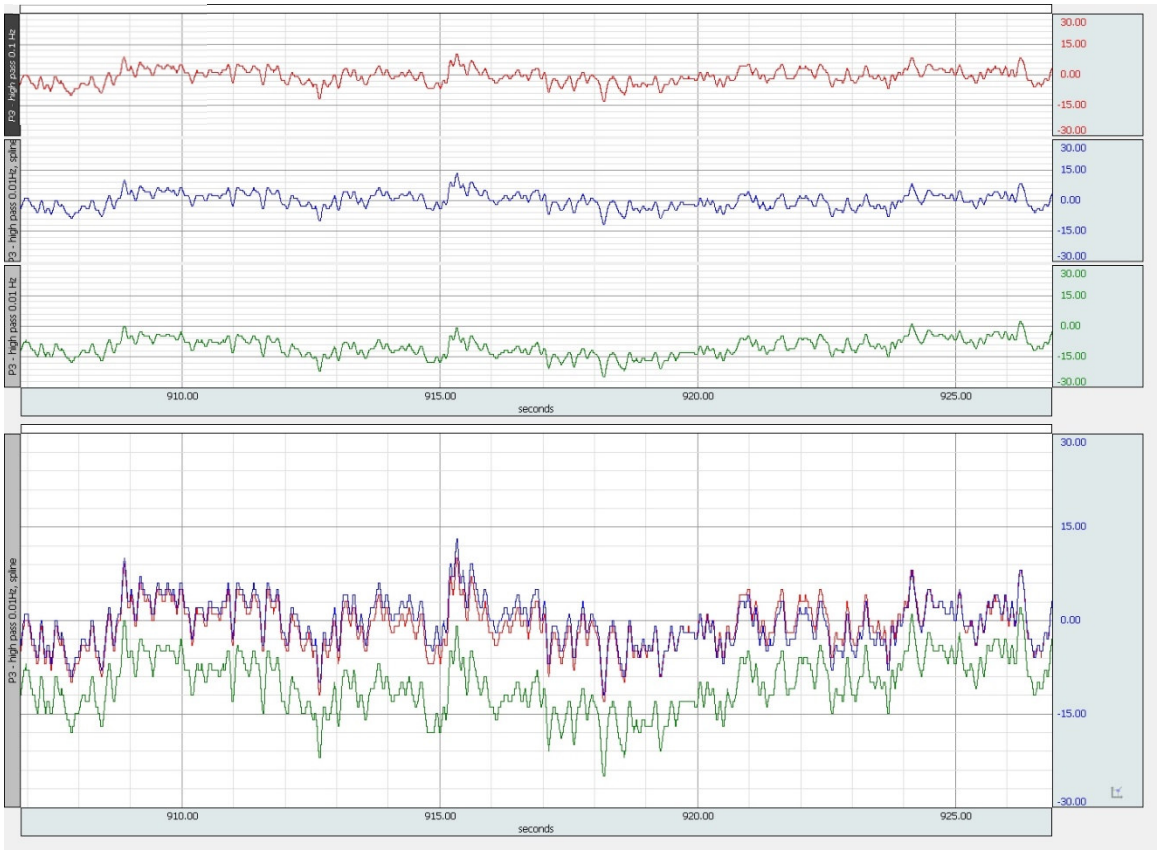

Fig. 4 EEG waveforms of one subject, applied low-pass filter at 8 Hz, channel P3, unshortened data starting at 906 sec with the duration of 20 sec. Green – high-pass filter 0.01 Hz, there are present slow waves with approximately 5 sec long period. Red – high-pass filter 0.1 Hz, slow waves are diminished. Blue – detrended by spline and high pass filter 0.01 Hz, results are similar to the case when the high-pass filter of 0.1 Hz is applied.

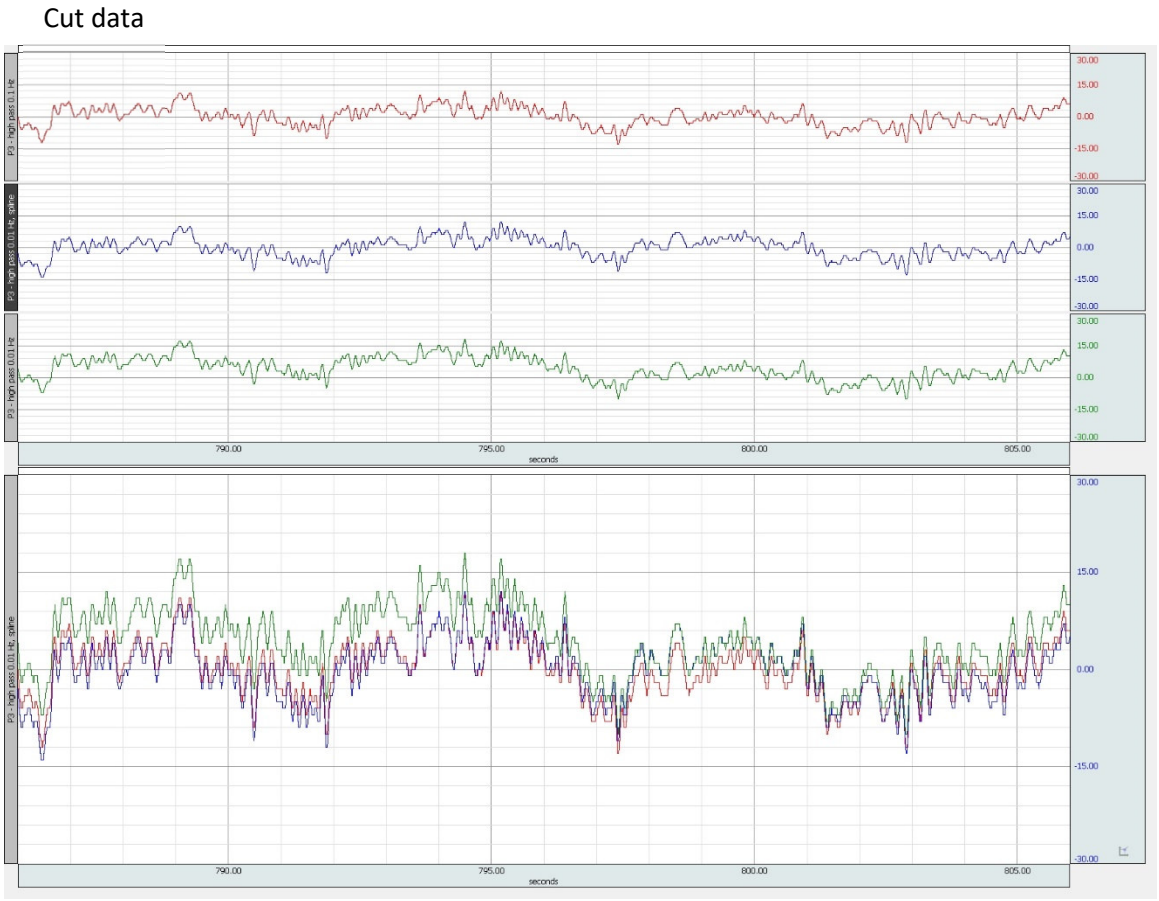

Fig. 5 EEG waveforms of same subject and of the same time frame as in Fig. 4, applied low-pass filter 8 Hz, channel P3, cut data from 786 sec with duration of 20 sec. Green – high-pass filter 0.01 Hz, Red – high-pass filter 0.1 Hz, Blue – detrended by spline and high-pass filter 0.01 Hz

4.1.2 Removal of Slow Drifts

The difference between 0.1 Hz and 0.01 Hz can be seen in subplots A and B of Fig. 6, respectively. Slow drifts are present in the sub-plot A, while higher high-pass filter was able to reduced them. In Fig. 7 we can see a visually similar result of applying high-pass filter of 0.1 Hz (red waveform) and detrending by polynomial spline function (de Cheveigné & Arzounian, 2018) with the high-pass filter of 0.01 Hz (blue). We decided to use detrending in combination with the high-pass filter of 0.01 Hz instead of the high-pass filter of 0.1 Hz, therefore, we lowered the risk of losing slow-frequency components of CDA.

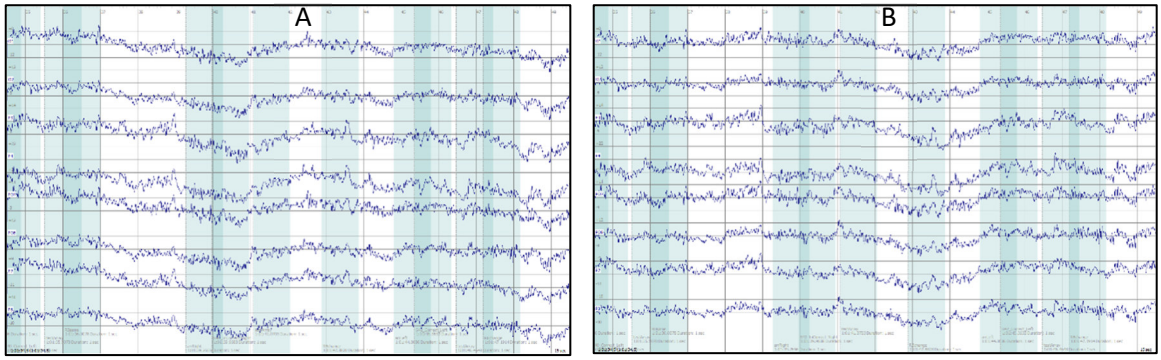

Fig. 6 EEG waveforms of one subject, window of 15 sec, applied low-pass filter of 22 Hz, slow waves of approximately 5 sec period are present in data. A – high-pass filter 0.01 Hz, B – high-pass filter 0.1Hz.

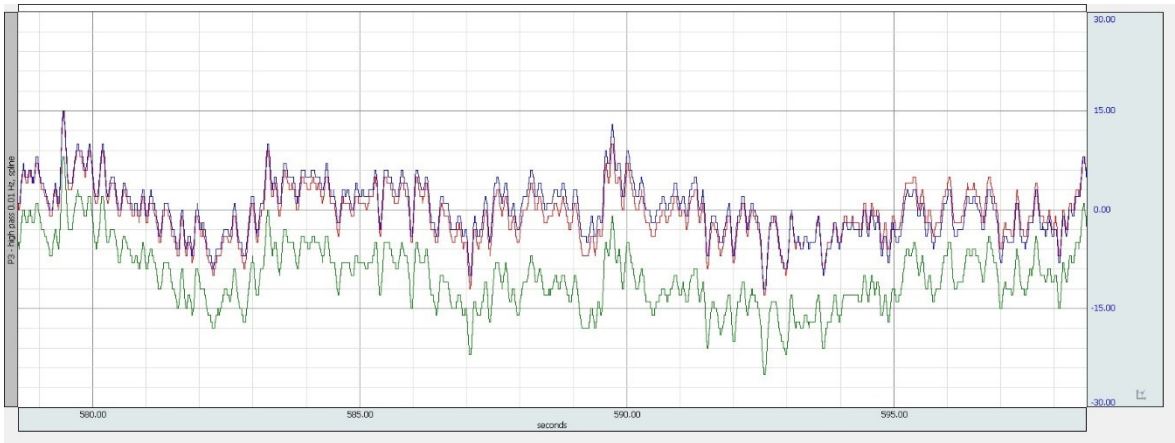

Fig. 7 EEG waveform of one subject, window of 15 sec, applied low-pass filter of 8 Hz, Green – high-pass filter of 0.01 Hz, Red – high pass-filter of 0.1Hz, Blue – detrended by spline smoothing and filtered by the high-pass filter of 0.01 Hz.

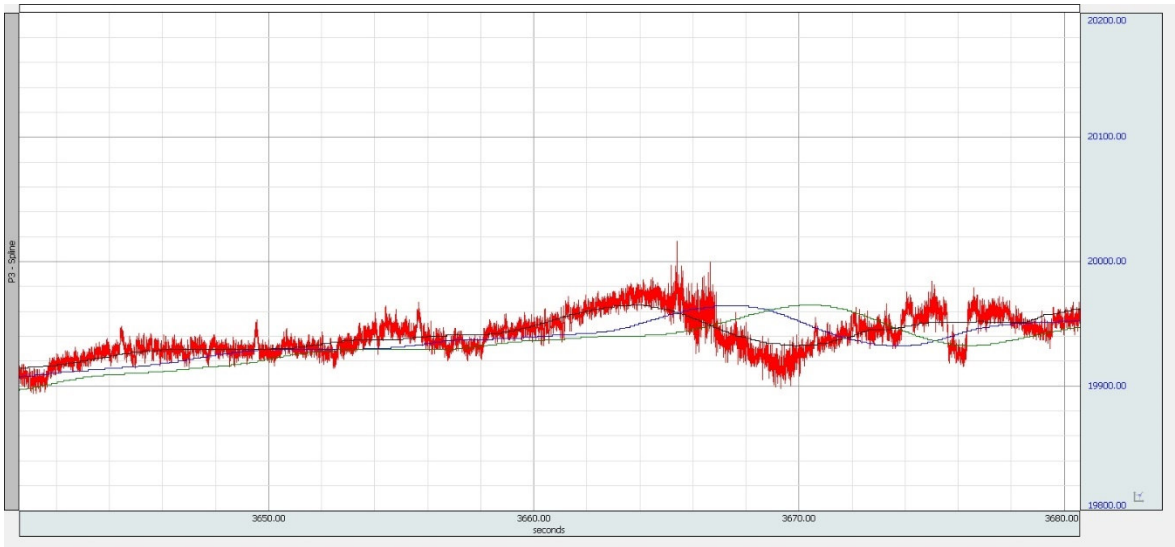

Fig. 8 Comparison of detrending methods: Red – EEG data 3640.5 sec – 3680.5 sec, Blue – spline, Green – spline with central nodes, Black – Savitzky-Golay

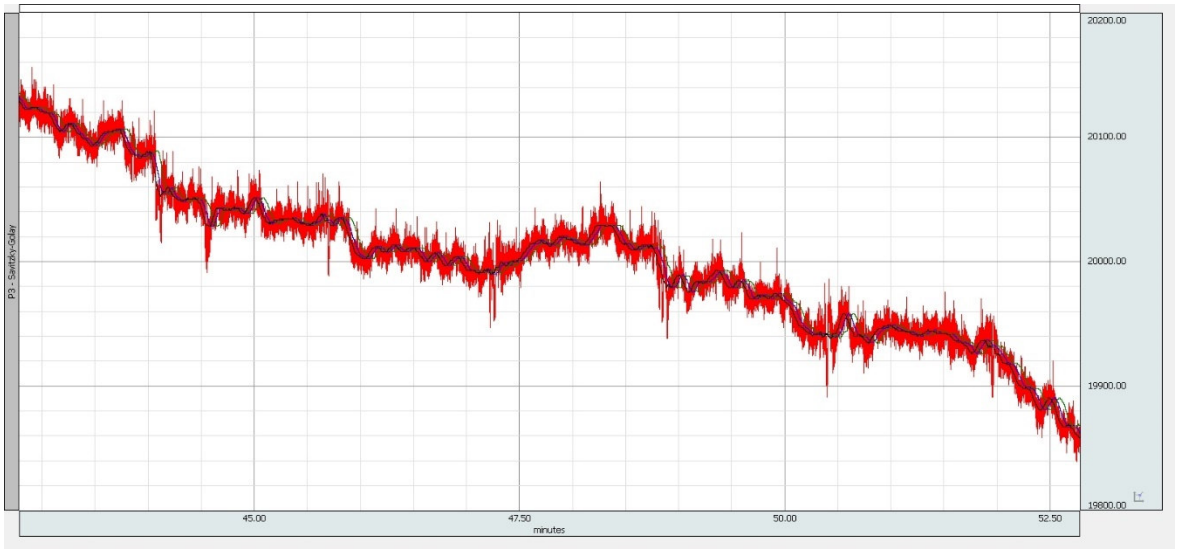

Fig. 9 Comparison of detrending methods: Red – EEG data 42.5 min – 52.5 min, Blue – spline, Green – spline with the central nodes, Black – Savitzky-Golay filter.

After comparing the spline, central spline and Savitzky-Golay methods for detrending, we decided to use the Savitzky-Golay filter. The Savitzky-Golay filter removed the slow drifts in the data while it did not affect the EEG data without slow drifts when applied on them.

4.1.3 Filtering

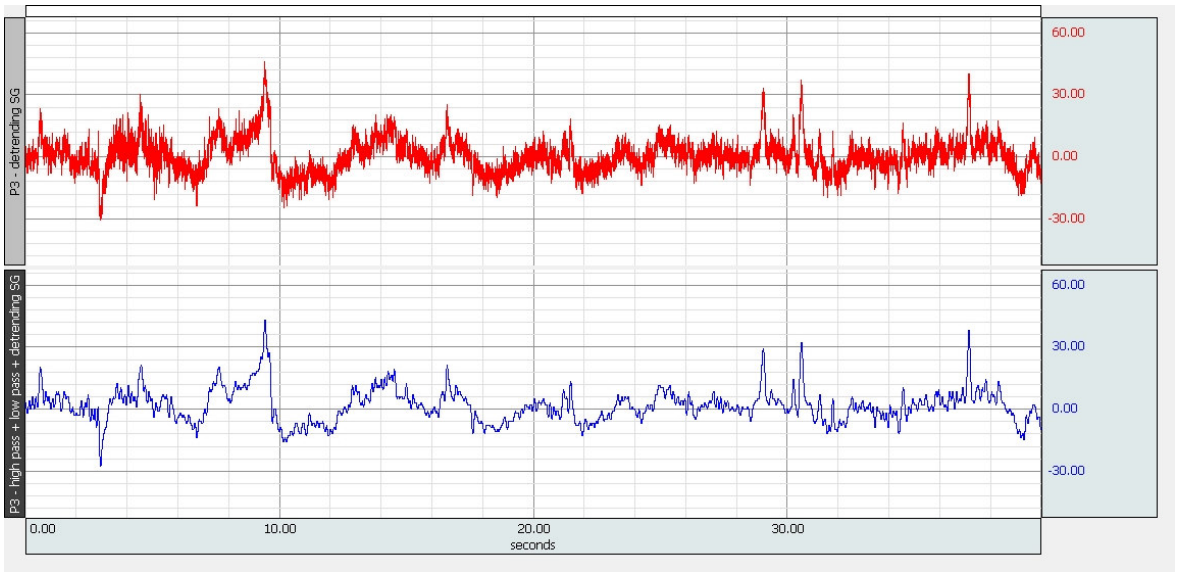

Fig. 10 Influence of the 0.01 Hz high-pass filter and 8 Hz low-pass filter. Red – only Savitzky-Golay detrending, Blue – Low-pass and high-pass filters applied on detrended data.

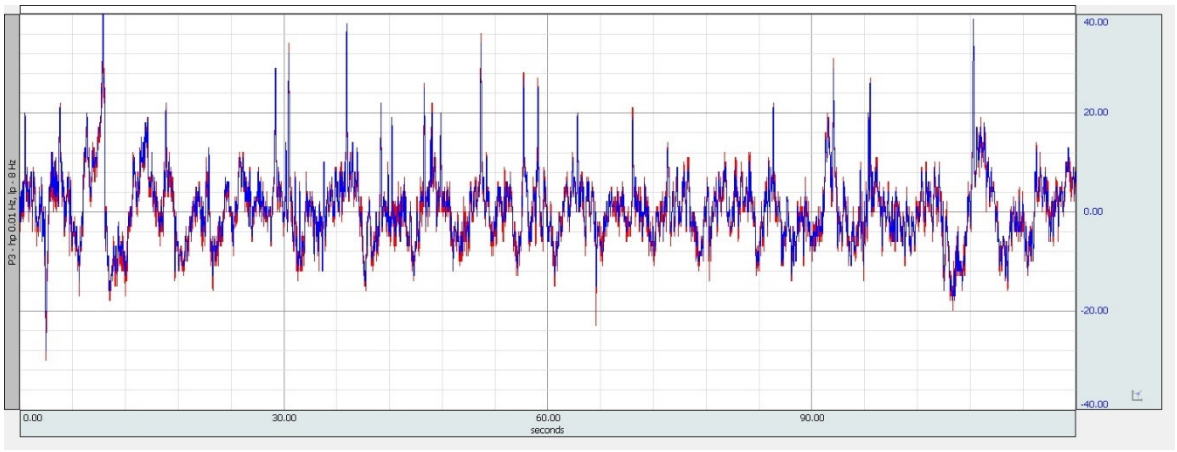

Fig. 11 Comparison of high-pass filters: Blue – 8 Hz, Red – 22 Hz and notch filter [8, 12]. Both filters filtered out the alpha oscillations.

The application of the 8 Hz low pass filter smoothed the CDA what simplified the visual analysis. The values of AUC for CDA did not differ when the low pass filter of 8 Hz was used instead of the notch filter for removing the alpha oscillation with the low pass filter of 22 Hz. Though, the later combination of filters had an effect on early ERPs, see 4.2.2.

4.1.4 Blinks, Saccades and Other Artifacts

All trials with at least one detected ocular artifact (blink, saccade) in EOG recording were rejected. The remaining trials were searched for other artifacts defined in 3.2.5.

The rejection after EOG artifact detection included all eight channels of a given trial. We rejected 619 trials of CDA1, 657 trials of CDA2, 809 trials of CDA 3 in KE group and 312 trials of CDA1, 342 trials of CDA 2, 312 trials of CDA3 in BA group.

The EEG artifact detection found markedly more artifacts in KE group than in BA group. The low activity was not detected at all in neither group and similarly peak-to-peak artifacts occurred barely (21 in KE, 12 in BA).

CDA 1 KE – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
AB65	640	43 (6.56)	60	0	49	11	0	39
BB67	639	115 (18.13)	50	0	31	19	0	27

DK 52	640	189 (28.91)	104	2	24	78	0	53
DL 51	640	26 (4.06)	21	0	10	11	0	13
KB 55	640	114 (16.72)	56	0	16	40	0	10
LM 61	640	22 (3.13)	4	0	2	2	0	3
MB 53	640	12 (1.88)	29	1	13	15	0	15
MB 54	640	17 (2.66)	23	0	10	13	0	15
MD 66	640	7 (1.09)	30	0	18	12	0	12
MM 60	639	7 (1.25)	138	0	23	115	0	37
MV 57	639	41 (6.25)	89	0	15	74	0	67
PJ 62	640	6 (0.94)	0	-	-	-	-	0
PL 56	640	7 (1.09)	22	0	4	18	0	14
SK 63	640	8 (1.25)	8	0	0	8	0	1
SO 69	640	5 (0.78)	6	0	1	5	0	4

Tab. 1 Statistics of rejected EOG artifacts and detected artifacts of **CDA 1** for all subjects in the **KE** group.

CDA 2 KE – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
AB65	640	72 (9.84)	143	8	73	62	0	54
BB67	640	127 (19.53)	0	-	-	-	-	0
DK 52	640	159 (24.22)	51	0	15	36	0	6
DL 51	638	17 (2.66)	116	0	36	80	0	63
KB 55	640	31 (4.53)	166	0	32	134	0	88
LM 61	638	28 (3.75)	10	0	4	6	0	6
MB 53	640	21 (2.81)	20	0	5	15	0	7
MB 54	638	29 (4.84)	0	-	-	-	-	0
MD 66	640	17 (2.34)	4	0	1	3	0	2
MM 60	640	8 (1.25)	50	0	14	36	0	14
MV 57	636	118 (16.72)	11	0	5	6	0	2
PJ 62	640	14 (2.19)	193	0	44	149	0	134
PL 56	640	5 (0.78)	0	-	-	-	-	0
SK 63	640	11 (1.72)	2	0	0	2	0	1
SO 69	635	3 (1.25)	22	0	0	22	0	6

Tab. 2 Statistics of rejected EOG artifacts and detected artifacts of **CDA 2** for all subjects in the **KE** group.

CDA 3 KE – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
AB65	640	50 (7.50)	158	0	128	30	0	94
BB67	640	146 (22.81)	17	0	0	17	0	15

DK 52	640	132 (20.16)	38	0	15	23	0	9
DL 51	639	26 (3.44)	26	0	11	15	0	16
KB 55	640	92 (13.59)	63	0	1	62	0	24
LM 61	640	37 (5.00)	15	0	3	12	0	14
MB 53	640	14 (2.03)	0	-	-	-	-	0
MB 54	640	4 (0.63)	0	-	-	-	-	0
MD 66	640	5 (0.78)	17	0	7	10	0	12
MM 60	640	7 (1.09)	61	0	28	33	0	36
MV 57	639	270 (36.09)	31	0	9	22	0	12
PJ 62	640	10 (1.41)	99	8	48	43	0	14
PL 56	640	1 (0.16)	68	0	8	60	0	59
SK 63	640	5 (0.78)	55	2	22	31	0	35
SO 69	640	10 (1.56)	4	0	1	3	0	3

Tab. 3 Statistics of rejected EOG artifacts and detected artifacts of **CDA 3** for all subjects in the **KE** group.

CDA 1 BA – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
DJ 37	640	0 (0)	0	-	-	-	-	0
FP 22	640	49 (7.03)	6	0	1	5	0	6
JM 24	640	13 (2.03)	0	-	-	-	-	0
JP 20	640	42 (6.56)	15	0	7	8	0	9
KK 35	640	2 (0.31)	0	-	-	-	-	0
MK 21	640	22 (3.44)	24	0	10	14	0	6
MP 27	640	2 (0.31)	83	0	0	83	0	47
MU 36	640	18 (2.66)	5	0	2	3	0	4
OK 34	640	7 (1.09)	13	0	6	7	0	7
PK 38	640	11(1.56)	0	-	-	-	-	0
RS 30	640	22 (3.44)	280	0	3	277	0	108
SD 28	640	4 (0.47)	1	0	0	1	0	1
SS 32	640	13 (1.72)	0	-	-	-	-	0
TM 33	640	22 (2.34)	31	0	9	21	1	9
VF 29	640	85 (13.13)	1	0	0	1	0	1

Tab. 4 Statistics of rejected EOG artifacts and detected artifacts of **CDA 1** for all subjects in the **BA** group.

CDA 2 BA – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
DJ 37	640	0 (0)	25	0	12	13	0	15
FP 22	640	35 (5.31)	6	0	4	2	0	3
JM 24	640	5 (0.63)	2	0	0	2	0	2
JP 20	640	56 (8.59)	1	0	0	1	0	1
KK 35	639	6 (1.09)	8	0	0	8	0	8

MK 21	640	12 (1.72)	1	0	0	1	0	1
MP 27	640	17 (2.19)	39	0	1	38	0	19
MU 36	640	28 (4.06)	44	0	0	44	0	26
OK 34	639	20 (3.28)	2	0	1	1	0	1
PK 38	639	10 (1.72)	0	-	-	-	-	0
RS 30	640	19 (2.97)	55	0	4	51	0	31
SD 28	638	13 (2.03)	137	0	1	136	0	73
SS 32	640	1 (0.16)	30	0	2	28	0	18
TM 33	640	67 (8.75)	15	0	1	14	0	14
VF 29	639	53 (7.34)	29	0	4	25	0	19

Tab. 5 Statistics of rejected EOG artifacts and detected artifacts of **CDA 2** for all subjects in the **BA** group.

CDA 3 BA – EOG Artifact Rejection and EEG artifact detection								
	Suitable trials	EOG artifacts # (% of rejected)	# of detected artifacts	P2p	Step	Beyond limit	Low activity	# of trials with at least one artifact
DJ 37	640	4 (0.63)	10	0	3	7	0	6
FP 22	640	26 (3.75)	55	0	12	43	0	32
JM 24	640	7 (0.78)	1	0	0	1	0	1
JP 20	640	18 (2.81)	33	9	12	12	0	12
KK 35	640	4 (0.63)	75	0	6	69	0	37
MK 21	640	10 (1.56)	4	0	2	2	0	2
MP 27	640	7 (0.78)	95	2	8	85	0	52
MU 36	639	6 (1.09)	4	0	2	2	0	2
OK 34	640	18 (2.81)	6	0	3	3	0	4
PK 38	639	5 (0.94)	3	0	2	1	0	2
RS 30	640	69 (10.63)	10	0	1	9	0	9
SD 28	640	22 (2.97)	8	0	5	3	0	2
SS 32	640	2 (0.31)	0	-	-	-	-	0
TM 33	640	26 (3.91)	4	1	1	2	0	2
VF 29	640	88 (12.19)	1	0	1	0	0	1

Tab. 6 Statistics of rejected EOG artifacts and detected artifacts of **CDA 3** for all subjects in the **BA** group.

4.1.5 Weighting and CDA Creation

We removed only the pair of electrodes, not all channels in the case of a detected trial at one of them. This resulted into two facts. A positive one, we could include into CDA higher number of trials, therefore increasing SNR. And a negative one, we had to overcome the problem with different number of trials under each pair of electrodes counted into CDA. Furthermore, this unequalness was transferred from individual level into averages by day

over all participants in corresponding sites. As a resulting tool, we programmed a weighted average method that solved the negative outcome.

Each trial that was not excluded after EOG artefact rejection, contributes to the CDA from the recorded electrode sites. In the tables Tab. 7 and Tab. 8 are counted all the time series from the electrodes of the contralateral site that are used for computing contralateral activity (maximally 640 trials per electrode per set size), furthermore they represent the weights by which each participant was included into averaged contralateral activity. Since we rejected the trials on whole electrode pair, we obtained equal number of trials that enters into ipsilateral activity. The CDA computed as a difference of ipsilateral and contralateral activities is therefore built from two times of number of contralateral trials (maximally 1280 per set size). The 4 set sizes (2,2; 2,0; 4,2; 4,0) used together maximally 5120 time series or 640 trials recorded on 8 electrode sites. Those numbers related to one participant and one CDA session. The maximal number of used trials for 15 participants and 3 CDA sessions was 28800 trials recorded on 8 electrodes, therefore 230400 time series per group (KE and BA). The total number of 221386 time series were used in BA group and 211472 time series in KE group for a CDA averaged by all days.

The weights were also calculated for electrode and set size when building CDA for each participant. Due to the large amount of those data (4 set sizes, 4 electrodes sites on each hemisphere, 3 CDA session, 15 participants per treatment condition - KE/BA), they are not published in this thesis.

This approach increased the number of used trials and therefore, the SNR. For example, the artifacts of participant AB 65's CDA3 were located primarily on electrode pair of P3/P4 what led to 131, 122, 126, 132 time series for 2,2; 2,0; 4,2; 4,0 set sizes respectively. If we rejected the whole trial when the artifact was located at least at one electrode, the weights for contralateral activities would be 524, 488, 504, 528 for respective set sizes, what is less by 47 (8.2%), 60 (10.9%), 48 (8.7%), 33 (5.9%) time series respectively.

CDA 1 KE	**2,2**	**2,0**	**4,2**	**4,0**
AB65	584	599	566	592
BB67	517	495	533	521
DK 52	452	380	463	457
DL 51	584	611	619	526
KB 55	547	531	499	532
LM 61	607	632	639	599

MB 53	623	622	619	625
MB 54	607	609	629	628
MD 66	631	624	629	630
MM 60	617	612	608	614
MV 57	580	589	585	569
PJ 62	640	632	632	632
PL 56	629	624	633	629
SK 63	632	632	628	632
SO 69	632	631	636	636
Sum	8882	8823	8918	8822

CDA 2 KE	**2,2**	**2,0**	**4,2**	**4,0**
AB65	563	543	544	573
BB67	520	512	520	508
DK 52	477	503	460	480
DL 51	594	602	607	613
KB 55	591	572	571	588
LM 61	617	618	601	620
MB 53	618	623	627	608
MB 54	604	596	616	620
MD 66	624	623	632	618
MM 60	632	628	617	625
MV 57	528	518	530	552
PJ 62	579	585	592	590
PL 56	640	628	636	636
SK 63	611	632	636	636
SO 69	621	628	637	628
sum	8819	8811	8826	8895

CDA 3 KE	**2,2**	**2.0**	**4.2**	**4.0**
AB65	571	548	552	561
BB67	487	480	513	479
DK 52	510	521	494	499
DL 51	624	606	610	613
KB 55	527	547	545	543
LM 61	611	602	604	601
MB 53	616	620	636	636
MB 54	636	636	636	636
MD 66	630	633	631	634
MM 60	632	613	632	611
MV 57	425	406	372	415
PJ 62	614	614	634	627
PL 56	625	625	627	619
SK 63	626	628	625	626
SO 69	635	616	634	631
sum	8769	8695	8745	8731

Tab. 7 Contralateral weights of three CDA in KE per participant. Numbers of time series used for building contralateral (or ipsilateral) waveforms in KE group summarized over the set sizes for each participant after rejecting artifacts on pair electrodes. The sum represented the total number of time series for averaged contralateral activity by day over all participants in KE group.

CDA 1 **BA**	**2,2**	**2,0**	**4,2**	**4,0**
DJ 37	640	640	640	640
FP 22	575	581	604	614
JM 24	616	624	636	632
JP 20	594	598	585	606
KK 35	640	640	640	632
MK 21	599	631	630	602
MP 27	612	628	612	625
MU 36	617	632	615	623
OK 34	635	627	630	633
PK 38	632	632	628	628
RS 30	572	569	557	551
SD 28	632	640	639	636
SS 32	620	632	632	632
TM 33	619	616	625	625
VF 29	564	552	555	552
sum	9167	9242	9228	9231

CDA 2 **BA**	**2,2**	**2,0**	**4,2**	**4,0**
DJ 37	637	635	635	638
FP 22	607	604	609	600
JM 24	639	640	628	635
JP 20	580	592	587	580
KK 35	625	635	625	639
MK 21	628	624	627	636
MP 27	631	610	614	620
MU 36	594	606	608	615
OK 34	604	624	632	615
PK 38	632	628	632	624
RS 30	608	620	617	595
SD 28	604	598	608	591
SS 32	630	627	636	637
TM 33	592	580	574	575
VF 29	593	603	568	583
Sum	9204	9226	9200	9183

CDA 3 **BA**	**2,2**	**2,0**	**4,2**	**4,0**
DJ 37	635	635	632	636
FP 22	615	614	616	583
JM 24	631	636	632	640

JP 20	614	620	626	616
KK 35	613	621	622	620
MK 21	636	627	627	628
MP 27	611	619	619	626
MU 36	635	636	627	632
OK 34	626	627	607	624
PK 38	636	640	628	630
RS 30	582	580	568	549
SD 28	614	621	623	620
SS 32	632	640	640	640
TM 33	615	608	611	624
VF 29	568	560	560	559
Sum	9263	9284	9238	9227

Tab. 8 Contralateral weights of three CDA in BA per participant. Numbers of time series used for building contralateral (or ipsilateral) waveforms in BA group summarized over the set sizes for each participant after rejecting artifacts on pair electrodes. The sum represented the total number of time series for averaged contralateral activity over all participants by day in BA group.

4.1.6 Final Preprocessing Chain

Recordings from 4 pairs of electrodes were used for the final analysis. We applied the Savitzky-Golay filter with 1500 points window (~ 5.86 seconds), low-pass filter of 8 Hz with stop at 10 Hz and high-pass filter of 0.01 Hz with stop at 0.005 Hz. The EOG artifact detection for a given trial led to the rejection of EEG channels where only one EEG artifact was detected. In the case of EEG data, if an artifact was detected on an electrode of the trial only the corresponding pair of electrodes of that trial was rejected. After the visual analysis of the participants trials and detected artifacts caused by the amplitude-beyond limits, the individual threshold was set for this type of artifact (Železníková, 2021). The CDA was built by weighted averages where the weights came of the number of trials at the electrodes after the artifact rejection. The window for the CDA started 370 ms after the MA stimulus onset and ended at the 850 ms.

4.2 ERPs after Preprocessing Methods

Since each component of the preprocessing influence the resulting ERPs, it is not possible to change the preprocessing steps at the end when the ERP waveforms are not satisfactory. Therefore, to see the influence of different preprocessing methods, we consider our main chain as basic, and we are going to compare every time only one component while the rest is the same as in the final preprocessing chain.

The red crosses at figures of ipsilateral and contralateral activities of the CDAs represent the early ERPs, P1, N1, P2, N2pc. The main experiment was oriented toward CDA, and its analysis can be found in Železníková (2021).

We compared the differences in ERP components caused by different preprocessing methods. The referential ERPs are those obtained from final preprocessing methods. However, some differences are visible only on individual levels because the averaging highlighted the common characteristics and suppressed individual features in the CDA. This can be seen on Fig. 12 and Fig. 13 displaying the CDA 3 of one participant and CDA 3 averaged by all participants.

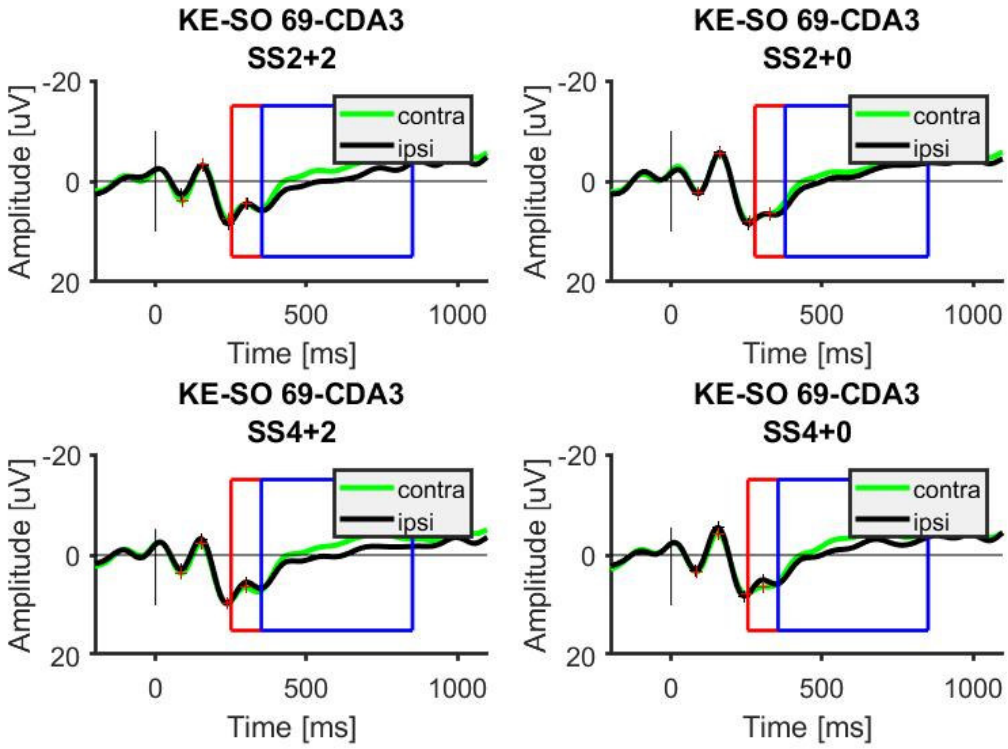

Fig. 12 Contralateral and ipsilateral activity CDA 3 of subject SO 69 generated from the final preprocessing chain. Red crosses represent P1, N1, P2, N2pc respectively.

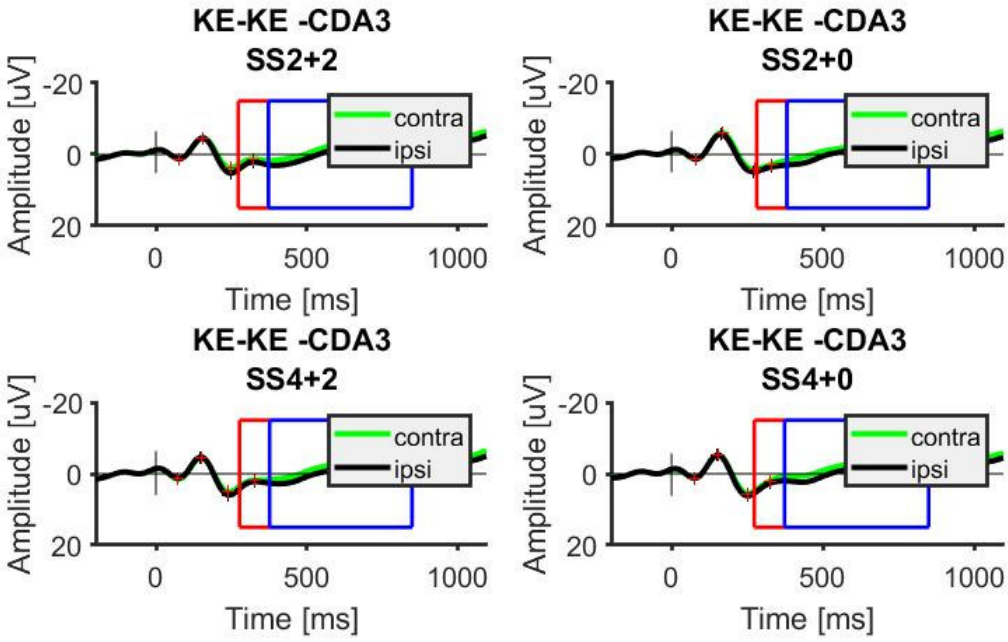

Fig. 13 Contralateral and ipsilateral activity of averaged CDA 3 by day over subjects in KE generated from the final preprocessing chain. Red crosses represent P1, N1, P2, N2pc respectively.

We can see the ERPs after the main preprocessing chain in Fig. 13. The filtering suitable for smoothing the CDA, mainly the low-pass filter of 8 Hz, is inappropriate for the early ERPs. The ERP are extensively smoothed, P1 usually found at 100 ms after stimulus onset is located at the too early latency of 70 ms. Since the preprocessing are focused on the smooth CDA waveform estimate, we preferred correct estimate of slow ERP components over the faster early ERPs components. This caused the distortion of the early ERPs. Therefore, the statistics of the early ERPs was not performed because results would not have meaningful and correct interpretation.

4.2.1 Cutting

The assumption that the "flying" data recorded during pauses between blocks would propagate into CDA waveforms and the fact that the drifts in EEG data were present even after detrending resulted in cutting the pauses between blocks of trials from the EEG data. The discontinuity between blocks caused by data cuts was negligible in comparison with the raw uncut data when we were looking on detrended waveforms.

Interestingly, the contralateral and ipsilateral waveforms of the CDA3 averaged by day over all participants in KE group did not differ when comparing the uncut and cut data.

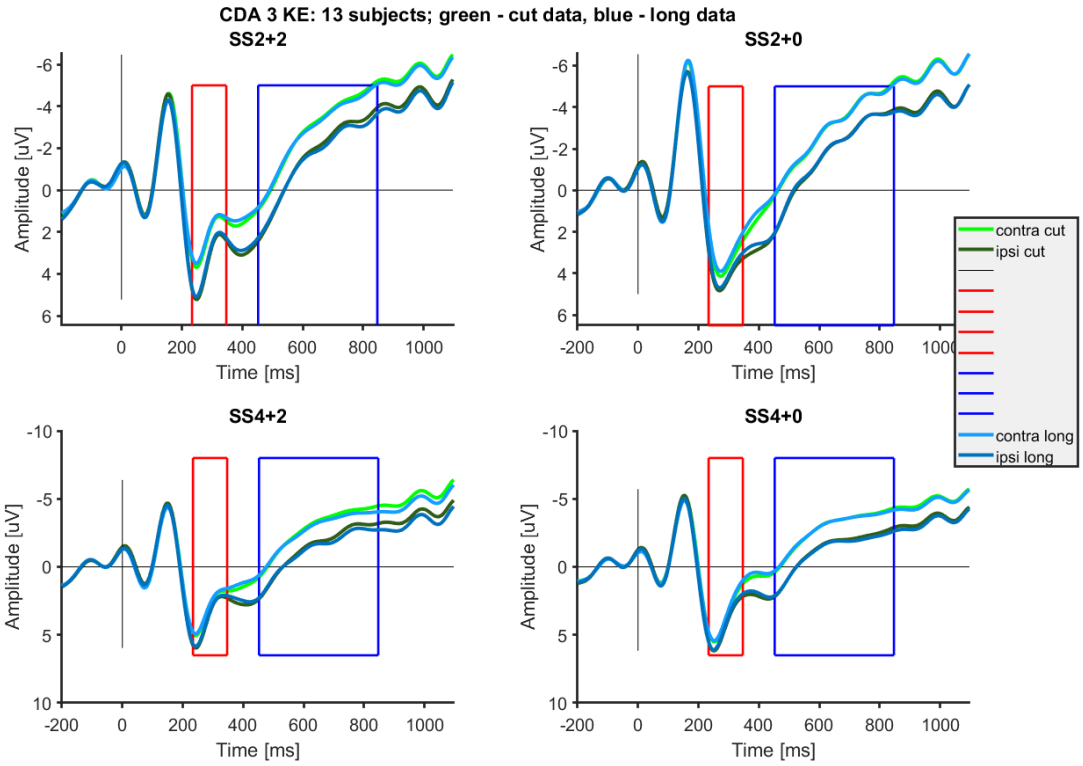

Fig. 14 Overlays of contralateral (lighter color) and ipsilateral (darker color) waveforms created from cut (green) and uncut (blue) EEG data. The waveforms belong to the CDA 3 session averaged by 13 participants in the KE group. The 2 participants had more than 40 trials in the uncut EEG data, therefore, they were excluded from the averages.

4.2.2 Detrending and Filtering

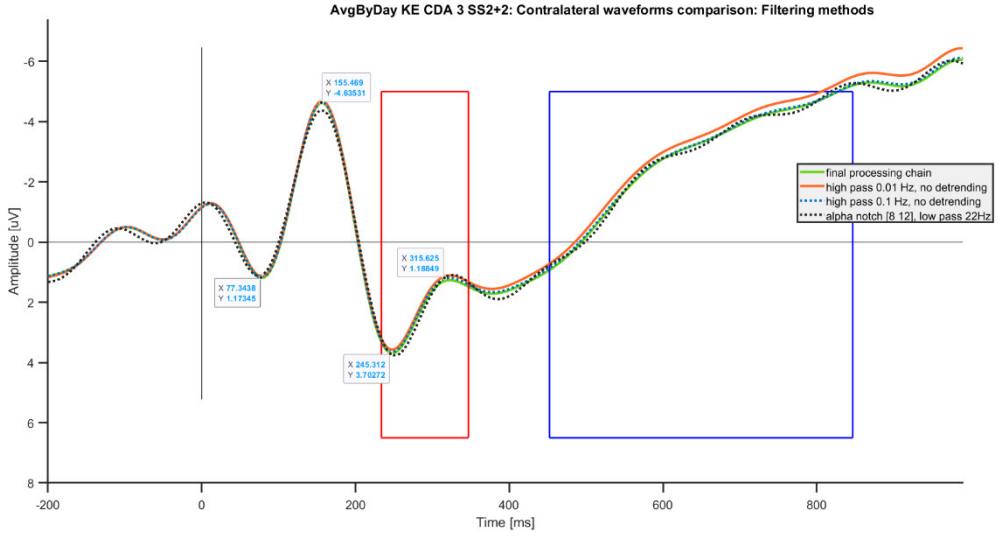

Fig. 15 Comparison of filtering methods on contralateral waveforms of CDA3 averaged by day over all subjects in the KE group, selected set size of 2 targets and 2 distractors.

The graph on Fig. 15 show a minimal variance in the contralateral waveforms averaged by day and calculated for 2 targets and 2 distractor set size. The processing pipeline with alpha notch filter (dotted black waveform) flatten the amplitude of the N1 ERP component and stretch the waveform in both directions. This causes sooner peak of the P1 ERP component and later peak of the P2 ERP component in comparison of the final processing pipeline. The difference was minimal and could be overlooked. However, the three other waveforms (final, 0.01 Hz, and 0.1 Hz) shared the shift in the early ERP latencies. In the case of the contralateral activity recorded during CDA 3 session and averaged by day over all participants in KE site, the P1 reached the peak at 77.3 ms, the N1 at 155.5 ms and P2 at 245.3 ms after the stimulus onset. The typical peak for the P1 ERP component is between 100 ms and 130 ms.

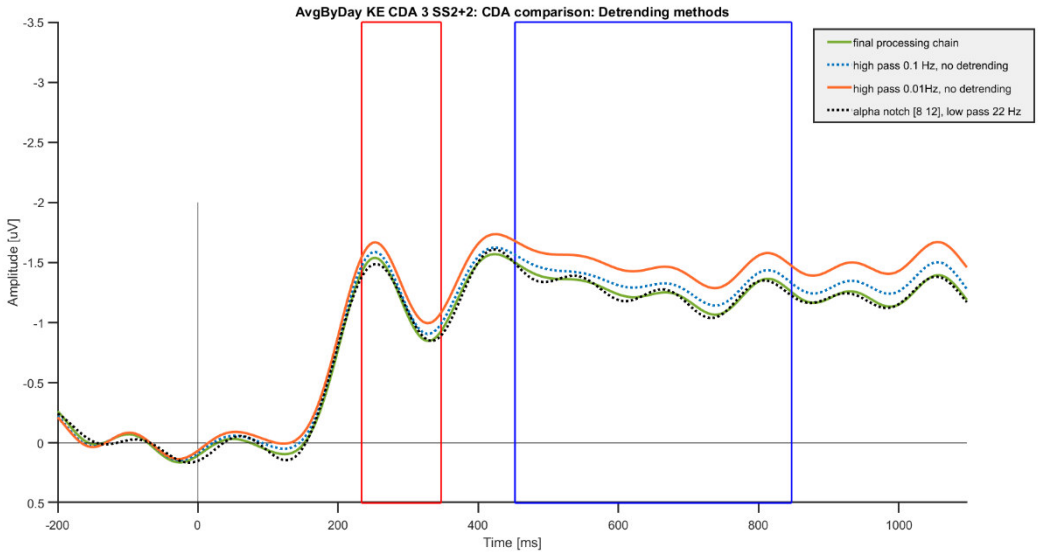

Fig. 16 Comparison of filtering methods on CDA 3 averaged by day over all subjects in the KE group, selected set size of 2 targets and 2 distractors.

The more visible effect of the filtering and detrending method can be seen at averaged CDA 3 of KE group (Fig. 16). The high pass filter 0.01 Hz was not sufficient in removing the unwanted slow drifts. Therefore, they propagated in the averaged CDA waveform and differed from the CDAs of the other filtering setups. The AUC values for N2pc and CDA of this specific example are accessible in Tab. 9 and Tab. 10 respectively.

N2pc auc	Final preprocessing chain [µV]	High pass 0.1 Hz, no detrending [µV]	High pass 0.01 Hz, no detrending [µV]	Alpha notch [8 12] Hz, low pass [22 25] Hz [µV]
SS2+2 Distractors:	-35.659	-37.231	-39.772	-35.390
SS2+0 Distractors:	-21.918	-21.730	-23.046	-23.827
SS4+2 Distractors:	-19.846	-19.632	-20.146	-19.215
SS4+0 Distractors:	-19.246	-19.021	-18.991	-19.457

Tab. 9 AUC values for N2pc of CDA3 averaged by day over all subjects in the KE group. The results were generated by the final preprocessing chain, a final chain with changed high pass filter to 0.1 Hz without detrending, a final chain with high pass filter 0.01 Hz without detrending and a final chain with alpha notch filter [8 12] Hz turned on with low pass filter of 22 Hz. The values are generated for all set sizes.

CDA auc	Final preprocessing chain [µV]	High pass 0.1Hz, no detrending [µV]	High pass 0.01Hz, no detrending [µV]	Alpha notch [8 12] Hz, low pass [22 25] Hz [µV]
SS2+2 Distractors:	-129.806	-137.189	-151.212	-126.714
SS2+0 Distractors:	-120.111	-123.428	-124.884	-124.218
SS4+2 Distractors:	-144.181	-145.751	-147.793	-145.503
SS4+0 Distractors:	-155.718	-152.479	-154.122	-158.628

Tab. 10 AUC values for CDA of CDA3 averaged by day over all subjects in the KE group. The results were generated by the final preprocessing chain, a final chain with changed high pass filter to 0.1 Hz without detrending, a final chain with high pass filter 0.01 Hz without detrending and a final chain with alpha notch filter [8 12] Hz turned on with low pass filter of 22 Hz. The values are generated for all set sizes.

4.3 CDA and Performance

We analyzed the influence of the correctness of the responses on the averaged CDA 3 waveforms of the trained group in KE. As can be seen on results, the CDA waveforms created by one type of responses did not differ from each other. In both cases, the set size of 4 targets and 2 distractors reaches the highest AUC values, as well as their waveforms are located above the waveforms of all the other set sizes. Similarly, the waveforms of the set size of 2 targets and any distractors lie beneath the other set sizes waveforms and AUCs are the smallest for them. The results suggest that the CDA did not change depending on the correctness of the response. So, the visual memory capacity is not influenced by a

performance. However, the diverse number of trials that enters into CDA creation for corrects and incorrect factors influences the SNR; the total number of trials per set size differed by approximately 800 trials.

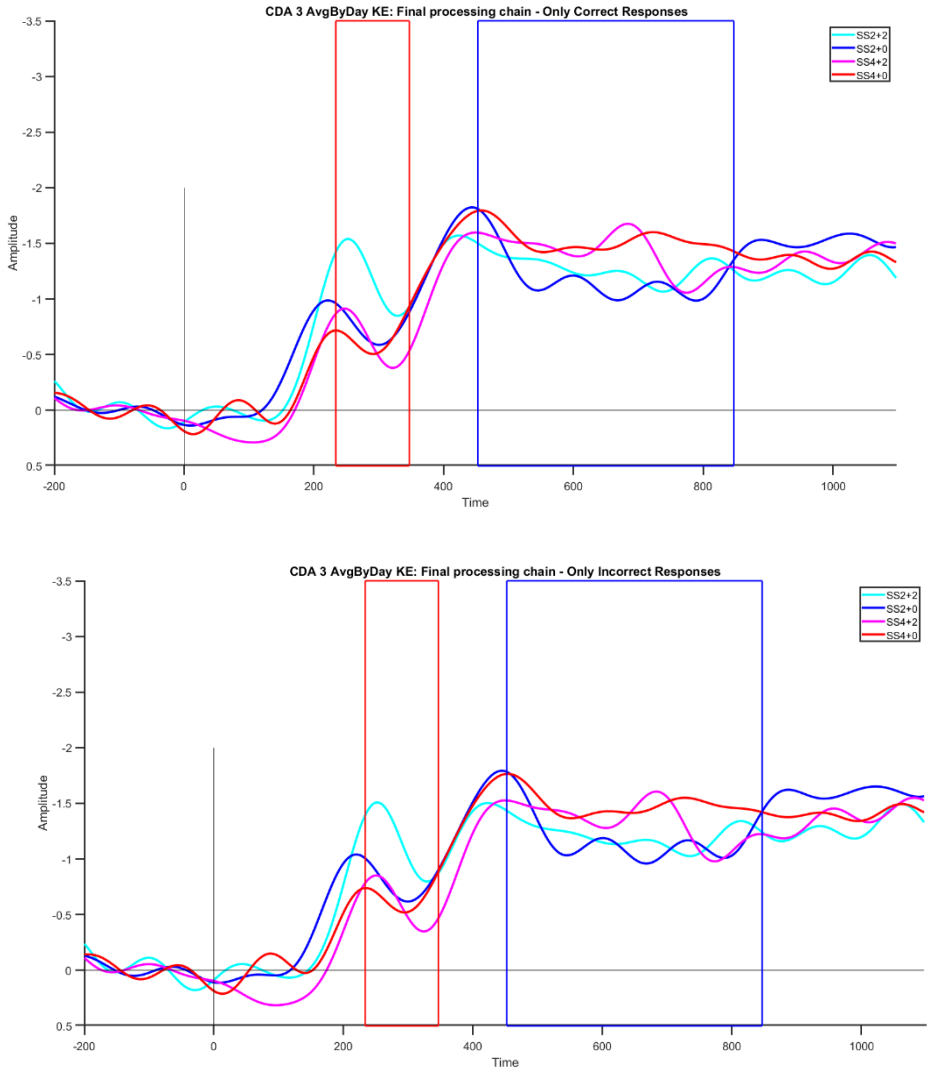

Fig. 17 CDA 3 averaged by day over all subjects in the KE group. Upper plot was assembled only from trials with **correct** responses. Lower plot was assembled only from trials with **incorrect** responses.

	O1/O2		**P3/P4**		**PO7/PO8**		**P7/P8**	
	Correct	*Incorrect*	Correct	*Incorrect*	Correct	*Incorrect*	Correct	*Incorrect*
2,2	2201	*2042*	2187	*2028*	2191	*2032*	2190	*2041*
2,0	2186	*2027*	2163	*2004*	2174	*2015*	2172	*2021*
4,2	2194	*2035*	2180	*2021*	2192	*2033*	2179	*2031*
4,0	2201	*2043*	2180	*2022*	2181	*2023*	2169	*2017*

Tab. 11 Number of trials used per electrode for unilateral activity (contralateral and ipsilateral) created by only correct or incorrect responses in CDT during CDA 3 session averaged by all participants in KE group.

	Correct responses CDA3 AvgByDay KE [µV]	**Incorrect responses CDA3 AvgByDay KE [µV]**
AUC N2pc		
SS2+2 Distractors:	-35.659	-34.460
SS2+0 Distractors:	-21.918	-22.843
SS4+2 Distractors:	-19.846	-19.142
SS4+0 Distractors:	-19.246	-19.354
AUC CDA		
SS2+2 Distractors:	-129.806	-123.073
SS2+0 Distractors:	-120.111	-119.358
SS4+2 Distractors:	-144.181	-136.280
SS4+0 Distractors:	-155.718	-151.448

Tab. 12 AUC values for N2Pc and CDA 3 averaged by day over all participants in KE created by only correct responses or incorrect responses.

4.4 Eye Blinks Effect on Performance

4.4.1 Eye Blinks during TA in CDA Session

The standard T-test performed in the MATLAB did not show any significant difference between Set 1 and Set 2 (trials with EOG artifacts in the interval [TA, TA + 500ms]. This suggests that the blinks did not influence the performance.

	Trials with TA blinks [#]	**Trials without TA blinks [#]**
Total	8270	12031
CDA 1	2280	3365
CDA 2	2978	4255
CDA 3	3012	4411
Stimulus type - 22	1906	2915
Stimulus type – 20	2346	3597
Stimulus type – 42	1816	2505
Stimulus type – 40	2202	3014

Tab. 13 Counts of trials with and without blinks during TA.

	Trials with TA blinks		Trials without TA blinks	
	Correct trials [%]	**Incorrect trials [%]**	**Correct trials [%]**	**Incorrect trials [%]**
Total mean	85.738 (±11.213)	14.280 (±11.239)	86.214 (± 10.838)	13.708 (±10.865)
CDA 1	84.303 (±12.244)	15.657 (±12.286)	85.204 (±11.589)	14.768 (±11.621)
CDA 2	87.071 (±10.107)	12.704 (±12.144)	86.761 (±10.433)	13.116(±10.492)
CDA 3	85.526 (±11.625)	14.357 (±11.610)	86.457 (±10.928)	13.471 (±10.915)
Stimulus type - 22	91.700 (±7.571)	8.239 (±7.590)	92.220(±7.318)	7.740 (±7.325)
Stimulus type – 20	93.707 (±6.503)	5.998 (±6.303)	94.130 (±5.909)	5.700 (±5.874)
Stimulus type – 42	78.031 (±9.002)	22.993(±10.231)	77.035 (±9.198)	22.879 (±9.222)
Stimulus type – 40	76.853 (±10.168)	21.969 (±9.002)	78.782 (±8.668)	21.218 (±8.668)

Tab. 14 Average percentage (and standard deviation) of correct trials with regard to the blinks in TA.

4.4.2 Pilot CDT Experiment with Eye Gaze Manipulation

The pilot study was limited by accessible participants. We tried to equalize the subjects' parameters. Both younger participants woman (24) man (29) used to play video games frequently while elder participants woman (58) and man (58) were non-gamers. In the case of both pairs, randomly selected one of them was assigned a random order of conditions (ZZ – changed gaze, FF – fixed gaze). The other one was assigned to the inverse order.

All participants had slept 6 to 8 hours the night before the experiment, they had no intake of nicotine, alcohol nor caffeine at least 20 hours. They didn't experience the eye discomfort before the experiment started.

According to the T-MENSTAT and subjective evaluation, all participant reported a full energy mode before the experiment; they were well rested, full of energy, prepared to concentrate on the task. However, after the experiment, they felt tired, sleepy and were only partially satisfied with their concentration during the whole experiment. One of the participants even reported a "boredom at the end of the experiment" and another one experienced "a rapid decrease in concentration" at the end of each condition.

The participants perceived differently the difficulty of following the instruction of the gaze unequally. One participant (IS 75) reported a fixed gaze (FF) condition as easier than a changed gaze (ZZ) condition. The other two participants (VS 67, NC 29) considered the ZZ condition being easier. The last one (IS 63) judged both conditions as equally difficult.

One of the participants reported a strategy during encoding the MA and subsequent decision making; in several trials during both conditions, he was able to create a pattern from several rectangles. In those cases, they saw a difference immediately (from Slovak metaphor "bil do očí" translated as "it was a torn in the eye"). In the rest of the cases, he reported a longer decision making (NC 29). Also, he reported a longer decision making in the ZZ condition what lead to an increased number of missed responses.

One participant (IS 63) stated that the boredom he felt at the end of the experiment resulted in worse concentration.

One participant stated that in several trials in the FF condition she lost the track of the cue arrow what exhort herto evaluate both hemifields (VS 67).

The memory capacity results

Cowan K - Descriptive Statistics

Gaze	Stim.Type[TgtDst]	Mean	Std. Deviation
FF	20	1.538	0.301
	22	1.445	0.394
	30	2.088	0.616
	32	2.030	0.625
	40	2.482	0.474
	42	2.022	1.064
ZZ	20	1.639	0.288
	22	1.566	0.186
	30	2.157	0.418
	32	1.969	0.400
	40	2.632	0.688
	42	2.056	0.785

Tab. 15 Descriptive Cowan's K – fixed gaze (FF) and changed gaze (ZZ) conditions

The average Cowan's Ks for different set sizes are listed in Tab. 15. The averaged maximal number of items held in the memory did not surpass 3 items, even in the cases of four targets (and zero or two distractors) the maximum could be 4 items. The set sizes of three and four targets reached similar values, suggesting that on average, those conditions had comparable difficulty.

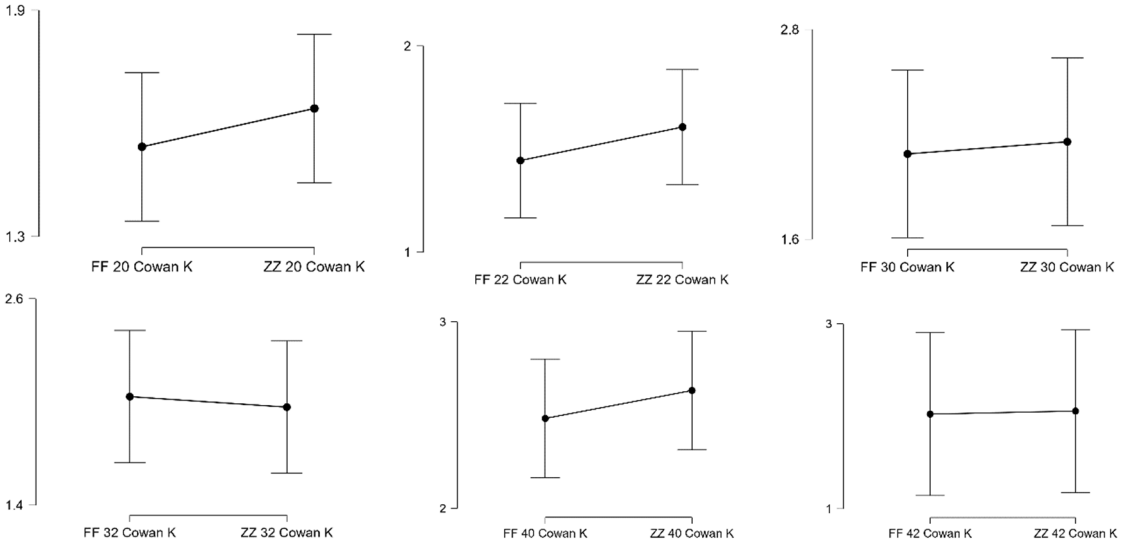

Fig. 18 Descriptive plots of the Cowan's K with error bars marked with the confidence level of 95%. While the difference between conditions was not significant, the result suggest the fixed gaze condition led to higher number of items held in the memory except for a 32 and 42 set sizes.

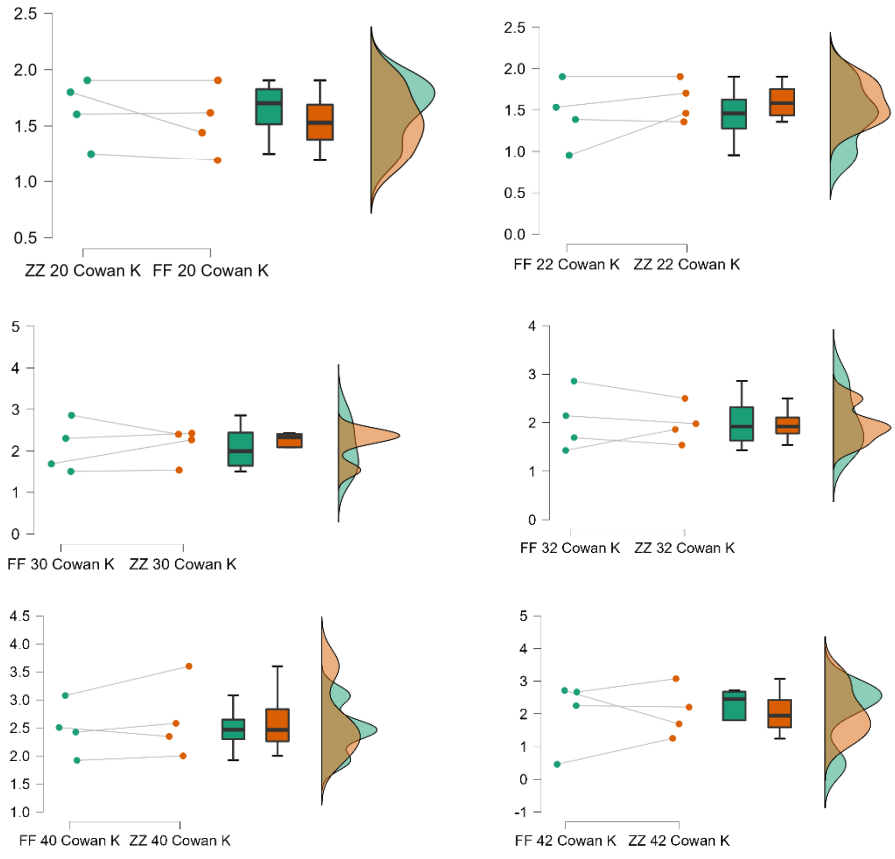

Fig. 19 Individual differences in Cowan's K in gaze conditions.

Because of the low number of participants, we looked also on individual differences in gaze conditions. Corresponding to the subjective reports of the conditions' difficulty, the participants had unequal memory load changes between the gaze conditions. Participant VS

67 reported a changed gaze condition as easier and her Cowan's K was higher for that condition. Participant NC 29 had lower cowan's K for 20, 22 and 42 set sizes in changed gazed condition that he reported being easier than in fixed gaze condition. IS 75 reported fixed gazed condition as easier and she had a higher Cowan's K in this condition for 20, 22 and 30 set sizes. IS 63, who considered both conditions to be of the same difficulty, had no differences in Cowan's K for 20 and 22 set sizes. The lower Cowan's K had for 3 targets in the changed gaze condition and reversely in the case of 4 targets.

Paired Samples T-Test

Measure 1		Measure 2	t	df	p
FF 20 Cowan K	-	ZZ 20 Cowan K	-1.161	3	0.330
FF 22 Cowan K	-	ZZ 22 Cowan K	-1.313	3	0.281
FF 30 Cowan K	-	ZZ 30 Cowan K	-0.328	3	0.765
FF 32 Cowan K	-	ZZ 32 Cowan K	0.356	3	0.745
FF 40 Cowan K	-	ZZ 40 Cowan K	-1.058	3	0.368
FF 42 Cowan K	-	ZZ 42 Cowan K	-0.087	3	0.936

Note. Student's t-test.

Tab. 16 The comparison of Cowan's K between fixed gaze and changed gaze condition by a paired sample T-test.

According the results in Tab. 16, there was no significant difference in memory capacity in the fixed gaze and changed gaze conditions across group.

Accuracy results

Correct trials [%] - Descriptive Statistics

Gaze	Stim.Type[TgtDst]	Mean	Std. Deviation
FF	20	0.869	0.094
	22	0.848	0.107
	30	0.825	0.129
	32	0.800	0.124
	40	0.756	0.075
	42	0.706	0.121
ZZ	20	0.881	0.125
	22	0.863	0.075
	30	0.844	0.080
	32	0.800	0.074
	40	0.794	0.107
	42	0.731	0.107

Tab. 17 Descriptive statistics of correct trials in percentage according set size and gaze condition.

The accuracy decreased with the increasing number of targets and distractors. The paired sample t-test showed for all set sizes worse accuracy in the fixed gazed condition than in the changed gaze condition. There were no statistically significant differences between the fixed gaze and changed gaze condition. The results may lead to the conclusion that the changes of gaze during the TA had no effect on accuracy of participants. However more participants are necessary to confirm either the null hypothesis of no difference between conditions or the worse accuracy in the standard CDT test without the change of the gaze.

Paired Samples T-Test

Measure 1		Measure 2	t	df	p
FF 20 correct %	-	ZZ 20 correct %	-0.397	3	0.718
FF 22 correct %	-	ZZ 22 correct %	-0.795	3	0.485
FF 30 correct %	-	ZZ 30 correct %	-0.441	3	0.689
FF 32 correct %	-	ZZ 32 correct %	-9.065e-16	3	1.000
FF 40 correct %	-	ZZ 40 correct %	-1.567	3	0.215
FF 42 correct %	-	ZZ 42 correct %	-0.632	3	0.572

Note. Student's t-test.

Tab. 18 The comparison of accuracy between fixed gaze and changed gaze condition by a paired sample T-test.

5 Discussion

5.1 Differences in preprocessing methods

The cutting of data was performed due to the excessive drifts caused by moving or electrode reattaching during the pauses between block. The trials started before the EEG was steadied and the drifts propagated into EEG during trials. The worries that the "flying" data would corrupt the final CDA were not confirmed, at least the final processing chain that we created did not show the differences.

In the step of removing the slow drifts in EEG data that could be caused by sweating, we observed an example of negative influence of the preprocessing method on data. The polynomial spline function with nodes set at the beginning of the processed time window did not remove the slow drifts completely; the smoothed signal proceeded the actual drift. The nodes calculated with the central step fit better, in some cases the method was too fine. The Savitzky-Golay filter represented a compromise between eliminating the slow drifts and not removing too much of the data because of excessively fine detrending method.

The influence of the 8 Hz filters was detected during the analysis of the early ERPs components. Both, the low pass filter of 8 Hz and its training equivalent the alpha notch filter of [8 12] Hz with low pass filter of 22 Hz smoothed the early ERP components. They aided to clear CDA estimates but distorted the amplitudes and the latencies of the early ERPs (mainly P1 and N1). For that reason, it is important to decide before a selection of preprocessing methods whether one wants to investigate early fast ERPs or later slower $N2_{pc}$ and CDA components. Evidently, the same process cannot be used for different types of analysis. Also, the similar course of the contralateral waveforms resulting in differences in CDA waveforms pointed out the unpredictable outcome of the averaging that can emphasize the common characteristics and filter out the individual differences.

The unequalness in the number of detected artifacts in KE and BA group lead to unequal numbers of trials (or time series in our case) of final CDAs. The difference could influence the signal-to-noise ratio and therefore it is hard to tell whether the final CDAs were impacted only by a training condition in KE group. Even though we applied the weighted average in combination with the electrode pair artifact rejection, the final CDAs of BA and KE groups did not have an equal representation in number of trials. Moreover, with only 15 participants in each group, this reduces a statistical power. Železníková performed a comparison of the least square means estimates for ANOVA factors (group, session, set size). The results

suggested that the two weeks training in VR led to a small change at the level of several decimals of μV in CDA; the difference was significant for set sizes of 4 targets ($p < 0.05$, 0.035) (Železníková, 2021). She also concluded that the higher statistical power would require more participants. It is necessary to mention that the original intention contained recordings of 20 participants per group, however the COVID-19 pandemic outbreak resulted in only 15 participants in each group.

The recordings of both groups were performed with the same instruments, they differed by researchers who collected the data. By looking on the numbers of detected artifacts, one may say that the recordings in BA group were done by higher precision and better data collection methodology. Therefore, to increase the probability of the approximately equal number of samples, we suggest to perform all recordings according to the same methodology by equally trained data collectors, if not by the same one.

Our decision to use a weighted average instead of an average for CDA creation gave us a possibility to reject only artifacts on pair of electrodes. We obtained more trials, so the signal-to-noise ratio increased with contrast to the case when channels of all electrodes were rejected. We tried to eliminate any unwanted consequences of this approach that were presented by Luck (2014).

The limitation of the preprocessing outcome is intertwined with the number of participants. Since it was not possible to record more participants, even the one with a lot of detected artifacts and rejected trials were included in the experiment. The participants were not randomized, they were selected at each site (KE, BA) according the prepared conditions. The initial ability to filter the distractor, that were the main research topic in the experiment, was not balanced between participant. A more difficult set sizes (higher number of targets and/ or distractors) for individuals with high initial abilities in filtering and inverse, easier settings of set sizes, could more accurately map the progress of visual working memory abilities across the experiment.

5.2 Blinks and Eye Gaze in CDA and Performance

The CDA is influenced by horizontal eye movements only during the MA and the retention period. Therefore, the saccades during the TA should influence only the behavioral performance. Since the blink lasts up to 400 ms (Sweeney & Raju 2013) and the TA is shown for 3 seconds, the blink should not cause missing of the visual input. Since we could not differentiate between blink and a saccade occurred during blink, we assumed that all blinks

contained saccades. This led to rejecting all trials that contained a detected EOG artifact during MA. Several participants in the CDA experiments were blinking systematically before their response. Without the knowledge of the influence of saccades during TA on the behavioral performance, we had to reject more trials what caused lower signal-to-noise ratio. The statistical power and noise removal from the data were behind the decision to look on effect of blinks and saccades on performance.

We studied the influences of the blinks during the TA on the accuracy in CDT. The data originally came from the CDA experiment. We manipulated the conditions and included participants from both groups. Our assumption was that the training in VR should not influence the accuracy caused by blinks. The Cowan's K, that represent the memory load, and the accuracy were calculated by MATLAB and tested by unpaired two sample t-test that confirmed the hypothesis about the non-differences between conditions. However, we were limited by a small sample and we assumed that each blink was accompanied by a saccade.

We were aware of the necessity to differentiate between the effect of blink and saccade. The original plan with the usage of eye-tracker for a modified CDT experiment had to be changed because of logistic and technical reason. So, we executed a pilot experiment with the aim of find out whether there may be differences in performance when one looks at a TA directly during a CDT. This manipulation should represent the horizontal saccadic movement.

Two set of CDT measurements were recorded, one with standard instruction to look at the center of screen. During the other one, the participants were asked to look on cued hemifield when TA was shown on the screen. We also asked of them to evaluate their performance and asses the difficulty of both conditions.

The results should be taken with a grain of salt. Only the four participants were of the non-representative sample (two different age groups, different habits in video games playing). The average Cowan's K and accuracy did not have a statistically significant differences between gaze conditions. The individual differences partially corresponded to reported difficultness of corresponding condition while they did not agree about which gaze condition was the easiest. Also, the impact of age on working memory was visible across group, with the highest Cowan's K present at the youngest participant. Participants reported an increasing fatigue and boredom throughout CDTs with increasing time that also influence their focus, as was reported. The results suggested that the fixed gaze condition could connected with a lower accuracy while the memory load seems to be individually dependent. The higher statistical power is necessary to confirm or reject this observation.

5.3 Relation to Cognitive Science

The diploma thesis had a broad spectrum of tasks. It was necessary to get familiar with the topic of contralateral delayed activity and its connection to the visual working memory. The understanding of the methods for EEG data processing, their implementation was crucial to the programing a MATLAB processing chain. We learnt about the impact of the chosen processing methods on a final CDA waveform and its neurological and behavioral implications. Similarly, we spent a lot of time with the PsychoPy software just to find out that its features were not sufficient for the intended research and therefore we had to modify not only the size of the additional CDT experiment but also the aims of the thesis. So, the computer science played in important role in assessing the pilot CDT experiment. The edit of the CDT resulted into an added self-evaluation and report of experience added a piece form the phenomenological aspect. After all, we gained a wealth of knowledge from various scientific fields and learned to combine them into a functioning machine.

Conclusion

The main aim of the thesis was a study of the neural measures and behavioral performance of the change detection task (CDT). We studied the principles of measurement and processing of the ERP components. We identified and described the ERP components related to CDT in MATLAB software. Finally, we studied the variability in ERP components as well as behavioral success caused by changed in the EEG data processing along with the changes in the CDT protocol. The ERP waveform is a difference of contralateral and ipsilateral activity CDA and it represents maintaining objects in working memory.

Our findings confirmed the assumption that the processing of neurological data may influence the analysis and the results. We showed the proofs on several examples, mainly concluding that the processing pipeline suitable for analysis of the later ERP components (CDA, N2pc) is not suitable for an analysis of the early ERP components (e.g., P1, N1).

Behavioral performance of the CDT, specifically the accuracy, may be affected by changes in the gaze direction. The additional research with significantly higher number of participant than was accessible during a pilot study and supported by an eye-tracker device needs to confirm the suggestion. However, we did not recommend including trials with the saccades and the blinks accompanied by saccades during a presentation of test array in the CDT when analyzing the behavioral performance.

Also, we suggest a further study of the possible link between a memory load during CDT and participants' self-evaluation of performance.

Concerning the differences of the number of artifacts between CDA groups, we advise to secure homogenous methodology of EEG data acquisition across the whole experiment.

The constrictions of COVID-19 outbreak on the experimental design was a sad reality and we hope that both experiments – the influence of the VR reality on the CDA and the influence of gaze direction during CDT – will be conducted again with a larger number of participants while maintaining a professional experimental design.

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