COMENIUS UNIVERSITY IN BRATISLAVA

FACULTY OF MATHEMATICS, PHYSICS AND INFORMATICS

ANALYSIS OF ELECTROPHYSIOLOGICAL CORRELATES OF SPATIAL WORKING MEMORY AND FILTRATION EFFICIENCY

Diploma thesis

2021 **Barbora Michalková**

COMENIUS UNIVERSITY IN BRATISLAVA
FACULTY OF MATHEMATICS, PHYSICS AND INFORMATICS

ANALYSIS OF ELECTROPHYSIOLOGICAL CORRELATES OF SPATIAL WORKING MEMORY AND FILTRATION EFFICIENCY

Diploma thesis

Study Programme: Cognitive Science
Field of study: 2503 Cognitive Science
Department: Department of Applied Informatics
Supervisor: RNDr. Barbora Cimrová, Phd.

2021 **Barbora Michalková**

88135171

Comenius University in Bratislava
Faculty of Mathematics, Physics and Informatics

THESIS ASSIGNMENT

Name and Surname:	Bc. Barbora Michalková
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: Analysis of electrophysiological correlates of spatial working memory and filtration efficiency

Annotation: Contralateral delay activity (CDA) measured by EEG over posterior regions is a known correlate of spatial working memory capacity. To make the most of the working memory capacity, it is important to effectively filter out irrelevant stimuli. This ability can be increased by training. Extraction of the resulting CDA curve is sensitive to thorough preprocessing of the EEG signal, especially to thorough removal of activity of non-cerebral origin (so-called EEG artefacts).

Aim: Perform an experiment on a control group of healthy volunteers, to record their EEG during the performance of the task on the visual working memory in three repeated sessions. Analyze the recorded EEG data in terms of final, event-related potentials of contralateral delay activity, with an emphasis on the thorough application of the combination of automatic and manual detection of artefacts in the Brain Vision Analyzer program (Brain Products, Gmbh). Evaluate the effect of task conditions and task repetition on the final amplitude of CDA waveforms.

Literature: Li, C. et al. (2017). Visual working memory capacity can be increased by training on distractor filtering efficiency. Frontiers in psychology, 8, 196.
Luria, R. et al. (2016). The contralateral delay activity as a neural measure of visual working memory. Neuroscience & Biobehavioral Reviews, 62, 100-108.

Supervisor:	RNDr. Barbora Cimrová, PhD.
Department:	FMFI.KAI - Department of Applied Informatics
Head of department:	prof. Ing. Igor Farkaš, Dr.
Assigned:	21.10.2020
Approved:	21.10.2020

prof. Ing. Igor Farkaš, Dr.
Guarantor of Study Programme

.... Student

.... Supervisor

88135171

Univerzita Komenského v Bratislave
Fakulta matematiky, fyziky a informatiky

ZADANIE ZÁVEREČNEJ PRÁCE

Meno a priezvisko študenta:	Bc. Barbora Michalková
Študijný program:	kognitívna veda (Jednoodborové štúdium, magisterský II. st., denná forma)
Študijný odbor:	informatika
Typ záverečnej práce:	diplomová
Jazyk záverečnej práce:	anglický
Sekundárny jazyk:	slovenský

Názov: Analysis of electrophysiological correlates of spatial working memory and filtration efficiency
Analýza elektrofyziologických korelátov pracovnej priestorovej pamäti a schopnosti filtrácie

Anotácia: CDA snímaná pomocou EEG nad posteriórnymi oblasťami predstavuje známy korelát kapacity priestorovej pracovnej pamäti. Pre maximálne využitie kapacity pracovnej pamäti je dôležité efektívne odfiltrovať irelevantné podnety. Túto schopnosť je možné tréningom zvýšiť. Extrakcia výslednej CDA krivky je citlivá na dôsledné predspracovanie EEG signálu, najmä na dôkladné odstránenie aktivity non-cerebrálneho pôvodu (tzv. EEG artefektov).

Cieľ: Realizujte experiment na kontrolnej skupine zdravých dobrovoľníkov, nasnímajte ich EEG počas plnenia úlohy na pracovnú vizuálnu pamäť v rámci troch opakovaných sedení. Analyzujte namerané EEG dáta v zmysle finálnych, na udalosť viazaných potenciálov (ERP) kontralaterálnej oneskorenej aktivity, s dôrazom na precízne využitie kombinácie automatickej a manuálnej detekcie artefaktov v programe Brain Vision Analyser (Brain Products, Gmbh). Overte efekt podmienok úlohy a jej opakovania na výslednú amplitúdu CDA kriviek.

Literatúra:
Li, C. et al. (2017). Visual working memory capacity can be increased by training on distractor filtering efficiency. Frontiers in psychology, 8, 196.
Luria, R. et al. (2016). The contralateral delay activity as a neural measure of visual working memory. Neuroscience & Biobehavioral Reviews, 62, 100-108.

Vedúci:	RNDr. Barbora Cimrová, PhD.
Katedra:	FMFI.KAI - Katedra aplikovanej informatiky
Vedúci katedry:	prof. Ing. Igor Farkaš, Dr.
Dátum zadania:	21.10.2020

Dátum schválenia: 21.10.2020 prof. Ing. Igor Farkaš, Dr.
garant študijného programu

....

študent vedúci práce

Declaration

I hereby declare that I elaborated this master's thesis independently without any unauthorised third-party support. Used literature and ideas taken from other sources are cited as such.

Bratislava, 2021

Acknowledgment

I would like to thank my supervisor RNDr. Barbora Cimrová, Phd. for sharing with me the knowledge about various aspects of EEG research and for her guidance throughout the whole course of the experiment. Also, I would like to thank Danijela and Terezka for their valuable advice in the writing process.

ABSTRACT

This study examines the neural corelates of working memory represented by contralateral delay activity (CDA) amplitude modulations associated with the number of remembered items. CDA is defined as a sustained negative voltage over the hemisphere that is contralateral to the memorized hemifield, its amplitude increases significantly with the number of representations being held in the memory and reaches a limit at each individual's memory capacity (Vogel et al., 2005). To achieve maximum usage of working memory capacity possible, it is necessary to be able to filter out all irrelevant stimuli efficiently, which is a skill that can be improved by training (Luria et al., 2016).

This thesis is part of a bigger project that hypothesizes that cognitive training in virtual reality (VR) can improve behavioural performance in working memory (tested offline in a different task outside VR) and that this effect will be visible on its neural correlate - the amplitude of CDA. We aim to determine whether performance in visual working memory (VWM) task and filtering efficiency itself are trainable and if so, whether this effect is observable also by its direct neurophysiological correlate. To be able to evaluate the effect of training in VR we need to have a control group without the training but with the same repeated measures of CDA. Only if there will be an effect of training (experimental group) but not the effect of repeated CDA measures (control group) we can conclude the training had the desired effect. We intended to contribute to the main project by carrying out an experiment on the control group of healthy participants, recording their EEG while they were performing the VWM task, and subsequent thorough analysis of recorded EEG to extract the final event-relate potentials (ERPs) in a form of CDA waveforms with the emphasis on the careful pre-processing of the data using Brain Vision Analyzer software.

We successfully collected data of the control group and recorded EEG of sixteen participants while they were performing VWM task. In order to prepare the data for further statistical analysis and comparison with data of the experimental group, we conducted an EEG analysis. Here, we present all the steps of the analysis that have led to the final CDA waveform as well as the theoretical background and practical tips suggested by other authors that helped us to set the appropriate parameters of pre-processing. In line with previous studies on CDA, the analysis of our data showed that number of items to remember affected the amplitude of CDA. No interaction of the number of distractor and session suggests that repeated measures of CDA do not have an effect on filtering ability. Whether the training in VR environment has an effect on filtering could and should be tested in subsequent steps.

Keywords: working memory, contralateral delay activity, electroencephalography, event-related potentials, EEG analysis, artifact rejection

ABSTRAKT

Práca skúma neurálne koreláty pracovnej pamäte, ktoré sú prezentované amplitúdovými moduláciami kontralaterálnej aktivity oneskorenia (contralateral delay activity, CDA) spojenej s počtom zapamätaných položiek. CDA je definovaná ako vytrvalé záporné napätie na hemisfére, ktorá je kontralaterálna k zapamätanej strane a jeho amplitúda sa významne zvyšuje s počtom položiek v pamäti a dosahuje limit na základe individuálnej kapacity jednotlivca (Vogel et al., 2005). Pre docielenie maximálneho možného využitia kapacity pracovnej pamäte, je potrebné mať schopnosť efektívne odfiltrovať irelevantné podnety, čo je schopnosť, ktorá môže byť vylepšená prostredníctvom tréningu (Luria et al., 2016).

Táto práca je súčasťou väčšieho projektu, ktorý predpokladá, že kognitívny tréning vo virtuálnej realite (VR) môže vylepšiť behaviorálny výkon pracovnej pamäte (testované nezávisle v inej úlohe mimo VR) a že tento efekt bude viditeľný na jeho neurálnom koreláte – CDA amplitúde. Naším cieľom je zistiť, či je výkon v úlohe vizuálnej pracovnej pamäte (visual working memory, VWM) a samotná účinnosť filtrovania trénovateľná, a ak áno, či je tento efekt pozorovateľný aj prostredníctvom jeho priameho neurofyziologického korelátu. Aby sme mohli vyhodnotiť efekt tréningu vo VR, musíme mať kontrolnú skupinu bez tréningu, ale zároveň s rovnakými opakovanými mierami CDA. Iba v prípade, že dôjde k efektu tréningu (experimentálna skupina), ale nie k efektu opakovaných meraní CDA (kontrolná skupina), môžeme dospieť k záveru, že tréning mal požadovaný účinok. Naším zámerom bolo prispieť do hlavného projektu uskutočnením experimentu na kontrolnej skupine zdravých participantov, zaznamenať ich EEG počas vykonávania VWM úlohy a následne dôkladne analyzovať zaznamenané EEG dáta s cieľom extrahovať finálne, na udalosť viazané potenciály (event-related potentials, ERP) vo forme kriviek CDA s dôrazom na precízne predbežné spracovanie nazbieraných dát pomocou softvéru Brain Vision Analyzer.

Úspešne sme nazbierali dáta kontrolnej skupiny a zaznamenali EEG šestnástich účastníkov, ktorí vykonávali VWM úlohu. Aby sme dáta pripravili na následnú štatistickú analýzu a porovnanie s dátami experimentálnej skupiny, vykonali sme EEG analýzu. V tejto práci prezentujeme všetky kroky analýzy, ktoré viedli k finálnym CDA krivkám, ako aj teoretické východiská a praktické tipy, ktoré navrhli iní autori a ktoré nám pomohli nastaviť príslušné parametre predspracovania dát. V súlade s predchádzajúcimi štúdiami o CDA, analýza

našich údajov ukázala, že počet položiek, ktoré si jedinec musel pamätať, ovplyvnil amplitúdu CDA. Žiadna interakcia počtu distraktorov a sedení nenaznačuje, že opakované merania CDA by mali vplyv na schopnosť filtrovania. To, či má výcvik vo VR prostredí vplyv na filtrovanie sa bude testovať v ďalších krokoch projektu.

Kľúčové slová: pracovná pamäť, CDA, elektroencefalografia, ERP, EEG analýza, odmietnutie artefaktov

Contents

List of Figures

List of Tables

Abbreviations

CDA Contralateral Delay Activity

EEG Electroencephalography

EOG Electrooculography

ECG Electrocardiography

ERP Event-related potential

VR Virtual reality

VWM Visual Working Memory

WM Working memory

Introduction

Working memory has been a point of interest in psychology and neurology research for a long time, since this executive function is involved in various types of cognition and in everyday life, too. The particular aspects of working memory have been broadly examined with the goal to define its main characteristics. One of the unanswered questions of working memory is whether it can be improved by a training and if so, what is the appropriate training. There have been many attempts to determine the trainability of working memory that have not resulted in a clear answer yet. Nevertheless, behavioural performance was usually considered in the evaluation of trainability of working memory. In this thesis, we present a study examining a phenomenon called contralateral delay activity (CDA). It is a direct correlate of visuospatial working memory defined as sustained negative voltage over the hemisphere, that is contralateral to the memorized and based on the number of items that are held in one's working memory. It is a relatively new concept that has been broadly investigated mostly in recent years but represents many unanswered questions in regard to its character and form.

This thesis represents a contribution to the project that tries to examine a direct neurophysiological correlate of working memory and to determine whether it can be affected and enhanced by a training in virtual reality (VR) environment. The aim of this study is to carry out an experiment on the control group of healthy participants and record the EEG while performing visual working memory tasks and to conduct an EEG analysis of the collected data in terms of final event-related potentials (ERP) of contralateral delay activity, emphasizing the precise use of a combination of automatic and manual artifact rejection in Brain Vision Analyzer. Furthermore, we intent to present guidelines and practical tips of how EEG experiment should be conducted, what are the pitfalls and strengths of such an experiment and what are the main rules to be followed in later analysis of the collected neurophysiological data.

First, we present a short general introduction into the issue of working memory to explain its main characteristics and hypnotized theories. Afterwards, we describe the neurophysiology behind visual working memory and the issue of CDA. The theoretical background is followed by an outline of the current research. The crucial part of the thesis is the section, where we talk about the specific aspects of EEG experiment and later analysis. The outcome of this study will be passed to the main project to be used as data of control group and to be compared with experimental group to make further statements.

1 Working Memory

Human cognition is a complex system involving various structures that help people to solve everyday problems and to adapt to dynamically changing environment. Memory is one of the crucial cognitive structures, it works in a collaboration with other functions that together create an effectively working cognitive system. By definition, memory presents a faculty of encoding, storing and retrieving information (Squire, 2009), divided into four basic types: sensory, short-term, long-term and working memory (WM) (Nelson Cowan, 2008). WM, a subsystem essential for our research, constitutes an ability to memorize information and to adaptively change it (Christophel et al., 2017), being in close connection with short-term memory. Cowan (2008) describes their relationship, claiming that WM includes short-term memory together with other additional processing mechanisms that help to make use of it. WM is defined as a limited capacity system that temporarily stores information in an accessible state and allows one to work on a complex task while holding this information in mind, and thereby supports human thought processes (Adams et al., 2018; Alan Baddeley, 2003). The limitation refers to the maximum number of objects that one can hold in WM, however, there are more opinions on the extent of this limitation. Miller (1956) interpreted it as a capacity of seven plus or minus two items ("magical number seven plus or minus two"). Number seven as an approximate capacity of WM was also supported later by Luck & Vogel (1997). Cowan opposed this assumption claiming that Miller's number seven was only rough estimate and suggests that number four is a more accurate number presenting the capacity of WM.

WM is often conceptualized as comprising two basic functions: short-term storage of information and executive processes that control what is retained (A Baddeley, 1992; D'Esposito & Postle, 2015). Hence, current conceptions understand WM as a dynamic system that includes both maintaining and manipulating information processes (Wingfield, 2016). Although it is certain that WM is limited, as also mentioned in the definition of WM (Alan Baddeley, 2003), Ma and collaborates (2014) argue that the WM definition becomes incomplete by ignoring quality of representations as an important factor of WM and considering only quantity of items to be maintained. Since the main concentration in investigating the capacity of WM is in its limitation and the quantity of representation that can be held, they highlighted the significance of the complexity of items affecting the WM capacity.

1.1 Working Memory and Attention

WM works in a close connection with other systems that allow it to operate effectively in a real world. There is a broad agreement that it is in close relationship and highly depends on attention (Awh et al., 1998; Nelson Cowan & Oxford University Press, 1997; Kiyonaga & Egner, 2013; Oberauer, 2009). Some believe that the nature of this cooperation lies in the attention's role in controlling the activation, maintenance, and manipulation of representations in WM (Kiyonaga & Egner, 2013). It is now considered a fact that a connection exists between WM and attention, however, what is not determined yet is to what extent one cannot operate without the other. The first problem is in the interpretation of attention itself, since it can be understood either as a limited resource, or as selective information processing (Oberauer, 2009). Attention as a resource assumes that this resource is responsible for the limited capacity of WM. In contrast, attention as a selection mechanism sees connection with WM in cognitive control and mechanisms that control its contents (e.g. filtering ability).

Chun & Turk-Browne (2007) agree with the view of the existing relationship between WM and attention, but they claim that with growing neuroimaging evidence the distinction between them becomes increasingly less clear. Teng & Kravitz (2019) agree that WM, specifically visual WM (VWM), is based on directing attention, and also argue that its impact extends to the levels of perceptual processing. Therefore, they see a strong connection between WM and perception as well, since their claims are based on neurophysiological evidence of overlapping of neuronal populations supporting VWM and perceptual processing.

1.2 Models of Working Memory

To understand the complex processes of WM, there have been many attempts to create a model to describe a series of its interactive components (short-term memory model [Bower, 1968], long-term working memory [Ericsson & Kintsch, 1995]). One of the most established models of WM was proposed by A. D. Baddeley & Hitch (1974) called multi-component model of WM (demonstrated in *Figure 1*). It was created by expanding the notion of passive short-term memory to an active, dynamic system that provides a basis for complex cognitive abilities (RepovŠ & Baddeley, 2006). The original model encompassed three components, including one central system, called central executive, and two unimodal storage systems - phonological loop and visuospatial sketchpad (A. D. Baddeley & Hitch, 1974; RepovŠ & Baddeley, 2006). For a long time, these three components were successful in giving integrated data from humans, but also neurophysiological, developmental and neuroimaging data. However, there are several phenomena (e.g. WM span task [1] [A. D. Baddeley et al., 2019]) that are not easily captured by the original model (Alan Baddeley, 2000). For that reason, a further component, termed episodic buffer, was added into the model (Alan Baddeley, 2000), representing a multimodal store capable of integration of the information into unitary episodic representations (RepovŠ & Baddeley, 2006). Each module in the model has its own specific function. The visuospatial sketchpad presents a temporary storage for visual and spatial input, the phonological loop represents a buffer of more immediate interest for spoken input (Wingfield, 2016) and the central executive serves as a control system of limited attentional capacity (Alan Baddeley, 2003).

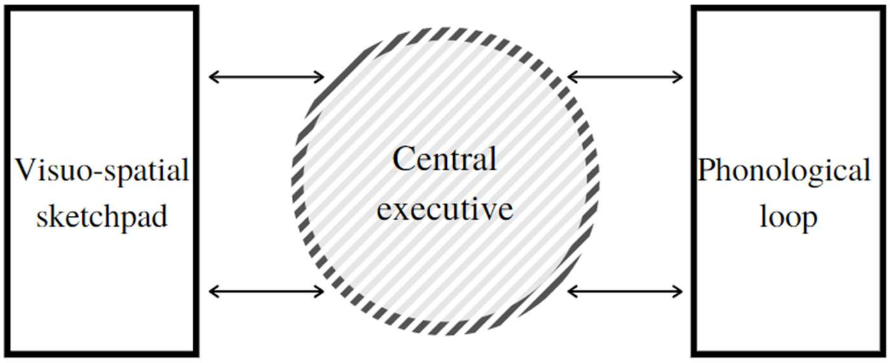

Figure 1 – Scheme of multi-component model of WM by Baddeley and Hitch (1974).

1.3 Visual Working Memory

Visual working memory (VWM), concerning central executive, episodic buffer and visuospatial sketchpad from the model previously described (phonological loop excluded), can be understood as an active maintenance of attention to the visual items important for the ongoing task or behaviour (Chun, 2011). It allows the visual information to be extended over time without the presence of the sensory input (N. Cowan, 2001). Similarly to WM in

[1] WM span task is used to measure WM capacity. The most used are counting span, operation span and reading span task (Conway et al., 2005).

general, VWM is limited as well. The ongoing question remains whether VWM is limited by fixed number of objects, or whether its capacity is reduced as object complexity rises? The answer to this question is still not completely clear since there is growing research and evidence on both sides of this open issue.

The first point of view suggests that fixed number of objects are presented in VWM, regardless of the complexity of them (Adam et al., 2017; Awh et al., 2007; S. J. Luck & Vogel, 1997; Vogel et al., 2001; Vogel & Machizawa, 2004; Xu & Chun, 2006). Although this opinion has a relatively strong support base in the general discussion about this topic, there is also evidence that supports the other point of view by reporting marked reductions in capacity as item complexity increased (Alvarez & Cavanagh, 2004; Eng et al., 2005). In the context of this issue, it might seem that both, number of items to be remembered and the complexity of them, play an important role in behavioural and neurophysiological performance in the VWM task. Xu and Chun (2006) support this notion, claiming that both, fixed number of objects and object complexity, determine VWM.

1.4 Neural Mechanisms of Visuospatial Working Memory

In this chapter, we are going to describe the neurophysiology of the processes described in the previous chapter. Visuospatial WM is a complex, highly organized system and there are several neural structures related to it. First, as it was already briefly outlined above, WM is not an individual separate unit but is tightly intertwined with other cognitive functions, therefore we cannot find its origin in a single brain area or specific neural circuit. As Logie et al. (2020) stated, whether considered from a cognitive or neural perspective, WM may not involve any discrete systems, but it may rather be understood as a functionality resulting from the control of sensorimotor and representational systems.

Neuroimaging studies suggest that prefrontal cortical areas show activation during the time when information is manipulated in memory (WM) (together with other executive functions like planning, emotional responses, etc.) (Gutierrez-Colina et al., 2021). The ongoing research regarding this topic still investigates neural responses during WM performance focusing on finding more information about which brain areas underlie its complicated processes. It is believed that a better understanding of WM as a cognitive process might lead to more accurate knowledge about its neural origin. Since from the neurological perspective, the concept of memory in general (mostly long-term memory [explicit and implicit]) is much better understood, the question remains to what extent WM is linked to processes of memory as such, or whether these are similar at all. A recent study indicates that the behavioural aspect of (V)WM does not make overt demands on memory, but it rather requires guidance from a priority map that is instantiated in the recurrent activity between the intraparietal sulcus and frontal eye fields (in humans located in the superior frontal cortex) (Bisley & Mirpour, 2019). Although neurons of frontal eye fields are known to be responsible for encoding information about recent saccade targets during free viewing behaviour in nonhuman primates (unspecific viewing target) (Mirpour et al., 2019), multi-voxel pattern analysis[2] (MVPA) of fMRI activity from the superior frontal cortex and intraparietal sulcus in humans suggests that the neural encoding of egocentric location is highly similar (Logie et al., 2020). This assumption also applies during WM performance with viewing targets when a person is preparing a delayed response to the same location when it must be remembered across a delay (retention interval in change detection task, Jerde et al., 2012). Significance of the frontal eye fields in VWM performance is also supported by Mackey et al., (2016), claiming that in case of prefrontal cortex damage, visuospatial WM is only disrupted if frontal eye fields are affected by this damage as well.

Moreover, recent MVPA studies have shown that during VWM performance with participants needing to maintain and manipulate stimulus-specific information, this process must not necessarily show elevated activity in the relevant brain area. This phenomenon was observed in the primary visual cortex that is believed to play an important role in remembering specific features of items in the VWM task. Serences and collegues (2009) investigated delayed period in VWM performance using fMRI and observed limited evidence of increases in mean activation in the primary visual cortex. Harrison and Tong (2009) also claim that overall levels of activity in the primary visual cortex are low, however, specific features (e.g. an orientation of items) can still be decoded from this low activity

[2] Multi-voxel pattern analysis (MVPA) is a method of determining how mental representations map onto patterns of neural activity by applying pattern-classification algorithms to multi-voxel patterns of fMRI or EEG data with the goal of decoding brain activity that presents some specific information at particular point of time (Norman et al., 2006). Recently famous inverted encoding modelling (IEM) (MVPA and IEM both types of multivariate analysis methods) presents a forward modelling approach that runs a dimensionality reduction on neural data to track population level representation of stimulus characteristics, model in IEM is trained by regressing against neural data, usually used with fMRI or EEG data (Logie et al., 2020).

patterns. This assumption was also supported by Emrich and colleagues (2013), who added that contents of VWM can be decoded from transient response to visual stimuli in visual cortex but not from regions with elevated, sustained activity during delay period.

We cannot forget the crucial attribute of VWM – vision. As mentioned above, VWM is based on the complex cognitive processes that are believed to occur mostly in prefrontal cortex, therefore in the visuospatial task, brain areas responsible for vision must be included in the processes too. Visual stimuli are processed through many separate maps, creating a visual pathway. There are two well-known visual pathways: "what" (ventral) visual pathway responsible for object identification and "where" (dorsal) visual pathway responsible for detecting spatial aspects of stimuli. Neurons in occipitotemporal cortical areas respond to the specific visual cues such as the colour and shape ("what"), whereas neurons in occipitoparietal, temporal and posterior parietal areas respond to the spatial information about the object ("where") (de Haan & Cowey, 2011; Ungerleider, 1994). Mentioned pathways contribute on executing the transfer of visual information from the senses to relevant parts of the brain which then further process the information. The "what" (VWM) and the "where" (spatial WM) pathways work together in parallel during WM performance.

The role of the prefrontal cortex in VWM processes is undeniable but the specifics of it are debated to this day. Since posterior regions are considered to stand in the centre of these processes (visual brain areas), a general role of the prefrontal cortex may be to provide top-down control to posterior regions (Curtis & D'Esposito, 2003; Gazzaley et al., 2007). Gazzaley with collaborators (2007) agree with this notion, claiming there is accumulating evidence that prefrontal cortex modulates the magnitude of neural activity in distant sensory regions via long-range projections, i.e. the mechanism of top-down control. Top-down modulation might play the role of the common link accounting for functional involvement of prefrontal cortex and posterior areas during selective attention and VWM task (Gazzaley et al., 2007). This process might be essential for both establishing high fidelity representations of task-relevant stimuli when they are perceived, as well as facilitating their internal maintenance when they are no longer accessible. Given the fact that representations that are supposed to be maintained are susceptible to interference by many types of distractions (either distractors present in the task or distractors from the environment) (E. K. Miller et al., 1996), top-down processing (comprising selective attention) is necessary for successful WM performance by restricting the contents of capacity-limited memory to task-relevant representations (Ploner et al., 2001; Vogel et al., 2005), which gives it an integral role.

VWM is highly researched through various neuroimaging methods that can best reflect its mechanisms. It is believed that more brain regions are involved in WM processing, however, they need to be joint together and somehow collaborate to achieve effective WM performance. Many authors believe that this is accomplished by neuronal phase-locking synchronization that binds together those neurons that present the same perceptual objects (A. Engel, 1997; A. K. Engel et al., 2001; Fries, 2005; Haenschel et al., 2007; Pina et al., 2018; Singer, 1999; Yu et al., 2008) while this binding tag would be a flexible code for linking neurons into assemblies (known as binding-by-synchronization hypothesis) (Fries, 2005). It was found that all frequencies of firing neurons[3] are involved in WM, however, it is believed that synchronization of these oscillations is essential for WM functioning (Daume et al., 2017).

As already specified, WM is highly based on prefrontal cortex, top-down processing, and persistent activity during delayed response, yet there are some initiating modulators needed to regulate and bind these processes. Several investigations have proved that WM performance is influenced by hormones acetylcholine, dopamine and norepinephrine (particularly during delayed response tasks) (Motley, 2018), each having a unique role. Acetylcholine is known to be critical for attention, hence it is important for WM because it supports increased attention to maintain persistent firing related to targets in the face of distractions (Decker & Duncan, 2020; Motley, 2018). The research indicates that dopamine is significant not only for WM functioning but also in improving WM capacity and performance (Söderqvist et al., 2012). Norepinephrine is thought to be improving the spatial tuning of delay cell firing, and thereby decreasing distractibility and improving behavioural performance in WM task (Arnsten, 2006). Clarke and colleagues (2006) found out there was

[3] The roles of frequencies in WM are only proposals of what function each of them might take. Those functions are suggested to be following: alpha-band as inhibition of task irrelevant information (Roux & Uhlhaas, 2014) , beta-band reflecting a default state interrupted by encoding and decoding (Lundqvist et al., 2016), theta-band underlying organization of sequentially ordered WM items (Roux & Uhlhaas, 2014), gamma-band standing behind encoding, decoding, WM load and generally active maintenance of WM (Lundqvist et al., 2016).

an increase of errors in WM tasks after serotonin depletion in the orbitofrontal cortex[4] which supports the motion that serotonin plays a role in WM, although this role is still unclear.

To summarise the operations described in this chapter, current research assumes there are 5 main neural processes that are involved in VWM: prefrontal cortex processing, top-down modulators, persistent neural activity, long-range synchronized oscillations and connectivity, and brainstem neuromodulators.

1.4.1 Contralateral Delay Activity and Filtering Ability

In the previous chapter, we talked about persistent neural activity as one of the crucial neural processes standing behind VWM. It occurs during delay response tasks when one is holding (or manipulating) information that is no longer available but is needed to be maintained. This neural process was first detected in studies with monkeys (Fuster & Alexander, 1971), later it was also attributed to humans and is still a great item in ongoing research. Contralateral delay activity (CDA) is a neural phenomenon (which falls under the category of persistent neural activity) that was detected later on and is considered to be a direct correlate of VWM.

The history of CDA goes back to the 90s when Ruchkin with colleagues (Ruchkin et al., 1990, 1992) first detected sustained EEG activity during VWM performance. Only since 2004, when Vogel & Machizawa (2004) first highlighted the uniqueness of CDA, there has been a constant increase in studies investigating it in a relationship with various visual tasks. In the last twenty years, CDA was broadly studied from two main perspectives: measuring CDA in order to investigate how VWM representations are affected by particular manipulation or in order to associate them with numerous individual characteristics (Luria et al., 2016).

In 2004, Vogel & Machizawa presented an amplitude with a strong activity modulated by the number of objects being held in memory. In this research, they measured event-related

[4] Orbitofrontal cortex is a ventral part of the prefrontal cortex involved in sensory integration, modulation of autonomic reactions, learning, prediction and decision making for emotional and reward-related behaviours (Kringelbach, 2005).

potentials of participants during a bilateral VWM task, focusing on retention interval (interval when participants hold given information in memory in order to correctly accomplish the task) and examining lateralized effects of the task. During this interval (200 ms after memory array) they observed large negative voltage over posterior parietal and lateral occipital parts of the brain, contralateral to the memorized hemifield with a growing tendency – contralateral delay activity. Considering it was not yet determined to which processes the CDA could be attributed, they tried to find out whether complexity of the task or number of representations affected its character. They excluded the possibility that CDA as an amplitude grows with the complexity of the task since they observed that it does not grow infinitely but reaches its asymptotic limit at each individual's memory capacity (3-4 items according to Cowan, 2001; Luck & Vogel [2013]).

CDA can be defined as a sustained negative voltage over the hemisphere contralateral to the memorized hemifield, persisting throughout the memory retention interval (Vogel et al., 2005). The term contralateral means the activity of the hemisphere opposite to the relevant hemifield, while ipsilateral activity means the activity of the hemisphere equivalent to the relevant hemifield. It is based on the activation of the posterior visual areas whereas this activation is thought to be maintained and coordinated by the top-down signals modulated from multisensory executive brain areas, such as prefrontal cortex (Awh & Jonides, 2001; Curtis & D'Esposito, 2003; Gutierrez-Colina et al., 2021; Miller et al., 1993). CDA directly correlates with VWM capacity which means that CDA demonstrates larger increase in amplitude in high capacity individuals when more items are encoded (Luria et al., 2016; Vogel et al., 2005). To validate this, Luria et al. (2016) carried out a meta-analysis of 11 studies investigating CDA (Diamantopoulou et al., 2011; Drew & Vogel, 2008; Jost et al., 2011; Kang & Woodman, 2014; Kundu et al., 2013; Kuo et al., 2012; Lefebvre et al., 2013; Leonard et al., 2013; Störmer et al., 2013; Umemoto et al., 2010; Vogel & Machizawa, 2004) and determined that these studies provide a strong evidence indicating that the CDA is sensitive to the number of objects maintained in VWM. Importantly, even though most high capacity individuals are considered to represent an evidence, not only their CDA supports this assumption but also its lesser occurrence in low capacity individuals (Luria et al., 2016).

When Vogel & Machizawa (2004) first found and described CDA, they tried to eliminate the possibility of CDA being a result of some aspects of WM other than the representation of items held in WM. In their experiment, they found out that increasing the number of items to be remembered (from one to two items and from two to three items) leads to a substantial increase of CDA amplitude. However, when they compared the answers from correct and incorrect trials, they observed that amplitude for incorrect trials was significantly smaller than the correct trials. This suggests that CDA specifically reflects the maintenance of successful representation in VWM. This assumption is also supported by McCollough et al. (2007) who demonstrated that CDA amplitude was significantly reduced on trials with incorrect answer in oppose to trials with correct responses, which is also in the line with the assumption that errors occur due to the loss of relevant information from VWM (Luria et al., 2016).

To obtain the CDA event-related potential waveform we need to use a special visual task. Fortunately, thanks to the separate visual pathways for left and right visual hemifields, an easy trick with the same visual information going to both hemispheres but only one of them to be remembered can be used. Two experiments, representing a breaking point for research of CDA (Vogel et al., 2005; Vogel & Machizawa, 2004) both used change detection task (CDT). Studies in later years were investigating CDA through different variations of this task (Adam et al., 2018; Feldmann-Wüstefeld et al., 2018; Ikkai et al., 2010; Peterson et al., 2015; Rajsic et al., 2019; Sander et al., 2011). The main difference between basic CDT and CDT to evoke CDA is its lateralized character. Every CDT requires an ability to detect change or lack of similarity over a specific time period (Rensink, 2002). In lateralized CDT, two hemifields containing various items appear, divided in time by a retention interval. The participant needs to detect potential change in colour or orientation of items in the relevant hemifield.

In previously mentioned studies investigating CDA, CDT was enriched by a cue – an arrow indicating the array to be remembered (left or right). Various types of items have been used in different studies: squares of various colours (Adam et al., 2018; Ikkai et al., 2010; Peterson et al., 2015; Rajsic et al., 2019; Vogel & Machizawa, 2004), colourful rectangles (Vogel et al., 2005), colourful circles (Feldmann-Wüstefeld et al., 2018) or black and white squares of different textures (Sander et al., 2011). Even though the shape of the items is not important, the lateralized character of the task must be maintained. The parts of CDT are cue (arrow pointing either to the right or to the left), memory array (presentation of targets and distractors), retention interval (representations disappear, usually involves only fixation point) and test array (presentation of targets and distractors with or without change), usually completed by inter-trial interval (fixation point, preparation for the next trial) (Vogel et al., 2005; Vogel & Machizawa, 2004). To make the task more complex, distractors are sometimes added to compete for participant's attention with targets. The goal is for the participant to ignore the distractors and focus only on the targets. The targets are usually distinguished from the distractors by colour, change in the task refers to change in orientation, position, or colour.

In their research, Vogel et al. (2005) highlighted another important aspect of CDA, an ability to filter out irrelevant items – so called filtering ability. They investigated CDA between two conditions: first condition included only relevant items (two or four targets), second condition included two targets and two distractors. They compared the CDA of two groups of participants and found out that CDA of high capacity individuals in conditions with two targets had very similar character as CDA in the condition with four items of which two were targets and two were distractors. This means that high capacity individuals were very efficient in filtering out irrelevant information. In contrast, CDA of low capacity individuals in condition with two targets was significantly different from the condition with two targets and two distractors, which was more similar to CDA in condition with four targets. Low capacity individuals had difficulties filtering out irrelevant information.

These findings suggest that people who could remember the correct objects from a spatial array and therefore were more successful in the task, also more efficiently excluded irrelevant objects. According to Nelson Cowan & Morey (2006) these results raise an important question about WM: why do high capacity individuals remember more and why do low capacity individuals fail? The first question might have more possible answers. Irrelevant items in the task work as a distractor (Vogel et al., 2005; Vogel & Machizawa, 2004) therefore they might affect the scope and control of attention (Nelson Cowan et al., 2006). To achieve the most successful performance possible, one's focus must efficiently zoom out to apprehend the most items or zoom in to maintain the task goal despite distractors. Nelson Cowan & Morey (2006) claim that if the same resources are needed for apprehending relevant items and filtering out irrelevant items, then filtering can come at cost. Regarding the second question, the answer might be that low capacity individuals strategically forego some extra processing or rely on pre-consolidation and sensory memory rather than taking the task as attention-demanding (Nelson Cowan & Morey, 2006). These are just theories and more research is needed to efficiently answer the questions about filtering ability. However, the fact remains that filtering ability plays an important role in determining the individual VWM capacity which was confirmed in a meta-analysis by Luria et al. (2016) in which the authors tracked 8 studies investigating these variables in relation and found strong overall correlation. Nonetheless, there is still one unanswered question regarding the character of CDA, and that is whether it is trainable or not. Many authors investigated if a training can improve behavioural performance in WM tasks and the conclusions of these studies were diverse[5]. Trainability of CDA as a direct correlate of VWM was not investigated before and such findings would present a great addition to the information we already know about CDA.

1.4.2 Calculation of CDA

In the previous chapter we introduced a definition of CDA with an emphasis on its main characteristics and specifics that are reflecting the capacity of VWM. However, the process of gaining the final CDA amplitude requires several necessary steps that need to be taken. First, participants need to complete a proper lateralized CDT while the EEG signal is being recorded. Then, EEG data must be analysed in terms of final ERPs to extract the CDA waveforms.

CDA amplitude is a wave observed during the retention interval on the posterior parts of the brain (Ikkai et al., 2010). After a precise pre-processing of EEG data, CDA can be extracted by subtraction of ipsilateral activity from the contralateral activity (mean difference waves averaged over the posterior sites) (Ikkai et al., 2010; Peterson et al., 2015; Vogel & Machizawa, 2004). As declared before, contralateral activity is the activity of the hemisphere opposite to the relevant hemifield, while ipsilateral activity is the activity of the hemisphere equivalent to the relevant hemifield. This activity in the form of an ERP waveform is time-locked to the memory array averaged across the lateral occipital and

[5] In 2012, Shipstead and collaborators performed a literature review and concluded that there is more research needed to directly demonstrate that WM capacity increases in response to training. Similar meta-analytic review was done a year later where the authors concluded that a memory training appear to produce short-term, specific training effects that do not generalize (Melby-Lervåg & Hulme, 2013). Another study (T. L. Harrison et al., 2013) demonstrated that training on complex WM span tasks led to improvement on similar tasks with different materials but that such training did not generalize to measures of fluid intelligence. Recent meta-analysis (Melby-Lervåg & Hulme, 2016) concluded that there is no convincing evidence that WM training produces general cognitive benefits.

posterior parietal electrode sites (Vogel et al., 2005). Considering the lateralization of the brain (right hemifield processed by left hemisphere and vice versa) a question might arise why ipsilateral activity is even taken under consideration in generating CDA? Authors have presented more opinions on this. According to Arend & Zimmer (2011), ipsilateral activity might reflect either a bilateral processing of relevant items or a lateralized processing of irrelevant, to-be-filtered-out items. Since in CDT the number of items on both sides is typically identical, authors could not determine which alternative was true. In general, authors agree on the assumption that ipsilateral activity reflects nonspecific, bilateral ERP activity and by its subtraction from contralateral activity, the waveform is cleaned from low level processes and local noise (Luria et al., 2016). Although the subtraction is universally used in CDA studies, many aspects of it are still not clear (e.g. it is not clear when the contralateral and the ipsilateral activities are negative or positive, since CDA only indicated the contralateral is more negative than the ipsilateral, but both could be positive [Luria et al., 2016]) and more research is needed in order to fully understand it.

2 Electroencephalography

Electroencephalography (EEG) is a non-invasive measurement of the brain's electrical activity. It uses electrodes placed on the scalp that record voltage potentials resulting from current flow in and around neurons (Biasiucci et al., 2019). For a long time, EEG has been used in a range of psychological and neurophysiological experiments investigating various aspects of cognitive processes. However, it is very difficult to use raw, continuous EEG data to examine the specific neural activity as a function of certain cognitive processes, by cause of the large amount of ongoing activity that is irrelevant to the studied phenomenon but inseparable at the same time. For that reason, this data is usually analysed in terms of event-related potentials (ERP) (Beres, 2017). The ERP technique provides a powerful method for exploring neural processes. ERPs are understood as small parts of continuous EEG recording which are evoked in response to stimuli, whereas this evoked activity is both time-locked and phase-locked to an event (Beres, 2017; Biasiucci et al., 2019). Most studies of evoked activity perform signal averaging by taking many trials of the same event to increase the signal-to-noise ratio[6] , ERP being an output of this operation (Biasiucci et al., 2019). The resulting averaged ERP waveforms consist of a sequence of positive and negative voltage deflections, called peaks, waves or components (Luck, 2014). An ERP component is defined by its latency (relative to the stimulus) and topography. However, they are often defined by their latency, amplitude and polarity at a given scalp location (Biasiucci et al., 2019). The sequence of ERP peaks reflects the flow of information throughout the brain, the voltage at each time point in the ERP waveform reflects brain activity at the precise moment in time (Luck, 2014).

An EEG device must have several necessary components to achieve a successful EEG recording resulting in usable data: a differential amplifier that measures potential between two electrodes, analogue filters, an amplifier that prepares the signal for analog-digital conversion and storage (Blinowska & Durka, 2006). An EEG must also involve a combination of electrodes composed of conductive materials, the contact between them and the scalp is improved with electrolytic gel (Biasiucci et al., 2019). The EEG cap might contain various numbers of active electrodes plus one reference (unipolar recording) and one ground electrode – these are combined to provide a single channel of EEG. The bipolar recording estimates the potential differences between two adjacent electrodes and therefore a reference electrode is not needed in the cap (Yao et al., 2019). The amplifier records the potential between the active and the ground electrode and the potential between the ground and the reference (signal noise is eliminated by subtraction of reference-ground potential from active-ground potential) (Luck, 2014).

3 Cognition in Virtual Reality

Virtual reality (VR) has been increasingly investigated in last years. The search for its proper definition though goes back to the nineties when Cruz-Neira et al. (1992) described the components of a VR experience in purporting that visualisation components, immersion

[6] Signal-to-noise ratio generally refers to the dimensionless ratio of the signal power to the noise power contained in a recording (Johnson, 2006) which simply means the size of the signal divided by the size of the noise (Luck, 2014).

and interactivity are central (*Augmented Reality and Virtual Reality*, 2017). VR presents an advanced technology with a form of user-computer interface involving real-time simulation of an environment that allows a user to interact via multiple sensory channels (Burdea, 2003) and is rapidly expanding across a variety of disciplines (Adamovich et al., 2009).

VR, as a digital mirror of a real world, is believed to have a great influence on human cognition. Ricci and colleagues (2015) emphasize the effects of VR and claim that vision of a virtual world might have a profound impact on human cognitive systems. The main argument lies in human imagination, the tendency of the brain to augment the reality without intentional stimuli. Thanks to this tendency and the known effect of VR consistent with real experience, it is believed that it can be used in various fields to affect (enhance, improve) human cognition. Also, VR might be used to design therapies that target neuroplastic mechanisms in the nervous system that would provide a training in complex environments which are impractical or impossible to create in the real world (Adamovich et al., 2009).

Various event-related potential (ERP) methods are used to detect possible neural effects and brain changes as a result of VR impact, EEG being the most common. Pugnetti et al. (2001) provided an overview of some studies investigating VR through EEG, however, this overview only served to analyse and review the usage of these methods in combination. Studying cognitive processing in the human brain during VR experience is still very challenging considering the vagueness of ERP signals and their tendency to aggravate with muscle movement.

Since our brain serves as an integration of our current perception of the physical world and our top-down memory based prediction, we actually see much more than what impinges on our retina (Ricci et al., 2015), therefore VR might affect our cognition, neural correlates or behavioural performance subconsciously in a very effective way. The research in this field is still very limited and full of unanswered questions but provides a great potential of revealing modern methods of influencing human cognition.

4 The Current Research

4.1 General objective

Previous research has shown that a CDA waveform presents a direct neurophysiological correlate of memory capacity and the number of visual objects that are held in one's memory while performing a VWM task. As mentioned earlier, this effect was investigated on various types of VWM tasks and conditions, however, not so much on the procedures that can affect and improve it.

This thesis is a part of a bigger project (Enhancing Cognition and Motor Rehabilitation in Mixed Reality, APVV-16-0202). It involves carrying out EEG measures on 16 participants and following fine analysis of recorded EEG data in terms of final ERPs to extract the CDA waveforms with the emphasis in the punctual pre-processing of the data using the Brain Vision Analyzer software. Performed measures will contribute as EEG data of control group in the main project. In the main project the authors hypothesize that cognitive training in virtual reality (VR) can improve behavioural performance in working memory (tested offline in a different task outside VR) and that this effect will be visible on its neural correlate - the amplitude of CDA. The main project has the following hypotheses:

H1: Cognitive training using virtual reality will affect (enhance, improve or speed up) perceptual and cognitive performance in healthy subjects.

H2: Experience with training in virtual reality will affect and enhance oscillatory sensory-motor rhythms.

This thesis has two main objectives:

1. To carry out an experiment on the control group of healthy participants and record the EEG while they will be performing visual working memory tasks.
2. To analyze collected EEG data in terms of final event-related potentials (ERP) of contralateral delay activity, emphasizing the precise use of a combination of automatic and manual artifact rejection in Brain Vision Analyzer.

4.2 Methodological Approach

The main aim of this thesis was to conduct an experiment on the control group and to further examine the effects of a training on neurophysiological correlates and behavioral performance of participants. Furthermore, it intended to objectively review the efficiency of a training in VR with an emphasis on precise EEG data processing. We conducted two experiments where participants were performing CDT while their brain activity was measured by EEG. One of them was conducted with training in VR, the other was without the training. Crucial aspect of the research aim was to conduct detailed and precise EEG data analyses to effectively evaluate the efficiency of the VR training. So far as known, CDA has not been investigated before in combination with VR training.

In the analysis, we applied several processes on raw EEG data to generate a CDA waveform. Particularly, we focused on precise semi-automatic artifact rejection to clean the signal from all undesired elements that could mask the target activity.

4.3 Hypotheses

H1: The number of items to be remembered in CDT will be reflected in the amplitude of the CDA waveform.

H2: Filtering ability of participants in the control group will not be improved by repeated measurement of CDT across three sessions within four weeks without an additional training.

5 Methods

5.1 Research sample

We recruited 30 participants (*Table 1*) of which 14 for the experimental and 16 for the control group. Participants were all healthy, neurologically normal university students with technical focus (informatics, mathematics, physics). All participants signed an informed consent and agreed with the procedures and conditions of their participation in the experiment. Furthermore, they understood their right to withdraw from the experiment at any time. The participants were all right-handed and had normal or corrected to normal vision, had no head injury and were not under strong medications that could influence their performance in the task.

Because of the videogame-like character of the CAVE training, we were looking for participants familiar with videogames, in order to avoid the interference of 'gaming' skills (otherwise it would be necessary to add an entry course to teach the less skilled participants how to use game controller and how to precisely follow the rules of the training. Also, participants with advanced 'gaming' skills have different cognitive skills in general, therefore inconsistency of the sample would make it impossible to correctly compare the data). This condition was mostly crucial in the experimental group with the training, however, we set the same conditions on the control group to preserve the consistency of the sample. The sex ratio in the experimental group was 4F/10M, 3F/13M in the control group. All participants who finished the whole course of the experiment (four sessions in control group + ten sessions of training in the experimental group) received a monetary reward.

Group	*Number of participants*	*Age Range*	*Mean Age*	*Gender*
Experimental	14	19-23	21.1	4 F/10 M
Control	16	21-25	22	3 F/13 M

Table 1 – Demographic data of the Participants

5.2 Stimuli

The stimuli were displayed on HP ProDesk personal computer, with 3.00 GHz CPU, running Windows 10 Pro. Stimuli were presented on a BenQ monitor with a refresh rate 60 Hz and a resolution 2560 x 1440. Participants viewed the screen from a distance of 70 cm. Responses were collected from two buttons (connected to trigger box) placed in front of a participant. Behavioural responses were transported to the computer via trigger box that was connected to the two response buttons placed in front of participants.

The change detection task (CDT) that we used in this experiment challenges participant's attention and WM, focusing mostly on spatial orientation and visual WM. The stimuli were implemented and presented to participants using PsychoPy software. The stimuli consisted of 40 blocks, each block presenting 16 trials. Each trial comprised six sections: Cue, Fixation, Memory Array, Retention, Test Array and Inter Trial Interval. The sequence and timing of the stimuli within one trial is shown in *Figure 2*. At the beginning of each trial, a black cross is presented to the participant as a fixation point. Then, a black arrow, pointing either to the right or to the left, appears in the middle of the screen and provides information on where the target will occur (Cue, 200 ms) (the cue has a great significance in an experiment intending to generate CDA in participants to lateralize their attention [Griffin & Nobre, 2003; Kuo et al., 2012; Nobre, 2008]). Next, there is a short period of fixation time consisting of black cross in the middle of the screen (Fixation, 300-500 ms). The fixation part is followed by a display of various number of rectangles on both sides, right and left; this is the crucial part of the experiment when the subject is instructed to remember a relevant side of the field (Memory Array, 200 ms). Then, a black cross in the middle of the screen appears again (Retention, 900 ms), followed by another display, either with or without a change of orientation of the rectangles (Test Array, 3000 ms). Finally, a black cross appears, giving the subject time to press a button and get ready for the next trial (Inter Trial Interval, 750 ms). The duration of one trial is 5350-5550 ms.

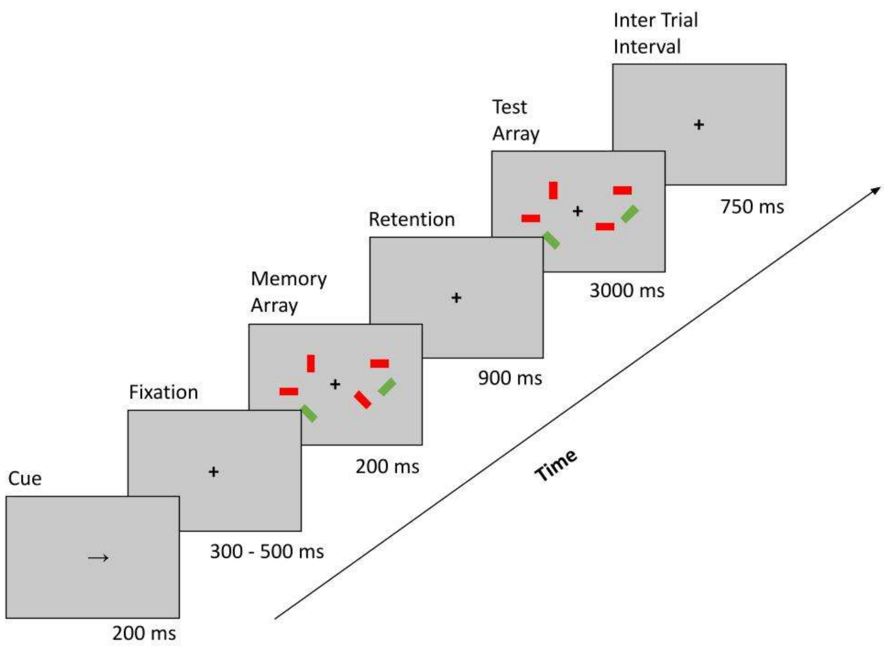

Figure 2 – Time sequence of CDT used in experiments.

Each trail of CDT and its display duration are based on the function they hold and the reaction they should evoke in participants. We decided that 200 ms is an appropriate time for the Cue, Fixation and Memory Array in order for the participants to be able to notice the direction of the arrow (Cue), fixate their gaze on the black cross (Fixation) and register the orientation and colour of rectangles (Memory Array). We set the duration of Retention on 900 ms, similarly as in previous research investigating CDA during retention interval (Vogel et al., 2004, 2005).

During Memory Array, a set of rectangles were presented on both sides of the screen. These rectangles were of three colours – red, green and blue, in which red rectangles represented targets, whereas green and blue rectangles represented distractors. The blocks of the task consist of four possible set size configurations of rectangles: 1. two targets and zero distractors, 2. two targets and two distractors, 3. four targets and zero distractors, 4. four targets and two distractors. Each trial, one of these sets appears on both sides of the screen, despite the lateralized relevance. Overall, each set size configuration appears 175 times during one session in randomized order. Each Memory array consisted of one of the four sets, selected from a set of four possible orientations (vertical, horizontal, left 45° and right 45°). The positions of the rectangles were randomly distributed around the screen on both hemifields (CDA amplitude is believed to be insensitive to low level visual attributes such as the distance between objects [McCollough et al., 2007]).

5.2.1 CDT Instruction

In the first entry session, participants received all the instructions concerning the CDT and they were told about the procedure, contents and timeline of the experiment. Participants were instructed to pay attention only to the red rectangles of the relevant hemifield and to press the right (green) button if there was a change and the left (red) button if there was no change in their orientation. They have been notified about the importance of the eye fixation on the black dot during the whole experiment. Participants were allowed to blink normally. However, they were reminded to try blinking during the Inter Trial Interval – this instruction had two main intentions. First, it allowed the participant to blink regularly and prevent them from eye fatigue. Second, the amount of potential blinking during Memory Array, Test Array and Retention that could damage the CDA waveform in the EEG signal and negatively affect the behavioural performance was reduced. Participants were instructed to press one of the buttons during Inter Trial Interval and were told about the chance of correcting themselves until the start of the next block. They were allowed to have as many breaks as they needed between blocks in order for them to be rested and ready for the next trial. Approximate number of breaks during one session was four. After each block, experimenter waited for the participant's signal that they are ready to move to the next block.

5.3 Training

In the experimental part of the research we used a collaborative automatic virtual environment (CAVE) system as a training. Experimental conditions required sufficient training that could effectively imitate components of CDT and positively stimulate visuospatial cognition, having this positive effect on both, behavioural and neurophysiological levels. We decided that a cognitively stimulating VR experience might match these conditions because of its authenticity and ability to creatively replicate CDT.

The VR system we used for the experiment is called LIRKIS CAVE. It was implemented and is now located at the Technical University of Košice, LIRKIS laboratory (Hudák et al., 2017). It is a transportable VR environment with 2.5x2.5x3 meters display area. Its visual output is presented on twenty 55-inch stereoscopic LCD screens, fourteen of which are positioned vertically along seven sides of a decagon and remaining six positioned horizontally forming the ceiling (three screens) and floor (three screens). CAVE therefore provides a 250-degree panoramic space. The CAVE can be connected to a range of user control devices, in our research we use mouse and keyboard through gaming devices (joystick, gamepad). An adequate representation of the scenes on the screens is achieved by a cluster of seven computers, equipped with the NVIDIA Quadro graphic cards.

Game played by the participants of the experimental group in CAVE is called *Tower Defence*. The essential visual component of this game is a fixed location with a form of defence turret that rotates to the right and left. This visual object is an alternative to the fixation cross in CDT. The tower has a function to shoot a line of fire that can be vertically adjusted. Attackers of the tower are represented by drones that are approaching it from the front, they can attack the tower or the city behind it. The player is in the role of the defence tower and their task is to defend it. The player can shoot on the drone only until it passes the tower position further towards the city, otherwise the drone bombs the city. The player wins if they can defend the city in given time. Described drones represent the red rectangles of CDT, however, there are also distractors in this game, so-called friendly drones that carry supplies necessary for survival of the tower and the city. The player needs to distinguish these two types of drones according to their shape, colour and behavioural differences.

5.4 Procedure and Data Collection

Participants were tested individually in a small, darkened, acoustically attenuated EEG recording room. Experiments were running in solitude in the presence of an experimenter (experimenter was sitting behind the participant out of their peripheral view, controlling the EEG signal, taking care of the blocks switching and correcting the EEG cap and electrodes if necessary).

Participants were seated in a comfortable chair in front of the monitor where the stimuli were presented. They were holding two buttons, one in the right and another in the left hand, with both hands placed on the desk. Participants were connected to the EOG and EEG while performing CDT. If the EEG signal was breaking, experimenter manipulated the electrodes and corrected the signal during the breaks between blocks. One experimental session lasted approximately for 75 minutes. Data collection was conducted in three time-segments which followed an introductory entry session. The scheme of the whole procedure of the experimental group can be found in the *Figure 3*).

Day 1	Day 2*	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13
Scales		Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales
EOG Sig-nal Test		restA CDA 1 restZ [EEG]					restA CDA 2 restZ [EEG]					restA CDA 3 restZ [EEG]
CDT prac-tice		Scales					Scales					Scales
		CAVE 1	CAVE 2	CAVE 3	CAVE 4	CAVE 5	CAVE 6	CAVE 7	CAVE 8	CAVE 9	CAVE 10	
CDT 1 [EOG]	CDT2 [EOG]	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	Scales	

Figure 3 – Procedure of the experiment. Experimental group performed all stages, participants in control group performed all stages except from CAVE, which represents training in the VR environment. Day 2 was optional; it is a repeat of the first session with CDT - occurred when a participant had low performance in the first session.

5.5 First Session

The first session of the experiment was essential, as we explained the whole procedure of the experiment to each participant and accordingly considered their participation in it. The main purpose of this session was to determine the suitability of the participant for the purposes of the study and to give them a chance to learn and practise the CDT. The introductory meeting had three main objectives: 1. introduce the participants to outline of the experiment, 2.determine whether the participants could follow the instructions and perform the task correctly, 3. teach them, how to perform the CDT, explain all the rules of the task and let them learn how to do the task efficiently.

The entry session started with a questionnaire that contained questions about demographic data of the participants, hand laterality, smoking habits, neurological anamneses, and frequency of playing video games. We also wanted to avoid an interference of caffeine affecting the performance, therefore we also included a question about the last time a participant drank coffee. Later during the experiment, they were instructed not to drink anything with caffeine at least three hours before the experimental sessions. We accepted only right-handed participants with no neurological problems. To preserve similar average age as in the experimental group, we accepted participant with age of 19-25.

Subsequently, participants were seated and connected to electrooculography (EOG). They had to perform a signal test that was based on a simple figure that consisted of fixation point and several objects placed around it (with the same distance as the distance of the rectangles from the fixation point in CDT) and served to calibrate blinks and horizontal eye movements of an individual participant. During the signal test, the participant performed approximately twenty eye movements from a fixation point to objects around it (in the signal test, the fixation point had a form of a head of a soccer player, objects placed around it had a form of soccer balls). EOG amplitudes and latency of blinks and horizontal eye movements are not the same for everyone, they differ and are defined by various values.

During the Signal test, we detected particular values of these eye movements to set the thresholds for EOG artefact detection and used them in the next part of the entry session and in later EEG analysis, too. This kind of entry test was also proposed by Luck (2014) who suggests to ask the subject to do some eye movements and blinks at the beginning of the session to see what the subject's artifacts look like. Nonetheless, he emphasizes to keep in mind that voluntarily produced blinks are usually larger than spontaneous blinks. In the signal test, participants' eye movements were task-based, however, they were instructed to also blink after each saccade, which makes these blinks triggered, or voluntarily produced. For that reason, we tried to be very careful in calibrating parameters for blinks and we tried to choose an average number among all the blinks (approximately twenty blinks in one signal test).

As mentioned before, since the laterality is a crucial factor of CDA, the CDA waveform could not be obtained if a participant doesn't gaze in the middle of the screen and instead looks to the sides during the VWM task. Although this part of the CDA instruction seems straight-forward enough, to perform it the correct way might be much more challenging than expected. In CDT, there is a cue pointing to the side at the beginning of each trial. This cue, in a form of a black arrow, automatically tempts the participant to look to a given side. For that reason, participants had to undergo practice consisting of longer blocks (one block lasted five minutes) of CDT in the entry session. This section served as a criterion of the participant's ability to fixate their eye gaze to the black dot and not move their eyes to sides during the experiment. They were connected to EOG while they performed the pilot CDT. This pilot trial served as a training of CDT task for participants and as a detection of their eye movements. After a participant finished, we used MATLAB to detect all trials in which participant blinked or looked to the relevant hemifield (EOG detection) using the values acquired in the signal test. If more than 20% of the trials were to be rejected, the participant was considered as not capable of performing the task and therefore not suitable for the experiment and was excluded from the experiment. If the participant succeeded, they could proceed to the experimental part.

5.6 Experimental Part of Data Collection

The experimental part of the procedure consisted of three parts: pre-, mid- and post- test. In the experimental group, these tests were divided by two-week-long breaks, each filled with four sessions of training. In the control group, these breaks remained empty. Each one of these three sessions had the same procedure. First, participants had to fill out a short questionnaire (questions about the last time that participant had caffeine, alcohol, nicotine; amount of sleep during last night; perceived concentration, enjoyment of the task, fatigue and motivation to do the task correctly) which was followed by performing the CDT, as described in the section *Stimuli* (p. 20). Before and after the CDT, two periods of rest were added to measure the baseline resting EEG (one rest period lasted for four minutes, two minutes with closed and two minutes with open eyes). Each session was closed with a questionnaire (questions about perceived concentration, enjoyment of the task, fatigue and motivation to do the task correctly). In the control group, all three sessions had the same proceedings, while in the experimental group, pre-test and mid-test were followed by a session of training and additional questionnaire.

5.7 EEG Recordings

During the pre-, mid- and post- test, EEG recordings were conducted while participants were performing CDT. Prior to the presenting of the stimuli, four disposable EOG electrodes have been attached to the face of the participant, two electrodes at the temples (as close to the outer canthi as possible, while trying to avoid any discomfort or disruption of participant's sight) to detect horizontal eye movements, and two electrodes above and below the right eye to detect blinks. Next, an elastic EEG cap was placed on the participant's head following the International 10/20 system, using 11 silver/silver chloride (Ag/AgCl) electrodes. The placement of the electrodes that was used is shown in *Figure 4*. The positioning of the electrodes was densest on the occipital and parietal parts of the brain which are the relevant parts for CDA detection. The ground electrode was placed on the forehead above the nasion and the reference electrode was placed at the earlobe. We were using a 16-channel amplifier g.USBamp 3.0 (from g.tec).

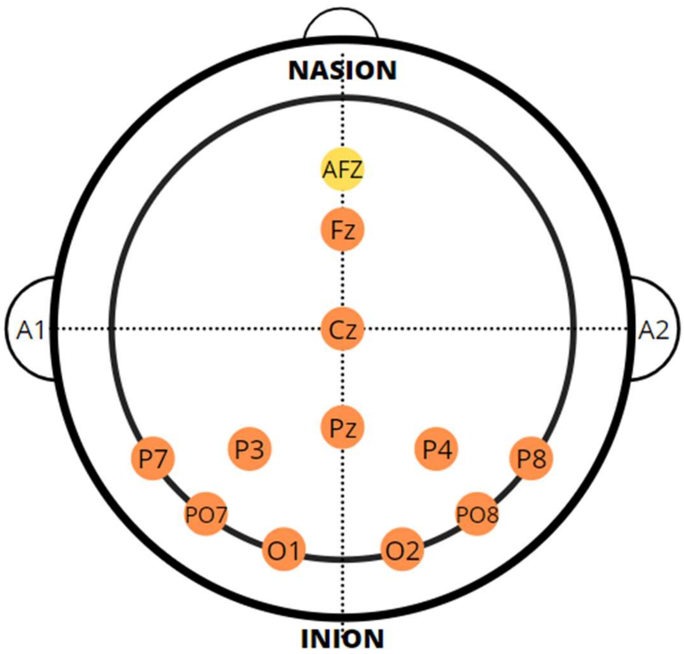

Figure 4 – Schema of EEG cap that we used in the experiment. Even numbers present right hemisphere, odd numbers present left hemisphere. Letters refer to brain areas: F – frontal, C - central, P – parietal, PO – parietal-occipital, O – occipital. Electrode AFZ is ground electrode, A1 presents a place of reference electrode. Orange labels are electrodes that were placed according to 10-20 electrode placement system.

We used a dedicated software g.RECORDER (from g.tec company) to record the EEG data and to visualize the signal. When the EEG cap was set and all channels connected to the amplifier, we started the g.RECORDER and calibrated the amplifier. We used the visualization tool to see the quality of the signal of each channel and accordingly we adjusted the signal by adding more gel or repeated scratching of the skin under the electrode to improve the connection between the scalp and the electrode. Sometimes none of the mentioned approaches helped to improve the signal, which was a sign of other issues that could be sweating, stress, or another psychophysiological factor. After achieving quality of the signal as good as possible, we turned on the notch filter, low-pass filter and high-pass filter. If the signal got worse during the experiment, we adjusted the EEG cap and the channels again. Additionally, we checked the signal and observed the occurrence of eye blinks during retention interval. To avoid rejection of more than 20% of the trails, we reminded the participants to blink in the inter-trial interval as was acknowledged during the entry session.

5.8 EEG Analysis

After conducting all EEG recordings, we first needed to pre-process the acquired data and prepare them for the later analysis. We used MATLAB programming software for majority of required operations and corrections. Neurophysiological and behavioural data were recorded in parallel and resulted in two separate files that we then merged into one. The resulting file contained markers representing correct/incorrect answer in eight types of conditions of the experiment. Furthermore, we created markers based on the detected eye movements (blinks and horizontal eye movements) that were later used in the analysis as labels of invalid trial/segment. We detected blinks and horizontal eye movements to see the number of invalid trials before the analysis. If the percentage of invalid trials was lower than 20%, we transformed the files into EDF format in order to provide compatibility with the Brain Vision Analyzer (BVA) software.

We used BVA to analyse the acquired EEG data. We chose this particular analysis-tool for its complexity and straight-forward character, to achieve effective and high-quality EEG data processing. BVA allowed us to create a workspace of operations that were applied to raw data. Given the number of operations needed to be applied to the raw data to get the clean EEG signal, it is important to carefully decide the order of their application and finetune all of the possible parameters. BVA is an EEG software whose biggest advantage is that history pipelines (work-trees of operations) log every operation applied to the data and based on them, templates can be created and then applied to other data. After the primary pre-processing in MATLAB, we imported the data into BVA and started to perform EEG analysis by applying series of operations on each of them.

It is necessary to mention that since there are no two identical EEG recordings, there are no general guidelines or a manual of how exactly the EEG analysis should be performed. It is a complex process of applying the appropriate operations, persevering desired signal, and rejecting what is contaminating it.

5.8.1 Artefacts of non-cerebral origin in the EEG recording

In the first step, we needed to use appropriate filters to get rid of non-cerebral artefacts that are present in the EEG recorded signal. EEG data can be contaminated by more types of noise that can mask the target signal, most common are physiological electrical activity and environmental noise (Biasiucci et al., 2019). Physiological noise is produced by cardiac, ocular, and muscular activity, and environmental noise includes noise from electric equipment and power lines. It is important to distinguish various types of noise and use an appropriate process to remove it from the signal.

Regarding muscular contamination, the most common of them are artifacts in EEG signal, we had to remove all muscle activity done mostly by facial muscle movements during the performance of CDT. This is also the reason why the breaks in experiments while EEG is recorded are essential. Even though participants are instructed not to make any muscle movements during the performance of the task, the signal can be also contaminated by increased muscle tension. Therefore, it is important for the participants to relax and release the muscle tension during the breaks.

Since any muscular activity strongly disturbs EEG signal and complicates data analysis, we needed to remove muscle artifacts from the signal, which might be challenging. The main reason for the unique challenges associated with removal of muscular activity lies in the fact that it contains high amplitudes in the signal, a wide frequency spectrum and broad anatomical distribution (Chen et al., 2016), which usually affects all channels. These artifacts are easily visually detected, however, there might be a problem removing them in the analysis when this activity overlaps with the target signal. Muscle activity shows a bandwidth of 20-300 Hz (Muthukumaraswamy, 2013) (frequency bandwidth of muscle activity is not a fixed value, Greco and colleagues [2007] say that muscle activity can reach frequency of 0.5-35-50 Hz, based on the source of the muscle contamination) and a voltage of ±75 µV (Nolan et al., 2010). Since our target signal usually does not occur in these frequencies, we could use filters to remove it.

Cardiac activity is defined by a bandwidth of approximately 0.6-1.7 Hz (Tamburro et al., 2019), in our recordings, we did not have problems with this type of EEG noise. Several times, electrocardiography (ECG) signal appeared at channel *A2* that was attached to the right earlobe. As Tatum (2013) declared, pulse artifact usually appears in a single channel as a periodic slow wave, occurring when electrode is in the position that is near, or at the artery, which was also our case. During our experiments, this happened when the electrode was directly touching a place of blood vessel and therefore it detected ECG signal, however, this was usually easily observed and corrected using the EEG visualization during recording. The rest of ECG artifacts that remained in the signal were removed by filtering and later averaging.

Regarding environmental noise from electric equipment and power lines (50 or 60 Hz, depends on a geographical place where EEG is recorded, in our case line frequency was 50 Hz), it is possible to use a notch filter that filters out a narrow frequency band and passes everything else (Steven J. Luck, 2014). Since we used low-pass filters that also included this range, it was not necessary to use notch filters in our case.

5.8.2 Filters

Filters in EEG data analysis are tools for reducing sources of noise that can be well approximated by sine waves (Steven J. Luck, 2014). Filters are very useful in EEG processing, nevertheless, they need to be handled carefully because they can significantly distort the data. The most common classes of filters are low-pass filters (passes low-frequency signals and attenuates high-frequency signal), high-pass filters (passes high-frequency signals and attenuates low-frequency signal), band-pass filters (attenuate both high and low frequencies, passing only specific range of frequencies according to given parameters) and notch filters (attenuate narrow band of frequencies and passes everything else) (Niedermeyer et al., 2011). Analog filters are integrated in the amplifier, filters that we use in EEG analysis are digital filters that can be only used after the data are stored.

To clean the data from noise, we used two types of butterworth infinite impulse response[7] (IIR) filters in the processing: high-pass filter and low-pass filter. We removed slow fluctuations and DC shifts[8] using a high-pass filter that is needed for reducing low frequencies coming from bioelectric flowing potentials (e.g. breathing) that remain in the signal after subtracting voltages toward ground electrode (Teplan, 2002). There are no agreed parameters that define the high pass filter. Luck (2014) describes parameters between 0.01 Hz, 0.1 Hz or 0.5 Hz in relation to this filter, suggesting mostly 0.01 or 0.1 to minimize offsets and drifts. However, he points out that this suggestion is only a guess and this parameter should be set according to the goal of the analysis. On the contrary, Teplan (2002) defines the high-pass filter as a cut-off frequency usually lying in the range of 0.1-0.7 Hz. We decided to use the high-pass filter set on 0.1 Hz because by using the lower parameter (e.g. 0.01 Hz) we would lose our signal of interest, since CDA is a slow deflection that could be mistakenly filtered out using a low cut-off frequency for high-pass filter. At the same time, we used low-pass filters set on 25 Hz to 'smooth' high-frequency components and to attenuate noise, caused mostly by muscular activity.

While setting up criteria for filtering, there was another important parameter needed to be selected – the order of the filter. The order determines the steepness of the amplitude cut-off, or in other words, determines how much of the past information is included after filters are applied (de Cheveigné & Nelken, 2019; Steven J. Luck, 2014). In both, high-pass and low-pass filters, we used the order 8 as the greatest possible steepness of the cut-off.

During the recordings, we observed common occurrence of the dominant alpha activity in the visualization displaying the EEG signal in the real time, which was later confirmed after the data was stored and pre-processed. Alpha-band oscillations (an example is displayed on *Figure 5*) are thought to have mostly inhibitory function, also playing an active

[7] Filters may be designed according to Butterworth or Chebyshev topologies, three most common methods for digital filtering are finite impulse response (FIR), infinite impulse response (IIR) and one frequency domain method – fast Fourier transform. The biggest advantages of IIR filter is that it is computationally cheaper, can obtain good performance with low order and can simply reproduce analogue filters (Niedermeyer et al., 2011).

[8] Direct current drifts, known as deviation from the surface levels that are thought to be caused by tonic depolarization of the apical dendrites of cortical pyramidal neurons (Voipio et al., 2003).

role in information processing and timing (Klimesch, 2012). In our case, alpha oscillations could reflect the fact, that participants were in a state of fatigue caused by a long duration of the experiment in a silence with only small changes in visual inputs. Furthermore, it could represent suppression and selection, as two fundamental functions crucial during attentional and WM performance. However, since alpha frequencies (8-13 Hz, mainly around 10 Hz [Niedermeyer et al., 2011; Teplan, 2002]) could contaminate final ERP by its high amplitudes, we decided to remove it from the data using appropriate filters. We conducted band rejection using finite impulse response (FIR) filter of fourth order with the main frequency of 10 Hz and bandwidth 4 Hz, therefore we filtered out the frequencies in a range of 8-12 Hz. We selected all EEG channels for this operation, EOG channels were not included.

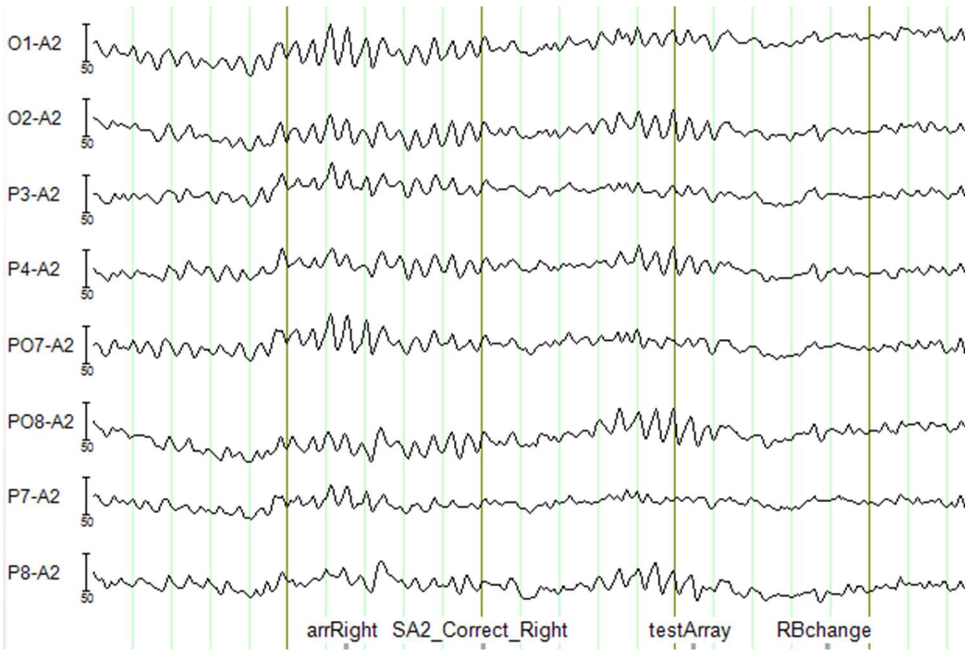

Figure 5 – Alpha oscillations present in the recording on eight channels.

5.8.3 Segmentation

EEG signal is very complex and cannot be easily interpreted without prior decomposition. First, it needs to be broken down into smaller pieces that we can make sense of. In EEG signals, these small pieces can take more forms. One form of them is characterized by ERPs, parts of continuous EEG recording which are evoked in response to stimuli (Beres, 2017).

ERP analysis is one of the most common method for investigating EEG signals, mostly by averaging of repeated time-locked recordings of the same event. These time-locked segments are obtained in the process of this decomposition called segmentation.

In the process of segmentation, we can also apply different inclusion and exclusion criteria for our recorded data based on which only clean desired trials become part of further analysis. This gives us a great freedom in detecting ERPs using BVA, however, there are some basic rules that should be followed to do the segmentation effectively. To extract trails for ERPs, we needed to generate epochs of the same length, relative to a reference marker. Such a marker could be any timestamp added during the recording or during later processing of the data and its function is to label a particular time event. By these markers we can define the beginning of a segment, its end or just a reference point to define the length and position of segments.

During EEG recordings, markers in the signal were created every time a significant event occurred (all markers were defined in the script). This was enabled thanks to an additional device called trigger.box that was connected to the amplifier. The trigger.box received signals from the computer via parallel port, from the additional photo-diode attached to the computer screen, and both response buttons. The program for the task presentation generated two types of these signals. A small square in the corner of the screen changed colour every time a new event occurred, which was detected by the photo-diode. This enabled perfect time synchronization of the events. Information about the type of the event (e.g. number of stimuli presented) was sent via the parallel port, recorded to the raw signal and later synchronized with corresponding timestamps – marker generated by the photo-diode.

In order to obtain clean segments without previously detected eye movements, the process of segmentation was applied in two steps. In the first step of segmentation, longer epochs containing almost the whole trial were extracted. The epochs were defined by a marker representing an onset of the cue (left or right arrow) that ends with a marker representing the onset of the test array. After the first step of segmentation, we obtained 320 segments for every recording - one recording included 40 blocks, one block having 16 trials (640 segments in total for one participant, 320 segments separately for one visual field). An excerpt of the first segmentation is displayed in the *Figure 6*.

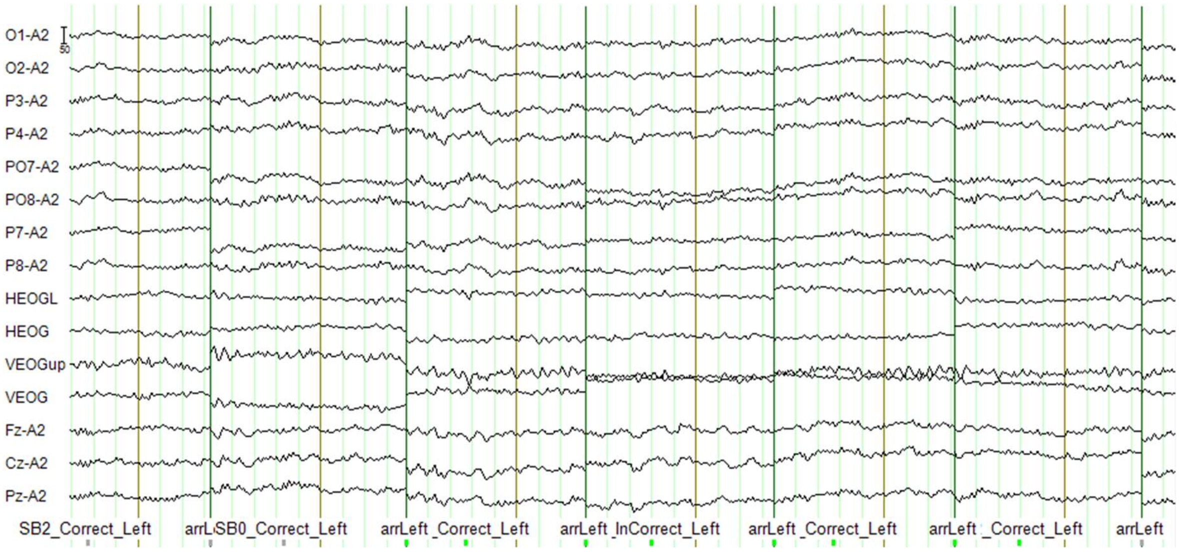

Figure 6 – Result of multi-channels segmentation based on defined start-marker and end-marker.

Subsequently, we applied the second step of the data segmentation. We set the criteria to reject segments where eye movements occurred in target moments of the experiment. To make this happen, we used an *Advanced Boolean Expression* to specify reference markers to isolate clean data from segments with eye movements in the segments obtained in the previous step. After this step, only segments (containing both, correct and incorrect behavioural responses) without blinks or saccades that would appear in a range from -700 ms before *Memory Array* to 1100 ms after *Memory Array* were maintained, the rest was rejected.

Boolean Expression applied in second segmentation:

not(EOG_saccade1(-700,1100) or EOG_saccade2(-700,1100) or EOG_blink2(-700,1100) or EOG_blink1(-700,1100) or EOG_blink(-700,1100) or EOG_saccade(-700,1100)).

The expression refers to the markers created during the recordings, based on eye movement calibration performed during the entry session by a signal test. Markers *EOG_saccade1* and *EOG_saccade2* refer to horizontal eye movements. Markers *EOG_blink1* and *EOG_blink2* mean blinks during retention interval. Through the process of second segmentation, we cleaned the data from sections where participants made eye movements - which suggest they looked on the target array of the screen and therefore no CDA would be generated. Segments with blinks were also rejected because blinks usually affect signal in all channels and the high amplitude of an eye blink artefact could contaminate the resulting CDA waveform leading to false results. However, as will be declared later, even after the calibration of eye movements of individual participants, some ocular artifacts might not have been detected because of their different character. To include only epochs of interest, after checking for artefacts in the longer segments, we shortened the trials for our needs too. The beginning of new epochs was set to 200 ms before the onset of a memory array and the end was 1100 ms later, which corresponded to the time of the onset of a test array. Therefore, it covered the whole retention interval, what was necessary to obtain the CDA ERPs. The result of the second segmentation is displayed in the *Figure 7*.

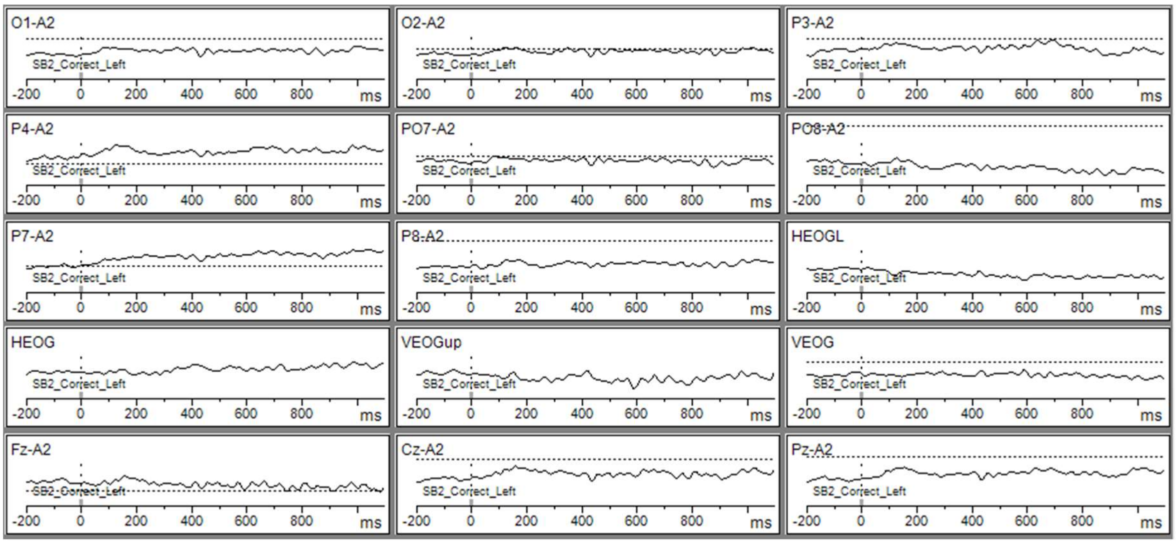

Figure 7 - Result of multi-channel segmentation according to Boolean expression based on eye movement markers detected in the experiment.

5.8.4 Baseline Correction

To correct the baseline of each segment we performed a baseline correction. This process creates an average of all points in the defined interval (in our case in a range from -100 to 0 ms before Memory Array) which is then subtracted from all points in the entire waveform (Steven J. Luck, 2014). Although this operation may sound simple, its effects can be complex and might lead to misinterpretation of the results, Hence, we needed to be careful with choosing the appropriate parameters for baseline correction.

Luck (2014) explains the pitfalls of baseline correction and claims it has a great effect on the amplitude measurements, since the baseline correction is based on subtracting the mean baseline voltage from the entire waveform, therefore, it affects the amplitude at each point in the waveform. Thus, after the subtraction, the voltage at each time point in the waveform represents the difference between that point and the average baseline voltage, which means that anything that has an impact on the baseline and influences post stimulus amplitude. For instance, any potential noise in the baseline could create a noise in the amplitude measurements, which is something we wanted to avoid. For this reason, the order of the operations is very important as well Accordingly, we applied a baseline correction after we applied filters and made epochs out of the signal.

Baseline correction is essential to prevent the data from temporal drifts and offsets and as mentioned above, it is crucial to set it up correctly using the appropriate parameters. More authors (Adams et al., 2018; Feldmann-Wüstefeld et al., 2018; Williams & Drew, 2021) suggest using baseline correction set up on -200 ms. Luck (2014) in general suggests using 20% of overall epoch duration for baseline correction, however, he also highlights that this parameter depends on the target of interest (whether we focus on early or late post stimulus components). He suggests using -100 if focusing on early components and -200 (or more) if focusing on late components. Our overall epoch duration is 1000 ms which leads to baseline correction set on -200. First, we used parameter -200, then we tried -100 and afterwards we compared the overall results of the analysis (after all operations were applied). These results suggested that parameter -100 would be more efficient in generating CDA. We determined that averaging by an interval of -100 – 0 ms sufficiently clears the waveform from all the drifts and prevents it from losing target signal.

5.8.5 Artifact Rejection

All operations applied to the data needed to be done in the right order. It was essential to perform baseline correction prior to artifact rejection, otherwise the drifts in the data might have led to poor detection of various kinds of artifacts (Luck, 2014) . In our analysis, artifact rejection was one of the most important parts of the whole process because it had to be done with a great thoroughness and precision. Even though other operations were automatic (we set up the parameters and the rest was done by the software automatically), we chose to do artifact rejection semi-automatically. In semi-automatic artifact rejection, we set up the parameters of artifacts that we wanted to remove from the signal. However, this was followed by our review of the selected artifacts and the review of the whole recording, where we were manually looking for other artifacts, undetected by the software.

Artifact rejection is a critical part of the EEG analysis, not only because artifacts negatively affect individual epochs, but also because an artifact present on one channel can spread to other channels easily (Jas et al., 2017). By artifacts, we understand all signals in the EEG recording which do not come from the brain (GuruvaReddy & Narava, 2013). EEG signal is almost always contaminated by artifacts. Those can have many characters, such as electrode impedance changes caused by headset motion, eye blink, eye movement, neck muscle movement, scalp muscle activities (Chang et al., 2020), bad electrode location, not clean or hairy skin, physiological artifacts or bioelectrical signals from other parts of the body (GuruvaReddy & Narava, 2013). In the past, noise removal from recorded EEG was done mainly by manual visual inspection, which could be time-consuming, laborious and subjective (Chang et al., 2020). However, this method of noise removal also has some advantages. In automatic artifact rejection, artifacts are detected according to some specific parameters set by the user. These values need to be adjusted in a way that most of the artifacts will be found in the signal whereas this process will not affect the target signal. Notwithstanding, some of the artifacts do not fit into the norm with the parameters and therefore cannot be detected by automatic rejection process.

We need to acknowledge that excluding subjects of EEG data due to contamination is highly subjective, as was also declared by Pedroni and collaborators (2019). However, not only manual artifact rejection can be understood as subjective. In automatic rejection, parameter selection is also quite subjective and depends on the discretion of the researcher. We decided to use semi-automatic artifact rejection to employ an accurate automatic artifact rejection together with subjective consideration and visual inspection.

In BVA, semi-automatic artifact rejection is a process that allows a user to specify parameters of signal that should be rejected, however, before the rejection, a whole recording is displayed with all the automatically detected artifacts highlighted. The user may then go through the whole recording and do an additional manual visual inspection by editing and modifying the recording. By this method, we wanted to remove those features of the data that were associated with “stereotypical” artifacts and were not removed in previous steps of analysis. Generally, we distinguish externally generated experimental artifacts (electrical interference) and subject-generated artifacts (blinks, saccades, muscle activity) (Bigdely-Shamlo et al., 2015). One of the most alarming artifacts in our recordings were blinks and eye movements.

Eye blinks are large voltage deflections observed over much of the head, usually much larger than ERP signal (Steven J. Luck, 2014). We removed most of the blinks in the second segmentation according to markers, yet, some of them remained in the recording. The same applies for horizontal eye movements - saccades, that are defined also as large voltage activity, usually with a frequency of range of 1-3 Hz (Mammone et al., 2012). Muscle artifacts were sufficiently removed in the filtering and therefore they were not present in this step of the analysis anymore. Electrical line artifacts (50 or 60 Hz) were also removed in the filtering, using low-pass filters. Bigdely-Shamlo and collaborators (2015) claim that also other undefined discontinuities may occur in the signal. For that reason, visual inspection is often required to improve the process of artifact removal.

In semi-automatic artifact rejection in BVA, we are able to define following parameters: maximal allowed voltage step, maximal allowed difference of values in the intervals, maximal allowed amplitude and lowest allowed activity. With every parameter, we can also set a time interval around the detection that should be, in other words, how many milliseconds before and after the event should be considered as an artifact. BVA provides a valuable and adequate number of parameters that need to be set. Thanks to their variability, the user is free to use as many criteria as necessary for detecting most of the artifacts that might have occurred in the recording. However, choosing the correct ones is quite a complex task. All parameters used in our analysis are summarized in *Table 2*.

	Channels	*Max Allowed Voltage Step*	*Max Allowed Diff. of Values*	*Max Allowed Amplitude*	*Lowest Allowed Activity*
Parameter	All	50 µV	100 µV	100 µV	0.5 µV
Time Sequence to be marked as incorrect (before and after the event)	-	200 ms	200 ms	200 ms	200 ms

Table 2 – Summarization of all parameters used in semi-automatic artifact rejection in BVA.

When we compare each parameter that needs to be set in artifact rejection, some of them provide more effective artifact detecting than others. Maximal allowed amplitude is a parameter that rejects an artifact if the voltage during epoch exceeds a user-defined threshold. This criterion is the vaguest in comparison with the rest, since generating a simple threshold which cannot be exceed is not very suitable for complex EEG data. This method can work well for blink rejections under some conditions because those are very large, however, as Luck (2014) declared, it is absolutely inadequate for detecting and rejecting more subtle artifacts, such as eye movements. It is also important to distinguish blinks and saccades in EEG analysis. Eye blinks are vertical eye movements usually marked as VEOG channels, the electrodes detecting them were placed above and below the left eye. Saccades are horizontal eye movements usually marked as HEOG channels, the electrodes were placed at the temples, as close to canthi as possible. These two kinds of EEG artifacts were the most common and they had to be treated individually in the analysis.

As mentioned before, there are no general rules or guidelines for proper EEG analysis. Nonetheless, Luck (2014) proposes several recommendations how to treat particular artifacts and how to effectively remove them using the appropriate parameters. Since blinks (usually reaching 50-100 µV, lasting 200-400 ms) could be effectively removed using maximal allowed amplitude parameter, we set this criterion on 100 µV, 200 ms before and after the event. Regarding saccades, using only the mentioned parameter would not be much effective. As Luck claims, saccade usually consists of a sudden step from one voltage level to another voltage level, where it would remain until the eyes moved again (in most of the experiments, participants make a saccade from the fixation point to some other location and then make another saccade to return to the fixation point). Since a simple voltage threshold to detect and reject eye movement artifacts is usually set on 100 μV (as also in our case), eye movement as large as 10° would escape the detection (e.g. if the voltage step would start at -80 μV, a 10° eye movement would cause a transition to +80 μV, which would be within the window of ± 100 μV). For that reason, Luck recommends using step function to remove the saccades, particularly small eye saccades. In our case, the step function is defined as the maximal allowed voltage step. Luck defines this function as a flat period of one voltage level followed immediately by another flat period at a lower or higher level. What this function does is that it finds the difference in the mean amplitude between the first and the second half of the epoch (e.g. between first and second 100 ms in 200 ms window). We used following criteria for maximal allowed voltage step: 50 μV/ms, 200 ms before and after the event. We used half the value in comparison to maximum allowed amplitude which was based on two main assumptions: 1. maximum allowed amplitude was set on 100 μV. By setting the maximum allowed voltage step on 50 μV, we prevented the function to exclude some lower blinks from artifact rejection; 2. we wanted to make sure that also smaller eye movements will be detected and removed. *Figure 8* shows what blinks and saccades look like after filters are applied.

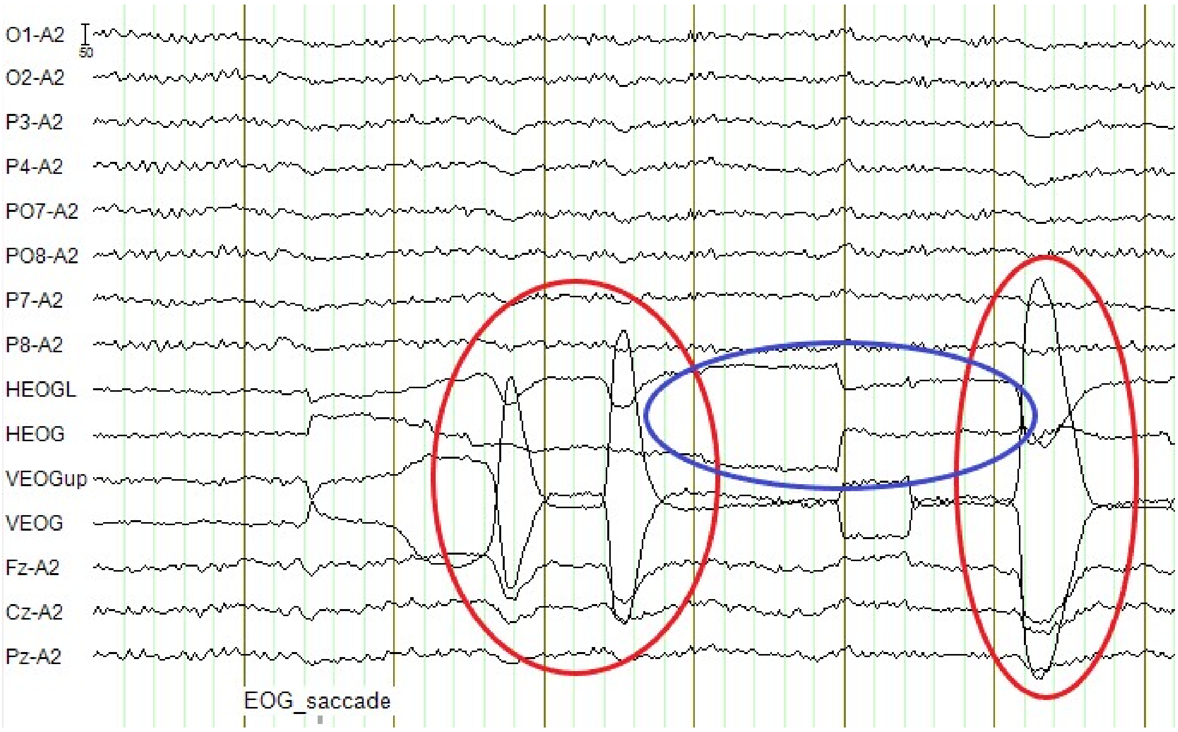

Figure 8 – Combination of blinks (red) and saccades (blue) present on channels HEOGL, HEOG, VEOGup and VEOG.

We also set up the maximal allowed difference of values in intervals (100 ms). This function is useful to detect most skin potentials artifacts, which would not be detected by step function because they usually grow gradually, therefore limit of 50 μV step would not meet the criteria. Skin potentials usually arise when sweat begins to accumulate in sweat glands, changing the impedance of the skin and therefore causing a change in the standing electrical potential of the skin over a period of many seconds (Steven J. Luck, 2014). These shifts can be also caused by a change of electrode position which is mostly produced by movements of the participant. For that reason, it is always important to make sure that the participant feels comfortable and prevent them from moving too much during the experiment. Skin potentials were the most common artifacts in our recordings, they might have been caused by the hot weather and high temperatures which lead to higher sweating of the participant. During the experiment, every time we noticed that signal is getting worse, we tried to add more gel into the electrode and scratched the skin below it. Sometimes this strategy did not help either and therefore it caused many skin potentials artifacts in the recordings. We set the parameter of maximal allowed difference of values in interval on 100 μV, 200 ms before and after the event.

Finally, regarding lowest allowed activity in intervals (100ms), we set the parameter on 0.5 µV, 200 ms before and after the event. Such a low continuous voltage in the signal might be cause by amplifier saturation, which causes the EEG to be flat for some period (Steven J. Luck, 2014). However, this is much rarer than the artifacts mentioned before. We set this parameter on 0.5 in order to prevent losing target signal occurring in even lower voltage.

The automated process of artifact rejection in BVA took all the parameters we set and highlighted the features in the recording that met the criteria. Then, we performed an additional manual visual inspection. We reviewed the artifacts detected by BVA and looked for others, undetected by the software. In case we found another component that we considered to be an artifact, we manually highlighted it and it was then added to the list of artifacts under a name *user-defined artifact*. After we went through all segments of the recording, we finished the process and all chosen artifacts were rejected. It is suggested to be careful with artifact removal and it is proposed to reject not more than 20% of the recording (Steven J. Luck, 2014), however, we also tried to be strict in the artifact detection and tried to clean the recordings from all big deflections. The main goal was to find a compromise between two goals – find the artifacts and clean the recording from all deflections, and not to reject too large proportions of the recording.

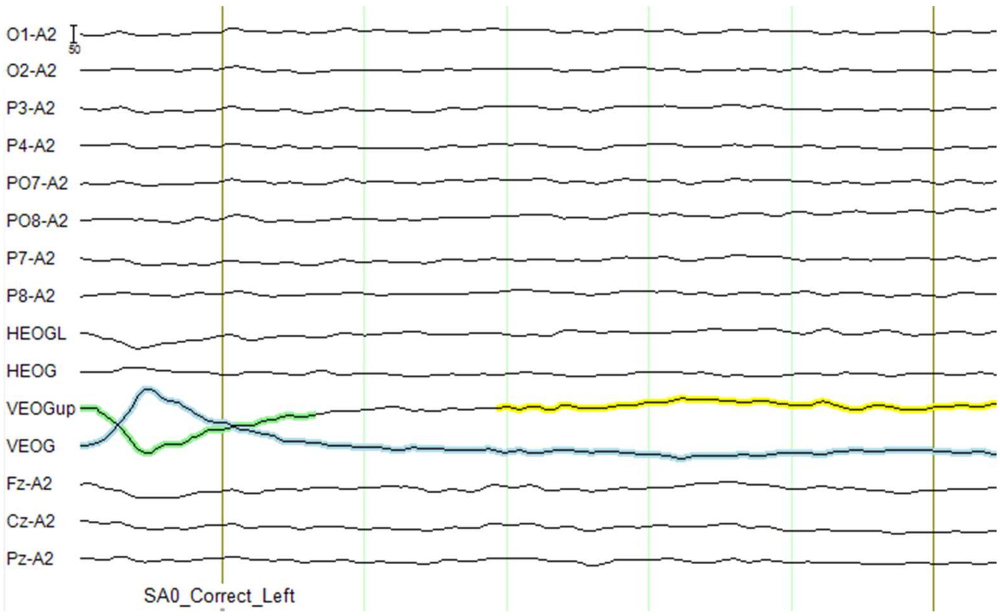

Figure 9 – Artifacts highlighted after semi-automatic artifact rejection was applied to the data. Blue and green artifacts represent an eye blink, yellow artifact shows a deviation caused probably by skin potentials.

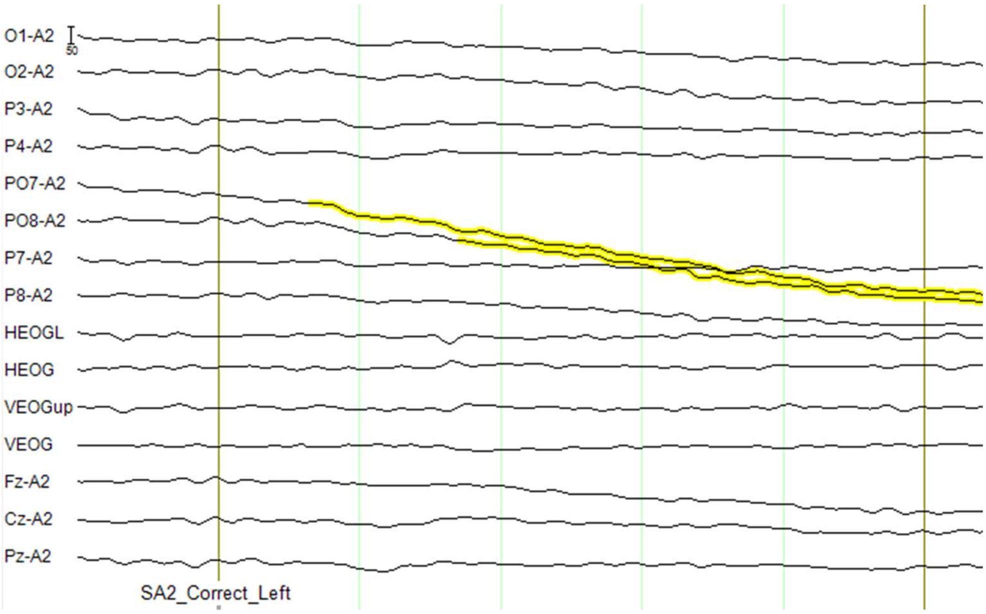

Figure 10 – Lines highlighted by yellow colour represents a skin potential artifact on two posterior channels. It was detected automatically by BVA according to set parameters.

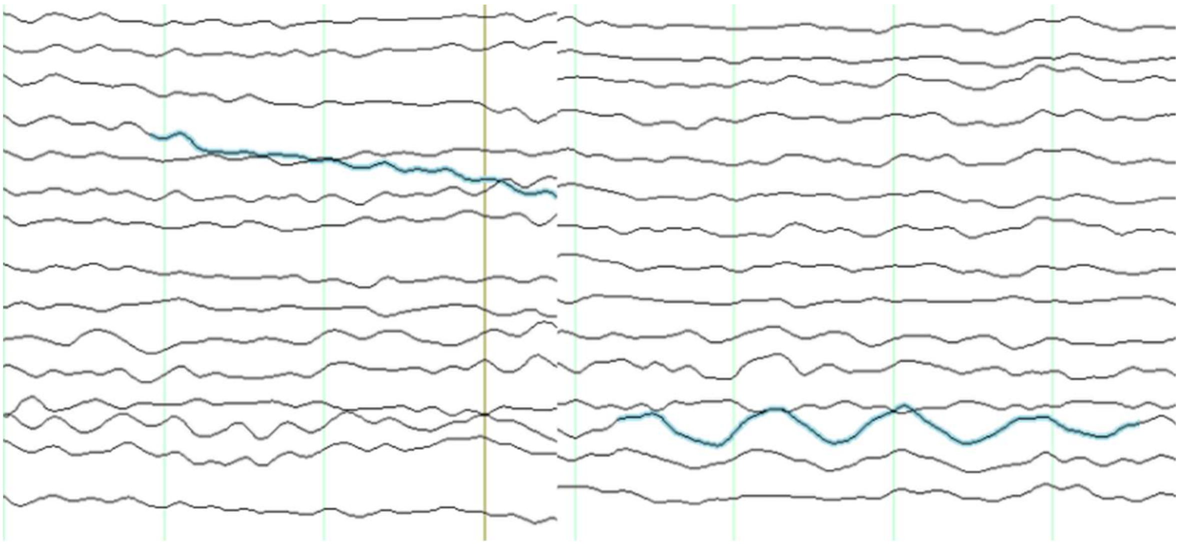

Figure 11 – Artifacts chosen and highlighted by the user in the manual inspection.

5.8.6 Averaging and CDA Extraction

In the next steps we needed to transform the pre-processed data into the form of CDA, which took several steps. First, we extracted all segments of one out of the four conditions

(2 targets, 0 distractors; 2 targets, 2 distractors; 4 targets, 0 distractors; 4 targets, 2 distractors), we did this separately for each condition. This process was quite easy and straight-forward. We used previously set markers to detect the relevant condition and rejected the rest (markers were created during the experiment). After specifying the condition, we conducted averaging of all electrodes of parietal occipital parts for the given hemifield, having the same weight (0.25). Averaging is a common technique in ERP analysis, it reduces the background EEG noise and irrelevant brain activity (Blinowska & Durka, 2006; Kotowski et al., 2019). Hence, in our analysis the averaging was mostly based on the intention to extract the CDA. We needed to average the activity from left and right posterior channels to get one waveform which can be then included into the final subtraction that leads to CDA. By using the described operations, we got to the root of the processing by counting the ipsilateral and contralateral activity. To get ipsilateral activity, we created an average of an activity in all ipsilateral segments (right hemifields + right cue and left hemifield + left cue). Afterwards, to gain contralateral activity, we applied the same process only by submitting opposite criteria (right hemifield + left cue and left hemifield + right cue). Finally, we subtracted the ipsilateral activity from the contralateral activity by applying a simple difference function in BVA to generate the final CDA waveform. *Figure 12* presents a combination of four final CDA waveforms – each presenting one condition in the experiment.

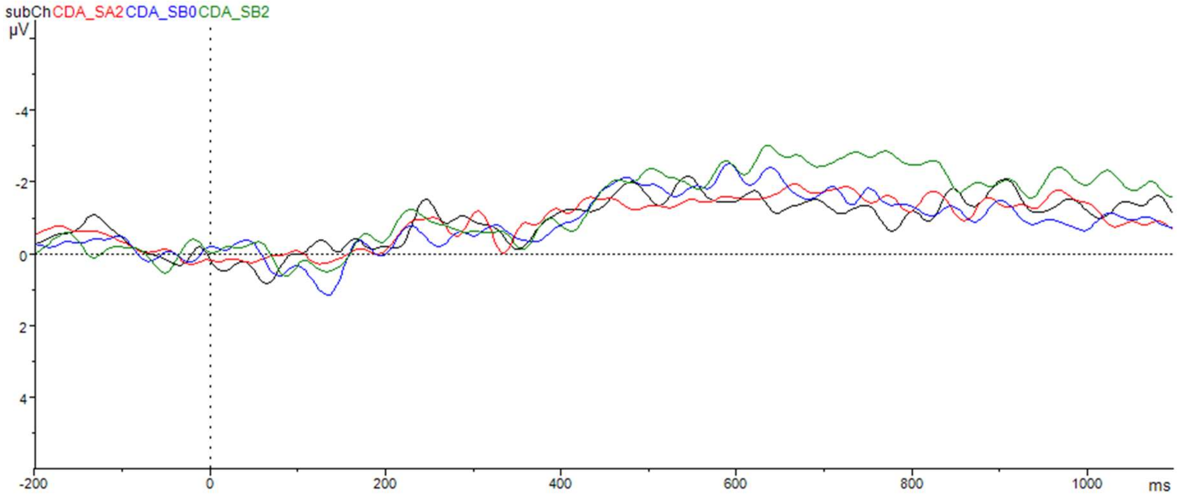

Figure 12 – Final CDA waveforms representing one hemifield of one participant. Colours distinguish the conditions of the experiment: black – 2 targets, 0 distractors, red – 2 targets, 2 distractors, blue – 4 targets, 0 distractors, green – 4 targets, 2 distractors.

All described processes were done in duplicate, separately for right and left visual fields (both having two main "branches" for right and left set size of electrodes).

6 Results

The resulting grand averages of CDA ERPs for the control group of participants are presented on *Figure 13*, *Figure 14* and *Figure 15* separately for three days of measurement *(*corresponding to three sessions of CDA recording for the experimental group: before the training, in the middle of the training and after the training*)*. On each figure, four lines represent the four conditions of trials with different set sizes (black – 2 targets, 0 distractors, red – 2 targets, 2 distractors, blue – 4 targets, 0 distractors, green – 4 targets, 2 distractors). We can clearly see the CDA – slow negative deflection with maximal amplitude in the interval from approximately 400 ms to 900 ms after the stimulus onset – is present on each of the ERP curves. Please notice that the negativity is plotted upward for voltages (vertical axis) according to historical convention in the ERP research. We can conclude the second goal of this thesis – to perform the EEG analysis to obtain clear CDA waveform was achieved successfully.

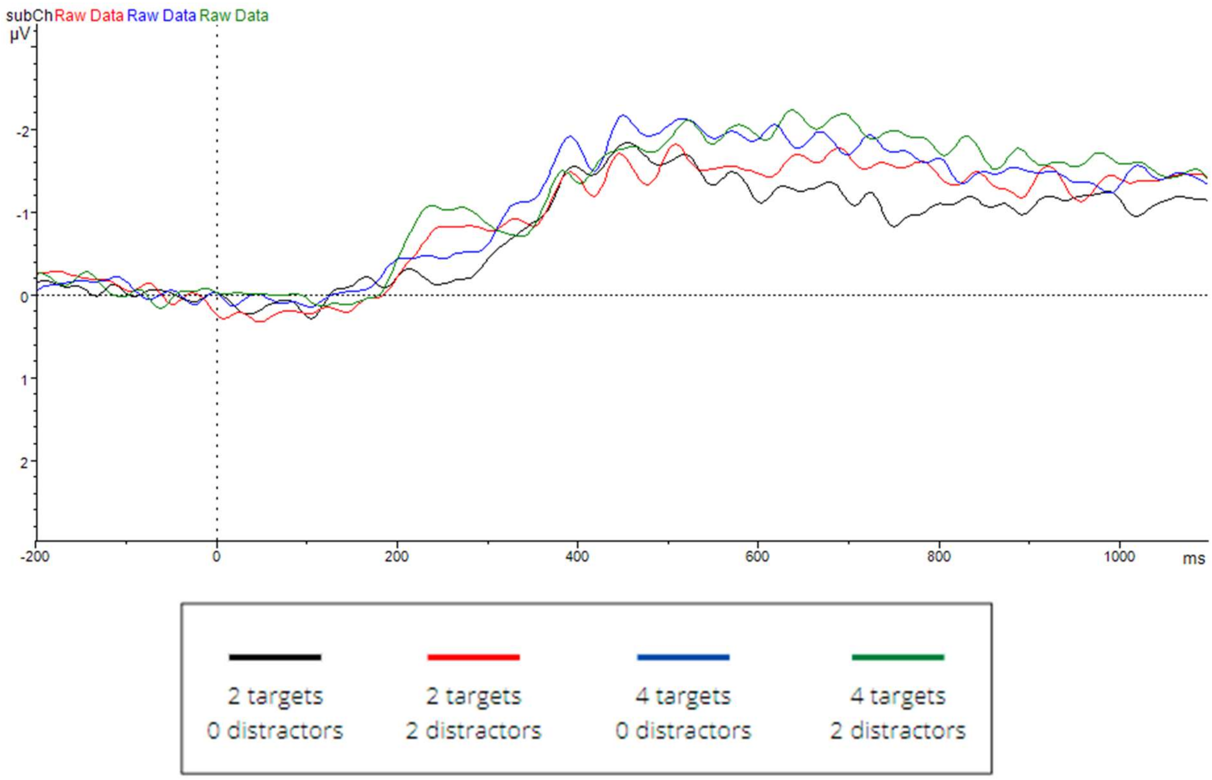

Figure 13 – Averaged CDA waveforms of sixteen participants performing the CDT in pre experiment.

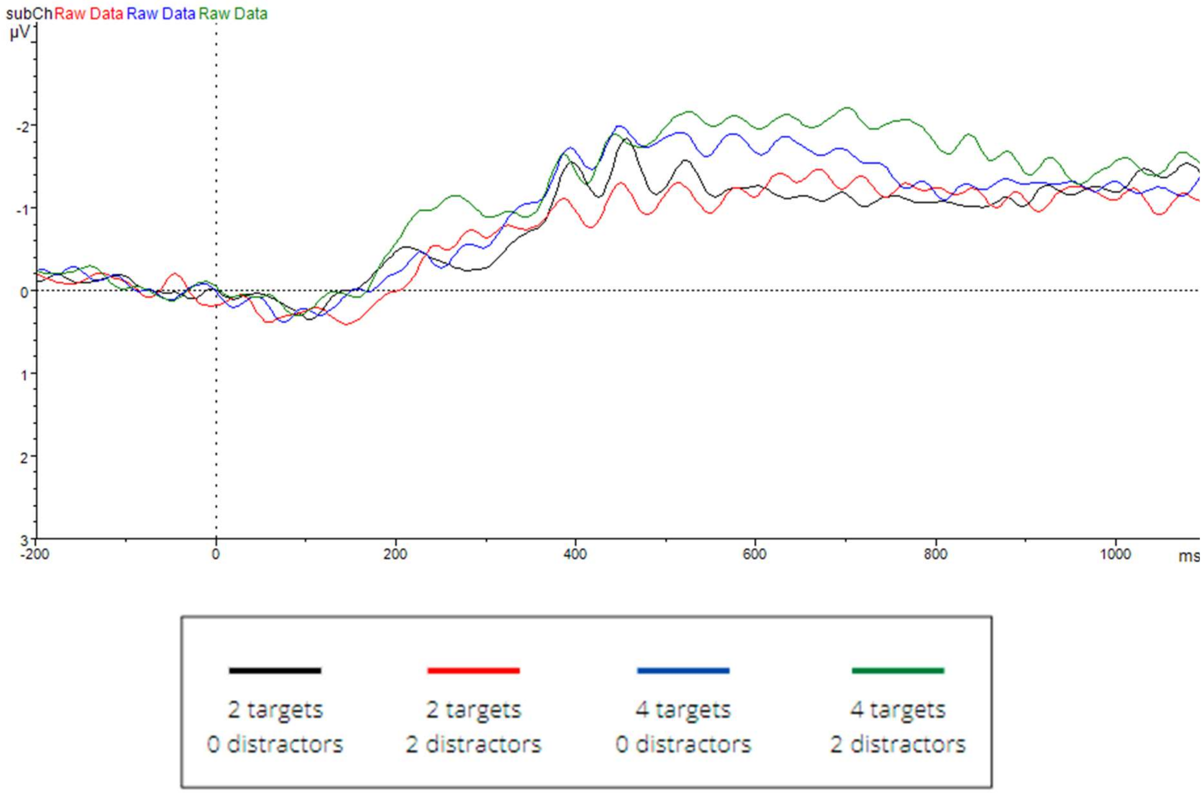

Figure 14 – Averaged CDA waveforms of sixteen participants performing the CDT in mid experiment.

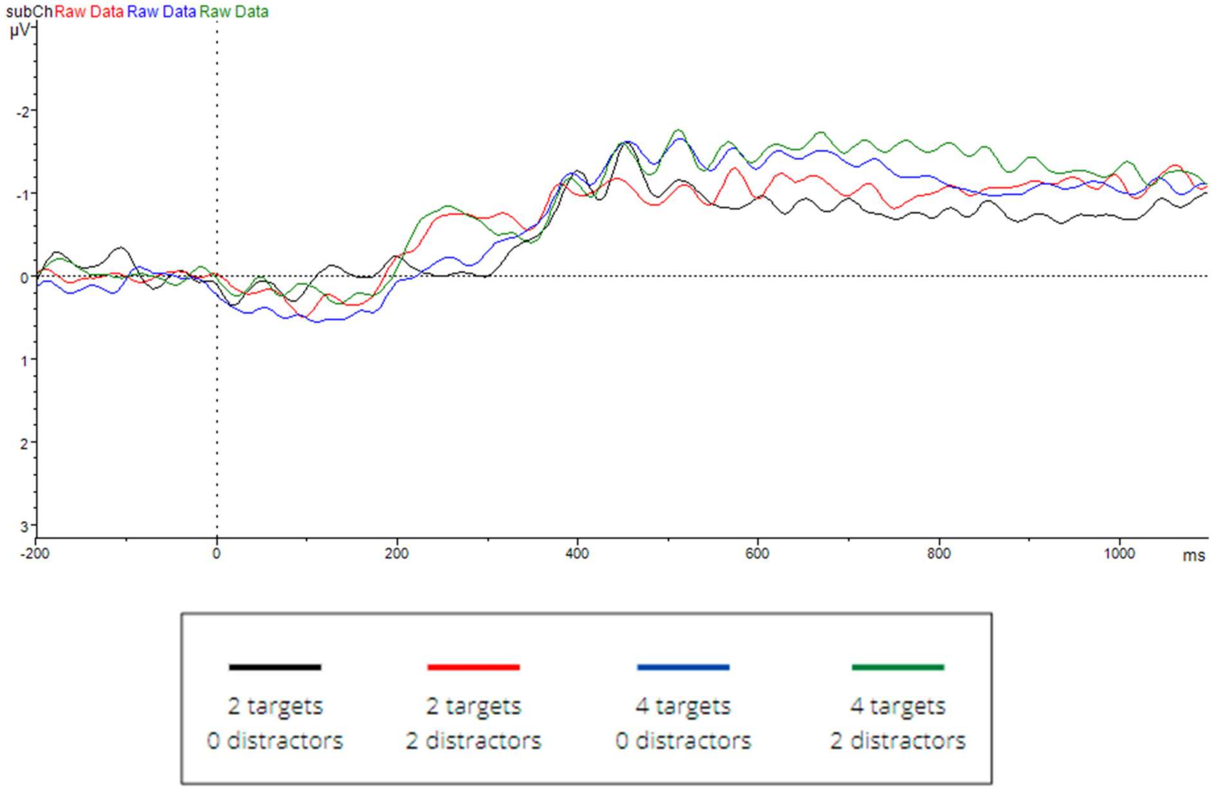

Figure 15 – Averaged CDA waveforms of sixteen participants performing the CDT in post experiment.

To be able to perform statistical analysis, it is necessary to transform graphical representations to numbers. For CDAs, this is usually achieved by calculating the area under the curve for a specific time interval – in our case and in line with recommendations from original studies of CDAs we extracted the area under the curves from the interval 400 ms to 900 ms, separately for each condition of the trial with different set size (2 or 4 targets x 0 or 2 distractors) and for each day of measurement. Extracted data were used for further analysis.

To further evaluate the obtained results in terms of different conditions and sessions in the control group, we conducted the statistical analysis using three way ANOVA with factors *Targets* (two vs. four), *Distractors* (zero vs. two) and *Day* (corresponding to three sessions: pre-, mid-, and post- training in the experimental group). We found a statistically significant main effect of *Target*, $F(1,14) = 33.565$, $p < 0.001$ and a significant main effect of *Day*, $F(2,28) = 7.939$, $p < 0.005$. Figure 14 shows the CDA amplitudes were higher (more negative) for four targets in comparison to two targets that participants had to remember for a prolonged period of time. Neither the main effect of *Distractors* nor any interaction between factors reached statistical significance, meaning the number of distractors did not have a consistent effect on CDA curves and that the found main effects were the same across conditions.

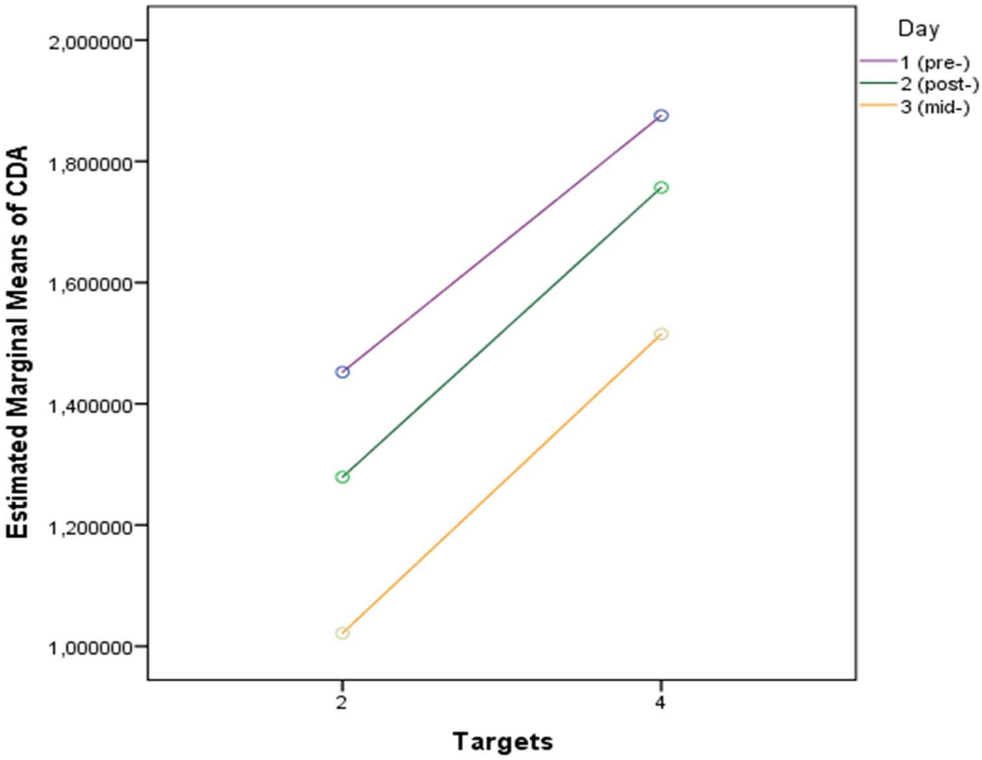

Figure 16 – Averaged area under the curves for CDAs from the range. Each line represents a group average for one of three sessions. The effect of *Day* was significant as well as the effect of number of *Targets.* As expected, the amplitude of CDA was higher (more negative) for more targets to be remembered (four compared to two). Interestingly, the amplitude was not stable across days.

7 Discussion

This thesis was a part of a bigger project and by its actions and outcomes it contributed to the main project called *Enhancing Cognition and Motor Rehabilitation in Mixed Reality*. As in many studies before, the project aimed to deeply investigate the presence of CDA in EEG signal, however, as one of the first studies also tried to train this neurophysiological correlate of spatial WM. In the experimental group of the main project, we wanted to see the effects of training in VR. EEG pre-processing needed to be done precisely and effectively in both groups in order to detect possible effects. In the final step of the big project, neurophysiological results of the control and experimental group will be compared and finalised to accept or reject the previously set hypotheses. Statistical analysis of amplitudes is different than analysis of behavioural performance; there are strict rules that need to be followed in both, but the character of the data differs. Behavioural performance returns a fixed value that cannot be transformed or updated anymore and is then treated like that in later analysis. In general, neurophysiological methods usually result in data that are rather fluctuable, their ambiguity is mostly observable when compared to behavioural data. The values of amplitude in the EEG signal are transforming according to the operations applied to the raw data during processing. Each step of the processing is slightly changing and adjusting the curves, and directly affects the form of the final amplitude and its values. Due to this fact, a proper EEG analysis is essential to acquire a valid final value that can be used in statistical analysis.

As mentioned in the theoretical overview (p. 9), in the past fifteen years there was a great interest in studying CDA and its various characteristics. Nonetheless, there are still some open questions in relation to its form and properties. One of them is the question of CDA being or not being trainable, and if so, what kind of training is the most efficient. The issue of trainability of neurophysiological corelates has been very popular in recent years. Its effectiveness is mostly showed in biofeedback[9] research. However, it is much more complicated to study trainability of neural correlate than behavioural performance. In behavioural performance we know exactly what to measure and how (e.g. if we measure reaction time, we know the stimulus causes the subject to take action, and that the reaction

[9] Biofeedback is a method that enables individuals to learn how to regulate their physiological activities in order to restore or maintain autonomic balance, mostly used in therapy and rehabilitation (Yu et al., 2018).

time is the value by which we can determine the response on given stimuli). With neurological correlates this process is more complicated, since neurophysiology works all the time, whether there is stimulus or not. It is challenging to determine whether an activity is a result of some specific stimuli or environmental effects. Since many authors confirmed that CDA is defined by the number of items a subject hold in a VWM, we find its character rather clear. The effect of the training has not been confirmed in behavioural performance yet, however, since its neurophysiological correlates have rather different character, we assume that the training might influence them.

If the results of the main project analysis show no significant effects of the training in the VR in the experimental group, it might be due to following reasons: 1. Filtering ability is not trainable, 2. The character of the training in VR was not appropriate and not effective enough to train the filtering ability and WM capacity, 3. There were some limitations in the way of the experiment was carried out that has made the training less effective. Nevertheless, to fully investigate a phenomenon that is still unknown, even negative results or refutation of hypotheses is a conclusion that leads to a better understanding. The reason for the effect of training not to be fully detected in behavioural performance in the past research might be due to the already mentioned character of the data. The effect of the training might be minor and therefore not observable in behavioural performance. However, CDA might demonstrate also such minor effects which will be determined after the final analysis.

Since Vogel & Machizawa (2004) investigated CDA in relationship with WM capacity and filtering ability, many others attempted to explore the phenomenon. Despite the great interest in this topic, clarifying the individual aspects and pitfalls of the analysis that leads to the final amplitudes have not been presented so far. By the experiment we carried out, we wanted not only to contribute to the main project by providing the data of the control group, but also to illustrate what an EEG experiment requires and to provide an overview of the necessary steps in the pre-processing and the analysis. Research usually contains many aspects that are never presented to the reader, like the considerations, practical challenges and decisions that need to be made. With this thesis, we wanted to share the experience we acquired during the research about various aspects of an EEG experiment, because actions taken during the experiment and parameters set during the analysis have led to the final results that will be used further in the main project.

We can conclude we successfully achieved the goals that we set at the beginning of the study. The main objectives of this thesis were: 1. to carry out an experiment on the control group of healthy participants and to record the EEG while they were performing visual working memory tasks, 2. To analyse collected EEG data in terms of final event-related potentials (ERP) of contralateral delay activity, emphasizing the precise use of a combination of automatic and manual artifact rejection in Brain Vision Analyzer. In order to achieve the first goal, we first had to find an appropriate number of healthy subjects who would participate in the experiment. This was quite challenging considering the length of the experiment, since one session lasted approximately two hours and particular sessions had to be separated by two weeks, therefore the whole procedure took almost 4-5 weeks. We wanted to get at least fifteen participants to have a similar sample as in the experimental group. A monetary reward was also motivation for potential subjects to consider the participation. At the end, we had to refuse some of them because they did not meet the conditions (e.g. left-handed participants). Moreover, some of the participants started the experiment but had to terminated it prematurely. Finally, we recruited twenty participants using online advertisement on various social media platforms, sixteen of them successfully finished the experiment.

It was challenging for us to carry out the EEG recordings considering the complicated global situation due to the COVID pandemic. This also resulted in some limitations of our performed experiment. We needed to be very careful during the experiment to minimize all possible risks. The experimenter wore a face mask during the whole process, participants were without masks since those could greatly affect their performance in CDT. Wearing the EEG cap itself was distressing to some of the participants and movement restrictions led them to feel stress and discomfort, face masks could increase these feelings even more. Another consequence of the COVID situation resulted in the disruptions of timeline of the experiment. Two participants had longer than two-week breaks between the sessions due to pandemic reasons, both participants successfully finished the whole procedure.

The procedure protocol of the main project was set before the start of the experimental recordings. Although we followed the steps precisely, some aspects of the procedure needed to be adjusted during the course of the experiment. According to the protocol, more than 80% of the trials had to be without saccades and blinks during retention interval, otherwise, if more than 20% of the trials were rejected, participant could not proceed in the experiment. However, we considered that the entry session might not have been enough time of training for some of the subjects who needed more time to train and learn how to do the task correctly. We added one additional session where they performed CDT with EOG again. If they achieved more than 80% of correct trials, they could proceed to the next stage. We performed this additional session in four cases.

Regarding the second goal of the thesis, it was directly related to the first one, therefore, the quality and precision of the recording affected the difficulty and outcomes of the analysis. For that reason, we tried to be very careful during the recordings to detect all the abnormalities in the signal that might have occurred (e.g. muscle activity during retention interval that would lead to rejection of many intervals, fluctuating signal on one or more channels that would affect the averaging of the posterior channels, etc.).

The analysis of the EEG and the detailed overview of all steps taken, represent not only a description of how such an analysis should look like, but could serve also as guidelines of what needs to be considered while choosing the appropriate parameters. As declared before, there are no general rules about how exactly the EEG analysis should be carried out. Researchers always need to take into consideration the goal of the research, hypotheses, and the qualitative aspect of the data. During the analysis, we tried to compare various approaches that were suggested by authors investigating similar phenomena. There were not many of them, therefore, we had to try various parameters and proceeded all steps to see the final CDA and compare it with another that resulted from the same data, only using different parameters. This process was quite time-consuming considering that the analysis consisted of many operational steps.

After many variations of the parameters and their order, we figured out what a final version of the analysis pipeline should look like. We tried to combine the knowledge acquired from the theoretical investigation with the outcomes of the practical inspection. Similarly, as many authors before, we started the analysis with filtering, followed by segmentation, artifact rejection and other required mathematical processes (averages and linear derivations). We needed to be careful mostly during segmentation and artifact rejection in order to persevere at least 80% of the data. As was also declared by Luck (2014), the researcher must be thoughtful during EEG analysis and rejecting more than 20% of the data is not recommended. Segments of EEG data were mostly rejected because they were contaminated by the presence of artifacts (or other qualitative reasons). Rejecting segments due to noise contamination is the correct action. However, too common occurrence of artifacts and their potential rejection leads to lower quality and validity of the data. This presents another general dilemma while conducting EEG analysis – whether to be rather strict during EEG analysis and reject everything that seem to be out of normal or being rather careful in the analysis, preventing of losing too much of the signal. The problem is that there is not fixed definition of what an artifact or EEG noise looks like and there is not a line that divides an artifact from a clean signal. Sometimes it is on the subjective consideration of the researcher whether to keep or reject a given segment. It is important to keep a balance between strictness and cautiousness during artifact rejection. Someone might argue that automatized processes of artifact rejection are much more accurate than manual visual inspection. To some level, this assumption might be true, but the question remains how a computer can efficiently detect an unclear artifact when even an experienced researcher needs to highly consider whether to reject it or keep it? To make our analysis as effective as possible, we decided to conduct semi-automatic EEG analysis. Although it is more time-consuming than automatic artifact rejection, we considered that additional visual inspection will make the artifact rejection more accurate.

Before we started the EEG analysis, we wanted to make sure that we have all necessary knowledge about what was done in the past studies and suggested by other authors. Although there are no general rules that can be followed, practical tips might always help, even by defining the problem that we can then find our specific solution for. This thesis also provides an overview of theoretical aspects of an EEG experiment and analysis. We investigated not only studies that focused on CDA itself, we tried to explore EEG papers that studied various aspects of human cognition and focused on different phenomena. This helped us to determine individual steps of the analysis and the whole course of the processing. Many studies performed the experiment and the analysis aiming to detect rather different phenomenon than we did, but provided some helpful tips, difficulties, and risks for such a project. Even though none of these studies explained the particular steps taken in EEG analysis, the more general description was beneficial in terms of determining various aspects of the processing. We consider mostly Luck's (2014) overview of ERPs and EEG very valuable and although he did not address CDA itself, he proposed many practical tips of how to proceed in the analysis. His rich and straight-forward explanations and suggestions helped us to better understand various aspects of the strategy in an EEG experiment and later analysis.

Complexity of the final CDA curves makes it somewhat difficult to summarize the data, however, we achieved to get waveforms that are quite similar than those presented by Vogel and colleagues in 2005. We can see that CDA waveforms are present in our data, which was achieved by a proper EEG processing. As displayed in *Figure 11*, *Figure 12* and *Figure 13*, curves representing higher number of targets demonstrate higher negativity (black and red curves represent two targets, green and blue curves represent four targets). Since mostly in mid and post experiment the blue and green curve were still quite different, it seems that most of the participants were not efficient in excluding the distractors. Black and red curves are different mostly in the pre experiment; mid and post experiment suggest that participants might have been more efficient in excluding distractors than in third and fourth condition (4 targets, 0 distractors and 4 targets, 2 distractors). To elucidate the exact reasons of such findings, further analysis on CDA from individual participants would be necessary.

The second goal of the thesis was achieved successfully, since the statistical analysis showed that the number of items to remember affected the amplitude of CDA. Hence, the amplitude displayed more negativity in the condition when participants needed to remember 4 items than in the condition with 2 items to remember. Generated waveforms confirmed the statement that the negativity of the amplitude is higher with rising number of items to be remembered, which was true for the whole group of participants, each day of the experiment outline (pre-, mid-, post-).

The CDA waveform was fluctuating across the individual sessions which was probably caused by the intraindividual variability that is a common phenomenon occurring in EEG recordings. It reflects the individual differences of participants' physical and mental state in each day (e.g. physical or mental fatigue). Intraindividual variability is based mostly on the biorhythm of each participant, therefore the fact that it affected the CDA is quite reasonable. Due to aforementioned limitations, our results should be taken with caution.

The main effect of distractors – to divert attention from the targets - was not detected in the analysis. One explanation might be that distractors influenced only some of the participants, which could have been caused by discrepancies in the filtering ability of individual participants. To successfully identify the effects of distractors in the final CDA waveforms, future research should individually analyse the data of the participants with low filtering ability and high filtering ability.

In line with our hypothesis we find no interaction of distractors and session in the control group. This suggest the pure repetition of the CDT measurement without additional training does not affect participants filtering ability, what was our main objective. Therefore, we can conclude that if there will be an improvement detected in experimental group between particular sessions, it will be presumably caused by the training, not the repeated performance of CDT.

7.1 Limitations

We need to acknowledge that this thesis has some limitations that should be improved in the future research. First, as mentioned before, to detect CDA in the signal and determine whether there were some improvements based on the training, the sample needs to be representative and big enough. In the future research, more subjects should participate in the experiment to see potential changes and trends in CDA. We managed to recruit sixteen participants (fourteen in the experimental group). This number was highly determined by the COVID situation which has led to lower number of participants who were willing to participate and also led to limited time when the experiment could run due to quarantine restrictions.

Another limitation might be found in the length of the experiment itself. Since we do not know whether CDA is trainable by VR training, we cannot be certain that two weeks of training is an appropriate time for improvements to occur. Potential future research could invest more time into the whole procedure of the training.

There are some limitations in relation to the EEG character of the experiment. First, EEG as a tool for measuring neural activity greatly affects subject's comfort with wires and electrodes attached to their body, as was also declared by Ganglbauer and colleagues (2009). According to the authors, it restricts the participants in terms of moving. This is a problem that we observed during the recordings when participants were complaining about stiff muscles and other discomforts resulting from the restriction of movements. Since in EEG, every slight movement of muscles and eye movements result in signal noise, mentioned aspects of EEG as a tool could also affect the signal, and therefore the results. Similarly as Bell & Cuevas (2012), we see artifact rejection as one of the main challenges, even though it was the main operation of the analysis. This claim is based mostly on the subjectivity and the duration of manual inspection of artifacts, although we facilitated the process by recording the EOG too, which helped with the detection of eye blinks and saccades.

Conclusion

We can conclude that we have successfully performed an EEG analysis and identified the CDA in the signal. After conducting a proper EEG recording and the analysis of the signal including multiple steps of data pre-processing we were able to show the final CDA waveforms. The processing itself was essential, however, also EEG recording must have been conducted correctly to achieve the desired quality of the signal. Final CDA amplitudes demonstrate an expected decrease in voltage with increased number of items to be remembered. In line with our hypotheses, we did not find an effect of distractors that would change across the three recording sessions in the control group. This suggests that performing a successful training of filtering ability in the experimental group in VR environment could be examined by repeated assessment of CDT.

Even though we already know that preliminary results did not show any significant difference in behavioural performance in the experimental group, we can still expect to see some effects visible in the neural correlates (CDA waveforms) that will be detected after the final analysis. Even though the effect of the VR training was not detected in behavioural data, neurophysiological data tend to demonstrate more subtle effects that could potentially provide some evidence of improvement. Nonetheless, even if this assumption will not be confirmed, the results of this thesis can still be considered as beneficial. First, as defined in our goals, we successfully performed the experiment followed by an EEG analysis. In this work we also provide an overview of the necessary practical steps together with the theoretical investigation which shows how a proper EEG study should be performed. This acquired knowledge can be used in following research in the future. Second, the results, either confirming or refusing the given hypotheses, will shed new light onto the topic of trainability of the filtering ability and WM capacity. We carried out an experiment on the control group and conducted EEG analysis, and by doing so, we contributed to the research of CDA and trainability of WM in general. In order to answer the question whether filtering ability is trainable and whether individuals' WM capacity can be improved, we think that future research should be designed within already acknowledged theoretical frameworks and try to set a question whether VWM is trainable and if so, what is the appropriate training and if its effects can be observable by CDA.

References

Adam, K. C. S., Robison, M. K., & Vogel, E. K. (2018). Contralateral Delay Activity Tracks Fluctuations in Working Memory Performance. *Journal of Cognitive Neuroscience*, *30*(9), 1229–1240. https://doi.org/10.1162/jocn_a_01233

Adam, K. C. S., Vogel, E. K., & Awh, E. (2017). Clear evidence for item limits in visual working memory. *Cognitive Psychology*, *97*, 79–97. https://doi.org/10.1016/j.cogpsych.2017.07.001

Adamovich, S. V., Fluet, G. G., Tunik, E., & Merians, A. S. (2009). Sensorimotor training in virtual reality: A review. *NeuroRehabilitation*, *25*(1), 29–44. https://doi.org/10.3233/NRE-2009-0497

Adams, E. J., Nguyen, A. T., & Cowan, N. (2018). Theories of Working Memory: Differences in Definition, Degree of Modularity, Role of Attention, and Purpose. *Language, Speech, and Hearing Services in Schools*, *49*(3), 340–355. https://doi.org/10.1044/2018_LSHSS-17-0114

Alvarez, G. A., & Cavanagh, P. (2004). The Capacity of Visual Short-Term Memory is Set Both by Visual Information Load and by Number of Objects. *Psychological Science*, *15*(2), 106–111. https://doi.org/10.1111/j.0963-7214.2004.01502006.x

Arend, A. M., & Zimmer, H. D. (2011). What Does Ipsilateral Delay Activity Reflect? Inferences from Slow Potentials in a Lateralized Visual Working Memory Task. *Journal of Cognitive Neuroscience*, *23*(12), 4048–4056. https://doi.org/10.1162/jocn_a_00068

Arnsten, A. F. T. (2006). Fundamentals of attention-deficit/hyperactivity disorder: Circuits and pathways. *The Journal of Clinical Psychiatry*, *67 Suppl 8*, 7–12.

Augmented reality and virtual reality. (2017). Springer Berlin Heidelberg.

Awh, E., Barton, B., & Vogel, E. K. (2007). Visual Working Memory Represents a Fixed Number of Items Regardless of Complexity. *Psychological Science*, *18*(7), 622–628. https://doi.org/10.1111/j.1467-9280.2007.01949.x

Awh, E., & Jonides, J. (2001). Overlapping mechanisms of attention and spatial working memory. *Trends in Cognitive Sciences*, *5*(3), 119–126. https://doi.org/10.1016/S1364-6613(00)01593-X

Awh, E., Jonides, J., & Reuter-Lorenz, P. A. (1998). Rehearsal in spatial working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(3), 780–790. https://doi.org/10.1037/0096-1523.24.3.780

Baddeley, A. (1992). Working memory. *Science*, *255*(5044), 556–559. https://doi.org/10.1126/science.1736359

Baddeley, A. D., & Hitch, G. (1974). Working Memory. In *Psychology of Learning and Motivation* (Vol. 8, pp. 47–89). Elsevier. https://doi.org/10.1016/S0079-7421(08)60452-1

Baddeley, A. D., Hitch, G. J., & Allen, R. J. (2019). From short-term store to multicomponent working memory: The role of the modal model. *Memory & Cognition*, *47*(4), 575–588. https://doi.org/10.3758/s13421-018-0878-5

Baddeley, Alan. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *4*(11), 417–423. https://doi.org/10.1016/S1364-6613(00)01538-2

Baddeley, Alan. (2003). Working memory: Looking back and looking forward. *Nature Reviews Neuroscience*, *4*(10), 829–839. https://doi.org/10.1038/nrn1201

Bell, M. A., & Cuevas, K. (2012). Using EEG to Study Cognitive Development: Issues and Practices. *Journal of Cognition and Development*, *13*(3), 281–294. https://doi.org/10.1080/15248372.2012.691143

Beres, A. M. (2017). Time is of the Essence: A Review of Electroencephalography (EEG) and Event-Related Brain Potentials (ERPs) in Language Research. *Applied Psychophysiology and Biofeedback*, *42*(4), 247–255. https://doi.org/10.1007/s10484-017-9371-3

Biasiucci, A., Franceschiello, B., & Murray, M. M. (2019). Electroencephalography. *Current Biology*, *29*(3), R80–R85. https://doi.org/10.1016/j.cub.2018.11.052

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.-M., & Robbins, K. A. (2015). The PREP pipeline: Standardized preprocessing for large-scale EEG analysis. *Frontiers in Neuroinformatics*, *9*. https://doi.org/10.3389/fninf.2015.00016

Bisley, J. W., & Mirpour, K. (2019). The neural instantiation of a priority map. *Current Opinion in Psychology*, *29*, 108–112. https://doi.org/10.1016/j.copsyc.2019.01.002

Blinowska, K., & Durka, P. (2006). Electroencephalography (EEG). In M. Akay (Ed.), *Wiley Encyclopedia of Biomedical Engineering* (p. ebs0418). John Wiley & Sons, Inc. https://doi.org/10.1002/9780471740360.ebs0418

Bower, G. H. (1968). *Psychology of Learning and Motivation, 2.* Elsevier. http://www.123library.org/book_details/?id=45688

Burdea, G. C. (2003). Virtual rehabilitation—Benefits and challenges. *Methods of Information in Medicine*, *42*(5), 519–523.

Chang, C.-Y., Hsu, S.-H., Pion-Tonachini, L., & Jung, T.-P. (2020). Evaluation of Artifact Subspace Reconstruction for Automatic Artifact Components Removal in Multi-Channel EEG Recordings. *IEEE Transactions on Biomedical Engineering*, *67*(4), 1114–1121. https://doi.org/10.1109/TBME.2019.2930186

Chen, X., Liu, A., Chiang, J., Wang, Z. J., McKeown, M. J., & Ward, R. K. (2016). Removing Muscle Artifacts From EEG Data: Multichannel or Single-Channel Techniques? *IEEE Sensors Journal*, *16*(7), 1986–1997. https://doi.org/10.1109/JSEN.2015.2506982

Christophel, T. B., Klink, P. C., Spitzer, B., Roelfsema, P. R., & Haynes, J.-D. (2017). The Distributed Nature of Working Memory. *Trends in Cognitive Sciences*, *21*(2), 111–124. https://doi.org/10.1016/j.tics.2016.12.007

Chun, M. M. (2011). Visual working memory as visual attention sustained internally over time. *Neuropsychologia*, *49*(6), 1407–1409. https://doi.org/10.1016/j.neuropsychologia.2011.01.029

Chun, M. M., & Turk-Browne, N. B. (2007). Interactions between attention and memory. *Current Opinion in Neurobiology*, *17*(2), 177–184. https://doi.org/10.1016/j.conb.2007.03.005

Clarke, H., Walker, S., Dalley, J., Robbins, T., & Roberts, A. (2006). Cognitive Inflexibility after Prefrontal Serotonin Depletion Is Behaviorally and Neurochemically Specific. *Cerebral Cortex*, *17*(1), 18–27. https://doi.org/10.1093/cercor/bhj120

Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review*, *12*(5), 769–786. https://doi.org/10.3758/BF03196772

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *The Behavioral and Brain Sciences*, *24*(1), 87–114; discussion 114-185. https://doi.org/10.1017/s0140525x01003922

Cowan, Nelson. (2008). Chapter 20 What are the differences between long-term, short-term, and working memory? In *Progress in Brain Research* (Vol. 169, pp. 323–338). Elsevier. https://doi.org/10.1016/S0079-6123(07)00020-9

Cowan, Nelson, Fristoe, N. M., Elliott, E. M., Brunner, R. P., & Saults, J. S. (2006). Scope of attention, control of attention, and intelligence in children and adults. *Memory & Cognition*, *34*(8), 1754–1768. https://doi.org/10.3758/BF03195936

Cowan, Nelson, & Morey, C. C. (2006). Visual working memory depends on attentional filtering. *Trends in Cognitive Sciences*, *10*(4), 139–141. https://doi.org/10.1016/j.tics.2006.02.001

Cowan, Nelson & Oxford University Press. (1997). *Attention and memory: An integrated framework*. Oxford University Press. http://www.oxfordscholarship.com/oso/public/content/psychology/9780195119107/toc.html

Cruz-Neira, C., Sandin, D. J., DeFanti, T. A., Kenyon, R. V., & Hart, J. C. (1992). The CAVE: Audio visual experience automatic virtual environment. *Communications of the ACM*, *35*(6), 64–72. https://doi.org/10.1145/129888.129892

Curtis, C. E., & D'Esposito, M. (2003). Persistent activity in the prefrontal cortex during working memory. *Trends in Cognitive Sciences*, *7*(9), 415–423. https://doi.org/10.1016/S1364-6613(03)00197-9

Daume, J., Gruber, T., Engel, A. K., & Friese, U. (2017). Phase-Amplitude Coupling and Long-Range Phase Synchronization Reveal Frontotemporal Interactions during Visual Working Memory. *The Journal of Neuroscience*, *37*(2), 313–322. https://doi.org/10.1523/JNEUROSCI.2130-16.2016

de Cheveigné, A., & Nelken, I. (2019). Filters: When, Why, and How (Not) to Use Them. *Neuron*, *102*(2), 280–293. https://doi.org/10.1016/j.neuron.2019.02.039

de Haan, E. H. F., & Cowey, A. (2011). On the usefulness of 'what' and 'where' pathways in vision. *Trends in Cognitive Sciences*, *15*(10), 460–466. https://doi.org/10.1016/j.tics.2011.08.005

Decker, A. L., & Duncan, K. (2020). Acetylcholine and the complex interdependence of memory and attention. *Current Opinion in Behavioral Sciences*, *32*, 21–28. https://doi.org/10.1016/j.cobeha.2020.01.013

D'Esposito, M., & Postle, B. R. (2015). The Cognitive Neuroscience of Working Memory. *Annual Review of Psychology*, *66*(1), 115–142. https://doi.org/10.1146/annurev-psych-010814-015031

Diamantopoulou, S., Poom, L., Klaver, P., & Talsma, D. (2011). Visual working memory capacity and stimulus categories: A behavioral and electrophysiological investigation. *Experimental Brain Research*, *209*(4), 501–513. https://doi.org/10.1007/s00221-011-2536-z

Drew, T., & Vogel, E. K. (2008). Neural Measures of Individual Differences in Selecting and Tracking Multiple Moving Objects. *Journal of Neuroscience*, *28*(16), 4183–4191. https://doi.org/10.1523/JNEUROSCI.0556-08.2008

Emrich, S. M., Riggall, A. C., LaRocque, J. J., & Postle, B. R. (2013). Distributed Patterns of Activity in Sensory Cortex Reflect the Precision of Multiple Items Maintained in Visual Short-Term Memory. *Journal of Neuroscience*, *33*(15), 6516–6523. https://doi.org/10.1523/JNEUROSCI.5732-12.2013

Eng, H. Y., Chen, D., & Jiang, Y. (2005). Visual working memory for simple and complex visual stimuli. *Psychonomic Bulletin & Review*, *12*(6), 1127–1133. https://doi.org/10.3758/BF03206454

Engel, A. (1997). Role of the temporal domain for response selection and perceptual binding. *Cerebral Cortex*, *7*(6), 571–582. https://doi.org/10.1093/cercor/7.6.571

Engel, A. K., Fries, P., & Singer, W. (2001a). Dynamic predictions: Oscillations and synchrony in top–down processing. *Nature Reviews Neuroscience*, *2*(10), 704–716. https://doi.org/10.1038/35094565

Engel, A. K., Fries, P., & Singer, W. (2001b). Dynamic predictions: Oscillations and synchrony in top–down processing. *Nature Reviews Neuroscience*, *2*(10), 704–716. https://doi.org/10.1038/35094565

Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. *Psychological Review*, *102*(2), 211–245. https://doi.org/10.1037/0033-295X.102.2.211

Feldmann-Wüstefeld, T., Vogel, E. K., & Awh, E. (2018a). Contralateral Delay Activity Indexes Working Memory Storage, Not the Current Focus of Spatial Attention. *Journal of Cognitive Neuroscience*, *30*(8), 1185–1196. https://doi.org/10.1162/jocn_a_01271

Feldmann-Wüstefeld, T., Vogel, E. K., & Awh, E. (2018b). Contralateral Delay Activity Indexes Working Memory Storage, Not the Current Focus of Spatial Attention. *Journal of Cognitive Neuroscience*, *30*(8), 1185–1196. https://doi.org/10.1162/jocn_a_01271

Fries, P. (2005). A mechanism for cognitive dynamics: Neuronal communication through neuronal coherence. *Trends in Cognitive Sciences*, *9*(10), 474–480. https://doi.org/10.1016/j.tics.2005.08.011

Fuster, J. M., & Alexander, G. E. (1971). Neuron Activity Related to Short-Term Memory. *Science*, *173*(3997), 652–654. https://doi.org/10.1126/science.173.3997.652

Ganglbauer, E., Schrammel, J., Deutsch, S., & Tscheligi, M. (2009). Applying Psychophysiological Methods for Measuring User Experience : Possibilities , Challenges and Feasibility

Gazzaley, A., Rissman, J., Cooney, J., Rutman, A., Seibert, T., Clapp, W., & D'Esposito, M. (2007). Functional Interactions between Prefrontal and Visual Association Cortex Contribute to Top-Down Modulation of Visual Processing. *Cerebral Cortex*, *17*(suppl 1), i125–i135. https://doi.org/10.1093/cercor/bhm113

Greco, A., Mammone, N., Morabito, F. C., & Versaci, M. (2007). *Semi-Automatic Artifact Rejection Procedure Based On Kurtosis, Renyi'S Entropy And Independent Component Scalp Maps*. https://doi.org/10.5281/ZENODO.1059954

GuruvaReddy, A., & Narava, S. (2013). Artifact Removal from EEG Signals. *International Journal of Computer Applications*, *77*(13), 17–19. https://doi.org/10.5120/13543-1175

Gutierrez-Colina, A. M., Vannest, J., Maloney, T., Wade, S. L., Combs, A., Horowitz-Kraus, T., & Modi, A. C. (2021). The neural basis of executive functioning deficits in adolescents with epilepsy: A resting-state fMRI connectivity study of working memory. *Brain Imaging and Behavior*, *15*(1), 166–176. https://doi.org/10.1007/s11682-019-00243-z

Haenschel, C., Uhlhaas, P., & Singer, W. (2007). Synchronous Oscillatory Activity and Working Memory in Schizophrenia. *Pharmacopsychiatry*, *40*(S 1), S54–S61. https://doi.org/10.1055/s-2007-990302

Harrison, S. A., & Tong, F. (2009). Decoding reveals the contents of visual working memory in early visual areas. *Nature*, *458*(7238), 632–635. https://doi.org/10.1038/nature07832

Harrison, T. L., Shipstead, Z., Hicks, K. L., Hambrick, D. Z., Redick, T. S., & Engle, R. W. (2013). Working Memory Training May Increase Working Memory Capacity but Not Fluid Intelligence. *Psychological Science*, *24*(12), 2409–2419. https://doi.org/10.1177/0956797613492984

Hudák, M., Korečko, X., n Sobota, B. (2017). Peripheral devices support for LIKES CAVE. *2017 IEEE 14th International Scientific Conference on Informatics*, 117-121.

Ikkai, A., McCollough, A. W., & Vogel, E. K. (2010). Contralateral Delay Activity Provides a Neural Measure of the Number of Representations in Visual Working Memory. *Journal of Neurophysiology*, *103*(4), 1963–1968. https://doi.org/10.1152/jn.00978.2009

Jas, M., Engemann, D. A., Bekhti, Y., Raimondo, F., & Gramfort, A. (2017). Autoreject: Automated artifact rejection for MEG and EEG data. *NeuroImage*, *159*, 417–429. https://doi.org/10.1016/j.neuroimage.2017.06.030

Jerde, T. A., Merriam, E. P., Riggall, A. C., Hedges, J. H., & Curtis, C. E. (2012). Prioritized Maps of Space in Human Frontoparietal Cortex. *Journal of Neuroscience*, *32*(48), 17382–17390. https://doi.org/10.1523/JNEUROSCI.3810-12.2012

Johnson, D. (2006). Signal-to-noise ratio. *Scholarpedia*, *1*(12), 2088. https://doi.org/10.4249/scholarpedia.2088

Jost, K., Bryck, R. L., Vogel, E. K., & Mayr, U. (2011). Are Old Adults Just Like Low Working Memory Young Adults? Filtering Efficiency and Age Differences in Visual Working Memory. *Cerebral Cortex*, *21*(5), 1147–1154. https://doi.org/10.1093/cercor/bhq185

Kang, M.-S., & Woodman, G. F. (2014). The neurophysiological index of visual working memory maintenance is not due to load dependent eye movements. *Neuropsychologia*, *56*, 63–72. https://doi.org/10.1016/j.neuropsychologia.2013.12.028

Kiyonaga, A., & Egner, T. (2013). Working memory as internal attention: Toward an integrative account of internal and external selection processes. *Psychonomic Bulletin & Review*, *20*(2), 228–242. https://doi.org/10.3758/s13423-012-0359-y

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Kotowski, K., Stapor, K., & Leski, J. (2019). Improved robust weighted averaging for event-related potentials in EEG. *Biocybernetics and Biomedical Engineering*, *39*(4), 1036–1046. https://doi.org/10.1016/j.bbe.2019.09.002

Kringelbach, M. L. (2005). The human orbitofrontal cortex: Linking reward to hedonic experience. *Nature Reviews Neuroscience*, *6*(9), 691–702. https://doi.org/10.1038/nrn1747

Kundu, B., Sutterer, D. W., Emrich, S. M., & Postle, B. R. (2013). Strengthened Effective Connectivity Underlies Transfer of Working Memory Training to Tests of Short-Term Memory and Attention. *Journal of Neuroscience*, *33*(20), 8705–8715. https://doi.org/10.1523/JNEUROSCI.5565-12.2013

Kuo, B.-C., Stokes, M. G., & Nobre, A. C. (2012). Attention Modulates Maintenance of Representations in Visual Short-term Memory. *Journal of Cognitive Neuroscience*, *24*(1), 51–60. https://doi.org/10.1162/jocn_a_00087

Lefebvre, C., Vachon, F., Grimault, S., Thibault, J., Guimond, S., Peretz, I., Zatorre, R. J., & Jolicœur, P. (2013). Distinct electrophysiological indices of maintenance in auditory and visual short-term memory. *Neuropsychologia*, *51*(13), 2939–2952. https://doi.org/10.1016/j.neuropsychologia.2013.08.003

Leonard, C. J., Kaiser, S. T., Robinson, B. M., Kappenman, E. S., Hahn, B., Gold, J. M., & Luck, S. J. (2013). Toward the Neural Mechanisms of Reduced Working Memory Capacity in Schizophrenia. *Cerebral Cortex*, *23*(7), 1582–1592. https://doi.org/10.1093/cercor/bhs148

Li, C.-H., He, X., Wang, Y.-J., Hu, Z., & Guo, C.-Y. (2017). Visual Working Memory Capacity Can Be Increased by Training on Distractor Filtering Efficiency. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00196

Logie, R., Camos, V., & Cowan, N. (Eds.). (2020). *Working memory: The state of the science*. Oxford University Press.

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10.1038/36846

Luck, Steven J. (2014). *An introduction to the event-related potential technique* (Second edition). The MIT Press.

Luck, Steven J., & Vogel, E. K. (2013). Visual working memory capacity: From psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, *17*(8), 391–400. https://doi.org/10.1016/j.tics.2013.06.006

Lundqvist, M., Rose, J., Herman, P., Brincat, S. L., Buschman, T. J., & Miller, E. K. (2016). Gamma and Beta Bursts Underlie Working Memory. *Neuron*, *90*(1), 152–164. https://doi.org/10.1016/j.neuron.2016.02.028

Luria, R., Balaban, H., Awh, E., & Vogel, E. K. (2016). The contralateral delay activity as a neural measure of visual working memory. *Neuroscience & Biobehavioral Reviews*, *62*, 100–108. https://doi.org/10.1016/j.neubiorev.2016.01.003

Ma, W. J., Husain, M., & Bays, P. M. (2014). Changing concepts of working memory. *Nature Neuroscience*, *17*(3), 347–356. https://doi.org/10.1038/nn.3655

Mackey, W. E., Devinsky, O., Doyle, W. K., Meager, M. R., & Curtis, C. E. (2016). Human Dorsolateral Prefrontal Cortex Is Not Necessary for Spatial Working Memory.

Journal of Neuroscience, *36*(10), 2847–2856. https://doi.org/10.1523/JNEUROSCI.3618-15.2016

Mammone, N., La Foresta, F., & Morabito, F. C. (2012). Automatic Artifact Rejection From Multichannel Scalp EEG by Wavelet ICA. *IEEE Sensors Journal*, *12*(3), 533–542. https://doi.org/10.1109/JSEN.2011.2115236

McCollough, A. W., Machizawa, M. G., & Vogel, E. K. (2007). Electrophysiological Measures of Maintaining Representations in Visual Working Memory. *Cortex*, *43*(1), 77–94. https://doi.org/10.1016/S0010-9452(08)70447-7

Melby-Lervåg, M., & Hulme, C. (2013). Is working memory training effective? A meta-analytic review. *Developmental Psychology*, *49*(2), 270–291. https://doi.org/10.1037/a0028228

Melby-Lervåg, M., & Hulme, C. (2016). There is no convincing evidence that working memory training is effective: A reply to Au et al. (2014) and Karbach and Verhaeghen (2014). *Psychonomic Bulletin & Review*, *23*(1), 324–330. https://doi.org/10.3758/s13423-015-0862-z

Miller, E. K., Erickson, C. A., & Desimone, R. (1996). Neural Mechanisms of Visual Working Memory in Prefrontal Cortex of the Macaque. *The Journal of Neuroscience*, *16*(16), 5154–5167. https://doi.org/10.1523/JNEUROSCI.16-16-05154.1996

Miller, E., Li, L., & Desimone, R. (1993). Activity of neurons in anterior inferior temporal cortex during a short- term memory task. *The Journal of Neuroscience*, *13*(4), 1460–1478. https://doi.org/10.1523/JNEUROSCI.13-04-01460.1993

Miller, G. A. (1956). The magical number seven plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97.

Mirpour, K., Bolandnazar, Z., & Bisley, J. W. (2019). Neurons in FEF Keep Track of Items That Have Been Previously Fixated in Free Viewing Visual Search. *The Journal of Neuroscience*, *39*(11), 2114–2124. https://doi.org/10.1523/JNEUROSCI.1767-18.2018

Motley, S. E. (2018). Relationship Between Neuromodulation and Working Memory in the Prefrontal Cortex: It's Complicated. *Frontiers in Neural Circuits*, *12*, 31. https://doi.org/10.3389/fncir.2018.00031

Muthukumaraswamy, S. (2013). High-frequency brain activity and muscle artifacts in MEG/EEG: A review and recommendations. *Frontiers in Human Neuroscience*, *7*, 138. https://doi.org/10.3389/fnhum.2013.00138

Niedermeyer, E., Schomer, D. L., & Lopes da Silva, F. H. (Eds.). (2011). *Niedermeyer's electroencephalography: Basic principles, clinical applications, and related fields* (6. ed). Wolters Kluwer, Lippincott Williams & Wilkins.

Nolan, H., Whelan, R., & Reilly, R. B. (2010). FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection. *Journal of Neuroscience Methods*, *192*(1), 152–162. https://doi.org/10.1016/j.jneumeth.2010.07.015

Norman, K. A., Polyn, S. M., Detre, G. J., & Haxby, J. V. (2006). Beyond mind-reading: Multi-voxel pattern analysis of fMRI data. *Trends in Cognitive Sciences*, *10*(9), 424–430. https://doi.org/10.1016/j.tics.2006.07.005

Oberauer, K. (2009). Chapter 2 Design for a Working Memory. In *Psychology of Learning and Motivation* (Vol. 51, pp. 45–100). Elsevier. https://doi.org/10.1016/S0079-7421(09)51002-X

Pedroni, A., Bahreini, A., & Langer, N. (2019). Automagic: Standardized preprocessing of big EEG data. *NeuroImage*, *200*, 460–473. https://doi.org/10.1016/j.neuroimage.2019.06.046

Peterson, D. J., Gözenman, F., Arciniega, H., & Berryhill, M. E. (2015). Contralateral delay activity tracks the influence of Gestalt grouping principles on active visual working memory representations. *Attention, Perception, & Psychophysics*, *77*(7), 2270–2283. https://doi.org/10.3758/s13414-015-0929-y

Pina, J. E., Bodner, M., & Ermentrout, B. (2018). Oscillations in working memory and neural binding: A mechanism for multiple memories and their interactions. *PLOS Computational Biology*, *14*(11), e1006517. https://doi.org/10.1371/journal.pcbi.1006517

Ploner, C. J., Ostendorf, F., Brandt, S. A., Gaymard, B. M., Rivaud-Péchoux, S., Ploner, M., Villringer, A., & Pierrot-Deseilligny, C. (2001). Behavioural relevance modulates access to spatial working memory in humans. *The European Journal of Neuroscience*, *13*(2), 357–363.

Pugnetti, L., Meehan, M., & Mendozzi, L. (2001). Psychophysiological Correlates of Virtual Reality: A Review. *Presence: Teleoperators and Virtual Environments*, *10*(4), 384–400. https://doi.org/10.1162/1054746011470244

Rajsic, J., Burton, J. A., & Woodman, G. F. (2019). Contralateral delay activity tracks the storage of visually presented letters and words: XXXX. *Psychophysiology*, *56*(1), e13282. https://doi.org/10.1111/psyp.13282

Rensink, R. A. (2002). Change Detection. *Annual Review of Psychology*, *53*(1), 245–277. https://doi.org/10.1146/annurev.psych.53.100901.135125

RepovŠ, G., & Baddeley, A. (2006). The multi-component model of working memory: Explorations in experimental cognitive psychology. *Neuroscience*, *139*(1), 5–21. https://doi.org/10.1016/j.neuroscience.2005.12.061

Ricci, A., Piunti, M., Tummolini, L., & Castelfranchi, C. (2015). The Mirror World: Preparing for Mixed-Reality Living. *IEEE Pervasive Computing*, *14*(2), 60–63. https://doi.org/10.1109/MPRV.2015.44

Roux, F., & Uhlhaas, P. J. (2014). Working memory and neural oscillations: Alpha–gamma versus theta–gamma codes for distinct WM information? *Trends in Cognitive Sciences*, *18*(1), 16–25. https://doi.org/10.1016/j.tics.2013.10.010

Ruchkin, D. S., Johnson, R., Canoune, H., & Ritter, W. (1990). Short-term memory storage and retention: An event-related brain potential study. *Electroencephalography and Clinical Neurophysiology*, *76*(5), 419–439. https://doi.org/10.1016/0013-4694(90)90096-3

Ruchkin, D. S., Johnson, R., Grafman, J., Canoune, H., & Ritter, W. (1992). Distinctions and similarities among working memory processes: An event-related potential study. *Cognitive Brain Research*, *1*(1), 53–66. https://doi.org/10.1016/0926-6410(92)90005-C

Sander, M. C., Werkle-Bergner, M., & Lindenberger, U. (2011). Contralateral Delay Activity Reveals Life-Span Age Differences in Top-Down Modulation of Working Memory Contents. *Cerebral Cortex*, *21*(12), 2809–2819. https://doi.org/10.1093/cercor/bhr076

Serences, J. T., Ester, E. F., Vogel, E. K., & Awh, E. (2009). Stimulus-Specific Delay Activity in Human Primary Visual Cortex. *Psychological Science*, *20*(2), 207–214. https://doi.org/10.1111/j.1467-9280.2009.02276.x

Shipstead, Z., Redick, T. S., & Engle, R. W. (2012). Is working memory training effective? *Psychological Bulletin*, *138*(4), 628–654. https://doi.org/10.1037/a0027473

Singer, W. (1999). Neuronal Synchrony: A Versatile Code for the Definition of Relations? *Neuron*, *24*(1), 49–65. https://doi.org/10.1016/S0896-6273(00)80821-1

Söderqvist, S., Nutley, S. B., Peyrard-Janvid, M., Matsson, H., Humphreys, K., Kere, J., & Klingberg, T. (2012). Dopamine, working memory, and training induced plasticity: Implications for developmental research. *Developmental Psychology*, *48*(3), 836–843. https://doi.org/10.1037/a0026179

Squire, L. R. (2009). Memory and Brain Systems: 1969-2009. *Journal of Neuroscience*, *29*(41), 12711–12716. https://doi.org/10.1523/JNEUROSCI.3575-09.2009

Störmer, V. S., Li, S.-C., Heekeren, H. R., & Lindenberger, U. (2013). Normative shifts of cortical mechanisms of encoding contribute to adult age differences in visual–spatial working memory. *NeuroImage*, *73*, 167–175. https://doi.org/10.1016/j.neuroimage.2013.02.004

Tamburro, G., Stone, D. B., & Comani, S. (2019). Automatic Removal of Cardiac Interference (ARCI): A New Approach for EEG Data. *Frontiers in Neuroscience*, *13*, 441. https://doi.org/10.3389/fnins.2019.00441

Tatum, W. O. (2013). *Handbook of EEG interpretation*. Demos Medical Pub. http://www.credoreference.com/book/spheegi

Teng, C., & Kravitz, D. J. (2019). Visual working memory directly alters perception. *Nature Human Behaviour*, *3*(8), 827–836. https://doi.org/10.1038/s41562-019-0640-4

Teplan, Michal. (2002). Fundamental of EEG Measurement. MEASUREMENT SCIENCE REVIEW. 2.

Umemoto, A., Scolari, M., Vogel, E. K., & Awh, E. (2010). Statistical learning induces discrete shifts in the allocation of working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(6), 1419–1429. https://doi.org/10.1037/a0019324

Ungerleider, L. (1994). 'What' and 'where' in the human brain. *Current Opinion in Neurobiology*, *4*(2), 157–165. https://doi.org/10.1016/0959-4388(94)90066-3

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*(6984), 748–751. https://doi.org/10.1038/nature02447

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*(7067), 500–503. https://doi.org/10.1038/nature04171

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *27*(1), 92–114. https://doi.org/10.1037/0096-1523.27.1.92

Voipio, J., Tallgren, P., Heinonen, E., Vanhatalo, S., & Kaila, K. (2003). Millivolt-Scale DC Shifts in the Human Scalp EEG: Evidence for a Nonneuronal Generator. *Journal of Neurophysiology*, *89*(4), 2208–2214. https://doi.org/10.1152/jn.00915.2002

Wang, C., Hu, L., Talhelm, T., & Zhang, X. (2019). The effects of colour complexity and similarity on multiple object tracking performance. *Quarterly Journal of Experimental Psychology*, *72*(8), 1903–1912. https://doi.org/10.1177/1747021818817388

Williams, L. H., & Drew, T. (2021). Maintaining rejected distractors in working memory during visual search depends on search stimuli: Evidence from contralateral delay activity. *Attention, Perception, & Psychophysics*, *83*(1), 67–84. https://doi.org/10.3758/s13414-020-02127-7

Wingfield, A. (2016a). Evolution of Models of Working Memory and Cognitive Resources: *Ear and Hearing*, *37*, 35S-43S. https://doi.org/10.1097/AUD.0000000000000310

Wingfield, A. (2016b). Evolution of Models of Working Memory and Cognitive Resources: *Ear and Hearing*, *37*, 35S-43S. https://doi.org/10.1097/AUD.0000000000000310

Xu, Y., & Chun, M. M. (2006). Dissociable neural mechanisms supporting visual short-term memory for objects. *Nature*, *440*(7080), 91–95. https://doi.org/10.1038/nature04262

Yao, D., Qin, Y., Hu, S., Dong, L., Bringas Vega, M. L., & Valdés Sosa, P. A. (2019). Which Reference Should We Use for EEG and ERP practice? *Brain Topography*, *32*(4), 530–549. https://doi.org/10.1007/s10548-019-00707-x

Yu, B., Funk, M., Hu, J., Wang, Q., & Feijs, L. (2018). Biofeedback for Everyday Stress Management: A Systematic Review. *Frontiers in ICT*, *5*, 23. https://doi.org/10.3389/fict.2018.00023

Yu, S., Huang, D., Singer, W., & Nikolić, D. (2008). A Small World of Neuronal Synchrony. *Cerebral Cortex*, *18*(12), 2891–2901. https://doi.org/10.1093/cercor/bhn047