Cognitive Conflict in Virtual Reality Based Object Selection Task

An EEG study to understand brain dynamics associated with cognitive conflict in a Virtual Reality 3D object selection task

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Certificate of Authorship/Originality

I, **Avinash Kumar Singh** declare that this thesis, is submitted in fulfilment of the requirements for the award of Ph.D. degree, in the School of Software, Faculty of Engineering and Information Technology at the University of Technology Sydney.

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2. **Singh, A.K.**, Gramann, K., Chen, H.T., and Lin, C.T., 2019. Velocity Profile Modulates the Prediction Error Negativity in a Virtual 3D Object Selection Task (drafted).
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List of Abbreviations

2D	Two-dimensional
3D	Three-dimensional
ACC	Anterior Cingulate Cortex
ADJUST	Automatic EEG artifact Detection based on the Joint Use of Spatial and Temporal feature
ANCOVA	Analysis of Co-variance
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Augmented Reality
BAS	Behavioral Activation System
BACh	Brain Automated Chorales
BCI	Brain-Computer Interface
BIS	Behavioral Inhibition System
BSS	Blind Source Separation
DAL	Dual-augmented Lagrange
DIPFIT	Dipole Fitting
EEG	Electroencephalogram
EMS	Electric muscle stimulation
ERN	Error-Related Negativity
ERP	Event-Related Potential
ERSP	Event-Related Spectral Perturbation
FFNN	Feed-forward Neural Network
FIR	Finite Impulse response
fMRI	Functional Magnetic Resonance Imaging
fNIRS	Functional Near-Infrared Spectroscopy
FPS	Frame per Second
FRN	Feedback-Related Negativity
GMM	Gaussian Mixture Modelling
GSR	Galvanic Skin Response
HCI	Human-Computer interface
HMD	Head Mounted Display
IC	Independent Component

ICA	Independent Component Analysis
ID	Index of Difficulty
IMU	Inertial Measurement Unit
IPQ	Igroup Presence Questionnaire
IQR	Inter-Quartile Range
ITC	Inter-Trial Coherence
LDA	Linear Discriminant Analysis
MMN	Mismatch Negativity
MoBI	Mobile Brain / Body Imaging
MR	Magnetic Resonance
N2	Negativity at 200ms
Ne	Negativity
OCD	Obsessive-Compulsive Disorder
oFRN	Observational Feedback-Related Negativity
OLED	Organic Light-Emitting Diode
P300	Positivity at 300ms
PCC	Posterior Cingulate Cortex
Pe	Positivity
PEN	Prediction Error Negativity
PET	Positron Emission Tomography
pre-SMA	pre-Supplementary Motor Area
QDA	Quadratic Discriminate Analysis
SASICA	Semi-Automatic Selection of Independent Components for Artifact
SCCN	Swartz Center for Computational Neuroscience
SD	Standard Deviation
SDK	Software Development Kit
SFG	Superior Frontal Gyrus
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine
TV	Television
UAV	Unmanned Aerial Vehicle
VE	Virtual Elements
VR	Virtual Reality

Abstract

Cognitive conflict is an essential part of everyday interaction with the environment and is often characterized as a brain's action monitoring and control system that activates when prediction based on previous experience acquired from the environment does not match with derived knowledge from sensory inputs from cognitive processing. Although cognitive conflict can be seen as an essential part of learning about the environment, it requires the brain to assign a higher number of cognitive resources such as attention, memory, and engagement compared to non-conflicting conditions. In this work, cognitive conflict has been evaluated in a three-dimensional (3D) object selection task in a virtual reality environment by assessing, evaluating, and understanding the factors of visual appearance, task completion time, movement velocity during interaction and its implications for a sense of agency, and presence in a virtual reality (VR) environment. An electroencephalogram (EEG)-based approach along with behavioral information is used. The results show that the amplitude of negative event-related potential (50-150 ms), defined as prediction error negativity (PEN), correlates with the realism of the rendering style of virtual hands during the interaction. It was also found that PEN amplitudes are significantly more pronounced in slow trials than fast trials. Based on these findings, a closed-loop BCI system has been designed to assess the effect of cognitive conflict in 3D object selection and provide the matrices which can improve users' feelings of a sense of agency towards VR. These findings suggest that a realistic representation of the user's hand, compatible task completion time and hand movement velocity are essential components for the better integration of information from both visual and proprioceptive systems during the interaction to avoid cognitive conflict due to a mismatch between action and expected feedback. The findings also suggest that the assessment of cognitive conflict measured by PEN can improve the overall experience of the 3D object selection task in a VR environment. Collectively, these findings provide a glimpse of understanding into how the brain dynamics behind interaction works and its implications in assessment for the content development industries in VR.

Chapter 1 : Introduction

1.1. Thesis Definition

There are several mechanisms involved when a human interacts with the surrounding environment. These mechanisms make use of information from different sensing modalities, such as visual, proprioception, tactile, olfactory etc. These sensory modalities work in combination with the brain's action monitoring system which instructs, plans and executes them. The process of the brain's action monitoring needs to be continuously updated according to the surrounding to avoid or handle any adverse changes. These adverse changes in surrounding produce a mismatch response known as a cognitive conflict. More specifically, it can be defined as a brain mechanism provoked when prediction based on previous experience acquired from the environment does not match with processed sensory inputs in the same environment. The occurrence of cognitive conflict requires more cognitive resources like redirecting attention, reconfiguration of the plan, as well as a break between continuous perceiving experiences and flow than in a non-conflicting situation. In this work, the cognitive conflict has been applied in a three-dimensional (3D) object selection task in a virtual reality (VR) environment in order to understand the underlying brain dynamics and develop techniques which can improve the interaction and simultaneously enhance the realism, sense of agency and control over events.

1.2. Cognitive Conflict in the field of Neuroscience

1.2.1. Cognitive conflict

Cognitive conflict occurs when a person makes or perceives an error, which can be detected with the help of an electroencephalogram (EEG) as an error-related potential (Falkenstein, Hohnsbein & Hoormann 1995; Falkenstein et al. 1991; Falkenstein et al. 2000). The cognitive conflict was first discussed in an article by Donchin et al. 1988 which was republished in 2010 (Donchin & Coles 2010), but there was no mention of the potential for errors related potential. This work found a modulation in P300 amplitude due to changes in the environmental settings. In subsequent years, (Falkenstein 1990; Gehring et al. 1990) presented a task known as the bimanual choice reaction task, finding two components of event-related potential as a consequence of cognitive conflict. The

first component, due to an erroneous response, is known as error-related negativity (ERN or Ne) (Falkenstein et al. 1991; Gehring et al. 1993), which is a negative event-related potential typically peaking around 50–150 ms, followed by a second component which is known as the error-related positivity (Pe), typically peaking around 200–400 ms after the erroneous response begins.

Since its proposal, several experimental scenarios have been tested demonstrating ERN and Pe. Kopp et al. showed that there was large negativity in the frontal and central region of the brain in a flanker task (Eriksen & Eriksen 1974), peaking around 0-200 ms i.e. N200 followed by P300 (Kopp, Rist & Mattler 1996) in incongruent condition compare to the congruent condition. Halgren et al. conducted another experiment derived from the standard oddball paradigm (Squires, Squires & Hillyard 1975) to distinguish targets and non-targets in an auditory discrimination task and found that large cortical systems were activated during the evoked potential around 200 ms i.e. N2 followed by P300 evoked around 300 ms (Halgren, Marinkovic & Chauvel 1998). West et al. (West & Alain 1999) also found increased negativity over the fronto-central regions and positivity over the fronto-polar regions in an incongruent condition in a Stroop task (Stroop 1935).

Due to the different natures of various experiments, other variants of conflict-related potential were also investigated. For example, error due to feedback during a reinforcement-learning task in a modified version of the Eriksen flanker task (Eriksen & Eriksen 1974), known as a feedback based ERN or also known as feedback-related negativity (FRN), was measured fronto-centrally around 200–300 ms after the feedback (Holroyd & Coles 2002). The FRN seems to be related to or can be seen as the same component as N200 (Holroyd, Pakzad-Vaezi & Krigolson 2008).

An error-related potential due to a person observing another person making an error is commonly known as observation error, as shown by van Schie et al. in an experiment where the participants either performed a choice reaction task based on a modified Eriksen flanker task or observed it (van Schie et al. 2004). Van Schie et al. found activity in the medial frontal cortex and in the motor cortex measure via ERN during the correctness of observed behavior when the observed behavior was incorrect. In another study, (Kang, Hirsh & Chasteen 2010) investigated observation errors where participants observed a friend or a stranger making an error in the Stroop task. The results showed

that there was a stronger activation of the anterior cingulate cortex (ACC) due to observational feedback-related negativity (oFRN) peaking around 250-350 ms for friends compared to strangers. The results suggest that participants had a higher feeling of cognitive conflict for those who were compared to strangers.

Most of these protocols used discrete feedback mechanisms, but Krigolson and Holroyd (Krigolson & Holroyd 2006; Krigolson & Holroyd 2007) also investigated errors-related potentials in a continuous tracking task. In this task, participants performed an experiment where they used a joystick to move a cursor which was 25 cm from a start position on the left-hand side of a computer display to the target position. In first aiming condition (control), the participant simply moves the cursor horizontally toward the target while for a second (correctable) and third (uncorrectable) aiming conditions, the target disappears and appears in different locations either 8 cm above or below the initial position. In the second condition, the participants needed to correct their initial movement by shifting toward diagonal direction while for the third condition, the cursor stopped moving in the diagonal direction. The authors demonstrated that event-related potential (ERP) components (N100 and P300) associated with visual and online motor control invoked in second and third condition (Krigolson & Holroyd 2007) but not in the first condition. These results again suggest cognitive conflict activity in the brain for correctable and uncorrectable conditions.

These researchers showed significant progress in cognitive conflict-related research toward the understanding of brain dynamics in the discrete and non-discrete task. On the other hand, researchers are also started investigating the underlying region of the brain behind the cognitive conflict.

1.2.2. The brain region involved in the cognitive conflict

The ACC, located in the medial surface of the frontal lobe, is assumed to be the most important part of the human brain for executive control (D'Esposito et al. 1995; Posner & Dehaene 1994). ACC is much debated and has been a topic of research investigation research since the 90s. In the 90s, (Falkenstein 1990; Gehring et al. 1990) demonstrated that error occurred in humans around 100 to 150ms after an incorrect response originating in the ACC. Interestingly, a study conducted using Functional magnetic resonance imaging (fMRI or functional MRI) (Carter et al. 1998) found that ACC also activated with correct responses and particularly to response-related processing (van Veen et al.

2001) shown in response-congruent condition tasks derived from Eriksen and Eriksen (Eriksen & Eriksen 1974). These studies show several clues that ACC and error have some complex relationship. It was assumed that probably that ACC is acting like an action-monitoring hub for the human brain for motor actions.

Further investigation (Zarr & Brown 2016) suggests that ACC is not simply involved in top-down attentional control but also evoked during a conflict situation of two cognitive controls. ACC found to be more active under a high conflict than a low conflict condition (Botvinick et al. 1999; Carter et al. 1998; MacDonald et al. 2000). Cognitive conflict in EEG studies is usually represented by a different kind of error-related negativity known as ERN (Gehring et al. 1990), N2 (Kopp, Rist & Mattler 1996), MMN (Wei, Chan & Luo 2002), and shown to have identical scalp distribution in fronto-central which also house ACC (van Veen & Carter 2002). Apart from several indications with cognitive conflict, ACC was also found to have a strong association with the motor control system (Schlüter et al. 2018), which suggests there must be some involvement of ACC to detect the cognitive conflict and communicate with motor action control.

It was shown in fMRI study that activation in ACC is distinguishable for internal (error response) and external (error feedback) kinds of errors (Holroyd et al. 2004). In a task where participants need to learn between two options using a trial-and-error method with feedback, which indicates monetary gain and losses. Another study shows that the superior frontal gyrus (SFG) (Fried et al. 1998) region centered on the pre-supplementary motor area (pre-SMA) (He, Dum & Strick 1995) is involved in action selection while ACC shows modulation for action and its consequences (Rushworth et al. 2004). Further investigation suggests that this modulation in ACC is governed by the midbrain dopamine system (Baker & Holroyd 2011).

Several evidences of ACC with conflict monitoring encourages researchers to explore the functional connectivity of this region with other parts of the brain. Some researchers (Badre & D'Esposito 2007; Christoff et al. 2009; Zarr & Brown 2016) came up with detailed hierarchical structures behind ACC. This hierarchical structure is formed by motor cortex representing motor primitives, a premotor cortex representing all combinations of motor primitives, a posterior motor cortex representing a further combination of these primitives' information and progressively moving to the anterior region of the brain. In another way, the abstract prediction error is represented in the

anterior region while the strong error is represented in the posterior region (Zarr & Brown 2016). In short, it is not wrong to speculate that the ACC plays an important role in action monitoring as well as action control.

Apart from action monitoring, the discrepancy in ACC functionality could be the indication of abnormality of brain function. These abnormalities can cause neuropsychiatric disorder including Schizophrenia (Ford 1999; Owen, Sawa & Mortensen 2016) and Obsessive-Compulsive Disorder (OCD) (Shin et al. 2014). ACC is shown to modulate differently for people with Schizophrenia or/and OCD compared to healthy people as a sign of dysfunction (Devinsky, Morrell & Vogt 1995).

In summary, ACC plays an important role in daily life from monitoring and playing an important role to correct our action to avoid adverse changes during an interaction. Inability to correct action due to the dysfunctionality of ACC could result in psychological disorders.

1.3. Cognitive Conflict in the field of HCI

An important part of interaction in daily life is an interaction with technology around us particularly computers. Interaction in the field of technology is commonly known as a human-computer interface (HCI) and grown a lot since the development of the first computer. The cognitive conflict has been also investigated extensively in the HCI community by the means of behavioral measures to evaluate and improve the interaction design. The major aims of these investigations were to improve the two-dimensional (2D) and three-dimensional (3D) interaction techniques to improve users' overall performance. The cognitive conflict-evoking tasks involved in HCI community are mostly derived from three types: conflict due to competing options, conflict due to visual appearance, and conflict due to an unexpected error.

1.3.1. Conflict due to competing options

Psychologists have constructed and studied a variety of conflict paradigms. Of these, the Stroop test (MacLeod 1991) is perhaps one of the most well-studied. In this test, participants are instructed to respond to the names of colors printed congruent or incongruent colors. The incongruent (conflict) condition arises when the name of the color differs from the printed color (e.g., the word "red" is displayed in blue letters). The congruent (no conflict) condition occurs when the name of the color is printed in the same color (e.g., the word "red" is displayed in red letters). In the incongruent case, the

processing pathways for reading out words and naming the color of the ink compete and result in a conflict. In the Eriksen flanker test (Eriksen & Eriksen 1974; Hodgins et al. 2010; MacLeod 1991), conflict arises when a centrally presented response-relevant stimulus (a "<" for a response "left") is surrounded by two different stimuli that indicate a different response (">" indicating to respond "right"). Another prominent paradigm, the Simon test (Simon 1969), generates conflict by creating a spatial mismatch between the location of a stimulus on display and the required response.

1.3.2. Conflicts due to visual appearance

Computer graphics researchers have investigated the complex interplay between a rendered image, animation, and human perception. For example, McDonnell (McDonnell, Breidt & Bulthoff 2012) investigated the impact of rendering style on viewers' perception of virtual humans, and Hodgins (Hodgins et al. 2010) studied how the degradation of human motion affects viewers' emotional responses. These findings also support the Uncanny Valley theory (Mori, MacDorman & Kageki 2012), which suggests that human look-alike robots are agreeable until they approach, but fail to attain, a lifelike appearance, at which point humans feel strong unease or possibly revulsion at even small imperfections.

Psychologists and neuroscientists have also examined brain activity when participants are presented with objects that have different levels of realism. The author (Perani et al. 2001) showed participants videos of both real and virtual hands in VR and 2D TV. The Positron emission tomography (PET) results reveal that only real actions in the natural environment activate a visuospatial network that includes the right posterior parietal cortex. (Han et al. 2005) found fMRI resulted in a higher level of brain activity when participants watched a live action movie compared to a cartoon movie. More recently, (Saygin et al. 2012) utilized the fMRI repetition suppression methodology and identified a stronger effect when participants watched the movement of a human-like robot compared to looking at a human or a robot, which supports the Uncanny Valley theory.

In these aforementioned experiments, the participants passively watched pre-rendered videos throughout the sessions. Researchers also studied participants' reactions in scenarios where they actively performed tasks in the virtual environment (VE) with altered virtual appearance. Yuan and Steed (Yuan & Steed 2010) measured galvanic skin

response (GSR) and reproduced the rubber hand illusion (Botvinick & Cohen 1998) in an immersive virtual reality. Interestingly, they also reported that the illusion could be negated by replacing the virtual hand with an abstract cursor. Lin et al. investigated six distinct hand styles in the rubber hand illusion experiment and compared the induced threat levels (Lin & Jorg 2016). The questionnaire feedback suggested that participants experienced similar levels of virtual body ownership regardless of visual appearance.

1.3.3. Conflicts due to an error

A conflict can also arise when the user is aware of making an error, or the application does not behave as expected. In the context of 2D object selection, researchers in the HCI community have accumulated profound knowledge about the prediction and modeling of errors (Wobbrock, Jansen & Shinohara 2011) as well as how users adjust their behavior to balance the tradeoff between error and time to complete the task (Banovic, Grossman & Fitzmaurice 2013; Guiard, Olafsdottir & Perrault 2011).

Beyond standard measurements such as time to complete a task, accuracy and error rate, Vi et al. (Vi & Subramanian 2012; Vi et al. 2014) proposed using the brain potential of ERN recorded from a consumer-level EEG headset to detect the occurrence of one's own or others' errors.

Although researchers in HCI community have been investigating the cognitive conflict due to competing options, visual appearance, and an unexpected error but still a major focus is the two-dimensional (2D) interaction to improve performance. The interaction in the 3D environment adds a statistically significant level of complexity due to complex human model involvement from the physical human body and space compare to 2D. The research in 3D space interaction is getting higher importance due to the development of technology like VR. Therefore, it is important to understand how interaction work in a 3D environment to study and apply cognitive conflict.

1.4. Interaction with the 3D environment

To acquire an object in the 3D world using human's hand, the user is required to perform a set of complex movements to the position their palm and fingers over the object. For each movement, the final position will determine whether the acquisition of an object has been achieved or not. If the acquisition is achieved, then a trigger needs to be sent to the user to confirm the acquisition. Such physical interaction using human models is constrained by human psychomotor behavior. There are two important components of

such behavior: understanding of model itself for which, Fitts' Law (Soukoreff & MacKenzie 2004) provides by far the most acceptable explanation, and understanding of visual and motor space provides the information required in 2D and 3D interaction behavior including the understanding of advanced 3D environment such that VR.

1.4.1. Fitts' law

Fitts' Law is a well-known psychomotor behavior model, which is being used widely in the field of HCI, human factors, and ergonomics. Fitts' Law estimates the time required to perform the movement toward target considering only physical properties of the acquisition task e.g. size of the target, the amplitude of movement etc.

Fitts' Law is designed for 2D interaction task but some work (Wingrave & Bowman 2005) showed that Fitts' law is still applicable for VR environments and related to the visual size of the object rather than physical size. Due to the imitation of usage of Fitts' Law in the human model in similar fashion, Meyer et al. (Meyer et al. 1988) proposed an optimized initial impulse model. Meyer proposed that acquisition of target with a human model in VR required a trajectory constitutes of a ballistic and corrective phase.

The ballistic phase is a fast and inaccurate movement phase followed by corrective phase, which is iterative slow and accurate movement until target achievement. In general, this model proposes that faster movement results in higher endpoint variability thus required more corrective movement to acquire the target, while slow movement results in smaller endpoint variability and thus required fewer corrective movements.

1.4.2. Visual and motor space

Visual and motor space are two important spaces required in 2D and 3D object selection. Motor space can be defined as the working space required to make a movement to select a target while visual space is a visual representation of the space where object selection is happening. Motor and visual space could be coupled as in the real world or in a VR/3D environment or decoupled such as in 2D cursor control where it is translated in visual space using a pointing device.

The 3D object selection task requires coupled visual and motor space while task accomplishment highly relies on proprioceptive feedback. On the other hand, the decoupled visual and motor space mostly rely only on visual feedback (Smith et al. 2000).

1.4.3. VR as a 3D environment

Recent advances in display and tracking technologies have brought an affordable and plausible VR experience to the mass market. Despite the long history of VR, this is the first time that a large quantity of creative and interactive content has been designed and produced specifically for VR from scratch; being able to experience content in VR is no longer a bonus feature or afterthought.

This paradigm shift from traditional passive visual stimuli to a more active immersive experience requires designers to reinvent new symbols and languages to facilitate communication and interaction in VR. This transition is challenging because these new interactions not only have to achieve good performance but should also avoid disrupting the users' immersive experience.

A range of measurements and visualization tools assists designers in the evaluation of the objective characteristics of interaction. However, for the subjective measurements that are important in many VR scenarios, such as level of presence, focus, or emotions, etc., designers still rely mainly on questionnaires and interviews, which can only be conducted at specific times and cannot reliably address the changing dynamics of the interaction (Holroyd, Pakzad-Vaezi & Krigolson 2008).

In searching for continuous and reliable measurement of subjective characteristics, researchers have suggested leveraging brain-imagining techniques, such as EEGs and functional near-infrared spectroscopy (fNIRS), to inform the interaction design (Frey et al. 2016; Solovey et al. 2009). As off-the-shelf EEG headsets are increasingly being made available to the mass market by companies like MINDO[1], Emotiv[2] , and Neurosky[3], it can believe that brain imaging will become a convenient and essential tool for interaction design.

1.5. Applying Neuroscience Methodology in HCI: Brain-Computer Interface

In the last decade, researchers have explored the use of non-invasive brain imaging technologies, such as EEG and fNIRS, as interfaces to provide computer applications

[1] http://www.bri.com.tw

[2] http://www.emotive.com

[3] http://www.neurosky.com

with the cognitive state of the user. Zander et al. (Zander et al. 2010) categorized the brain-computer interface (BCI) into three types: active, reactive and passive. Active BCI directly maps a user's brain pattern to a specific input command, e.g., control the mouse cursor with thought (Fabiani et al. 2004). Reactive BCI leverages the brain's response to external audio or visual stimuli as an input to the system, e.g., P300 speller (Donchin, Spencer & Wijesinghe 2000). The Passive BCI system translates brain activity without voluntary control into high-level cognition feedback, such as emotion, attention, etc., usually for monitoring or evaluation (Frey et al. 2016; Frey et al. 2013).

Most work investigating the interaction technique utilizes reactive and passive BCI. A number of studies (Holroyd, Pakzad-Vaezi & Krigolson 2008; Peck et al. 2013; Yuksel et al. 2016) were recently undertaken, based on the relatively new brain imaging technology of fNIRS. For example, Afergan et al. (Afergan et al. 2014) used fNIRS to measure workload in path planning task for multiple unmanned aerial vehicles (UAVs) in simulation and showed that by adding or removing UAV, it is possible to reduce errors by 35% and improve the target selection performance. Peck et al. (Peck et al. 2013) demonstrated that fNIRS is a valid tool for measuring the impact of visual design in a task. In his task, the participants are presented with slides of bar and chart graph and instructed to estimate the size difference with nearest 10% of a smaller section of the graph in the current slide to a larger section in the previous slide. The brain automat chorales (BACh) system (Yuksel et al. 2016) adaptively adjusts the difficulty level of music learning tasks based on the cognitive state of the learner. More details can be read in the article by Yuksel et al (Yuksel et al. 2015).

Before the emergence of fNIRS, EEGs had already been widely adopted by the HCI community (Frey et al. 2013). The characteristic of high temporal resolution makes EEGs particularly suitable for interaction that involves an immediate user response. Lee et al. (Lee et al. 2016) leveraged mismatch negativity and P3a to evaluate audio notification in realistic environments with ambient sounds when users faced different levels of workload. (Cherng et al. 2016) studied user perceptions of graphics icons and provided an EEG-based evaluation of the semantic distance between icons. (Yuksel et al. 2010) built a P300-based BCI based on a multi-touch surface. The surface generates different flash patterns and elicits event-related potentials in the EEG signals, which can be used for various tasks such as object selection.

Given the possibility of knowing when a participant is making an error, a passive BCI can be designed to measure the error-related potential in the ongoing task. Ferrez et al. (Ferrez & Millan 2008) tested if error also elicited when the error is made by the interface during the recognition of the participant's intent. A simulated human-robot interaction task performed by means of a green cursor which can appear on any 20 positions along a horizontal line with a goal to bring the cursor to target that randomly appears either on the left or right of the cursor. In the normal condition, the participants need to bring the robot cursor to a target 2 or 3 steps either to the left or right from initial position while in an error condition, cursor reached the target in 5 steps. The authors were able to detect an error related potential in a single trial with an average accuracy of 79.2%. Thus, this also proved that similar error can be measured through continuous interaction which is common compared to laboratory settings. Similarly, Chavarriaga et al. showed that error-related EEG signals can be used to infer the optimal agent behavior by tuning to certain behavior. A task was derived from Ferrez et al's human-robot interaction task where participants did not send commands to the robot and were asked to only assess if robot performs properly (Chavarriaga & Millan 2010). Chavarriaga et al. showed that the participant still invokes error related potential.

The understanding of interaction mostly focused on the task derived from 2D interactions due to the limitation of the environment, tools, and data processing methods although it is highly required in the understanding of human brain dynamics in motor interaction**,** as a tool for 3D content assessment, and for the development of better techniques in interaction**.** Building upon this line of research, this thesis focuses on *how active interaction with the 3D environment affects behavioral and cognitive responses during a fundamental user interaction task in an immersive virtual environment, namely, 3D object selection through direct 3D inputs (tracked hand motions) and how to improve overall interaction performance*. To fulfill the goal, the following three research questions (RQs) were investigated:

RQ1. How to measure cognitive conflict in a virtual reality-based 3D object selection task during active interaction?

RQ2. What factors affect the cognitive conflict and its implications for the 3D object selection task?

RQ3. How to design and develop a system for continuous assessment of the effects of cognitive conflict in 3D object selection task?

1.6. Aims and Objectives

To answer the research questions, the following aims and objectives are set:

Aim 1: *Find a biomarker for cognitive conflict and evaluate its modulating factors.*

This aim will be accomplished by designing a novel EEG experimental scenario for the object selection task to evoke cognitive conflict in the user. The collected EEG data will be analyzed to find the most accurate representation of a biomarker in the human brain. It is hypothesized that cognitive conflict most often occurs in the front-central region of the brain, commonly known as ACC and can be seen as a negative component in event-related potential after the response. The result will lead to a biomarker which can correctly represent the cognitive conflict.

Following the finding of the biomarker, the effect of visual representation and task completion time will be evaluated. It is hypothesized that a higher level of visual representation with longer completion time will result in a higher level of cognitive conflict compared to a low level of visual representation and shorter completion time (**Hypothesis 1 and 2**). The results will lead to a better understanding of how visual representation and completion time affect the users' sense of cognitive conflict in the VR environment and will help in the development of better VR content. This aim will fulfill the RQ1 and partially RQ2.

Aim 2: Evaluate the effect of hand movement velocity and its implications on VR sense of agency.

To achieve this aim, the effect of hand movement velocity on cognitive conflict will be investigated. It is hypothesized that the faster the users' corrective phase, the less information the user will acquire from the environment, therefore, there will be less cognitive conflict, whereas the slower the users' corrective phase, the more information will be acquired by the user thus higher cognitive conflict (**Hypothesis 3**). Further, this thesis evaluates how the user's sense of realism, sense of agency and past game playing experience affect hand movement velocity and task completion time.

In light of the results, a model will be designed to explain the relationship between the visual and proprioceptive feedback of the user. It is hypothesized that visual feedback

dominates if the user moves faster in the corrective phase while proprioception feedback dominates when the user moves more slowly in a corrective phase (**Hypothesis 4**). The combination of these results will provide a standard guideline for the VR content developer on how to manipulate these two senses in a close manner to improve the overall VR experience of the user. This aim will answer the RQ2.

Aim 3: Development of a closed-loop BCI system to mitigate cognitive conflict.

This aim will be achieved in accordance with the findings from Aim 1 and Aim 2. A closed-loop BCI system will be designed for the object selection task of VR. This system will detect cognitive conflict for the selection made by the user and is based on the measured cognitive conflict level. This measurement will provide assessment matrices for interaction task. It is hypothesized that normal selection behavior is not always necessary for less cognitive conflict level but strongly depends on the individual user's experience and could be changed (**Hypothesis 5**). This aim will answer the RQ3.

Demonstration of a closed-loop system will provide a platform to evaluate the content of the VR. Figure 1-1 shows the summary of all task performed corresponding to aims.

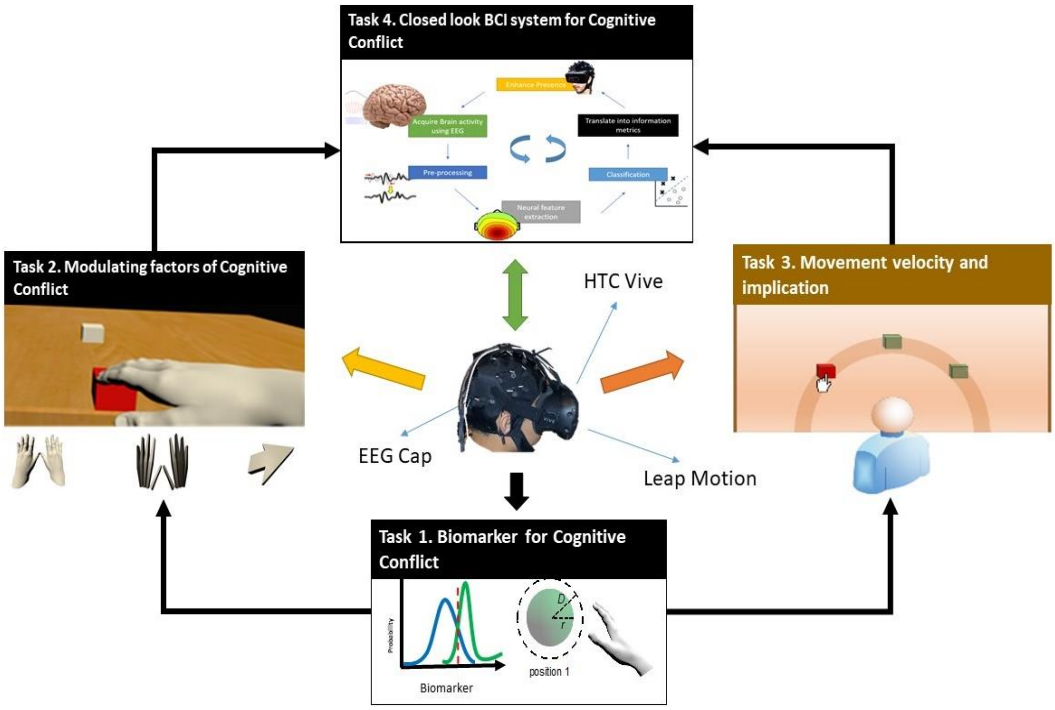


Figure 1-1 Summary of all tasks performed toward this thesis work; where task 1 represents the development of novel scenario and finding the biomarker for cognitive conflict; task 2 is about evaluating the modulating factors of cognitive conflict in object selection in VR; task 3 is about evaluating the effect of movement velocity and its implication on the participant's behavior like realism and sense of agency ; and task 4 is about developing the closed-loop brain-computer interface system to assess and evaluate the level of cognitive conflict in VR

1.7. Stakeholders

The primary stakeholders of this research output will be the VR content developers. VR content is currently assessed using the traditional questionnaire-based approach to evaluate the quality of content, which is highly subjective and could be biased based on the type of participants. They can utilize cognitive conflict-based matrices to evaluate the content in an objective way, which will be bias-free and provide accurate measurements. In addition to evaluating the quality of content, it is also possible to utilize the techniques of cognitive conflict to design an adaptive and personalized system for users, which continues to assess the user's level of cognitive conflict to augment the content in the way that improves the users' VR experience.

1.8. Approach

The work presented in this thesis uses non-invasive electrical recordings from the human scalp using EEG during an experimental setup designed specifically to invoke cognitive conflict. The experimental setup utilizes VR-based an experimental scenario called the 3D object selection task while tracking participants' hands using Leap motion and simultaneously recording EEG signals using 32 and 64 EEG electrodes.

The recorded EEG data is analyzed using state-of-the-art approaches with the help of the EEGLab toolbox in MATLAB 2016 (MathWorks Inc, USA). Some of the approaches used for preprocessing the EEG signals are down-sampling, filtering, independent component analysis (ICA) (Makeig et al. 1996), dipole source localization (Scherg 1990), and automatic artifact removal (Kothe & Jung 2016; Lin et al. 2018; Mognon et al. 2011). The preprocessed EEG data are clustered by a neural network (NN) (Bishop 1995) for all the participants.

The resultant data is used to measure ERP (Luck 2014), event-related spectral perturbation (ERSP) (Makeig 1993), and time-frequency (Boashash 2015) based analysis followed by source localization of the evoked cognitive information, extraction of biomarkers related to cognitive conflict, and statistical test of significance.

The final approach is to classify the EEG signals into the different levels of cognitive conflict in a closed loop manner and provide assessment matrices for the content of VR in the 3D object selection task.

1.9. Findings

The results of the first experiment (Chapter 4) show that for the participants with high behavioral inhibition scores (BIS), the amplitude of the negative event-related potential at approximately 50-250 ms is correlated to the level of realism of the virtual hands. The findings suggest that the more realistic the representation of the user's hand is, the more sensitive the user is towards subtle errors, such as tracking inaccuracies. Further, the results also show that cognitive conflict-related amplitudes were significantly more pronounced in a longer task completion time compared to a shorter task completion time. The results suggest that a longer task completion time results in better integration of information from both visual and proprioceptive systems as the basis to detect a mismatch between action and the expected visual feedback.

The results from the second experiment (Chapter 5) show that cognitive conflict biomarker amplitudes are significantly more pronounced when there is fast movement velocity compare to slow movement velocity. Further, the results also show that the effect of task completion time becomes less pronounced compared to hand movement velocity. It was found that task completion time and hand movement velocity have implications on users' feelings to the VR experience of realism, sense of agency, and control over events.

The results from the third experiment (Chapter 6) demonstrate the feasibility of the closed-loop brain-computer interface system that can online assess interaction in the VR scene due to the effect of cognitive conflict. The results also show that there is a difference between individual preferences toward the selection radius during the 3D object selection.

1.10. Thesis Structure

The thesis is divided into 7 chapters as follows:

Chapter 1, the '*Introduction*', provides background information and reviews the work of cognitive conflict in the field of neuroscience and HCI. It also discusses the motivation behind this research, the main research questions and hypotheses underpinning these research questions. This chapter also explains the importance of this research for potential stakeholders and the contribution of this work toward advancing scientific knowledge.

Chapter 2, entitled '*Methodology*', provides a detailed description of all the methods used to analyze the EEG data, collect behavioral information, evaluate the relationship between behavioral information, and cognitive conflict.

Chapter 3, entitled '*Evoking the Cognitive Conflict in Virtual Reality and its Modulating Factors*', explores the experimental scenarios used to conduct and evoke cognitive conflict with a novel object selection task. This chapter also presents the extensive results on a biomarker to represent cognitive conflict. Further, this chapter talks about how to use the biomarker to evaluate the visual representation of the different hand styles used for the object selection task and the effect of task completion time on cognitive conflict.

Chapter 4, entitled '*Movement Velocity and Implications for Cognitive Conflict in Virtual Reality*', explores the extended version of the experimental paradigm develop in Chapter 3 to invoke the different hand movement profiles of the participants. This chapter presents the extensive results on the effect of different movement velocities on cognitive conflict, the correlation between behavioral information with cognitive conflict, and its implications for users' feelings about VR.

Chapter 5, entitled '*Closed-loop Brain-Computer Interface for Cognitive Conflict in Virtual Reality*', demonstrates the possibility of using a cognitive conflict-based biomarker in a closed loop brain-computer interface. This chapter presents the framework for using cognitive conflict in a closed-loop manner to improve the users' overall experience in VR. This chapter also details the results achieved by such a system on the object selection task discussed in Chapters 3 and 4.

Chapter 6, entitled '*Discussion and Limitations*', explores and discusses the results presented in Chapters 4, 5, and 6. This chapter proposes and presents a framework derived from the cognitive conflict effect on the brain and presents the limitations of the current research presented in this thesis and potential directions to overcome them.

Chapter 7, entitled '*Conclusion and Future Work*', summarizes the findings from Chapters 4, 5, and 6 with future directions to extend the work. This chapter also discusses some of the ongoing extension work derived from the research presented in this thesis.

Chapter 2 : Methodology

EEG provides a non-invasive and inexpensive method of recording temporal brain activities from the scalp. These properties of EEG make it an excellent tool to study brain activity on a millisecond level (Burle et al. 2015). However, EEG signals are highly prone to different kinds of electrical artifacts, such as muscles movement, eye blinks, saccade eye movements, electrical interference etc. (Britton JW, Frey LC & al. 2016). These artifacts present a challenge when trying to extract brain-related information from EEG data. These challenges require robust signal preprocessing methods to minimize the artifact contamination of EEG signals in order to obtain cleaner EEG data for further analysis. The cleaned EEG data can be analyzed further to obtain useful brain dynamics information. The following section in this chapter describes the experiments conducted and methods applied to analyze the collected EEG and behavior data.

2.1. Participants and Environment

EEG data were recorded from a total of 56 male participants and 4 female participants in three experiments. The mean age of the participants was 22.7 years, with an age range of 20-30 years. Following an explanation of the experimental procedure, all participants provided informed consent before taking part in the study. This study obtained the approval of the Human Research Ethics Committee of National Chiao Tung University, Hsinchu, Taiwan and the Human Research Ethics Committee of the University of Technology Sydney, Australia and was conducted in a temperature-controlled and sound controlled room. None of the participants had a history of any psychological disorders, which could have affected the experiment results.

2.2. VR Setup

All the performed experiments used the HTC Vive (*VIVE™ | Discover Virtual Reality Beyond Imagination* 2017) as the head-mounted display (HMD). The Vive uses an organic light-emitting diode (OLED) display with a resolution of 2160 x 1200 and a refresh rate of 90 Hz. The user's head position was principally tracked with the embedded inertial measurement units (IMUs), while the external Lighthouse tracking system cleared the common tracking drift with a 60 Hz update rate.

The participants' hand motions were tracked with a Leap Motion controller attached to the front of the HTC Vive. The Leap Motion controller tracked the fingers, palms, and arms of both hands up to approximately 60 cm above the device. The tracking accuracy has been reported to be 0.2 mm (Weichert et al. 2013), and the latency has been reported to be approximately 30 milliseconds (*Understanding Latency: Part 1*). (See Figure 2-1)

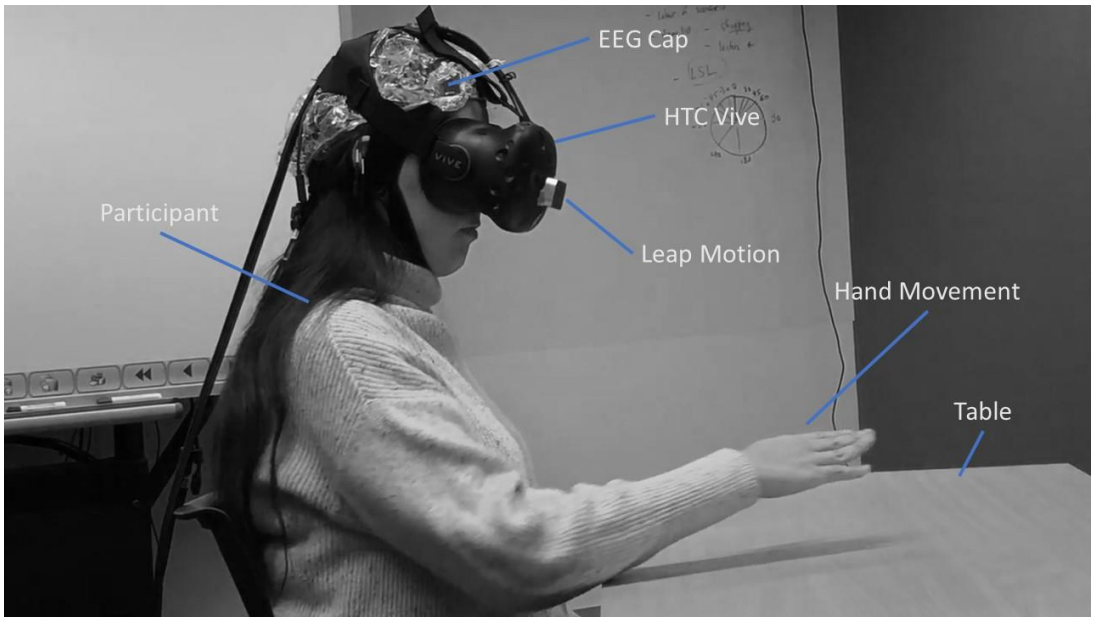


Figure 2-1 EEG-based experiment setup (from experiment 1). In this setup, user wore a 32 electrodes EEG cap on the top of VR HMD including Leap Motion installed in front of HMD and performed the 3D object selection task

2.3. EEG Setup

EEG-based data were recorded with 32 and 64 Ag/AgCl electrodes with reference linked to mastoids and the central reference electrode respectively. The placement of the EEG electrodes was consistent with 10-20 system (Chatrian, Lettich & Nelson 1985). The contact impedance was maintained below 5kΩ. The EEG recordings were collected using a Scan SynAmps2 Express and Curry 8 system, both from Compumedics Ltd., VIC, Australia. The EEG recordings were digitally sampled at 1 kHz with a 16-bit resolution.

2.4. EEG Data Analysis

2.4.1. Downsampling and filtering

The recorded EEG data were preprocessed using the EEGLab toolbox (Delorme & Makeig 2004) in MATLAB 2016 (MathWorks Inc, USA). The EEG data was first downsampled to 500 Hz and 250Hz for data reduction followed by filtering 1Hz high-

pass (-6 dB) and 40Hz low-pass finite impulse response (FIR). The filter response for magnitude and phase for 1 Hz and 40 Hz can be seen in Figure 2-2. The subsequent resultant data were subject to the further inspection for artifacts.

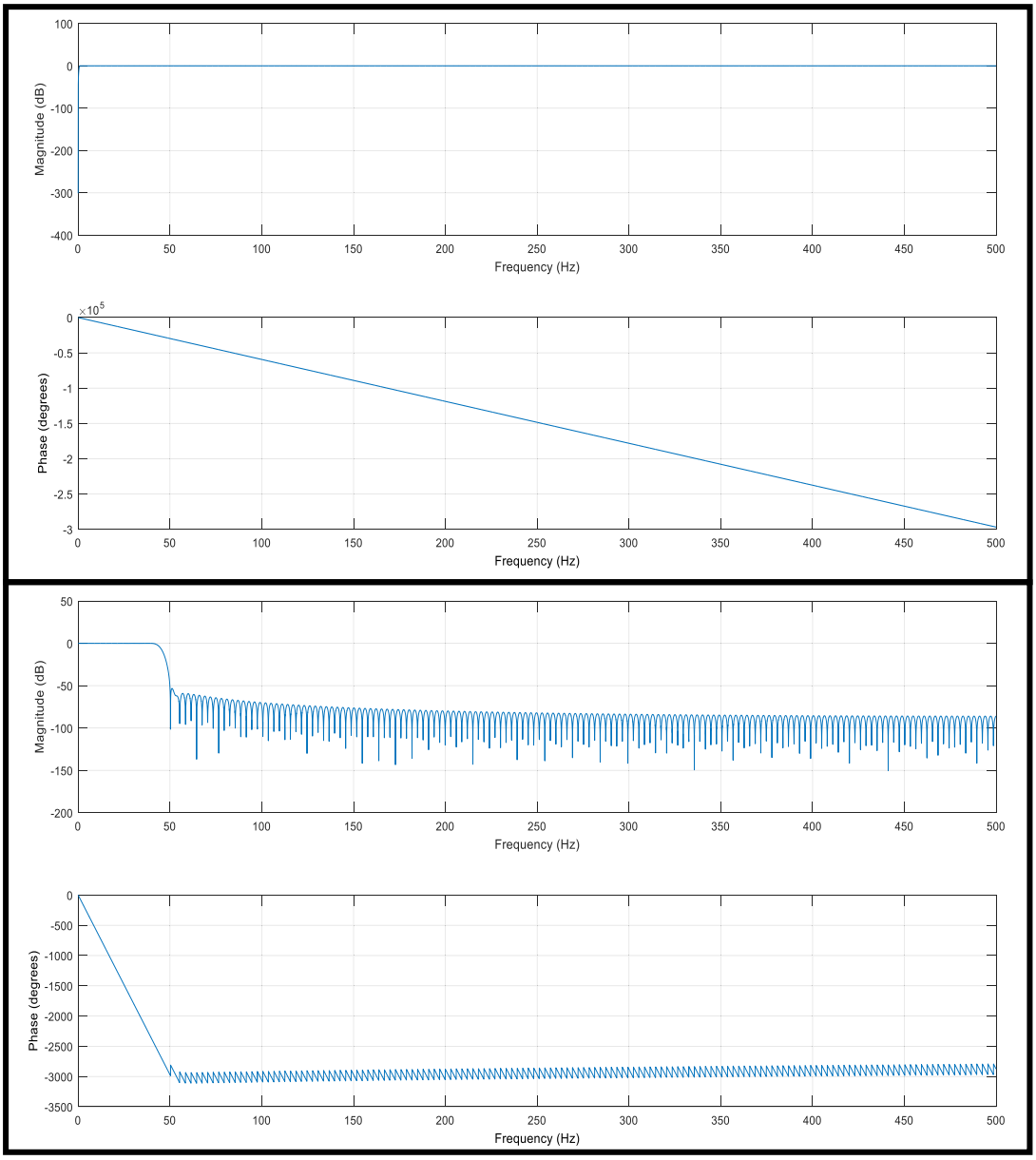


Figure 2-2 FIR for band-pass filtering. A) represents the 1 Hz high-pass filter (outputting magnitude and phase), and B) represents the 50 Hz low-pass filter (also outputting magnitude and phase)

2.4.2. Noisy electrodes

A subset of EEG electrodes was subject to possible noise due to external electrical device interference, poor impedance or a poor connection with the scalp. It is important to remove such noise before further processing the EEG signals. The kurtosis method (Westfall 2014) to detect noisy electrodes was applied and the detected electrodes were removed. Kurtosis is the 4th order cumulant of the data where mean being the first

cumulant and the variance the second. The removed electrodes were interpolated using the spherical method (Perrin et al. 1989) in EEGLab to keep the same number of electrode among all the participants for analysis purpose. Kurtosis method can be expressed as

$$kurt(X) = m_4 - 3m_2^2 \quad (2\text{-}1)$$
$$m_n = E\{(x - m_1)^n\} \quad (2\text{-}2)$$

where m_n is n^{th} central moment of all activity values of given data, m_1 is the mean, and E an expectation function.

2.4.3. Independent component analysis

The resultant data after down-sampling, filtering, and noisy electrode detection were processed using ICA, which is a blind source separation (BSS) method (Cardoso 1998) to segregate, identify and localize sources of a signal originated in a different part of the brain. ICA provides an excellent approach to not only identify the actual brain sources but also separate the actual brain signals with the possible artifacts (Britton JW, Frey LC & al. 2016) such as muscles movements, eye blinks, saccade eye movements, and electrode displacement (see Figure 2-3).

Let us assume that there are a linear mixing model and n-channel scalp EEG signals, $x = [\, x_1, x_2, x_3 \ldots x_n \,]$ are generated by m independent sources $s = [\, s_1, s_2, s_3 \ldots . s_m]$, then signal x can be represented by:

$$x = As \quad (2\text{-}3)$$

where A is the $n \times m$ mixing matrix in the model. After ICA, the recovered source signals u, can be estimated by applying an unmixing matrix $W\ (m \times n)$ to the observed EEG data x as:

$$u = Wx \quad (2\text{-}4)$$
$$x = W^{-1}u \quad (2\text{-}5)$$

where each row of W is a spatial filter for estimating independent components (ICs) and each column of W^{-1} consists of electrode weights (i.e., a spatial projection) of an independent component.

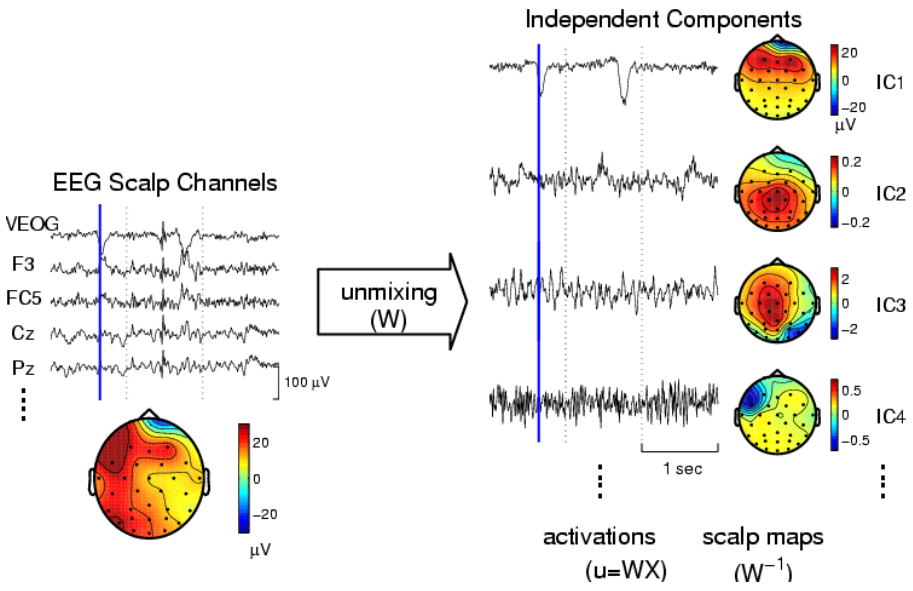


Figure 2-3 An example of ICA decomposition method where all EEG scalp electrodes were decomposed in multiple independent components based on the unmixing matrix. (Image Source: SCCN[4])

Figure 2-4 shows the ICA decomposition scalp maps from one participant. It can be seen clearly that there are several components, which does not look like a brain source. For example, IC1, IC4, IC22, and IC6 are related to eye blink, saccadic eye movements, broken electrode, and brain signal respectively. (See Figure 2-5).

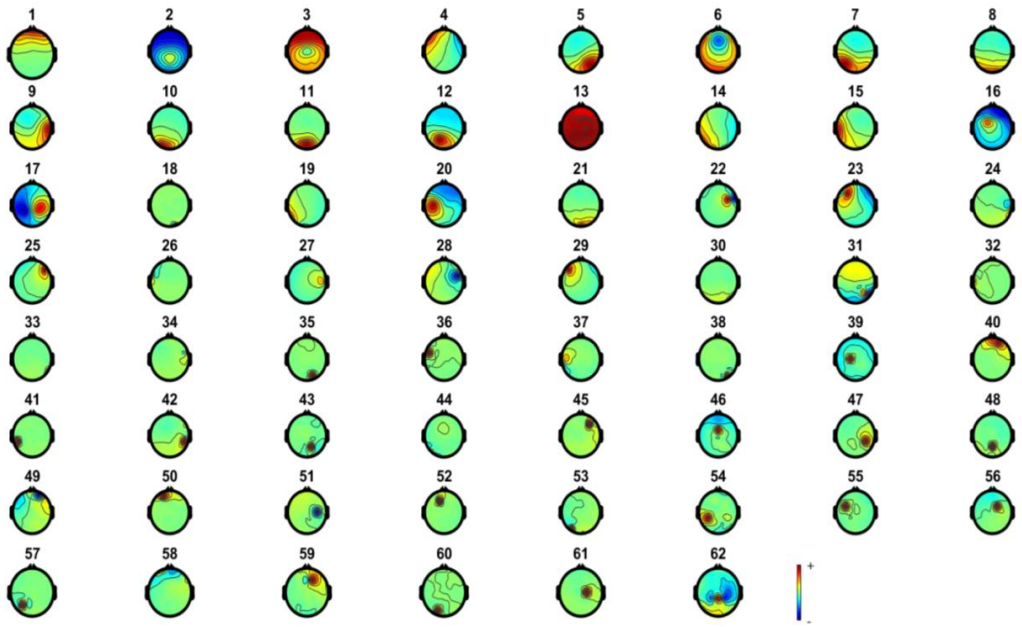


Figure 2-4 ICA component scalp maps from one participant based on 64 electrodes EEG signals (participant#2)

[4]https://sccn.ucsd.edu/

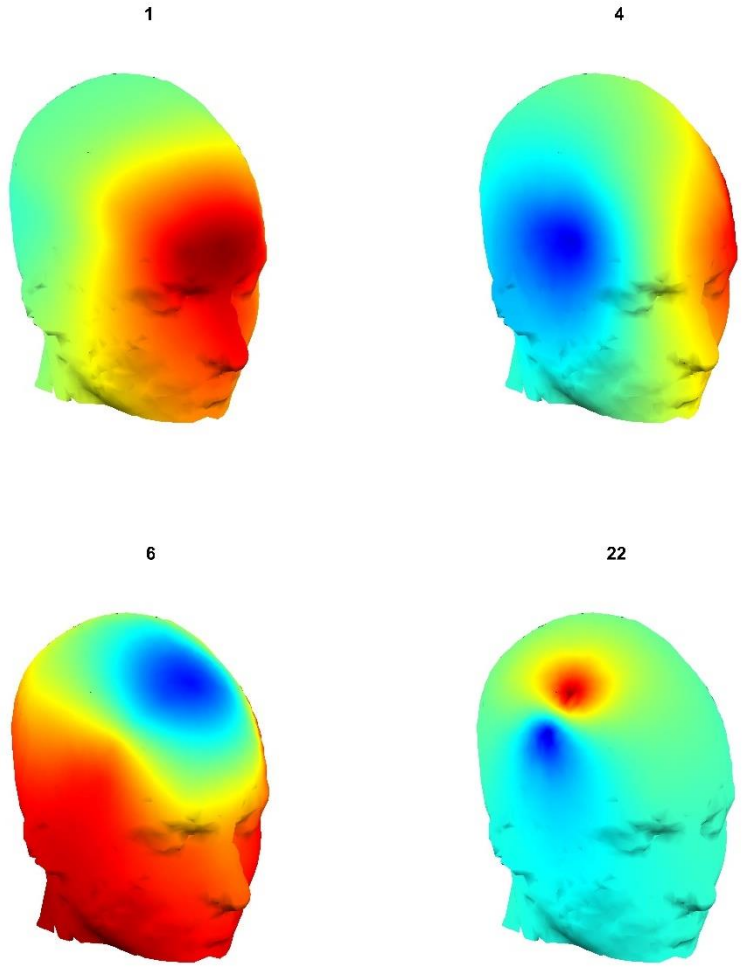


Figure 2-5 Selected ICs are representing eye blinks (top-left), saccadic eye movements (top-right), brain signal (bottom-left), and broken EEG electrode (bottom-right) from participantt#2

2.4.4. Dipole fitting

EEG data collected from the scalp is the composition of different activity from different sources of the brain. It is possible to decompose signals to find the actual source. The solution to this problem is commonly referred to as the EEG inverse problem. The EEG inverse problem comes with several assumptions about the nature of the distribution and tries to provide a solution in a way that explains the maximal amount of topographical variance of such a scalp distribution. These solutions result in an equivalent dipole whose summed projection is nearly equivalent to the observed EEG scalp distribution.

An ICA-based unmixing matrix provides dipole-like projections on the scalp map based on a default spherical head model with four surfaces i.e. skin, skull, CSF, and cortex. Dipole fitting (DIPFIT) toolbox is used to calculate the dipoles using the ICA

unmixing matrix. It utilizes the Spherical 4 shell (BESA) (Berg & Scherg 1994) model to fit the dipoles with the help of a grid search and non-linear fitting method on several ICA components. The resultant dipoles are projected on standard magnetic resonance (MR) images of the brain to provide visualization (see Figure 2-6 for dipole fitting result from one participant).

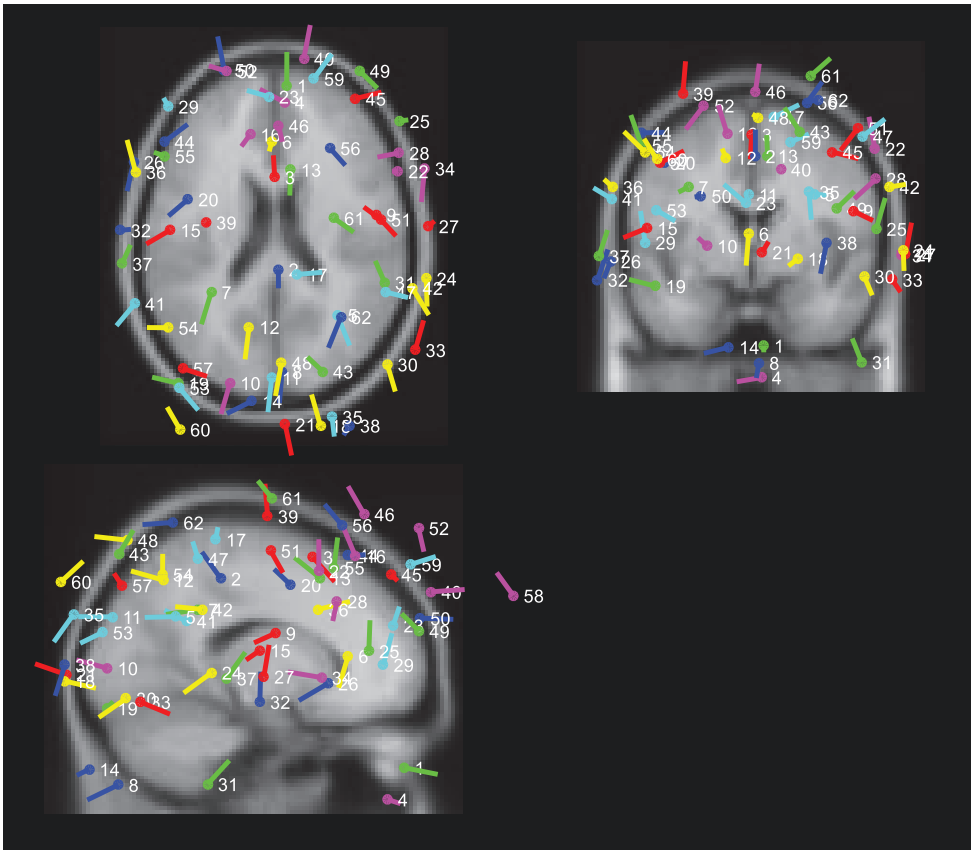


Figure 2-6 The clustered dipoles projected on a standard MRI image

2.4.5. Detecting noisy independent components

EEG data with the computed ICA and dipole were further investigated to detect and reject any noisy components from the data. This was achieved using a combination of methods based on different conditions as follows:

- Threshold-based criteria on the dipole fit based on residual variance (<15%) i.e. variance of mismatch between ICs and dipole fit,
- Autocorrelation for each component with a 20ms window or lag of EEG signals,
- Focal source component(s) such that the component(s) surrounded the electrode(s) with a default Z-score,
- Signal-to-noise (SNR) ratio below 1, and

- Automatic EEG artifact detection based on the joint use of spatial and temporal features (ADJUST) toolbox (Mognon et al. 2011).

Figure 2-7 shows the detected components after applying different methods of artifact removal on one participant.

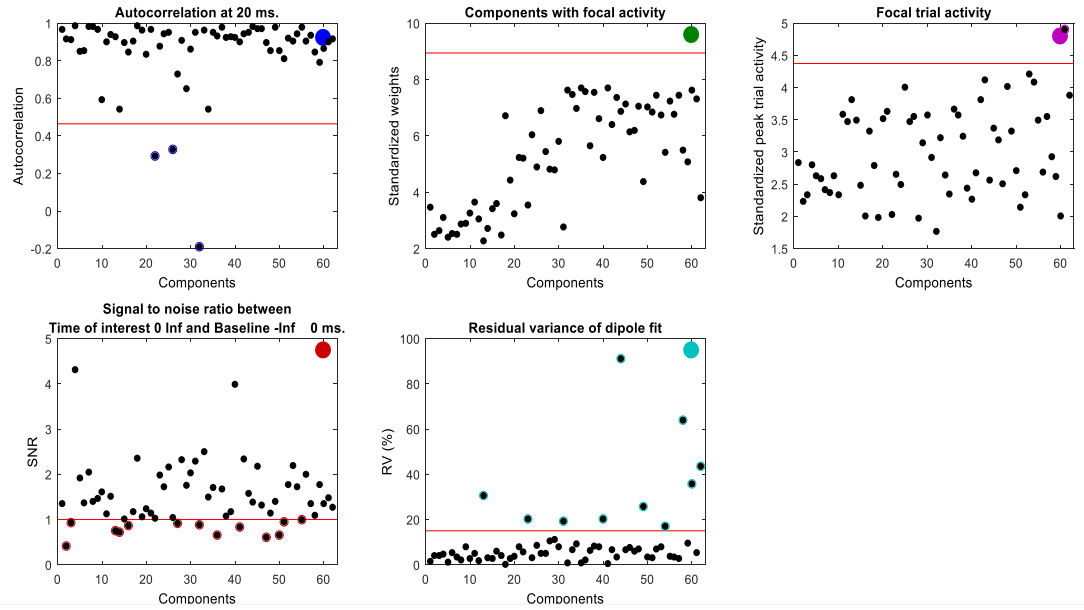


Figure 2-7 The output from artifact rejection based on different criteria of autocorrelation, focal activity overall, focal activity based on trials, SNR, and residual variance of dipole fit

2.4.6. Clustering

The next step after cleaning the EEG data is to find common components among all the participants. This has been achieved using a clustering algorithm (Onton, Delorme & Makeig 2005). The clustering method tries to maximize the closest relative component based on different criteria provided using the neural network methodology (Bishop 1995). (See Figure 2-8 for clustered components and its average for all participants).

The criteria of clustering were:

- ERSP,
- Inter-trial coherence (ITC) (Makeig & Inlow 1993),
- Spectral information, and
- Dipole positions.

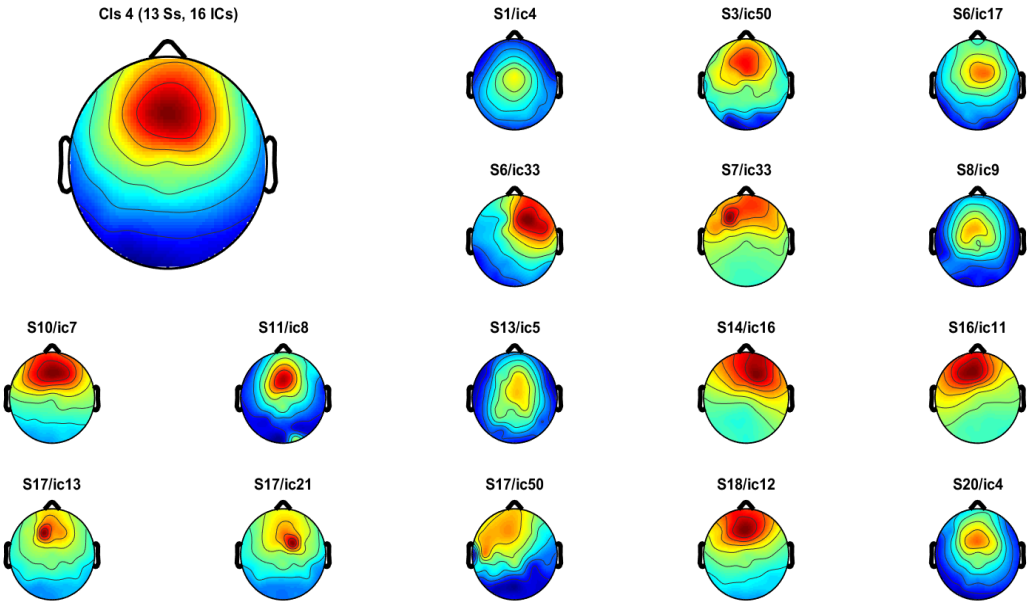


Figure 2-8 The scalp map of the average clustered component (top-left) and all the sub-components which contributed to it from one participant

Cluster components were further inspected to find if chosen components by the algorithm were correct and not representing noise. If there were any, then removed manually. This was achieved by modifying some cluster's component to match the correct component cluster representation. (See Figure 2-9 for the averaged clustered components).

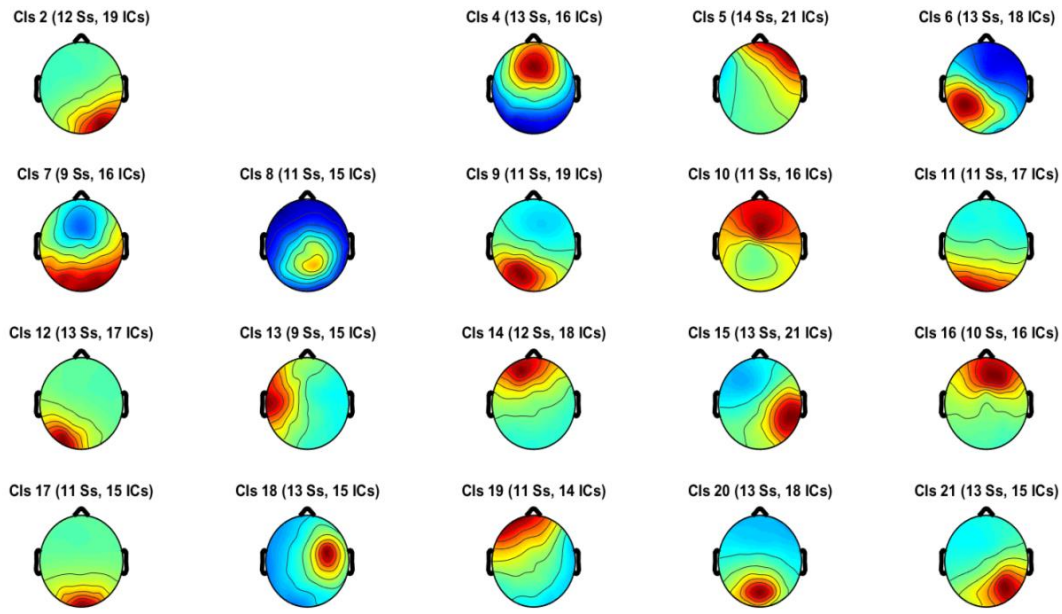


Figure 2-9 The average scalp maps of all the clustered components from all participants

The results of the cluster's components also can be extended to clustered dipole fitting. The clustered dipoles provide supporting visual information to select the region of interest for analysis. These dipoles are further inspected to see if the dipoles were clustered as expected and whether their location match with the average ICs clusters (see Figure 2-10). Once the clustering process was finished, then further analysis, calculation, and statistics were performed on the resultant EEG data.

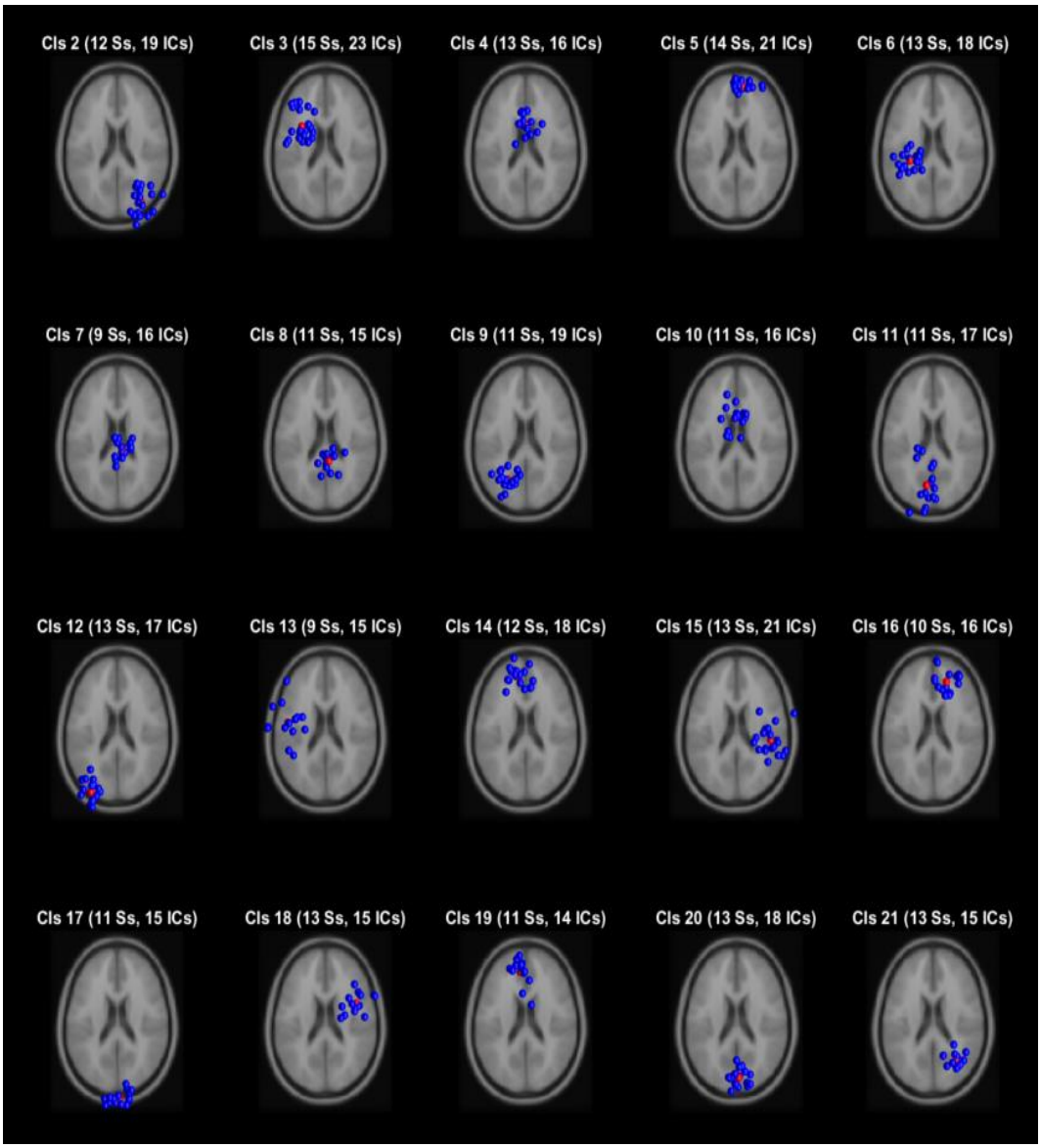


Figure 2-10 The corresponding clustered dipole for all the participants where the blue dipoles represent dipoles from one participant while the red dipoles represent the average of all the blue dipoles

Further analysis of EEG data was based on time and time-frequency domain analysis.

2.4.7. Event-related spectral perturbation

The average dynamic changes in amplitude in the given frequency spectrum in the time-locked to the experiment is known as ERSP. ERSP is computed by combining the baselined spectrum from the preceding experimental event. Each epoch is then divided into the overlapping window while calculating the moving average of spectra and then normalized. All the epochs with spectra are averaged to calculate ERSP (Makeig 1993). Figure 2-11 shows an example of a calculated ERSP.

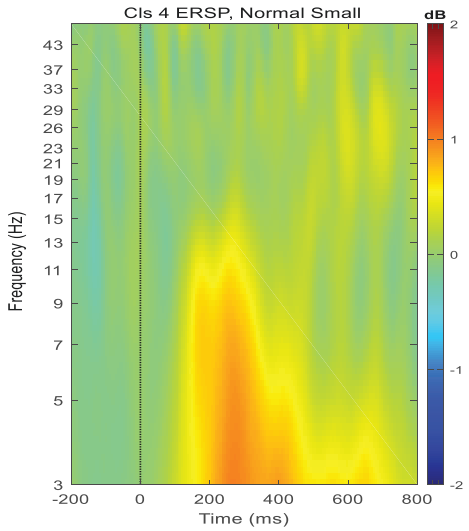


Figure 2-11 ERSP from a clustered IC component in the normal condition of the 3D object selection task

2.4.8. Extracting prediction error negativity and positivity

Prediction error negativity (PEN) and positivity (Pe) represent the main biomarkers for cognitive conflict in this thesis. PEN was extracted by calculating the mean minima amplitude from 50-150ms after response-locked with ±2 adjacent points. Similarly, Pe was calculated by the mean maxima amplitude from 250-350ms after response-locked with ±2 adjacent points. PEN and Pe can be formulated as follows:

$$PEN = \frac{\left(\min(ERP_{50to100}) \pm {}^{SR}/_{100})\right)}{N} \tag{2-6}$$

$$Pe = \frac{\left(\max(ERP_{250to350}) \pm {}^{SR}/_{100})\right)}{N} \tag{2-7}$$

where SR is the sampling rate of EEG signals, and N is a corresponding number of data points from the nominator.

2.5. Machine Learning Methods

In this work, several linear and non-linear machine-learning methods were used to test and classify the cognitive conflict level for each trial for a closed-loop BCI system to assess the cognitive conflict. These methods are detailed in the following subsections.

2.5.1. Linear discriminant analysis

Linear discriminant analysis (LDA) is a popular method derived from Fisher's discriminant (McLachlan 2004). LDA is used in a wide range of pattern recognition and machine learning tasks to find a linear combination of features for two or more classes. The LDA method tries to maximize the scatter between different classes by projecting the data into a new space with the assumption that data is normally distributed. This projection can be defined as follows:

$$Y = W^T \mathrm{X} \tag{2-8}$$

where Y is project data, X is original data, and W^T is projected space.

Let us assume the mean of data for each class i can be represented as:

$$Y_i = \frac{1}{n_i} \sum_{x \in D_i} X \tag{2-9}$$

where D_i is the set of data x for a class, and the projection on Y_i is as follows:

$$\overline{Y_i} = W^T Y_i \tag{2-10}$$

then the scatter matrix of class i can be computed as

$$E_i = \sum_{x \in D_i} (X - Y_i)\ (X - Y_i)^T \tag{2-11}$$

2.5.2. Bayesian classification

Bayesian classification is a statistical classifier based on Bayes' theorem (Rish 2001). It assigns a posteriori probability to a feature vector of a given class. Let us say X is a vector of n features as follows:

$$X = (x_1, x_2, x_3 \dots x_n) \tag{2-12}$$

then, the probabilities of this n will be as follows:

$$p(C_k|\, x_1, x_2, x_3 \dots x_n) \tag{2-13}$$

where k possible outcome or classes.

Using Bayes' theorem, the conditional probability can be defined as:

$$p(C_k|\, x) = \frac{p(C_k)p(x\,|C_k)}{p(x)} \tag{2-14}$$

2.5.3. Support vector machine

A Support vector machine (SVM) (Cortes & Vapnik 1995) method uses a discriminate hyperplane to separate different classes. The major part of the SVM methodology is to find the optimal hyperplane, which maximizes the margin between the classes.

Let us assume there are two groups of data sets, $D1$ and $D2$, with i elements. Assume x_i is the mean in data set $D1$ and $D2$ where set $i = 1, 2, 3 \dots . k$. Then, the elements and the corresponding label in the data set can be defined as:

$$y_i = \begin{cases} 1, if\ x_i\ in\ class\ 1 \\ -1, if\ x_i\ in\ class\ 2 \end{cases} \tag{2-15}$$

the hyperplane between these classes can be defined by:

$$w^T x + b = 0 \tag{2-16}$$

then again, labels of the classes can be represented by:

$$y_i = \begin{cases} 1, if\ w^T x_i + b > 0 \\ -1, if\ w^T x_i + b < 0 \end{cases} \tag{2-17}$$

where parameters w and b are chosen in the maximal margin by finding the maximal distance between $w^T x + b = 1\ and\ w^T x + b = -1$. The maximal distance can be defined as:

$$max \frac{2}{||w||} = min \frac{w^T w}{2} \tag{2-18}$$

The objective function based on maximal distance is defined as:

$$min \frac{\|w\|^2}{2} \; subject\ to\ y_i\ (w^T x_i + b) - 1 \geq 0\ \forall i \tag{2-19}$$

The Lagrange multiplier method (Bertsekas 1999) is applied here to transform it into a quadratic equation:

$$L\ (w, b, \alpha) = \frac{\|w\|^2}{2} - \sum_{i=1}^{N} \alpha_i\ [\ y_i(w^T x_i + b) - 1] \tag{2-20}$$

The extreme point also known as support vectors can be defined as:

$$y_i(w^T x_i + b) - 1 = 0, \alpha_i\ \geq 0 \tag{2-21}$$

$$y_i(w^T x_i + b) - 1 > 0, \alpha_i\ = 0 \tag{2-22}$$

2.5.4. Feed-forward neural network

Feed-forward neural networks (FFNNs) (Bishop 1995) are one of the most commonly used artificial neural networks (ANNs). It contains an input layer, a hidden layer and an output layer where the input layer enters the hidden layer by the neuron weights and then the output layer receives the output of the hidden layer to provide the results.

The hidden layer can be defined as:

$$f: Q^D\ \rightarrow\ Q^L \tag{2-23}$$

where D is the size of the input vector x and L is the size of the output vector $f(x)$, further:

$$f\ (x) = F\ (b^{(2)} + W^{(2)}(s\ (b^{(1)} +\ W^{(1)}x))) \tag{2-24}$$

where $b^{(1)} b^{(2)}\ are$ bias vectors , $W^{(1)}$, $W^{(2)}$ are weight matrices, and F and s are activation functions.

The activation function s can be defined by the sigmoid function as:

$$sigmoid\ (a) = {}^{1}/_{(1 +\ e^{-a})} \tag{2-25}$$

Then, the output vector can be obtained by:

$$f\ (x) = F\ (b^{(2)} + W^{(2)}(h(x)) \tag{2-26}$$

2.6. Object Selection Methods

2.6.1. Fitts' law

Fitts' Law (Soukoreff & MacKenzie 2004) estimates the time required to perform the movement toward the target considering only the physical properties of the acquisition task e.g. size of target, amplitude of movement etc. Let us assume time T is required to acquire a target of width W at distance A, and then Fitts' Law can be formulated as:

$$T = a + b \log_2\left(\frac{A + W}{W}\right) \tag{2-27}$$

where a and b are regression coefficients and the logarithmic term is called the index of difficulty (ID). The intercept a is sensitive to the additive factors such as reaction time (time to locate and acquire an object) and the inverse of the slope $1/b$ is the index of the performance of the task.

2.6.2. Optimized initial pulse model

(Meyer et al. 1988) proposed an optimized initial impulse model applicable to the 3D object selection task in a VR environment. Meyer's acquisition model of the target with a human model in VR requires a ballistic and corrective phase.

Meyer formulates the relationship between speed and accuracy as:

$$S = k\frac{D}{T} \tag{2-28}$$

where S is the standard deviation of the endpoint, D is the distance covered, and T is the movement time.

2.7. Subjective Measures

2.7.1. Questionnaire on realism

Table 1 shows the self-reported ratings on a 5-point Likert scale for the level of realism, personal preferences, suitability for selection change for the level of conflict, and the influence of the experiment such as the level of dizziness and level of immersiveness. (See Appendix B: Questionnaire for VR Testing for more detail)

2.7.2. Behavioral inhibition system / behavioral activation system

The Behavioral inhibition system (BIS)/ behavioral activation system (BAS) scale (Carver & White 1994a) is a 24-item self-report questionnaire where BIS and BAS

represent the motivation and approach towards the aversive outcomes and goal-oriented actions. BIS/BAS is based on a 4-point Likert scale with four subscales. One of these subscales belongs to BIS while remaining is a part of BAS. Table 2-2 shows all variables, measurement units and a number of questions for each variable used in the BIS/BAS questionnaires. (See Appendix C: BIS and BAS Questionnaire for more detail).

Table 2-1 Questionnaire description for realism

Variable	Measurement (unit)	Min-max measure	Frequency	Data type
Realism	5-point Likert scale	1-less suitable, 5-most suitable	end of the experiment	continuous
Suitability	5-point Likert scale	1-less suitable, 5-highly suitable	end of the experiment	continuous
Preference	5-point Likert scale	1-less preferable, 5-highly preferable	end of the experiment	continuous
Level of conflict	5-point Likert scale	1-low conflict, 5-highly conflict	end of the experiment	continuous
Dizziness	5-point Likert scale	1-less dizzy, 5-highly dizzy	end of the experiment	continuous
Immersiveness	5-point Likert scale	1-less immersive, 5-highly immersive	end of the experiment	continuous

Table 2-2 Questionnaire description for BIS/BAS

Variable	Measurement (unit)	Min-max measure	Frequency	Data type
BAS-drive	4-point Likert scale	1-very true for me, 4- very false for me	end of the experiment	continuous
BAS-fun seeking	4-point Likert scale	1-very true for me, 4- very false for me	end of the experiment	continuous
BAS-reward responsiveness	4-point Likert scale	1-very true for me, 4- very false for me	end of the experiment	continuous
BIS	4-point Likert scale	1-very true for me, 4- very false for me	end of the experiment	continuous
Fillers	4-point Likert scale	1-very true for me, 4- very false for me	end of the experiment	continuous

2.7.3. Igroup presence questionnaire

The Igroup presence questionnaire (IPQ) (Regenbrecht & Schubert 2002; Schubert 2003) is a scale for measuring the sense of presence experienced in a VE which is the result of several surveys with a total of 500 participants. IPQ was originally constructed in German but has been extended to other languages. It comprises 14 questions on a 7-point Likert scale to measure the three main aspects of a VE:

- Spatial presence- the sense of being physically present in the VR,
- Involvement - the measure of the attention devoted to the VR, and
- Experienced realism - measuring the subjective experience of realism in the VR.

Table 2-3 shows the detail of the questionnaire. Also, check Appendix E: Presence Questionnaire.

Table 2-3 Questionnaire description for modified version of IPQ

Variable	Measurement (Unit)	Total Questions	Frequency	Data Type
Age	number	01	end of the experiment	number
Gender	binary	01	end of the experiment	nominal
Gaming experience	number	04	end of the experiment	number
Realism	7-point Likert scale	07	end of the experiment	continuous
Possibility to act	7-point Likert scale	04	end of the experiment	continuous
Quality of interface	7-point Likert scale	03	end of the experiment	continuous
Possibility to examine	7-point Likert scale	03	end of the experiment	continuous
Self-evaluation of performance	7-point Likert scale	02	end of the experiment	continuous

2.8. Statistical Analysis

The statistical analysis was undertaken to test if the observed information from the EEG analysis and behavior analysis rejects the null hypothesis and supports the alternative hypothesis. The hypothesis test is highly dependent on the p-value and is interpreted as follows:

- A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, thus reject the null hypothesis.
- A large p-value (> 0.05) indicates weak evidence against the null hypothesis, thus fail to reject the null hypothesis.
- p-value very close to the cutoff (0.05) or (=0.05) is considered to be marginal and depend on the condition to decide if the null hypothesis fails to reject or not.

To test these hypotheses, the following measurements were performed:

2.8.1. Repeated measure analysis of variance

Repeated measure analysis of variance (ANOVA) is a statistical measure to test the null hypothesis on repeated measure designs (Iversen et al. 1987). It considers the within-subjects factor (the qualitative independent variable), while the dependent quantitative variable on which each participant is measured as the dependent variable.

2.8.2. Repeated measure analysis of covariance

Repeated measure analysis of covariance (ANCOVA) is a statistical measure to test the null hypothesis on repeated measure designs while one independent variable behaves as a covariate (Stevens 2012). It also considers the within-subjects factor (the qualitative independent variable), while the dependent quantitative variable on which each participant is measured as the dependent variable.

Chapter 3 : Evoking the Cognitive Conflict in Virtual Reality and its Modulating Factors

3.1. Experiment

3.1.1. Participants and environment

EEG data were recorded from 32 right-handed male participants to determine the prediction error effect for three different rendering styles of hand conditions with 95% power to detect 5% significant level based on G*Power (Faul et al. 2007). The median age of the participants was 22.7 years, with a range of 20-26 years. Following an explanation of the experimental procedure, all participants provided informed consent before participating in the study. This study obtained the approval of the Institute's Human Research Ethics Committee of National Chiao Tung University, Hsinchu, Taiwan and was conducted in a temperature-controlled and soundproofed room. None of the participants had a history of any psychological disorders, which could have affected the experiment results.

3.1.2. VR setup

The experiment used the HTC Vive (*VIVE™ | Discover Virtual Reality Beyond Imagination* 2017) as the head-mounted display. The Vive uses an OLED display with a resolution of 2160 x 1200 and a refresh rate of 90 Hz. The user's head position was principally tracked with the embedded IMUs, while the external Lighthouse tracking system cleared the common tracking drift with a 60 Hz update rate.

Participants' hand motions were tracked with a Leap Motion controller attached to the front of the HTC Vive. The Leap Motion controller tracked the fingers, palms, and arms of both hands up to approximately 60 cm above the device. The tracking accuracy has been reported to be 0.2 mm (Weichert et al. 2013), and the latency has been reported to be approximately 30 milliseconds (*Understanding Latency: Part 1*).

Figure 3-1 EEG-based experiment evaluated the interaction techniques in VR by measuring intentionally elicited cognitive conflict.

3.1.3. EEG setup

In this EEG-based experiment, each participant wore an EEG cap with 32 Ag/AgCl electrodes, which were referenced to linked mastoids. The placement of the EEG electrodes was consistent with the extended 10-20 system (Chatrian, Lettich & Nelson 1985). The contact impedance was maintained below 5kΩ. The EEG recordings were collected using a Scan SynAmps2 Express system (Compumedics Ltd., VIC, Australia). The EEG recordings were digitally sampled at 1 kHz with a 16-bit resolution.

An assistant helped the participants put on the EEG cap first, followed by the HMD. HTC Vive has put the top belt of the central electrode of the EEG cap. However, participants also found these firmly pressed EEG electrodes uncomfortable. Thus, the top belt of HTC Vive was manually adjusted to avoid or reduce the pressure applied by the EEG channels. (See Figure 3-1)

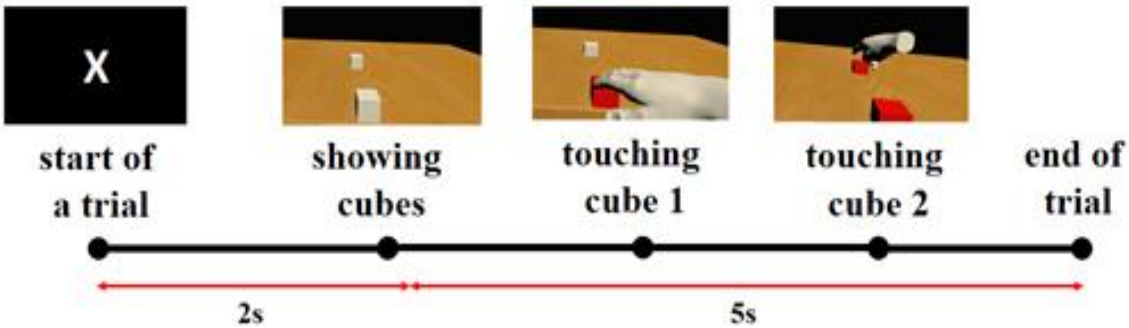


Figure 3-2 Experiment design for the 3D object selection task in VR

Each participant performed the 3D object selection task with their dominant hand tracked by the Leap Motion controller in VR. Figure 3-2 displays the scenario for a single trial. Each trial was seven seconds long. In the first two seconds, participant looked at a fixation screen with his right hand on the lap. Afterward, two cubes were displayed on a table. The participant was instructed to reach and select (touch) cube 1, and then cube 2. The cube would turn red when it was touched. The participant was expected to finish the task within 5 seconds. Otherwise, the trial was stopped and marked as incomplete.

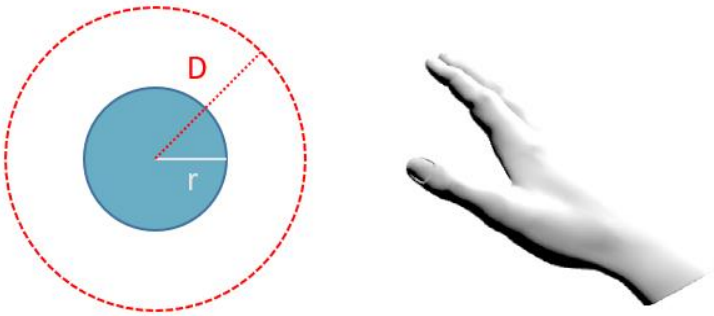


Figure 3-3 Change in the selection distance. 'r' is the normal radius, and 'D' is the changed radius that elicited the cognitive conflict

The selection distance of the second cube changed in 25% of the trials to create conflict condition, such that 75% of the trials used distance 'r' (D1) for no conflict condition and the remaining trials used distance 'D' (D2) for conflict condition (see Figure 3-3). Note that although the analysis was focused on the ERP of cube 2, the two-cube setup was designed

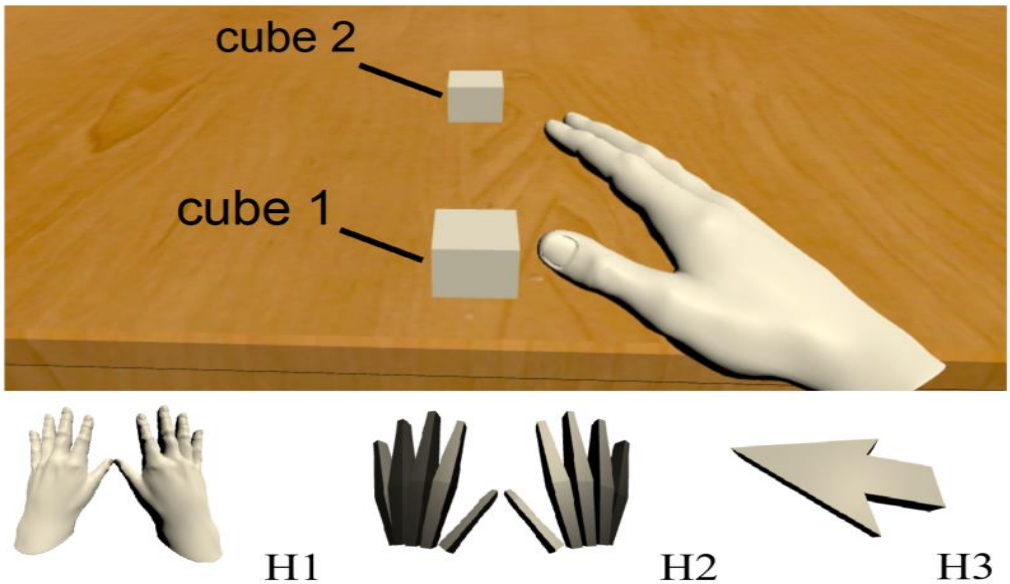


Figure 3-4 Top subfigure shows the scene of experiment. Each participant was instructed to touch cube 1 and then to reach for cube 2. The three subfigures at the bottom are the three hand styles used.

to ensure that the participants approached the second cube with similar hand motions (Figure 3-4, top).

There were three levels of the rendering style of the virtual hand: a realistic hand (H1), a robotic hand (H2), and a 3D arrow (H3) (Figure 3-4, bottom). The experiment consisted of three sessions, with one session for each hand style. Each session consisted of 120 trials. The order of the sessions was counterbalanced.

At the end of the experiment, the participants were presented with two sets of questionnaires. The first questionnaire asked for subjective ratings regarding the level of realism and personal preference towards each of the three different hand styles. The second questionnaire was the BIS (Carver & White 1994a), which contained 24 questions. The BIS questionnaire is commonly used to evaluate punishment sensitivity due to aversive events, such as conflict, which has been shown to correlate with ERP amplitudes (Balconi & Crivelli 2010).

Overall, the experiment used a 3 by 2 repeated measures factorial design with two factors: hand style (realistic hand, robotic hand, and 3D arrow) and selection distance (D1, equal to the size of the cube; and D2, twice the size of the cube). On average, the experiment took about two hours, including the initial setup of the EEG cap, the HMD, and the completion of the questionnaire.

3.2. Data Analysis

EEG data processing was performed using the EEGLAB toolbox in MATLAB. Raw EEG signals were filtered using a 0.5-Hz high-pass and a 50-Hz low-pass FIR filter. Subsequently, the data were downsampled to 500 Hz and subjected to the visual inspection of the artifacts.

An ICA was applied (Makeig et al. 1996) on resultant data, and epochs were extracted from 200 ms from the onset of the touching event for cube 2 to 800 ms after the response. Final artifact rejection was done on the epoched data by visual inspection. The EEG signals, without the components related to eye artifacts and muscle movement activity with a spectral peak above 20 Hz, were reconstructed using the back-projection method to selected channels to analyze the ERPs.

Following (Amin et al. 2015; Balconi & Crivelli 2010; Luck 2014), the amplitude of the PEN was calculated by extracting the negative peak value at the electrode location

FCz between 50-150 ms for conditions D1 and D2, and subsequently computed the difference wave by subtracting the ERPs with the onset of D1 from the ERPs with the onset of D2. Similarly, the amplitude of Pe was calculated by extracting the positive peak value at FCz between 200 ms – 275 ms for conditions D1 and D2 and then subtracting both conditions. Note that when using the ERP amplitude as the measurement, the factor selection distance was eliminated.

3.3. Task Completion Time

The task completion times for all participants for both normal and conflict trials was defined as the time from touching the first cube to touching the second cube. Within-participant factor task completion times were calculated by computing a median-split of all trials for each participant and grouping them into short task completion times and long task completion times group (fast and slow group respectively). This resulted in one shorter completion times (fast) group with 1284 trials (individual trial numbers varied with Median = 76; SD = 15) and one long completion time (slow) group with 1292 trials (individual trial numbers varied with M = 76; SD = 20). The distribution of individual trials to both groups were left-skewed (Median = 85, IQR = 20.75 for fast group; Median = 83, IQR = 26.75 for slow group). Some participant's trials were overlapping between short and long task completion times; therefore, the top 40% trials were taken as short task completion time group and bottom 40% trials as long task completion time group after median splitting the trials. A similar procedure has been adopted in between-participant factor.

3.4. Statistical Analysis

The statistical analyses were carried out using the SPSS Statistical tool (SPSS Inc Version 24). For each group, Pearson correlation coefficients (Benesty et al. 2009) between completion times with the PEN and Pe is evaluated.

3.5. BIS Based Results

3.5.1. Behavior results

Figure 3-5 shows the average task completion time, i.e., from cube 1 to cube 2 in seconds. A repeated measures ANCOVA was conducted to compare the task completion times for the three different hand styles in the two conditions, using the continuous BIS scores as a covariate. This included all the interaction terms between the hand styles and the task completion times as the within-participants factors. Levene's test and normality

checks (Gaur & Gaur 2006) were carried out, and the assumptions were met. There were no significant differences of the within-subject factor hand style (F (2, 60) = .337, p = .715) nor for the covariates as a between-subject effect (F (1, 30) = 3.865, p = .059). There was also no significant hand styles * condition interaction (F (2, 60) = .337, p = .641) or among the hand styles * condition * BIS scores (F (2, 60) = .288, p = .674). The results demonstrate that different rendering styles did not lead to statistically significant different behaviors during the task (Rabbitt & Rodgers 1977).

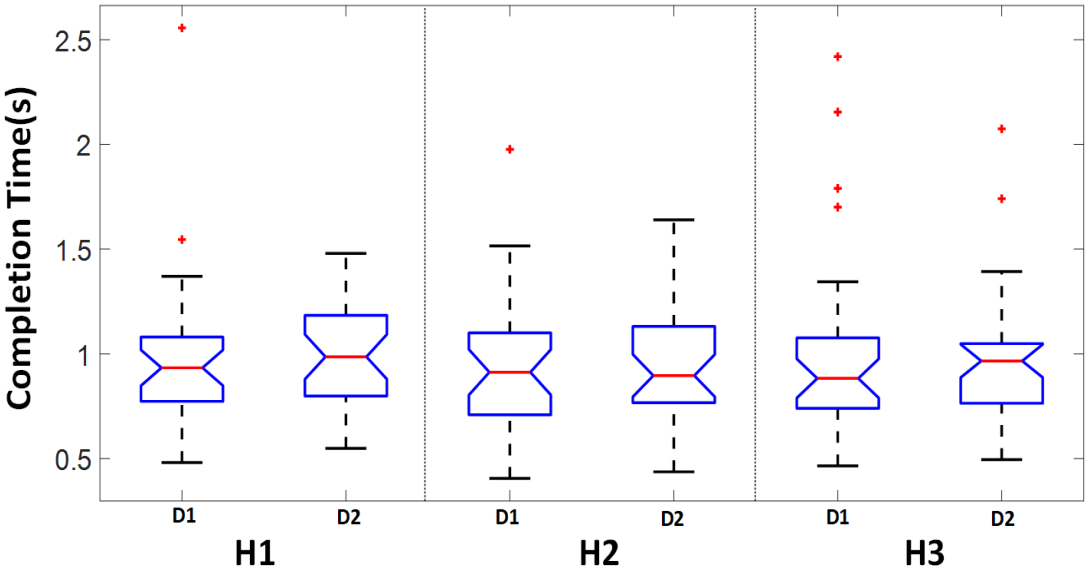


Figure 3-5 Average of task completion time (in seconds) for all participants

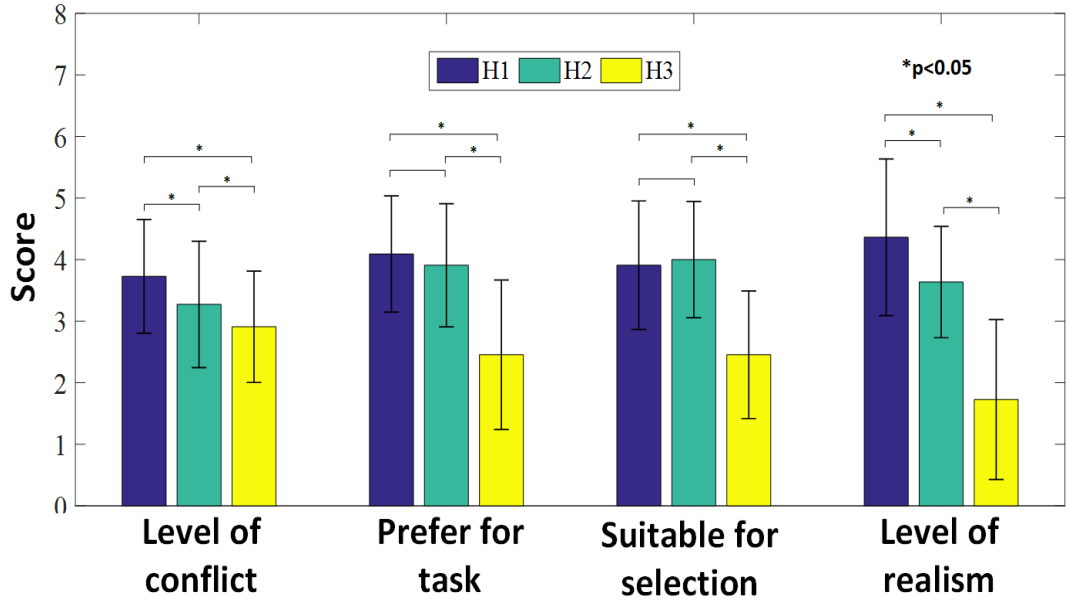


Figure 3-6 Questionnaire results for a realistic level of the hand styles

As shown in Figure 3-6, all participants considered the realistic hand style to be more realistic than the robotic hand and the arrow hand. Surprisingly, the results showed that there were no significant differences between the realistic and the robot hand style in the ratings regarding the preference and suitability for the object selection task.

The results showed that the participants did prefer the realistic hand style over the cursor style. However, this was not because of its realistic rendering style but rather because of the more naturalistic mapping between the physical hand and the virtual hand. This might also explain the absence of a significant difference in the preference ratings between H1 and H2. Interestingly, some users suggested that they preferred H2 for the 3D object selection tasks because it occluded the target less.

3.5.2. EEG results

For the measurement of the PEN amplitude, a repeated measures ANCOVA was conducted to compare the effect of the hand styles on the two conditions while treating the BIS scores as covariates. There was a significant difference in the within-subject factor of the hand style ($F(2, 54) = 3.586$, $p = .035$, partial $\eta 2 = .117$) but not for the covariate as a between-subject effect ($F(1, 27) = 3.015$, $p = .094$, partial $\eta 2 = .100$). Interestingly, there was a significant interaction between hand styles and continuous BIS scores ($F(2, 54) = 3.605$, $p = .034$, partial $\eta 2 = .118$). This leads us to further examine the continuous BIS scores as a between-subject factor, which was performed by dividing all the participants into two groups, namely, a high BIS group and a low BIS group (low BIS Score<=14; high BIS Score>=15). This resulted in 17 participants being labeled in the high BIS group and 15 participants in the low BIS group (Unger, Heintz & Kray 2012) with effect size (Cohen's $d = 2.37$ for H1, $d = 0.057$ for H2 and $d = 0.14$ for H3). A mixed measures ANOVA was performed to compare the effect of the hand styles on the amplitude between the BIS groups. It was found that there was a significant interaction effect between hand styles and BIS groups ($F(1, 30) = 11.984$, $p = .002$, partial $\eta 2 = .285$).

Figure 3-7 shows the ERP plots of the two groups based on the BIS scores with the different hand styles grouped together, with high- and low-sensitive participants. The hand style 1 * high BIS interaction revealed a clear negative ERP component, while the low BIS group participants showed only a Pe component, which is commonly evoked by relevant changes in visual stimuli (Polich 2007).

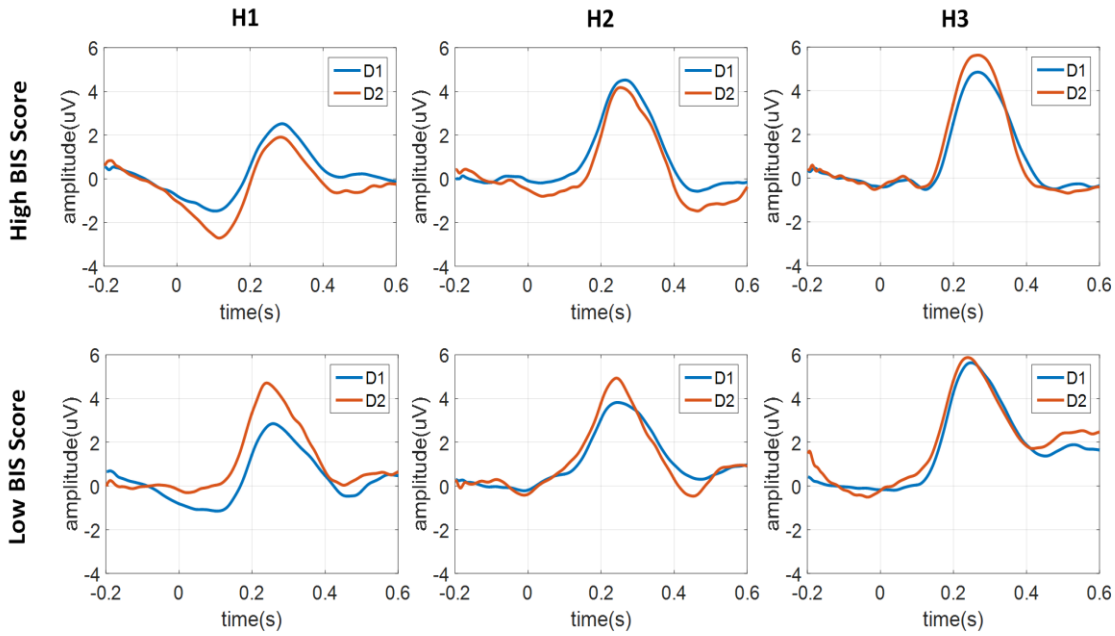


Figure 3-7 Average ERPs from all participants in response to hand style 1 (H1), hand style 2 (H2), and hand style 3 (H3) with the two conditions of the normal (D1) and conflict radii (D2) over FCz based on the high and low BIS score-based groups

The topoplots were calculated (see Figure 3-8) for the high BIS group (top row) and the low BIS group (bottom row). The high BIS group exhibited higher negativity in response to condition H1 than to H2 and H3, whereas the low BIS group exhibited strong positivity (Pe) in response to H1 compared to H2 and H3.

The correlation analyses between the BIS groups and both the PEN and the Pe amplitude revealed a significant negative correlation between the high BIS scores and the amplitude of the negative ERP component in response to conflict during the realistic hand style condition ($r = -0.9833$; $p < .001$). Low BIS scores were positively correlated ($r = 0.8386$; $p < .001$) with a change in the ERP negativity amplitude. Low BIS scores were further revealed to have a significant positive correlation with the Pe amplitudes in the realistic hand style (H1) condition. No significant correlation coefficients were observed for any of the other hand styles (all p's > 0.05).

3.6. Task Completion Time based Results

3.6.1. For intra-trial task completion time

i. Behavior results

Participants responded correctly in most trials with only a small percentage of misses or incorrect trials (e.g., missing to touch the second cube). As expected, task completion times fluctuated for trials within participants; therefore, all trials were sorted from each

participant and divided them into two groups (short and long completion time group) as mentioned in the methodology section. As per repeated ANOVA analysis, it was found that large and short trials were a significant different for normal condition ($F(1, 32) = 37.028$, $p < .001$) and conflict condition ($F(1, 32) = 67.476$, $p < .001$). Table 3-1 Statistics for all normal and conflict condition trials before and after splitting into short (fast) and long (slow) completion times group of trials (also see Figure 3-9).

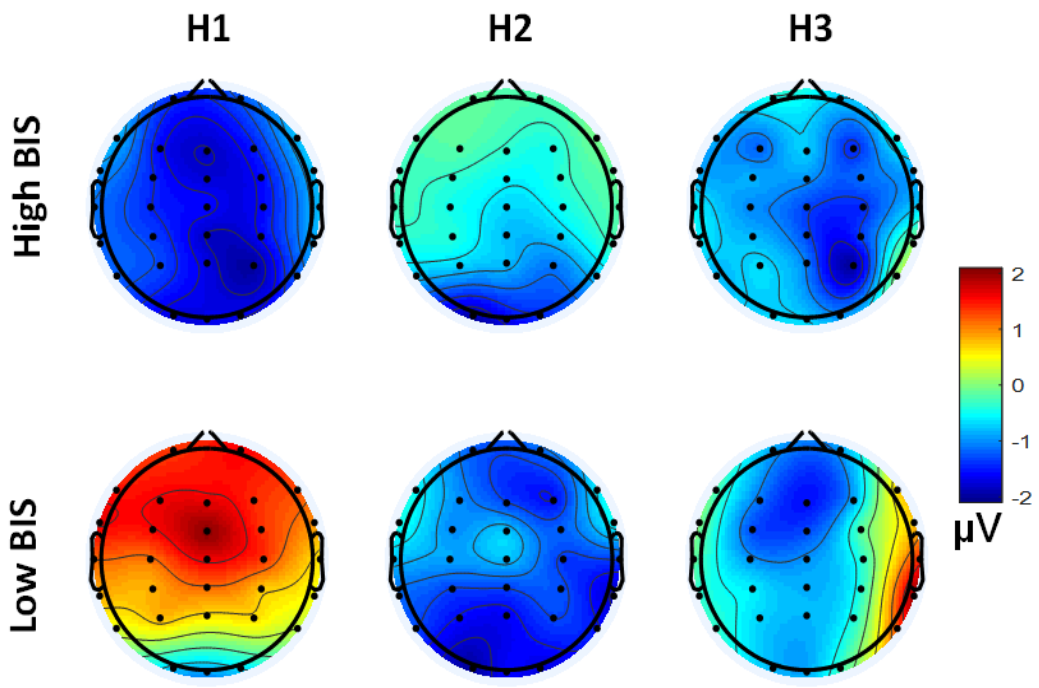


Figure 3-8 Average topoplots of the differences between the two conditions (change - normal) for participants with high (upper row) and low (lower row) BIS scores

Table 3-1 Statistics for all normal and conflict condition trials before and after splitting into short (fast) and long (slow) completion times group of trials

Overall completion time (ms)			
Condition	Median	Standard deviation	Range (min-max)
Normal	424	131	189-677
Conflict	458	100	250-670
Short completion time (ms)			
Normal	312	57	189-436
Conflict	374	60	250-497
Long completion time (ms)			
Normal	550	54	424-677
Conflict	541	53	412-670

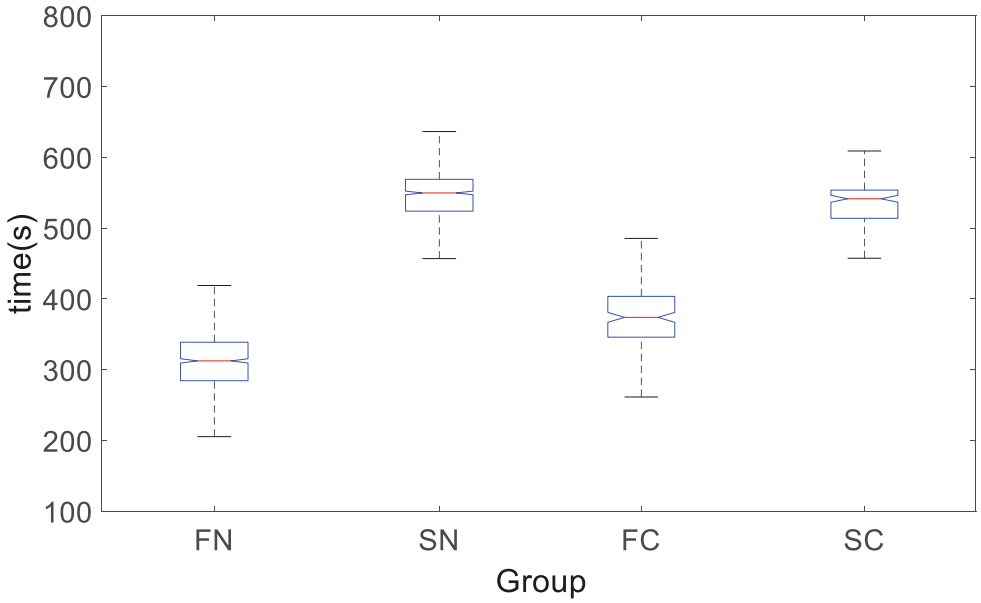


Figure 3-9 Boxplot for short (fast) and long (slow) completion times trials for the normal and conflict condition (FN= fast trials with the normal condition; SN = slow trials with the normal condition; FC= fast trials with conflict condition; SC= slow trials with conflict condition)

ii. EEG results

It was evaluated if the task completion time played any role in participants' electrocortical response towards the conflict. It was also evaluated how task completion time affects the amplitude of the PEN and Pe using an ANOVA with repeated measures. It was found that trials with fast task completion times showed a clear Pe component with the onset of the visual feedback while trials with slow task completion times revealed a PEN together with a subsequent Pe component in the ERP (see Figure 3-10).

As can be seen in Figure 3-10, there was no statistical significant ($F(1, 32) = .017$, $p = .896$) difference between PEN for normal trials between the fast and slow trials and also no statistical significant difference ($F(1, 32) = .449$, $p = .583$) was found for the Pe between fast and slow trials within the normal condition. On the other hand, in the conflict condition, there was a statistical significant ($F(1, 32) = 7.623$, $p = .009$) difference for the PEN for the fast and slow trials but no statistical significant difference ($F(1, 32) = 2.455$, $p = .127$) was found for Pe. In the comparison between normal and conflict trials condition for the fast and slow trials, there was also no statistical significant difference (fast trials: $F(1, 32) = .420$, $p = .522$; slow trials: $F(1, 32) = 1.745$, $p = .196$) found for PEN. Similarly, in the comparison between normal and conflict trials, there was no statistical significant difference ($F(1, 32) = .307$, $p = .583$) for Pe for the fast trials but

there was a statistical significant ($F(1, 32) = 7.623$, $p = .009$) difference for the slow trials regarding Pe.

Figure 3-11 shows the ERP from all participants for the slow and fast trial group in the intra-trial analysis.

Further evaluation was performed by the topographical distribution of the PEN and Pe component. According to Figure 3-12, it can be seen that the PEN effect is more prominent over the fronto-central region of the brain while fast task completion times showed less PEN compare to the slow trials. On the other hand, it is not true for normal condition.

Similarly, as per Figure 3-13, it can be seen that the difference between the conflict and the normal condition for slow completion times demonstrated a Pe over the frontal-central region of the brain while fast completion times showed no such difference. As well as Pe seems to more prominent on slow trials compare to the fast trials for conflict condition.

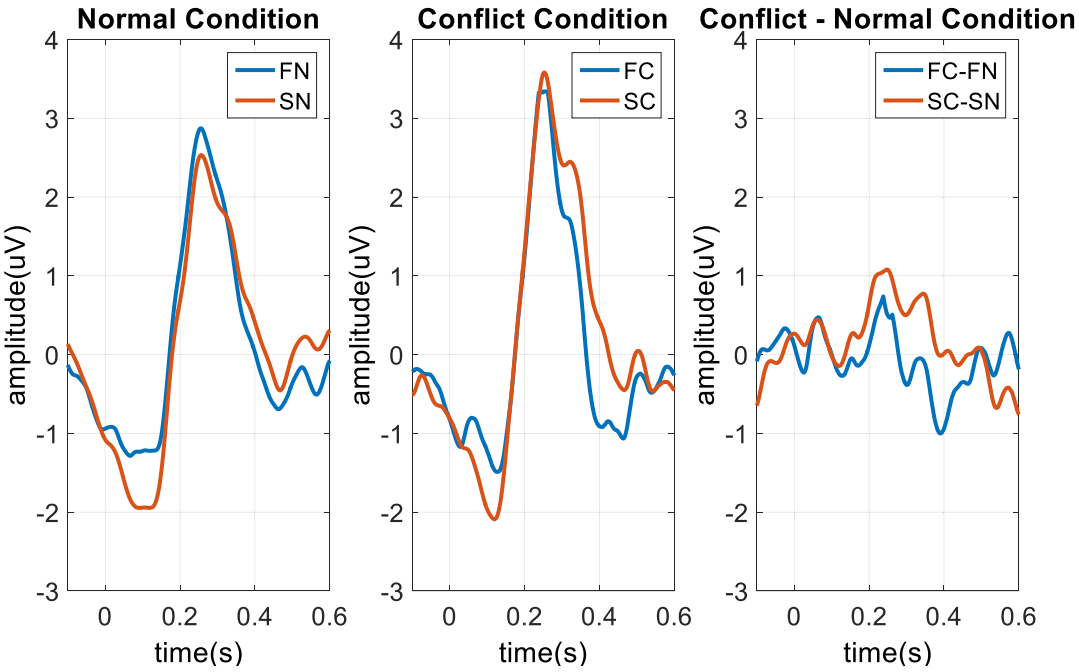


Figure 3-10 ERP for short (fast) and long (slow) completion times trials for normal and conflict conditions (SC= slow with conflict condition; SN = slow with normal condition; FC= fast with conflict condition; FN= fast with normal condition).

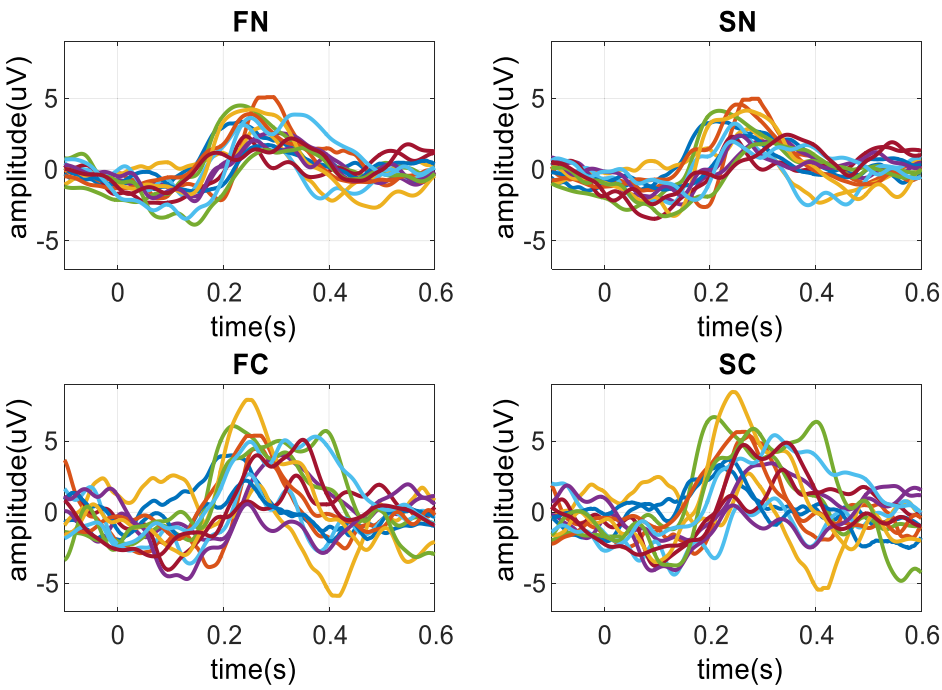


Figure 3-11 ERP for short (fast) and long (slow) completion times trials for all participant in normal and conflict condition (SC= slow with conflict condition; SN = slow with the normal condition; FC= fast with conflict condition; FN= fast with the normal condition)

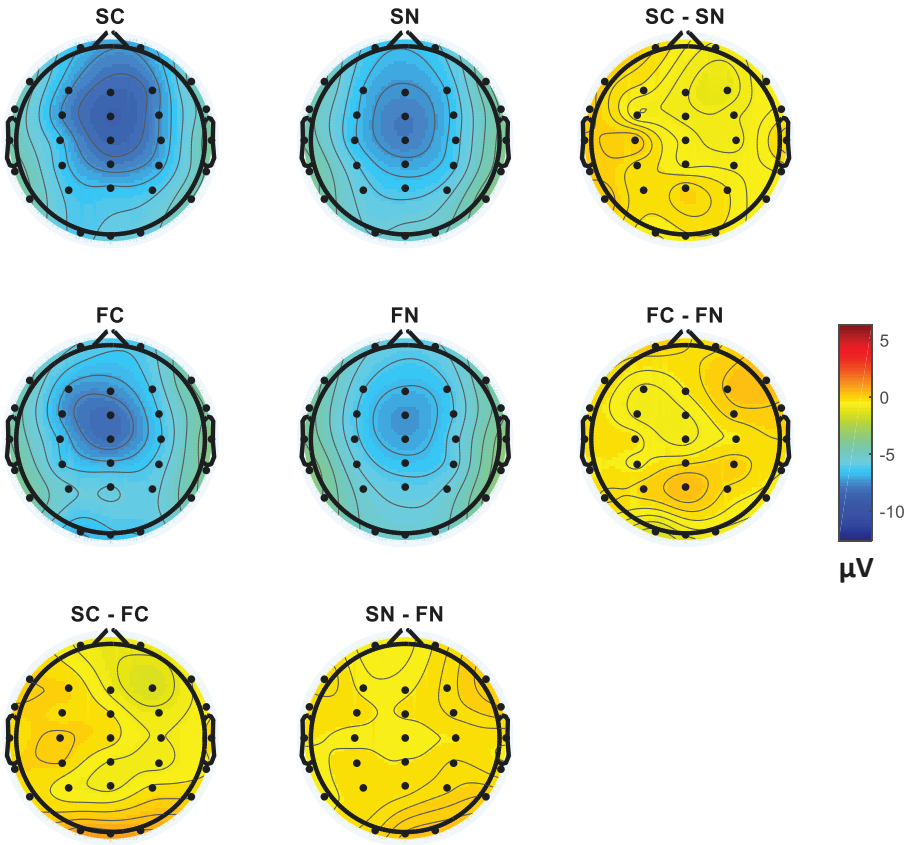


Figure 3-12 Topoplots for PEN component at 50-150ms for normal and conflict condition for short (fast) and long (slow) task completion times trials (SC= slow with conflict condition; SN = slow with the normal condition; FC= fast with conflict condition; FN= fast with the normal condition)

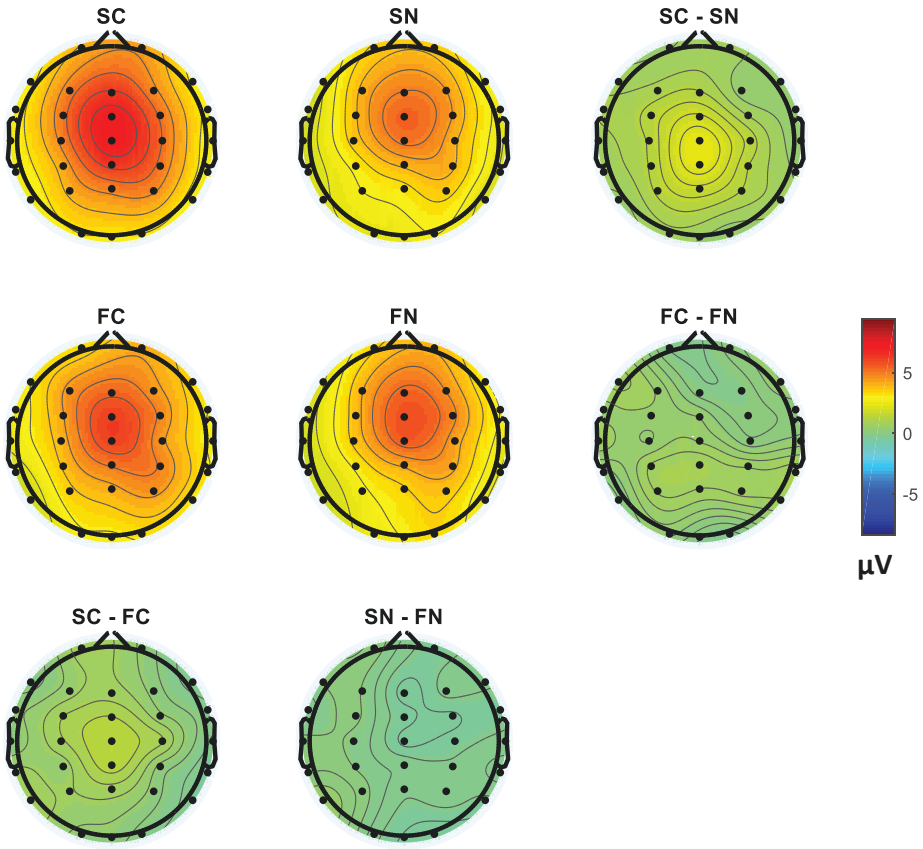


Figure 3-13 Topoplots for Pe at 250-350ms for normal and conflict condition for short (fast) and long (slow) task completion times trials (SC= slow with conflict condition; SN = slow with the normal condition; FC= fast with conflict condition; FN= fast with the normal condition)

It was also evaluated if chosen EEG channel was the optimal choice for PEN and Pe analysis. As shown in Figure 3-14, that PEN found to be most negative over the 'Cz' electrode compared to 'Fz' and 'FCz' for all conditions. Similarly, the Pe found to be most positive over 'Cz' electrode compared to 'Fz' and 'FCz' for all conditions.

Further, as shown in Table 3-2 and Figure 3-15, for slow trials, PEN and Pe were statistically significant (PEN: $r = -0.2280$, $p < 0.05$; Pe: $r = 0.2839$, $p < .001$) correlated but with small r with task completion time. On the other hand, PEN for fast trials was not correlated statistically significant ($r = -0.0446$, $p = 0.611$) with task completion time. Interestingly, Pe demonstrated a statistically significant positive ($r = 0.2180$, $p < 0.05$) correlation with task completion time. Overall, slow trials and fast trials showed a negative correlation with PEN while such a pattern was not observed for Pe, which demonstrated a positive correlation with task completion time for the fast and slow group of trials.

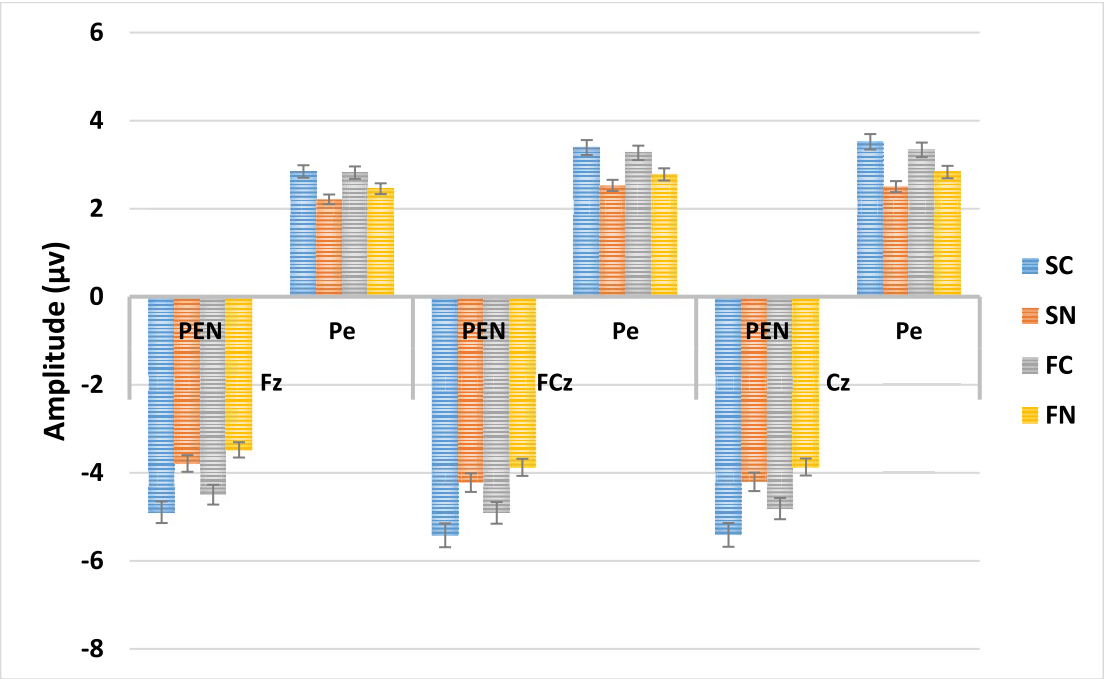


Figure 3-14 Grand average of PEN and Pe over Fz, FCz, and Cz for normal and conflict conditions in short (fast) and long (slow) task completion times trials for all participants (SC= slow with the conflict condition; SN = slow with the normal condition; FC= fast with the conflict condition; FN= fast with the normal condition)

*Table 3-2 Correlation matrix between short (fast) and long (slow) task completion times with PEN and Pe over Fz, FCz, and Cz (** p < 0.01 and *p < 0.05)*

Correlation	Channel	Short completion time	Long completion time
PEN	Fz	-0.1126	-0.0365
	FCz	-0.0195	-0.1491
	Cz	-0.0446	**-0.2280****
Pe	Fz	0.2185	-0.0297
	FCz	**0.2331****	0.1387
	Cz	**0.2180***	**0.2839****

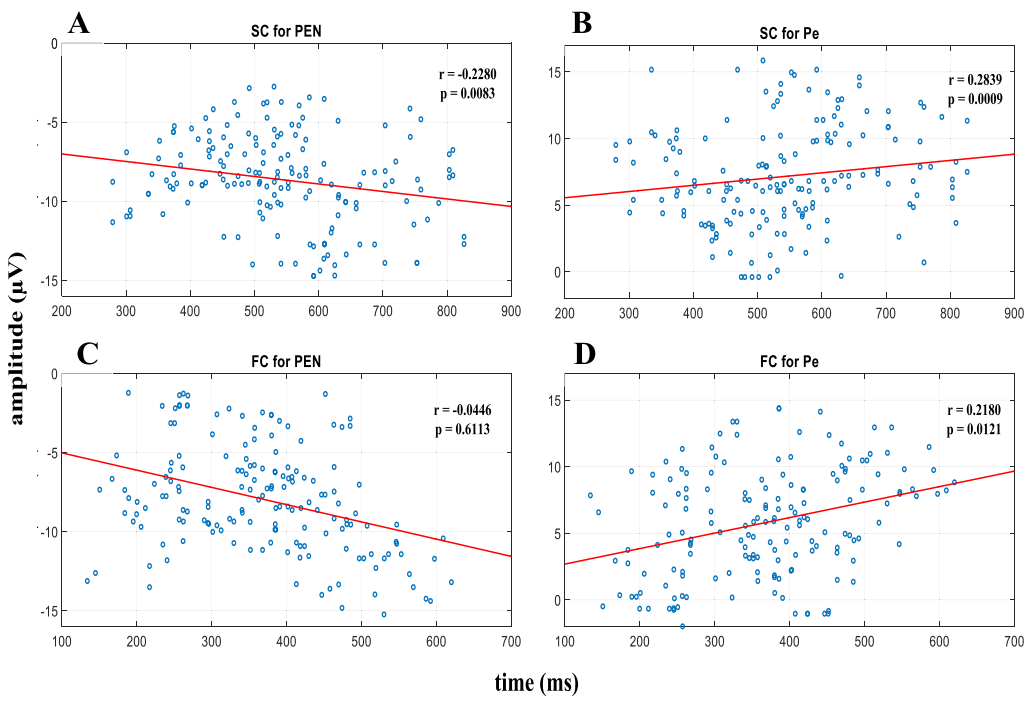


Figure 3-15 Intra-trial regression analysis of short (fast) and long (slow) task completion times with PEN and Pe; A) slow conflict for PEN, B) slow conflict for Pe, C) fast conflict for PEN, and D) fast conflict for Pe

3.6.2. For inter-trial task completion

i. Behavior results

Participants responded correctly in the majority of trials with only a small percentage of misses or incorrect trial such that the participant did not touch the second cube. As expected, task completion time fluctuated among participants for each trial; therefore, all trials were sorted from all participants and divided into two groups based on a median split (see Figure 3-16 and Table 3-3) similar to intra-trial analysis. As per repeated

ANOVA analysis, it was found that large and short task completion times trials were a statistically significantly difference for normal condition (F (1, 32) = 37.028, p < .001) and conflict condition (F (1, 32) = 67.476, p<.001).

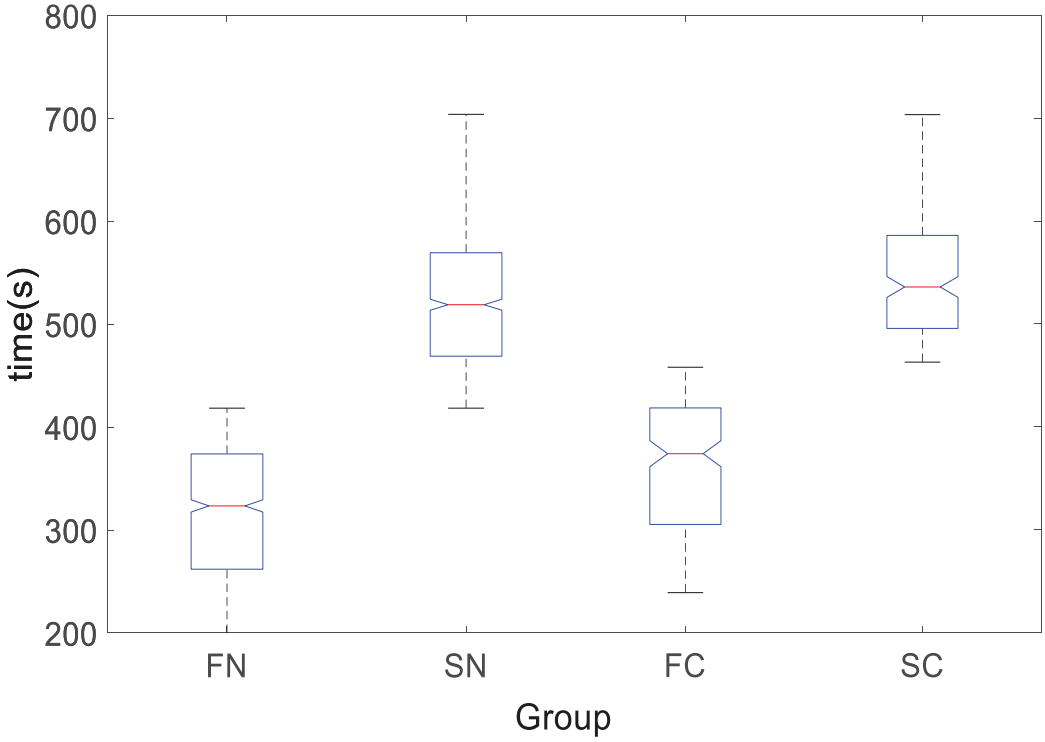


Figure 3-16 Task completion times for two groups of trials for normal and conflict condition (SC= slow with the conflict condition; SN = slow with the normal condition; FC= fast with the conflict condition; FN= fast with the normal condition)

Table 3-3 Behavioral results

Overall completion time (ms)			
	Median	**Standard deviation**	**Range (min-max)**
Normal trials	418	69	167-527
Conflict trials	460	110	239-549
Longer completion time (ms)			
Normal trials	519	70	418-704
Conflict trials	536	61	463-704
Smaller completion time (ms)			
Normal trials	323	70	167-419
Conflict trials	374	64	239-458

ii. EEG results

It was also evaluated that if inter-trial completion time plays any role in participants electrocortical response towards conflict. It was found that trials with fast completion times showed a clear Pe component with the onset of the visual feedback while trials with

slow completion time revealed a PEN together with a subsequent Pe component in the ERP (see Figure 3-17).

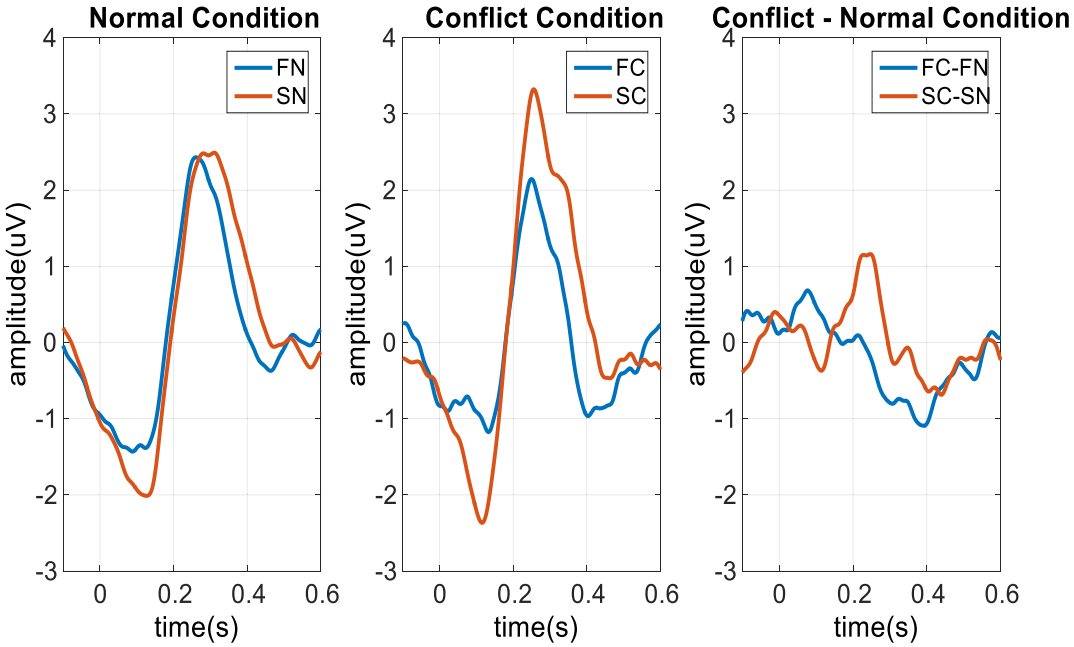


Figure 3-17 ERP for short (fast) and long (slow) task completion times trials for normal and conflict condition back-projected to electrode Cz from selected components (SC= slow with the conflict condition; SN = slow with the normal condition; FC= fast with the conflict condition; FN= fast with the normal condition)

As can be seen in Figure 3-17, there was a statistically significant (F (1, 32) = 7.623, p = .009) difference between short and long task completion times trials for the normal condition for the PEN but no clear Pe. In contrast, in the conflict condition, a statistically significant PEN (F (1, 32) = 8.533, p = .019), as well as subsequent Pe (F (1, 32) = 6.084, p = .040), was revealed.

It was further evaluated the topographical distribution of the PEN and Pe component. According to Figure 3-18, it can be seen that difference between conflict and normal condition for slow completion time group shows PEN over a frontal-central region of the brain while fast completion time group shows that difference is not statistically significant.

Similarly, as per Figure 3-19, it can be seen that the difference between the conflict and the normal condition for slow completion times demonstrated a Pe over the frontal-central region of the brain while fast completion times showed no such difference.

It was also evaluated if chosen EEG channel was the optimal choice for PEN and Pe analysis. As shown in Figure 3-20, that PEN found to be most negative over the 'Cz' electrode compared to 'Fz' and 'FCz' for all conditions. Similarly, the Pe found to be most positive over 'Cz' electrode compared to 'Fz' and 'FCz' for all conditions.

*Table 3-4 Correlation matrix for slow and fast user trials over Fz, FCz, and Cz (** p < 0.01 and *p < 0.05)*

Correlation	Channel	Large completion time (slow)	Small completion time (fast)
PEN	Fz	**-0.2057****	**-0.1780****
	FCz	**-0.2084****	**-0.2046****
	Cz	**-0.2304****	-0.1236
Pe	Fz	-0.0685	-0.0515
	FCz	0.0834	0.0017
	Cz	**0.1416***	0.0847

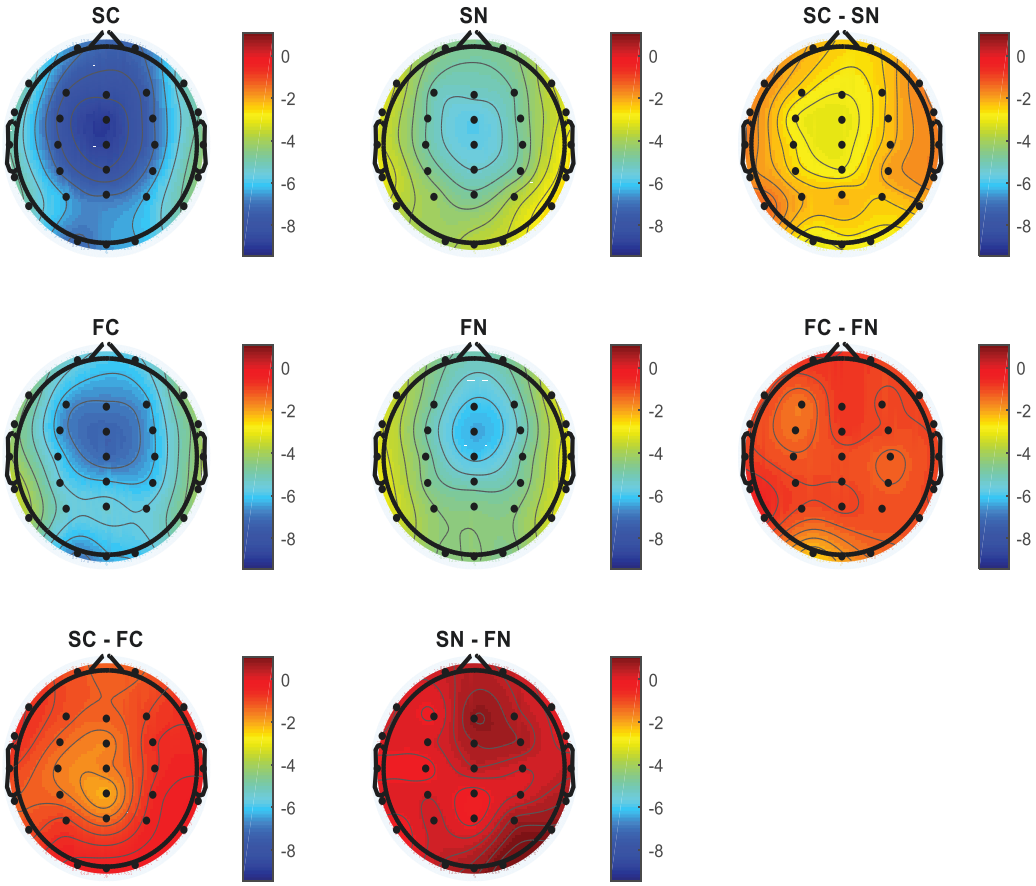


Figure 3-18 Topoplots for PEN component for normal and conflict condition for short (fast) and long (slow) task completion times trials (SC= slow with conflict condition; SN = slow with the normal condition; FC= fast with conflict condition; FN= fast with the normal condition)

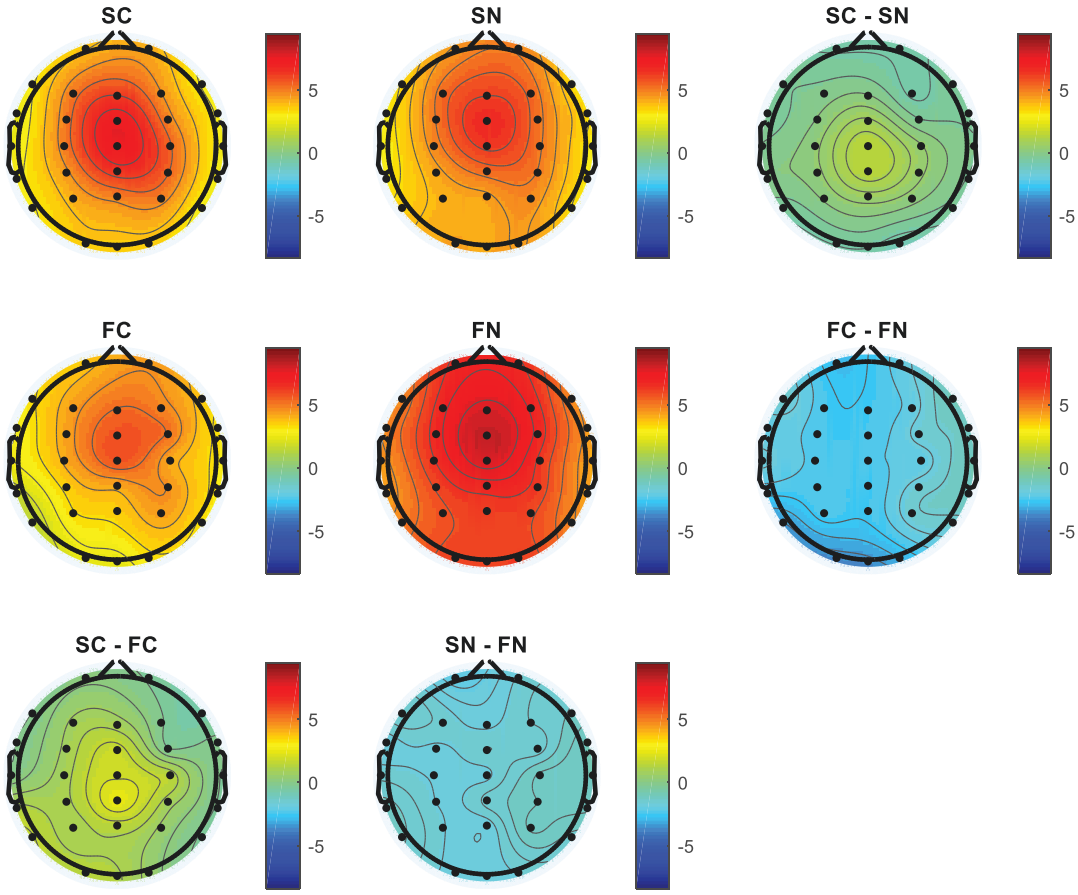


Figure 3-19 Topography for Pe component for normal and conflict condition for short (fast) and long (slow) trials (SC= slow with conflict condition; SN = slow with the normal condition; FC= fast with conflict condition; FN= fast with the normal condition)

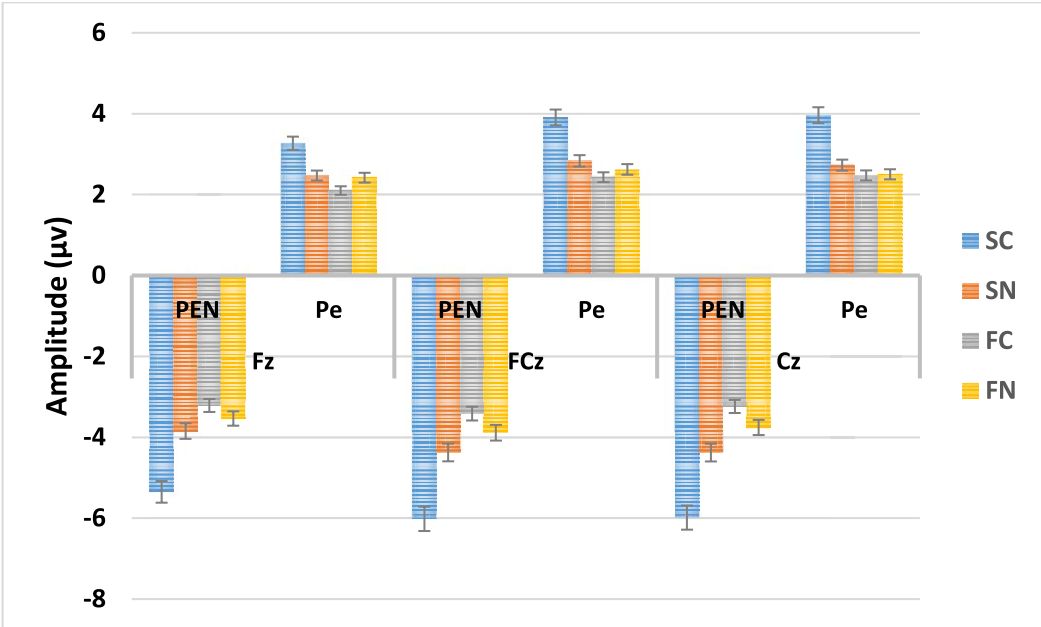


Figure 3-20 PEN and Pe over Fz, FCz, and Cz for normal and conflict condition (SC= slow with the conflict condition; SN = slow with the normal condition; FC= fast with the conflict condition; FN= fast with the normal condition)

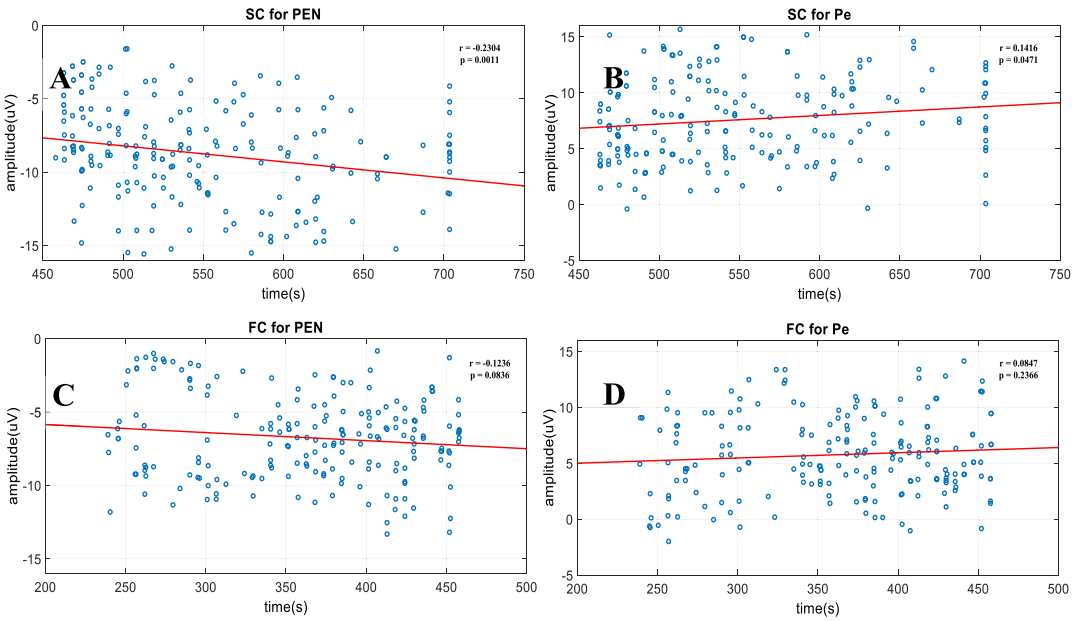


Figure 3-21 Inter-trial regression analysis of short (fast) and long (slow) completion times with PEN and Pe; A) slow conflict for PEN, B) slow conflict for Pe, C) fast conflict for PEN, and D) fast conflict for Pe

Further, as shown in Table 3-4 and Figure 3-21, for slow trials, PEN and Pe were significantly (PEN: $r = -0.2304$, $p < 0.05$; Pe: $r = 0.1416$, $p < 0.05$) correlated with task completion time. On the other hand, PEN for fast trials were not significantly ($r = -0.1236$, $p = 0.0836$) correlated with task completion times. Similarly, Pe for fast trials were no significant correlated ($r = 0.0847$, $p < 0.2366$) with task completion times. Overall, slow trials and fast trials showed a negative correlation with PEN while such a pattern was not observed for Pe, which demonstrated a positive correlation with task completion times for the fast and slow group of trials.

3.7. Summary

In summary, it was found that there was a modulation in PEN amplitude due to the visual appearance of hand style used, inter and intra-trial task completion times. The participant felt a higher level of cognitive conflict for the visual appearance with a higher level of realism compared to others. For the task completion time, the participants show a significantly higher level of cognitive conflict when they were taking higher task completion time to compare to slow task completion time. These results proved that realism is an important factor to perceive the information in VR while same time results also showed that there is a higher level of sensory integration based on temporal information of the participants during the 3D object selection task.

Chapter 4 : Movement Velocity and Its Implication on Cognitive Conflict in Virtual Reality

4.1. Experiment

4.1.1. Participants and environment

EEG data were recorded from 20 participants (two female and eighteen males) to determine the effect of movement velocity on prediction error with 95% power to detect 5% significant level based on G*Power (Faul et al. 2007). The median age of the participants was 23.3 years, with a range of 18-30 years. Following an explanation of the experimental procedure, all participants provided informed consent before participating in the study. This study obtained the approval of the Human Research Ethics Committee of the University of Technology Sydney, Australia and was conducted in a temperature-controlled room. None of the participants had a history of any psychological disorders, which could have affected the experiment results.

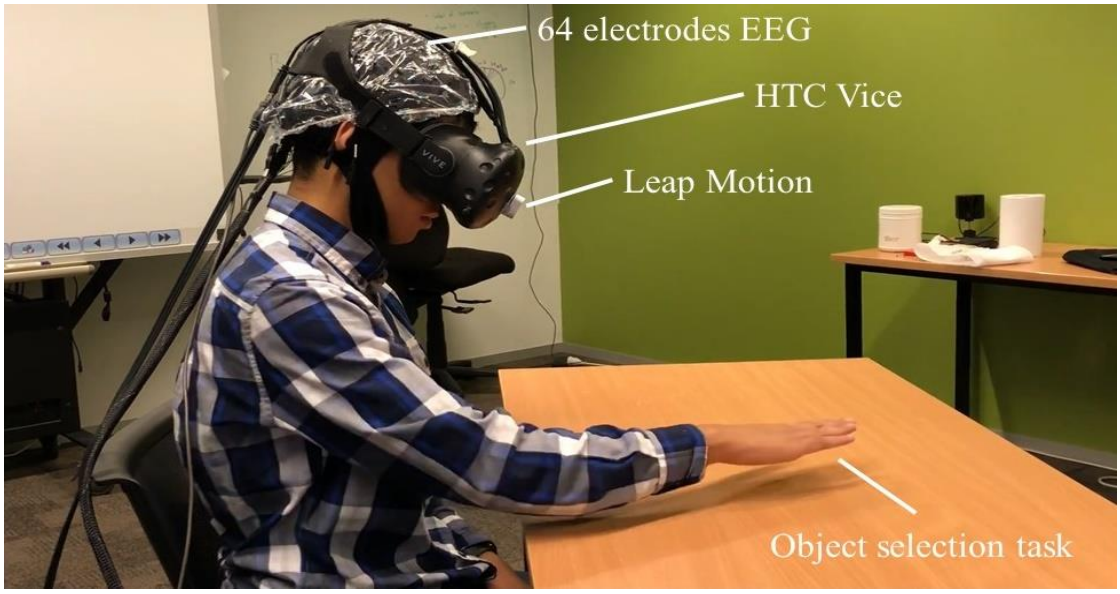


Figure 4-1 Experiment setup showing the 64 electrodes EEG cap on the top of HTC Vive and Leap Motion while the participant performs the 3D object selection task

4.1.2. VR setup

HTC Vive as the head-mounted display together with Leap Motion used for this experiment similar to the experimental setup in Chapter 4.

4.1.3. EEG setup

EEG data were recorded from 64 Ag/AgCl electrodes, which were referenced to an electrode between Cz and CPz. The placement of the EEG electrodes was consistent with the extended 10% system (Chatrian, Lettich & Nelson 1985). The contact impedance was maintained below 5kΩ. The EEG recordings were collected using a Curry 8 SynAmps2 Express system (Compumedics Ltd., VIC, Australia). The EEG recordings were digitally sampled at 1 kHz with a 16-bit resolution.

First, the participants were required to put on the EEG cap then the separator cap (shower plastic cap). The participant wears the HMD on top of the separator cap. The separator cap was used to minimize or avoid the interference between the EEG cap and its conductive gel with the HMD (see

Figure 4-1). In order to ensure the participants, have an effective VR experience, a table was installed with the same size and color to the one used in the VR environment. The height of the table in the VR and the real world were mapped so that the participants were not able to distinguish between the real and the virtual environment.

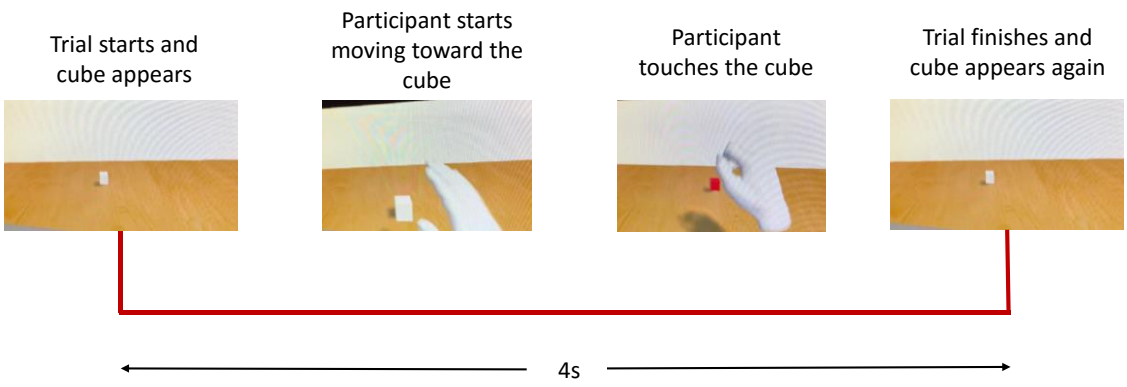


Figure 4-2 Experiment scenario for a single trial

4.1.4. Experiment scenario

Each participant performs the 3D object selection task with their dominant hand tracked by the Leap Motion controller in the VR while simultaneously collecting the

trajectory data on touching the cubes. Figure 4-2 displays a scenario for a single trial. Each trial was four seconds in length. The scenario starts with the instructions and the experiment starts once the participant press any button. The trial starts when the cube appears on the table and the participants were instructed to reach out and select (touch) cube. The cube turns red when it is touched to as feedback to the participant. The participant was expected to finish the task within 4 seconds. Otherwise, the trial was stopped and marked as incomplete.

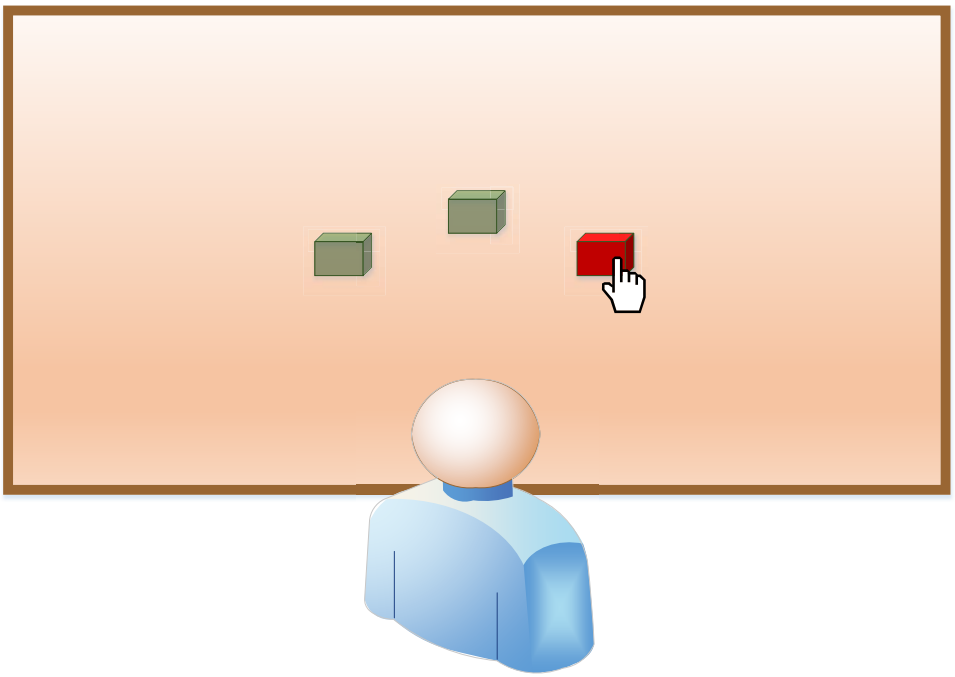


Figure 4-3 The cubes appears in three different locations randomly in the scenario

The cubes were two sizes, small and large, to invoke different velocity profile to touch the cube. The small cubes usually invoke a slower velocity profile while the large cubes invoke a fast velocity profile, on average. The selection distance of the cubes changed in 25% of the trials, such that 75% of the trials used distance 'r' (D1/d1) as a normal condition and the remaining trials used distance 'D' (D2/d2) as conflict condition (see Figure 4-4). The position of the cube also slightly varied by 30% in left and right from center to create variety in the velocity profile and to keep the participants engaged (see Figure 4-3).

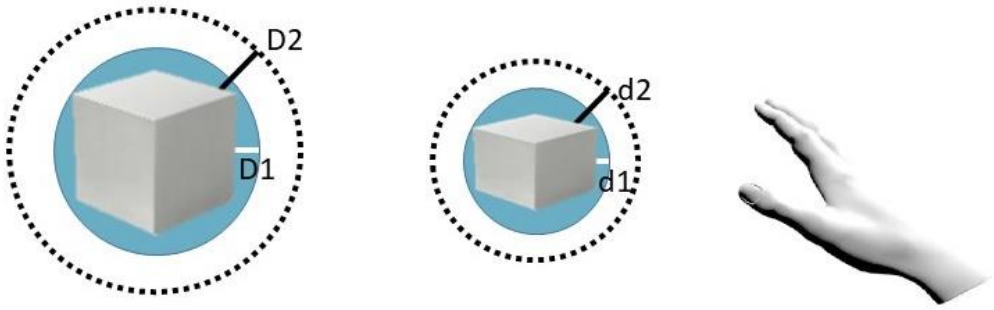


Figure 4-4 D1 and D2 are the radii for the large cubes (left); d1 and d2 are the radii for the small cubes (right)

At the end of the experiment, the participants were required to complete a questionnaire (Schubert 2003) which asks the participant to subjectively rate the different parameters of realism, experience and controlling event, and also to state their past experience of game playing on a 7-point Likert scale to assess the overall experience of the participant. The 24-item questionnaire was a modified version of IPQ with some additional questions about game playing experience.

The experiment used a 2 X 2 X 3 repeated measures factorial design with two factors: velocity profile (slow and fast velocity due to the small and large cubes), selection distance (d1/D1, equal to the size of the small/large cubes and d2/D2, twice the size of small/large cubes), and three positions of the cube (left, center, and right). The experiment was conducted over two sessions, each session comprising 250 trials of about 16 min long. In total, the experiment took about 1.5 hours, including the initial setup of the EEG cap, the HMD, the experiment, and the completion of the questionnaire.

4.2. Data Analysis

4.2.1. EEG data analysis

EEG data were processed using the EEGLAB toolbox in MATLAB 2016 (MathWorks Inc, USA). The raw EEG signals were filtered using a 0.1-Hz high-pass and 40-Hz low-pass FIR filter. The data were downsampled to 250 Hz.

The resultant data were inspected to detect and remove the noisy electrodes using the Kurtosis methods, followed by an ICA. The resultant ICs were further processed to detect artifact-related ICs using the SASICA plugin (Chaumon, Bishop & Busch 2015) which uses different autocorrelation, focal ICs, eye blink, and information from the ADJUST

(Mognon et al. 2011) plugin to mark the possible noisy artifacts. These artifacts were marked and excluded from the resultant data.

The resultant data were epoched from 500 ms from the onset of the touching event for the cube to 1000 ms after the response for all conditions. The epoched data were further inspected for any artifact using the Kurtosis method. The artifact-free epoched data were further processed in EEGLab. Figure 4-5 summarizes the data analysis pipeline used for preprocessing the EEG data.

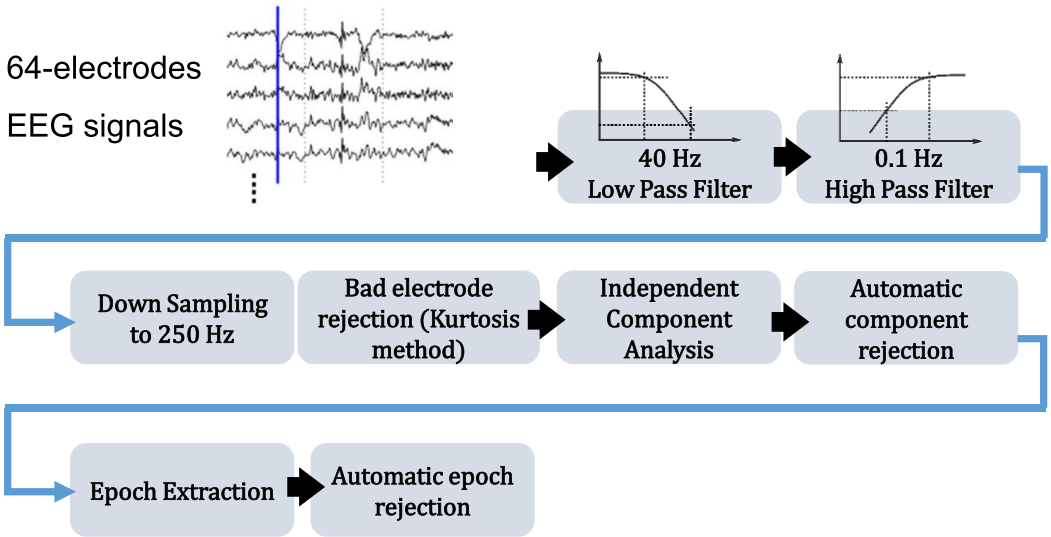


Figure 4-5 Data processing pipeline

The components of all the participants were clustered for similarity based on the IC activation matrix for each participant and their corresponding dipole positions. Further analysis focuses on the IC component derived from the cingulate cortex. It is well-known that ACC, in particular, plays a major role during the cognitive conflict mechanism. Extracted clustered components were further used for ERSP, extracting PEN/Pe and back-projected ERPs on selected electrodes.

PEN and Pe were extracted from the back-projected ERPs. PEN was calculated by mean minima 50-150ms after the response with ±2 adjacent points. Similarly, Pe was calculated by mean maxima 250-350ms after the response with ±2 adjacent points.

4.2.2. Behavior data analysis

i. Task completion time

Task completion time was calculated by the difference in the time from showing the cube to the time the participant selects it.

$$t_{avg.\ completion\ time} = \sum_{i=1}^{n}\left(t_{select}^{ith} - t_{appear}^{ith}\right)/_{n} \quad (4\text{-}1)$$

where n = number of trials.

ii. Motion trajectory data

For every participant, different kinds of trajectory data, such as velocity, hand position (palm, finger, etc.), the number of frames in each processed VR scene, the time required for each frame are recorded. The major focus of this experiment was to understand how the velocity profile affects PEN, therefore the magnitude of velocity was calculated for each trial as follows:

$$V_{mag} = \sqrt[2]{{V_x}^2 + {V_y}^2 + {V_z}^2} \quad (4\text{-}2)$$

$$V_{avg} = \sum_{\mathrm{i=1}}^{\mathrm{n}} V_{mag}^{ith}/_{\mathrm{n}} \quad (4\text{-}3)$$

where n is the number of trials.

iii. Questionnaire data

While there was no standard method for measuring the presence, most researchers use questionnaires to allow retrospective self-report by users. In the current experiment, a modified version of IPQ with the participant's experience of game playing was used to measure the presence of participants. The questionnaire comprised a total 24 number of questions to be answered on a seven-point Likert scale, yielding a possible presence result of seven (minimum) to 98 (maximum).

iv. Correlation analysis and statistics

The statistical analyses were carried out using the SPSS statistical tool (SPSS Inc Version 24). For each group, Pearson correlation coefficients for the trajectory data, behavioral data, and self-reported questionnaires with the PEN, Pe, spectral power, and ERSP were evaluated.

4.3. Behavior Results

Figure 4-6 shows the average velocity of all participants for all conditions. A repeated measures ANOVA was conducted to compare the task completion times for the two conditions and two sizes of cubes. There was a statistically significant differences of the within-subject factor condition ($F(1, 17) = 89.454$, $p < .001$) and size of cubes ($F(1, 17) = 80.687$, $p < .001$). There was also statistically significant interaction in condition * size of cubes ($F(1, 17) = 146.904$, $p < .001$). Post-hoc test using Bonferroni correction revealed that there was a statistically significant ($p < .001$) difference for normal and conflict conditions as well statistically significant ($p < .001$) difference for small and large cubes for task completion times. Interestingly, on average, the small cubes show higher hand movement velocity compared to the large cubes, which is the opposite of what was expected. This behavior may cause due to averaging over whole trajectory rather than in part as explained below in velocity movement profile.

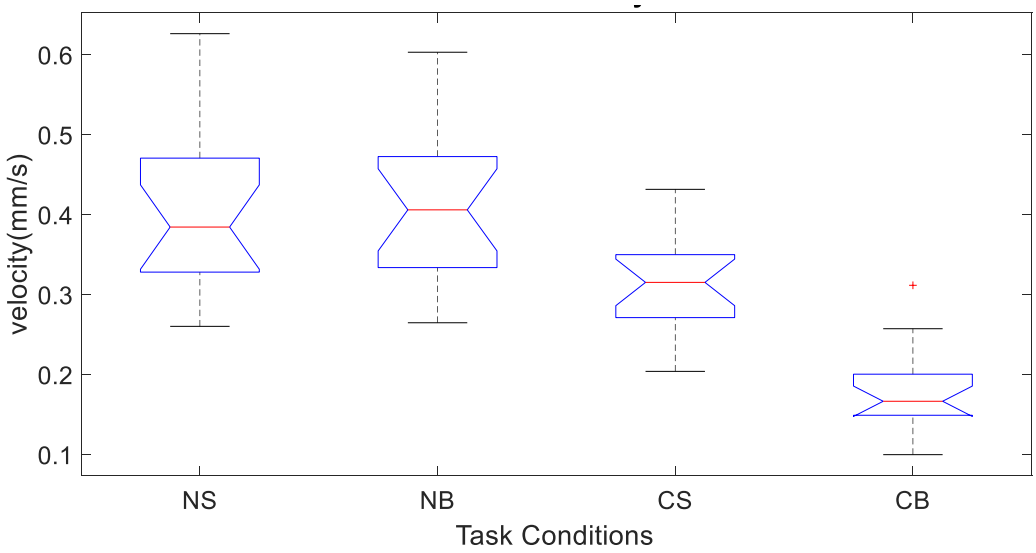


Figure 4-6 Mean velocities of all participants for different conditions (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

Figure 4-7 shows the box plot for the average task completion time for all trials for all participants. A repeated measures ANOVA was conducted to compare the task completion times for the two conditions and two sizes of cubes. There were a statistically significant differences of the within-subject factor condition ($F(1, 19) = 191.074$, $p < .001$) and size of cubes ($F(1, 19) = 191.074$, $p < .001$). There was also statistically significant interaction in condition * size of cubes ($F(1, 19) = 5.358$, $p = .032$). Post-hoc

test using Bonferroni correction revealed that there was a statistically significant ($p < .001$) difference for normal and conflict conditions as well statistical significance ($p < .001$) difference for small and large cubes for task completion time.

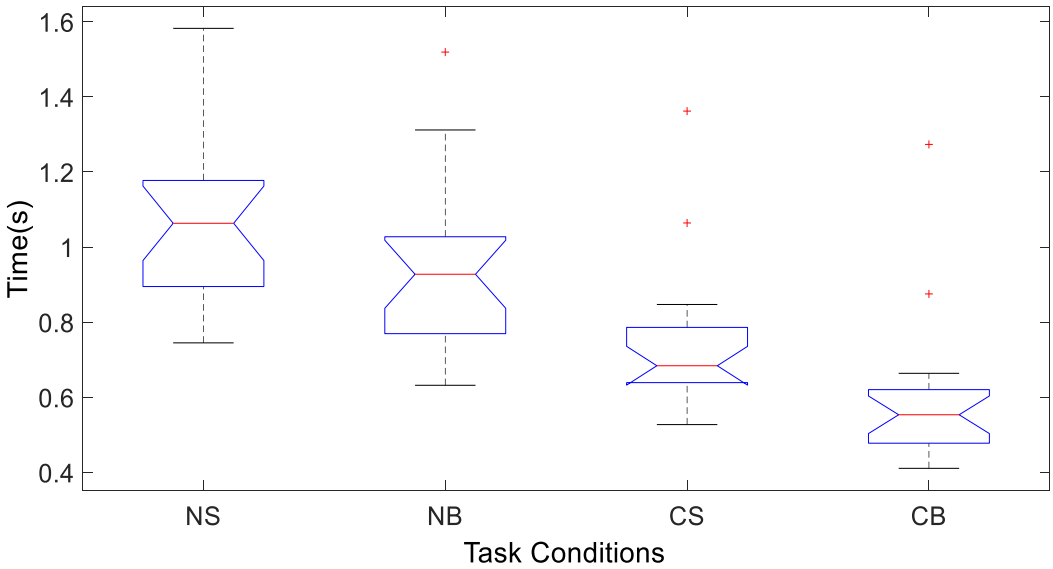


Figure 4-7 Mean task completion time for all participants over all conditions (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

In addition to calculating the average velocity for all participants, the overall velocity trend was also calculated to see how velocity behaves over time. It can be seen from the Figure 4-8 (A) and Figure 4-8 (B) that for normal trials for the small and large cubes respectively, the hand movement trajectory first increases sharply for about 40 frames and then slowly decreases until a cube was selected. The hand movement trajectories for velocity for the small and large cubes in normal trials are behave in similar manner. However, as can be seen from Figure 4-8 (C) and Figure 4-8 (D), the hand movement velocity for the small cubes requires the participant to sharply increase velocity until about 40 frames and then slowly decrease velocity for the remaining duration of the trials until the cube is selected. On the other hand, there was no steady decrease in the hand movement trajectory for the large cubes compared to the small cubes.

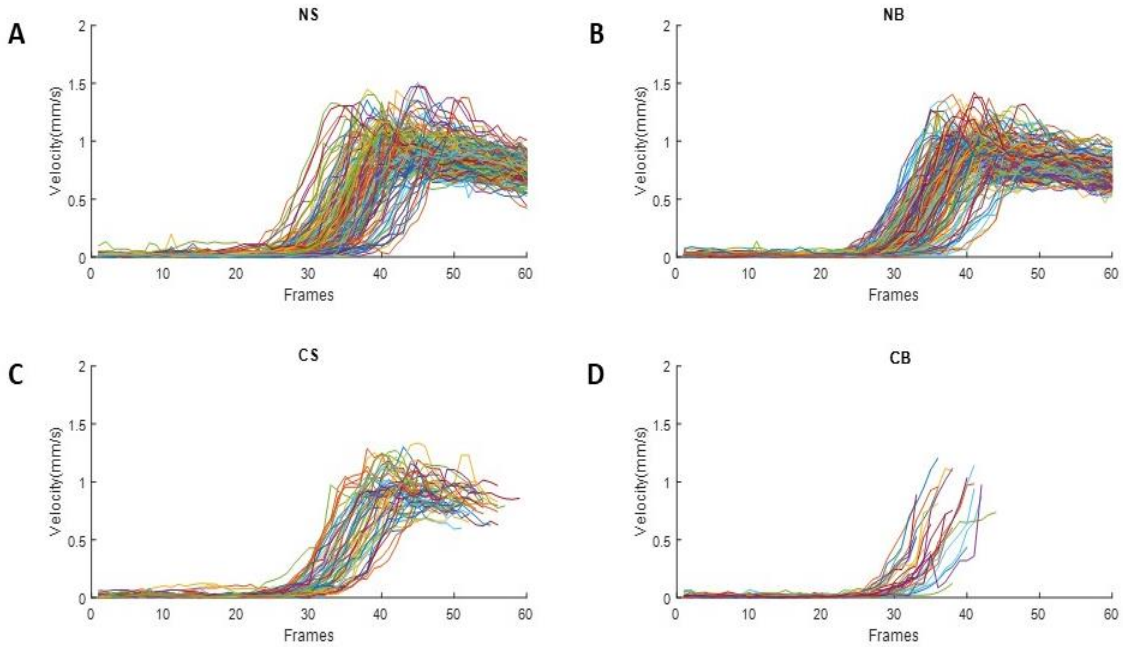


Figure 4-8 Hand movement trajectories for all conditions for one participant. A) normal condition for small cubes (NS); B) normal condition for large cubes (NB); C) conflict condition for small cubes (CS); D) conflict condition for large cube (CB)

To understand the interaction between the behavior data with PEN and Pe, correlation analysis was performed, and the following results were obtained.

As shown in Figure 4-9, the correlation analysis between task completion times and amplitude reveal that there was no statistically significant correlation between PEN and Pe for the small and large cubes with task completion times, even though the correlation between PEN for the small and large cubes were negatively correlated ($r = -0.167$, $p > 0.05$; $r =- 0.425$, $p > 0.05$). Similarly, Pe for small and large cubes was negatively ($r = -0.05$, $p > 0.05$) and positively ($r = 0.095$, $p > 0.05$) correlated.

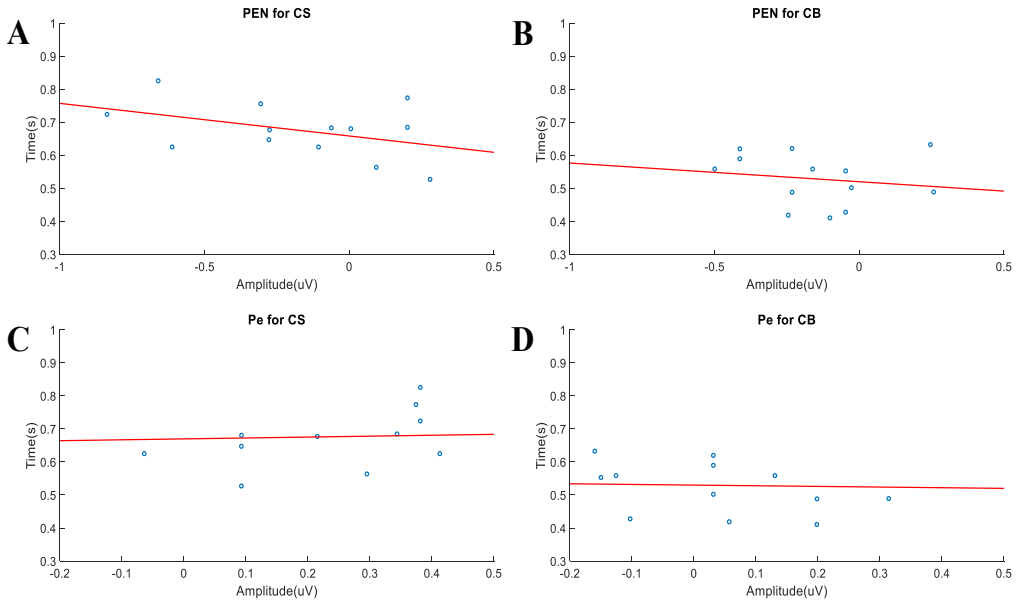


Figure 4-9 Correlation between task completion times and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

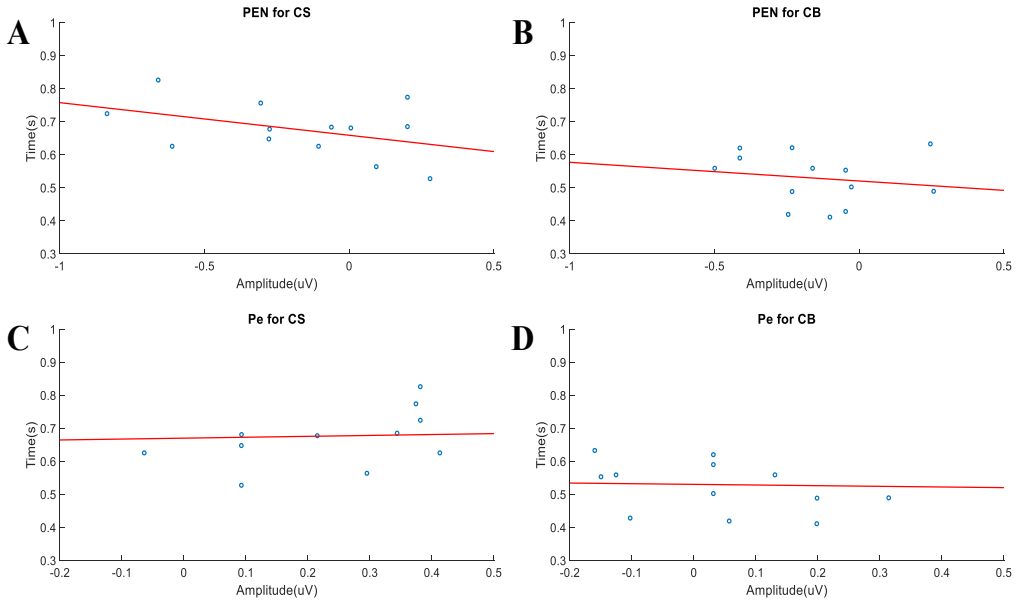


Figure 4-10 Correlation between hand movement velocity and amplitude for all participants in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

As can be seen from Figure 4-10, PEN for the small cubes was statistically significantly negatively correlated with hand movement velocity ($r = -0.622$, $p < 0.05$) while PEN for the large cubes was positively correlated with hand movement velocity ($r = 0.741$, $p < 0.05$). It was evident that Pe shows no statistically significant correlation with hand movement velocity ($r = 0.175$, $p > 0.05$) while at the same time, Pe shows a statistically significant negative correlation with hand movement velocity ($r = -0.602$, $p < 0.05$). Figure 4-11 shows the correlation between the peak latency of PEN and Pe with its amplitude. The results reveal that there was no correlation between latency for PEN and its amplitude for the small and large cubes ($r = -0.060$, $p > 0.05$; $r= -0.269$, $p > 0.05$) as well as no correlation between latency for Pe and its amplitude for the small and large cubes ($r = -0.121$, $p > 0.05$; $r = -0.411$, $p > 0.05$).

To understand the relation between self-reported questionnaires with PEN and Pe, correlation analysis was performed, and the results were reported in the following.

On one hand, it can be seen from Figure 4-12 that PEN for the small cubes was statistically significant positively correlated ($r = 0.644$, $p < 0.05$) with the IPQ score of realism while PEN for the large cubes was not statistically significantly correlated with the IPQ score for realism ($r = -0.261$, $p > 0.05$). Interestingly, Pe shows no statistically significant correlation for the small cubes ($r=0.035$, $p>0.05$) and the large cubes ($r = 0.096$, $p > 0.05$). On the other hand, the correlation between sense of agency represented by 'possibility to act' with PEN reveals that there was also a statistically significant positive correlation ($r = 0.709$, $p < 0.05$) for the small cubes and a statistically significant negative correlation ($r=-0.677$, $p>0.05$) for the large cubes. The correlation for Pe also shows that there was no statistically significant correlation for the small cubes ($r = 0.023$, $p > 0.05$) and the large cubes ($r = 0.340$, $p > 0.05$) (see Figure 4-13).

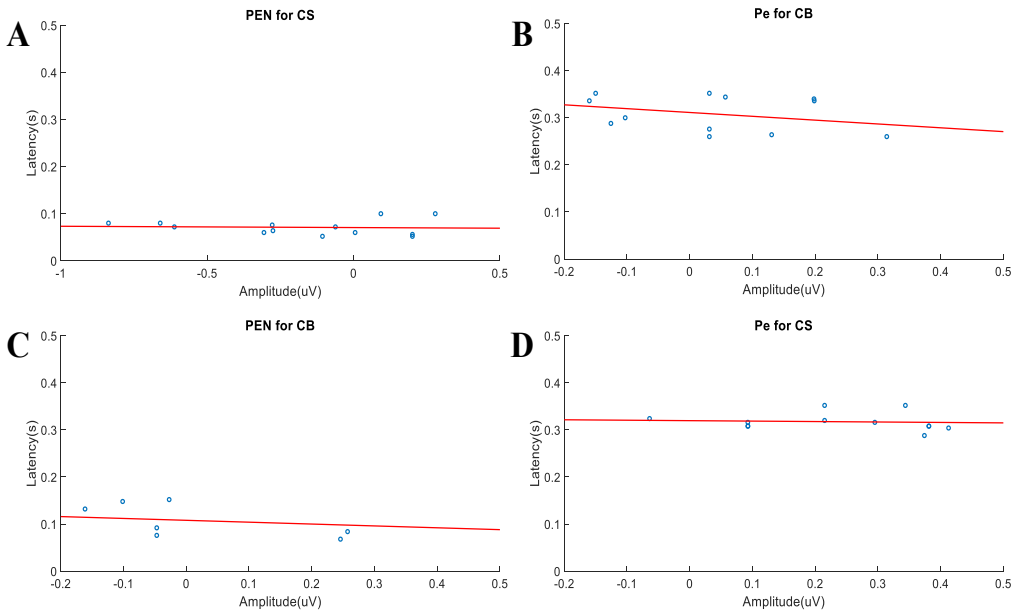


Figure 4-11 Correlation between latency and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

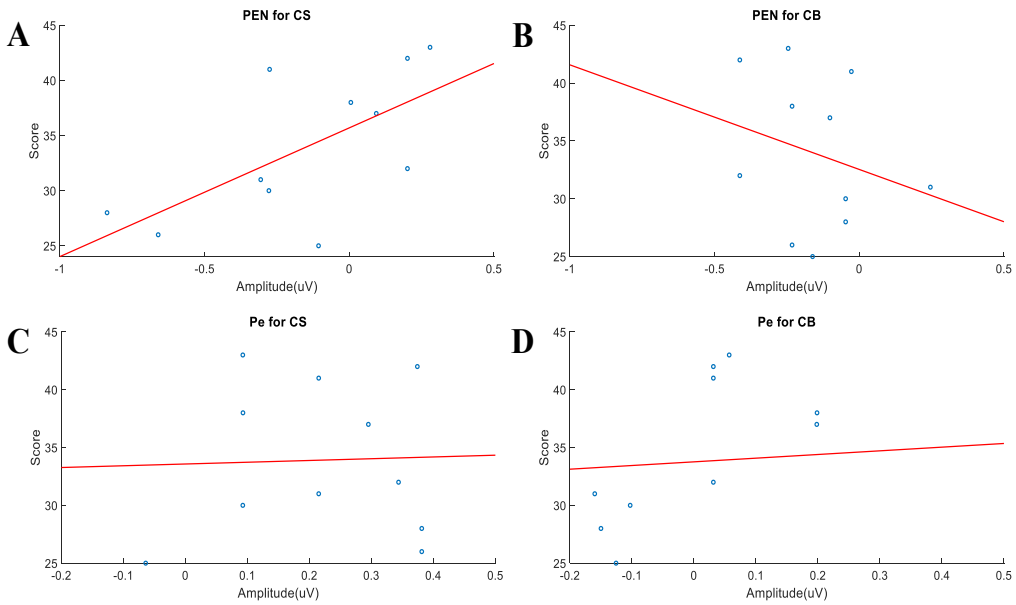


Figure 4-12 Correlation between realism (IPQ questionnaire) and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

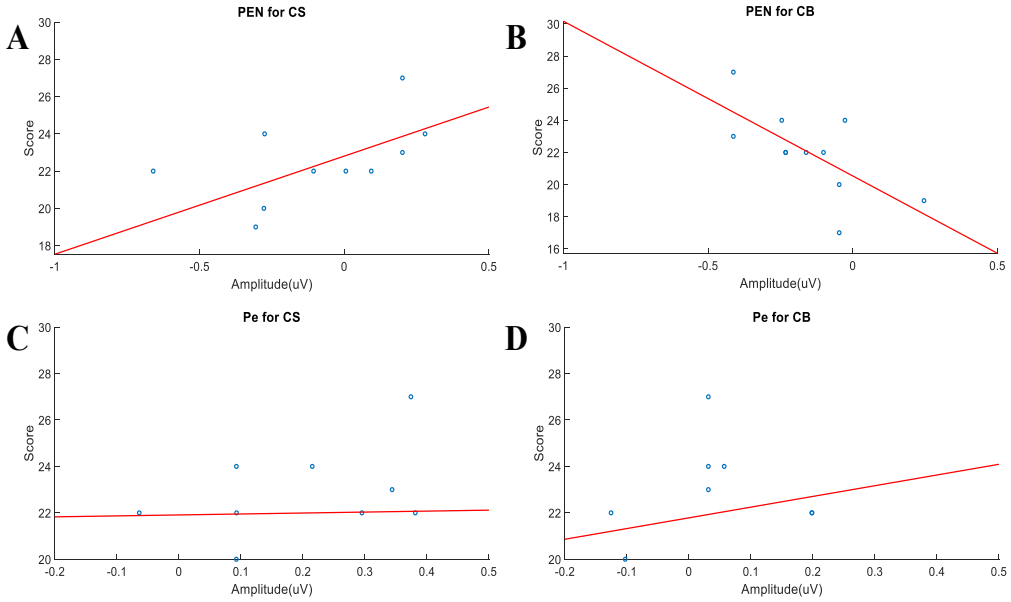


Figure 4-13 Correlation between possibility to act (IPQ questionnaire) and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

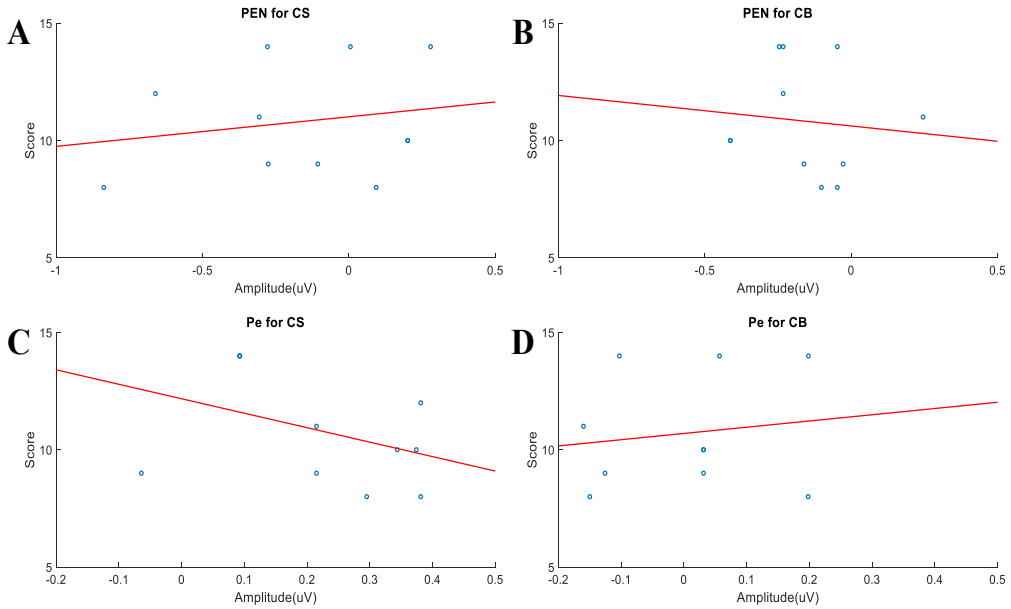


Figure 4-14 Correlation between quality of interface and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

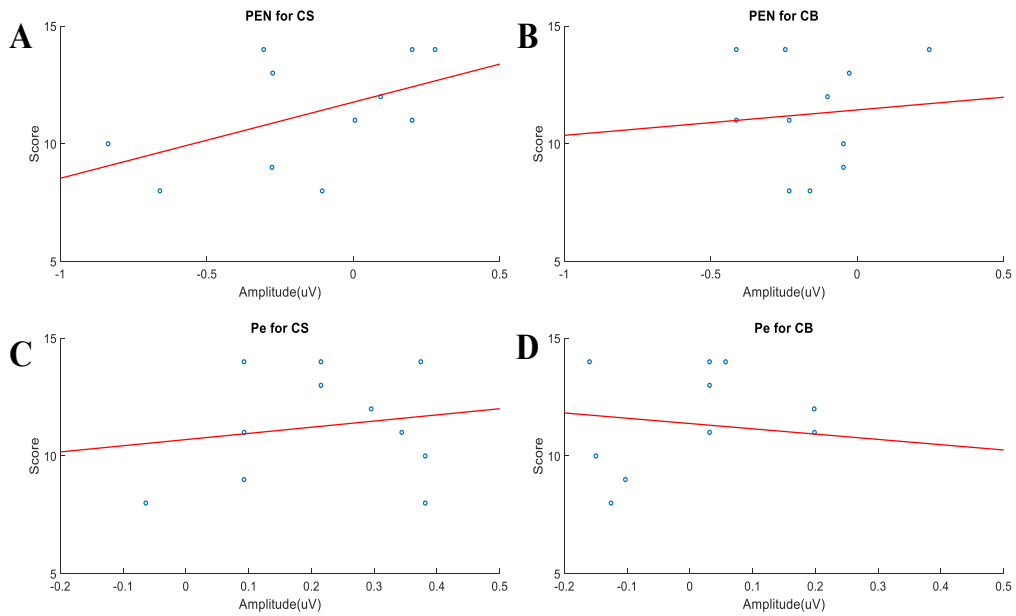


Figure 4-15 Correlation between self-evaluation of performance and amplitude in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

As shown in Figure 4-14, there was no statistically significant correlation between the quality of the VR interface with PEN amplitude for the small and large cubes ($r = 0.193$, $p > 0.05$; $r = -0.104$, $p > 0.05$) and no statistically significant correlation with Pe for small and large cubes ($r = -0.393$, $p > 0.05$; $r = 0.223$, $p > 0.05$). Similarly, as shown in Figure 4-15, it is clear that there was no statistically significant correlation between self-evaluation of performance with PEN for both the small and large cubes ($r = 0.501$, $p > 0.05$; $r = 0.088$, $p > 0.05$) and also no statistically significant correlation with Pe for the small and large cubes ($r = 0.169$, $p > 0.05$; $r = -0.191$, $p > 0.05$).

Figure 4-16 shows the score for all the participants in the experiment. The highest scores in realism show that the participants perceived the environment well while the second highest scores show that most of the participants think that there was a possibility to act with the hand rendering which represents a sense of agency toward it. The results for the quality of the interface and the self-evaluation of performance were very similar to each other and shows that the participants might expect a higher level of presence in the environment (see the score related to the quality of the interface and self-evaluation).

For a better understanding of the participants' behavior, the interaction between latency with task completion time and latency with velocity were evaluated with the results reported as follows.

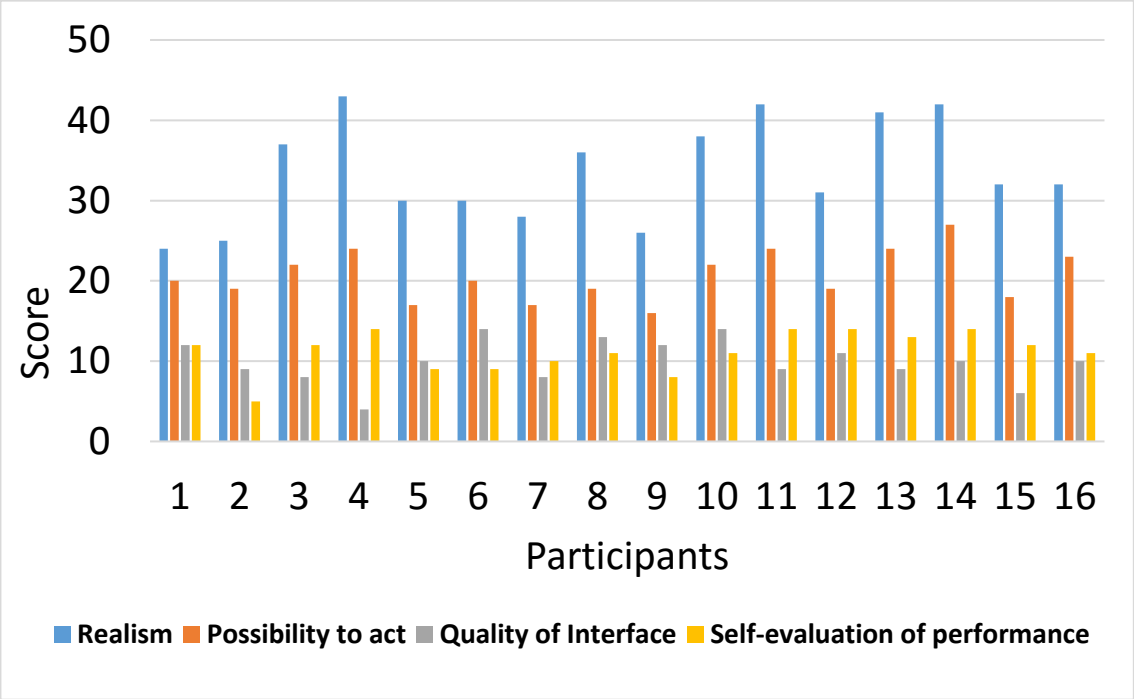


Figure 4-16 IPQ questionnaire scores for all participants

Figure 4-17 shows that there was no statistically significant correlation between task completion times and the latency of amplitude for PEN for the small and large cubes ($r = 0.038$, $p > 0.05$; $r = -0.386$, $p > 0.05$) and similarly, there was no statistically significant correlation for Pe for the small and large cubes ($r = 0.133$, $p > 0.05$; $r = -0.440$, $p > 0.05$). Figure 4-18 shows that there was no statistically significant correlation between latency of amplitude for PEN and movement velocity for the small and large cubes ($r = 0.008$, $p > 0.05$; $r = 0.010$, $p > 0.05$) and similarly, there was no statistically significant correlation between latency of amplitude and Pe for the large cubes ($r = -0.306$, $p > 0.05$) but interestingly, there was a statistically significant correlation between latency and velocity for Pe in small cubes ($r = -0.670$, $p < 0.05$).

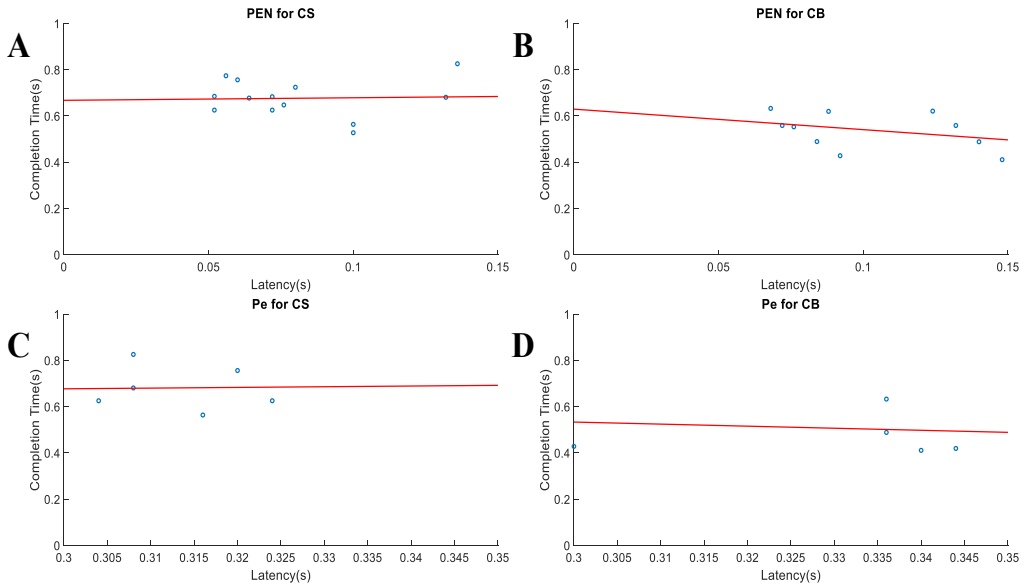


Figure 4-17 Correlation between latency and task completion times in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

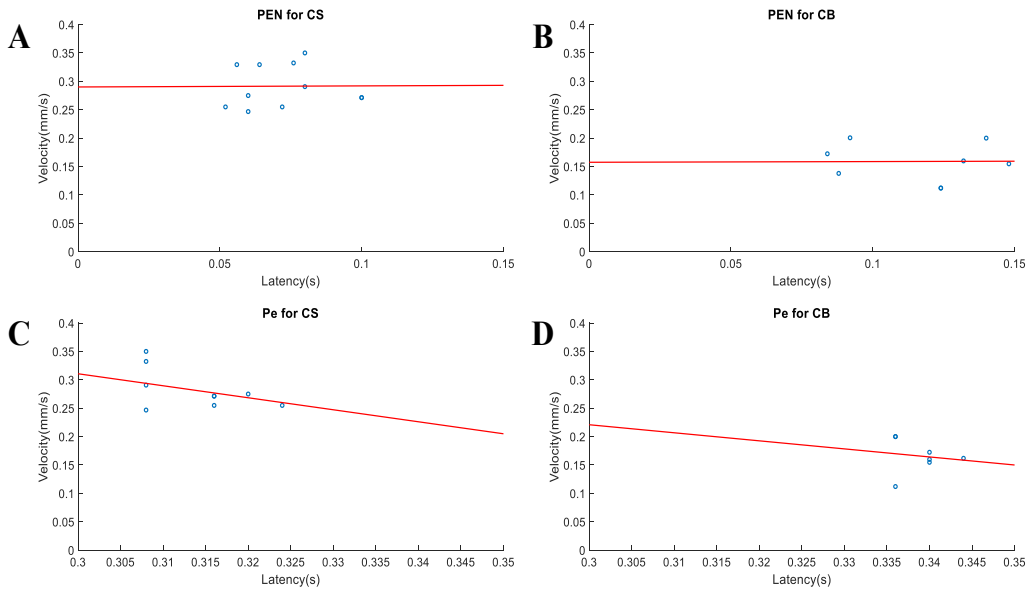


Figure 4-18 Correlation between latency and hand movement velocity in A) PEN for CS= conflict condition for small cubes, B) PEN for CB= conflict condition for large cubes, C) Pe for CS= conflict condition for small cubes, D) Pe for CB= conflict condition for large cubes

4.4. EEG Results

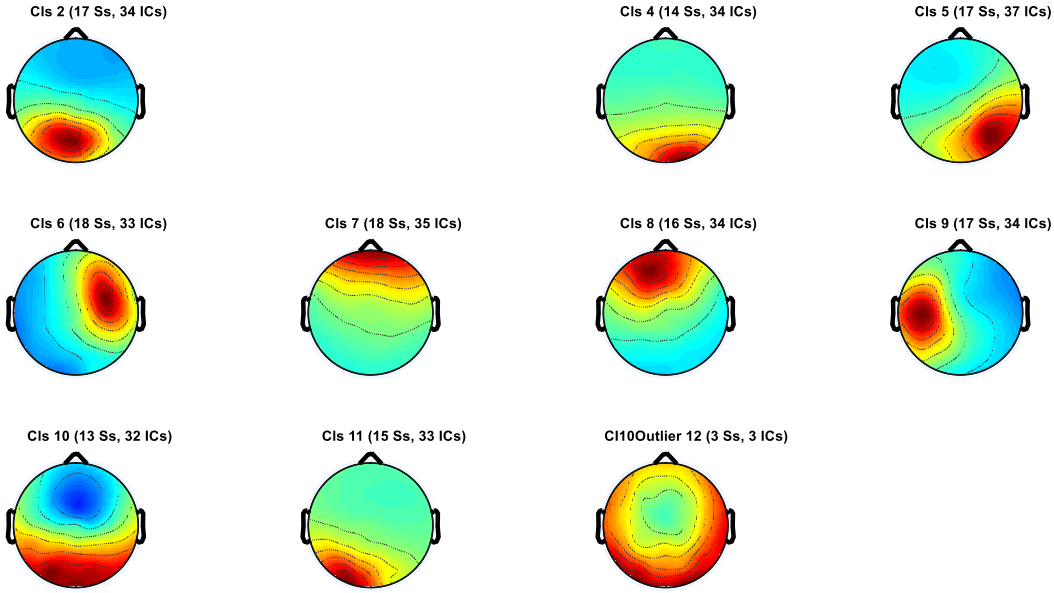


Figure 4-19 Clustered ICA component scalp maps for all participants

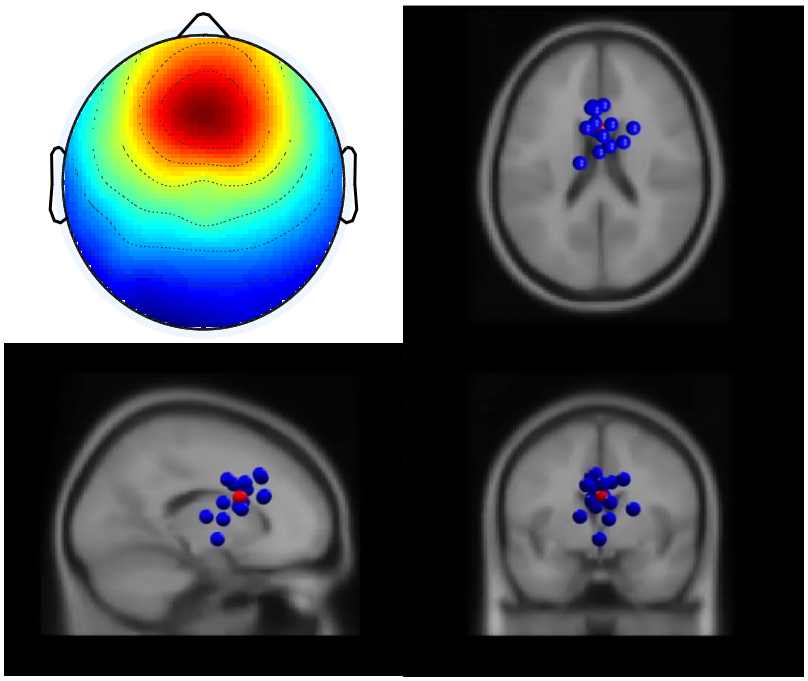


Figure 4-20 Clustered components selected as anterior cingulate cortex (ACC) and its dipoles

Every participant had a different set of independent source localized components; therefore, to combine these components together to get a representative component, an EEGLab toolbox was used with the help of neural network to find similar components among the participants using their properties from a spectral, inter-trial coherence, event-

related potential. This methodology was able to extract the clustered components as shown in Figure 4-19.

From these components, as shown in Figure 4-20, ACC was assumed to be the most important component for all kinds of cognitive conflict conditions, particularly due to interaction with the environment. By evaluating and inspecting the properties of the different clustered components, the component shown in Figure 4-20 was found to be the closest representation of ACC. Therefore, it was marked and used for further analysis.

The main purpose of extracting the ACC component from the participants was to see their cognitive conflict-related brain activity, which can be clearly seen in event-related potential (ERP). The average ERP for all the participants was evaluated (shown in Figure 4-21), which clearly shows that there was a statistically significant difference ($F(1, 14) = .320$, $p = .002$) in amplitude between the two conditions and also statistically significant difference ($F(1, 14) = 8.114$, $p = .002$) in amplitude for two sizes of cubes. There was also a statistically significant difference ($F(1, 14) = .542$, $p = .002$) in PEN/Pe for two conditions in two size of cubes. To clearly see the difference in the effect of the small and large cubes conditions, a difference in ERP was calculated (shown in Figure 4-22). It is very clear that there was indeed a difference in the ERP between the small and large cubes, particularly around 150-220 ms.

Some existing research (Brewer, Garrison & Whitfield-Gabrieli 2013) also suggests that the posterior cingulate cortex (PCC) represents the sense of awareness which is highly related to the sense of agency or the participants' feelings of what is going on around them. Therefore, based on the cluster (Figure 4-19), the closest representation of PCC is chosen to see the effect on ERP, as shown in Figure 4-23. The ERP of PCC suggests that there was a statistically significant higher cognitive conflict for the small cubes ($F(1, 14) = .431$, $p = .004$) compared to the large cubes (see Figure 4-24) which was also clear from the results of the difference in ERP, shown in Figure 4-25.

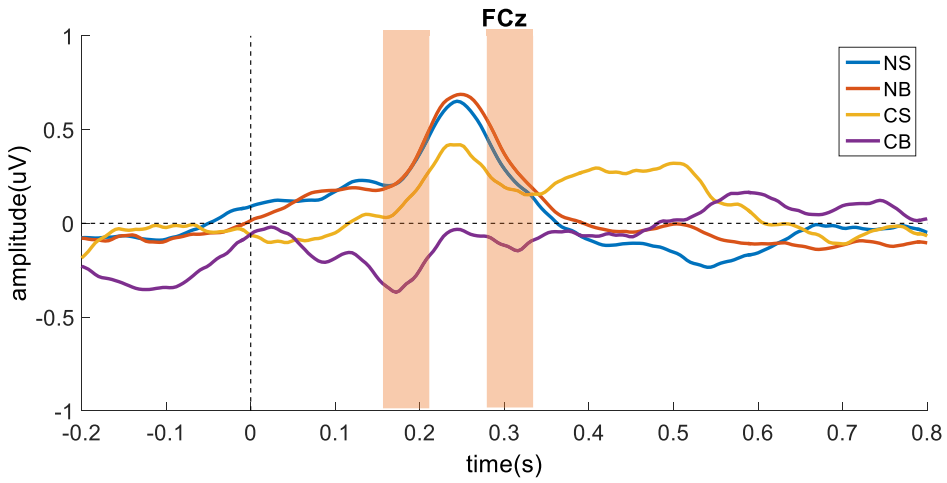


Figure 4-21 Averaged ERP for all participants over FCz back-projected from ACC IC (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

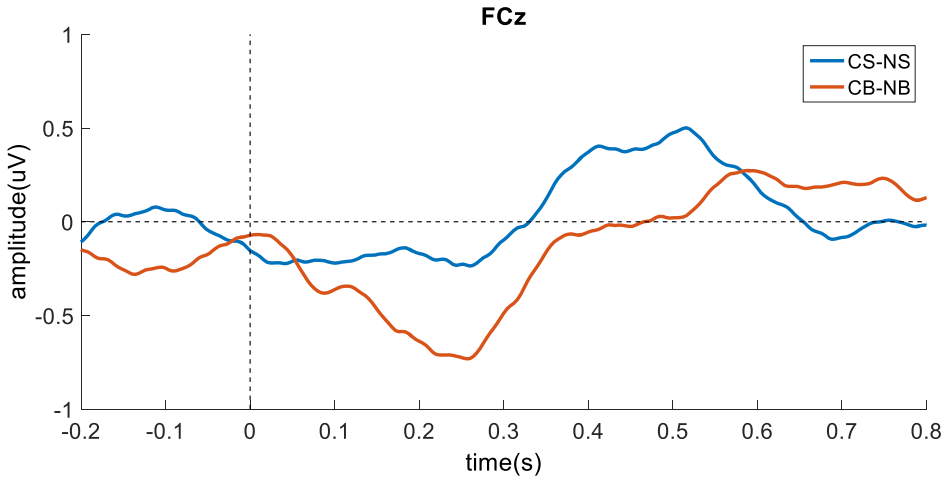


Figure 4-22 Difference in ERP for ACC IC (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

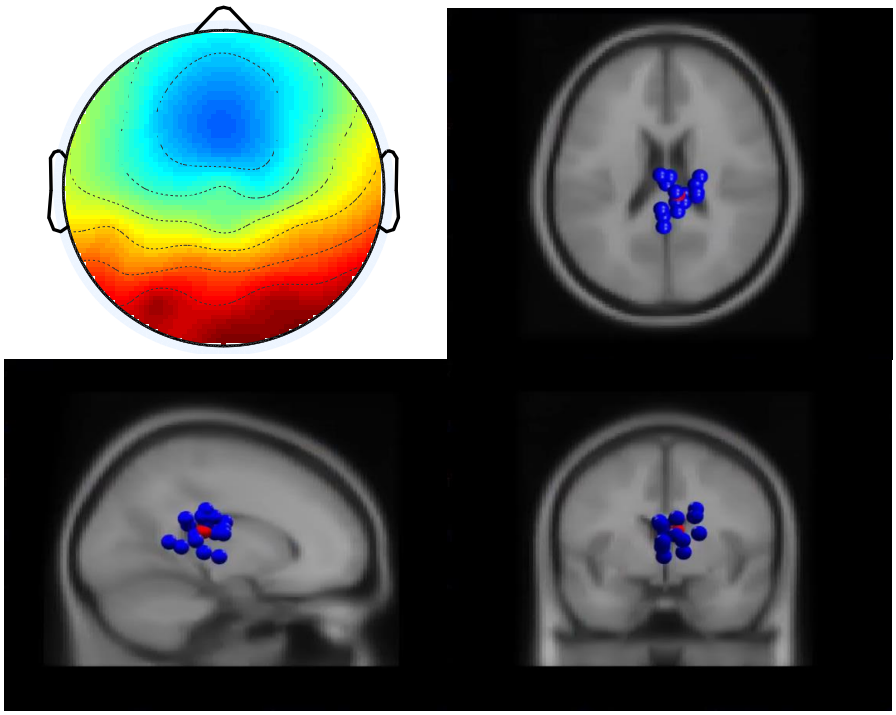


Figure 4-23 The selected components representing posterior cingulate cortex (PCC) from the clustered ICs

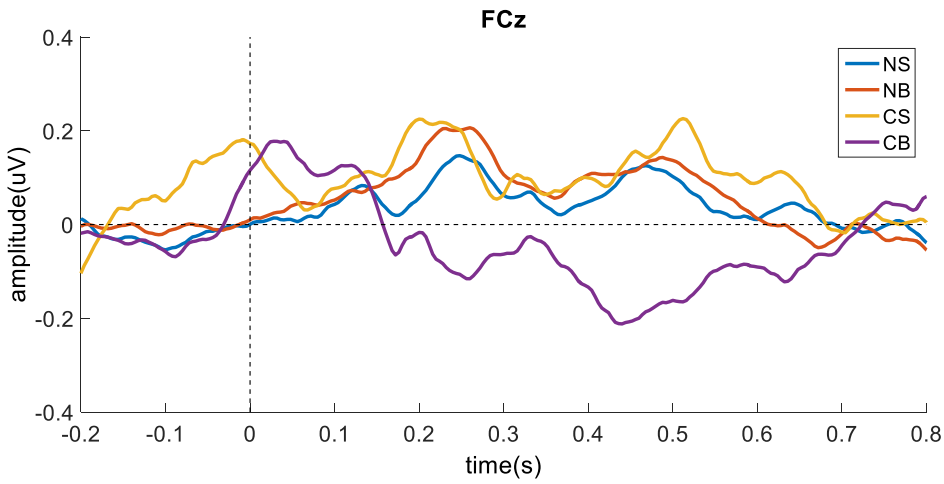


Figure 4-24 ERP back-projected to FCz from PCC IC (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

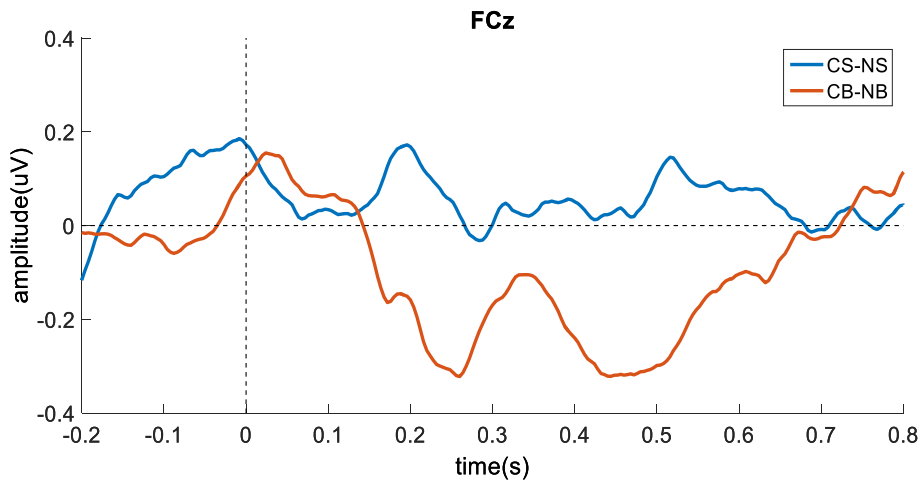


Figure 4-25 Difference in ERP for PCC IC (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

The topoplots were calculated for the ERP derived from the ACC component for PEN (50-150ms) and Pe (250-350ms) in the normal and conflict conditions for the small and large cubes, including the differences. It can be seen very clearly that the PEN was significantly more negative ($p < 0.05$) for the conflict trials compared to the normal trials (see Figure 4-26). In relation to the difference between the small and large cubes, there was no significant difference ($p > 0.05$) in the normal condition for PEN while there was a significant ($p < 0.05$) difference for the conflict condition. Similarly, as shown in

Figure 4-27, it can be seen that the results for the normal trials are significantly more positive (Pe) compared to the conflict trials, while the small cubes show a higher Pe compared to the large cubes in the conflict condition. There was no significant difference ($p > 0.05$) for the normal trials for the small and large cubes.

Further spectral analysis was performed on ACC and PCC to evaluate if there were any significant differences in power band at different time points. The results are based on as follows.

As shown in Figure 4-28 for ACC, it can be seen clearly that there was a significant difference ($p < 0.05$) in the normal condition between the small and large cubes for the upper alpha band (10-12 Hz). Similarly, in the conflict condition, there was a significant difference ($p < 0.05$) between the small and large cubes at around 50 ms for the theta

band (4-8 Hz), around 100 ms for the alpha band (8-13 Hz) and around 450-500 ms for the theta and alpha band. A statistically significant difference ($p < 0.05$) was found between the normal and conflict conditions for the small cubes around 50-200 ms and 350-600 ms for theta and alpha band range while for the large cubes, a statistically significant difference was found around 200 ms for the theta band only.

Similarly, for PCC (see Figure 4-29**),** it can be seen clearly that there was a statistically significant difference ($p < 0.05$) in the normal condition between the small and large cubes around 0-200 ms for the theta band. Similarly, in the conflict condition, there was a statistically significant difference ($p < 0.05$) between the small and large cubes around 100 ms and 200 ms in the upper alpha band (10-12) and the beta band (12-30Hz), as well as around 200 ms in the alpha band. In relation to the normal and conflict condition, there was a statistically significant difference ($p < 0.05$) around 0-400 ms in the theta and alpha power band for the large cubes and a statistically significant difference was found around 200-400ms for the theta and alpha power band as well.

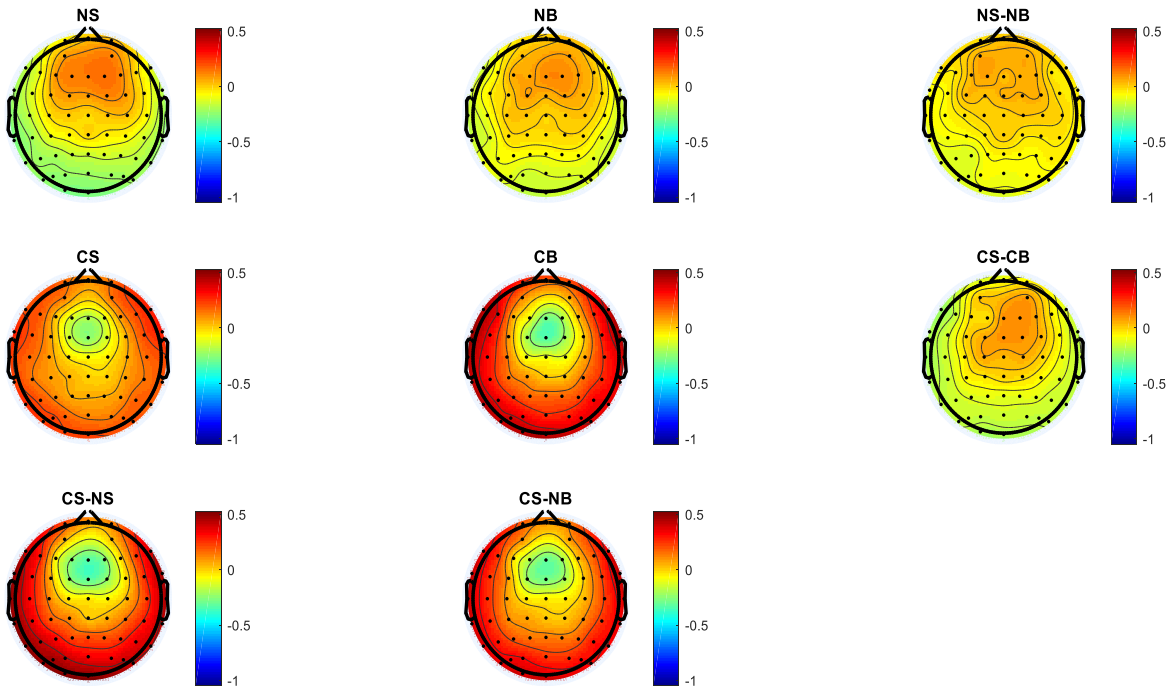


Figure 4-26 Topoplots for PEN (50-150ms)

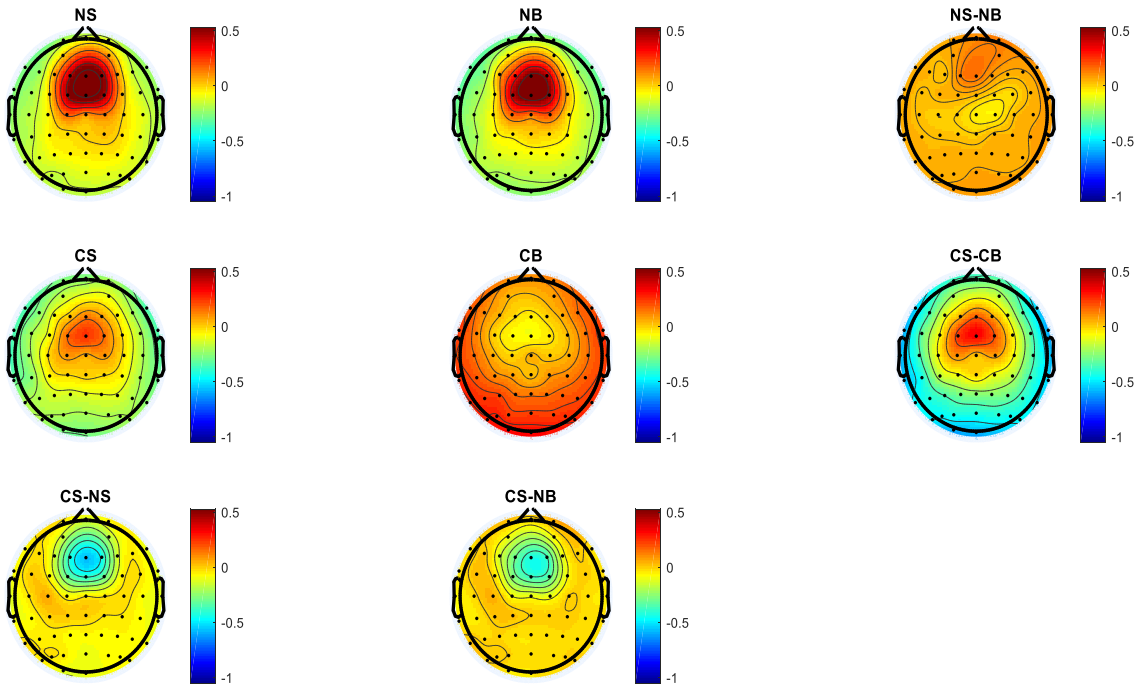


Figure 4-27 Topoplots for Pe (250-350ms)

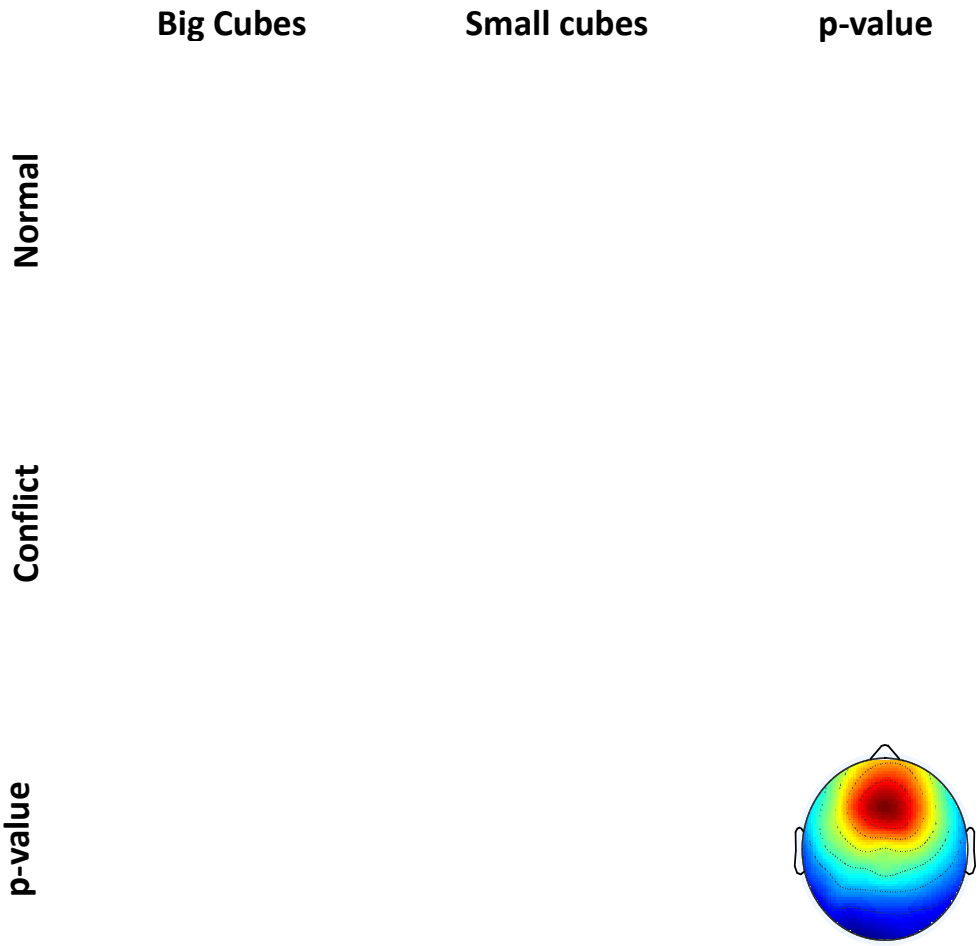


Figure 4-28 ERSP from ACC IC

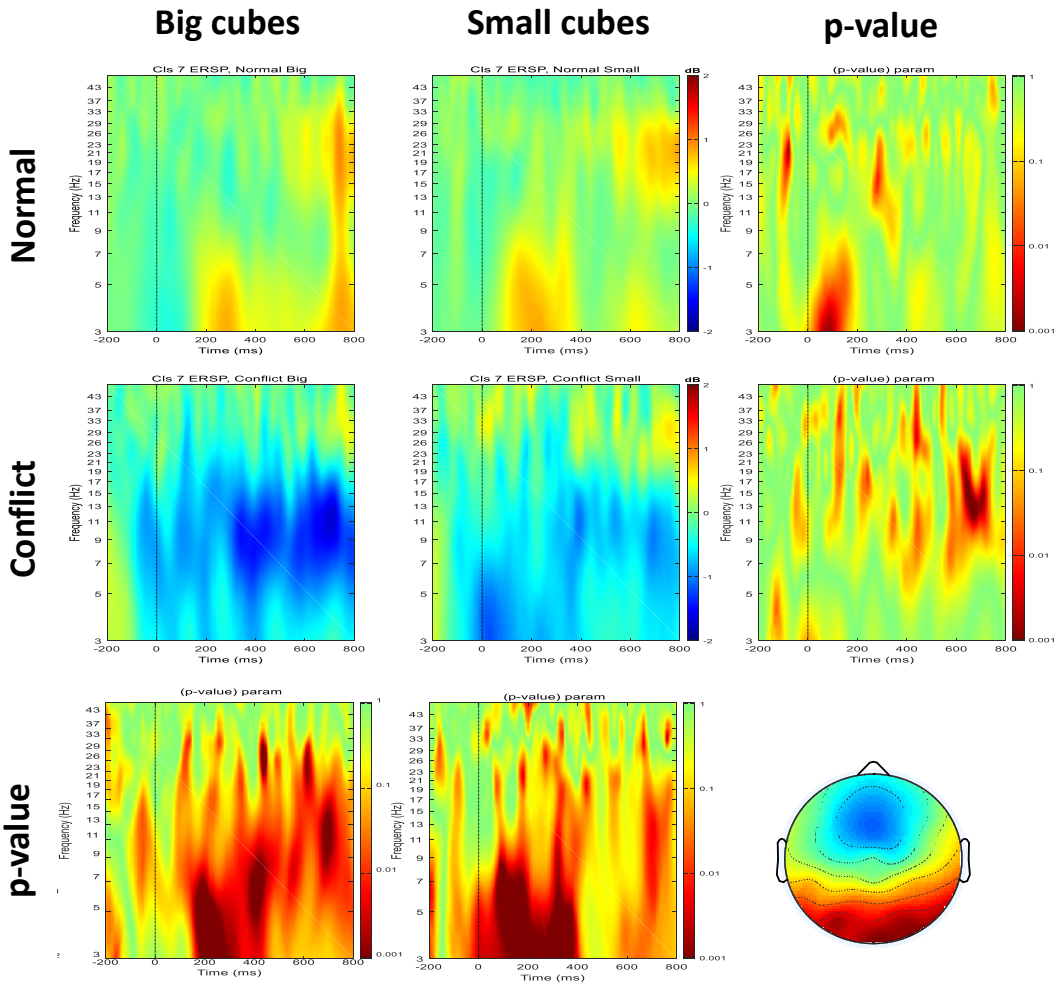


Figure 4-29 ERSP from PCC IC

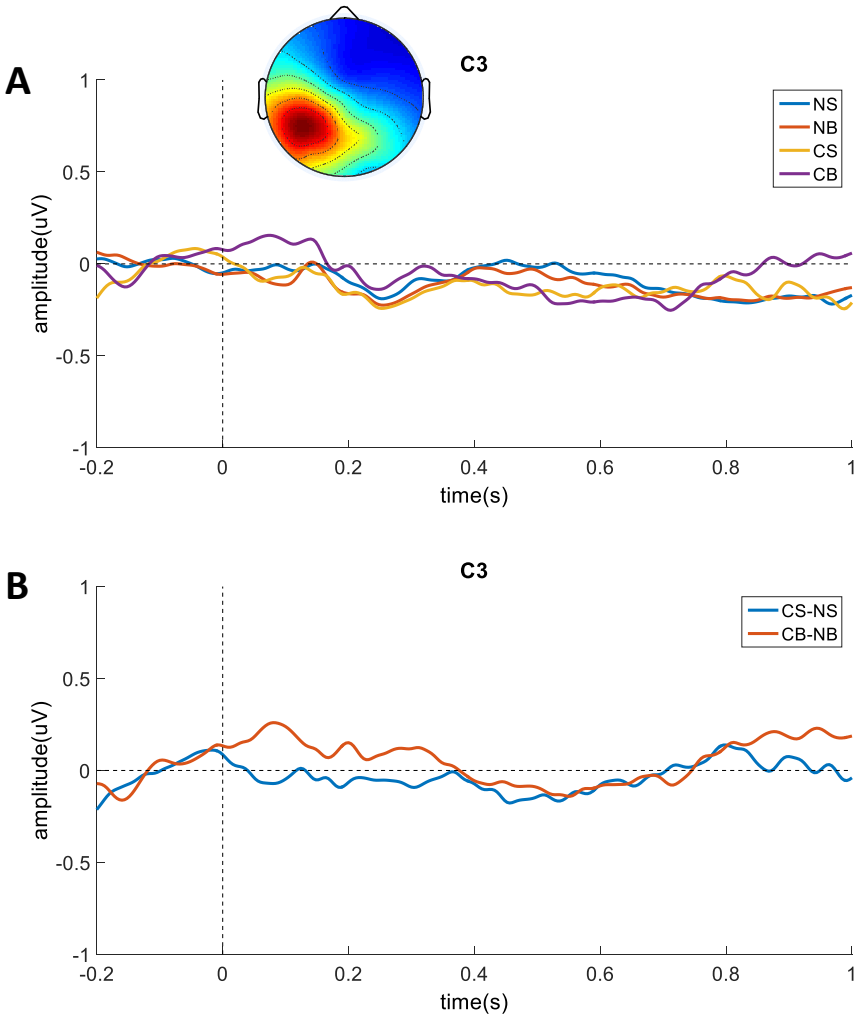
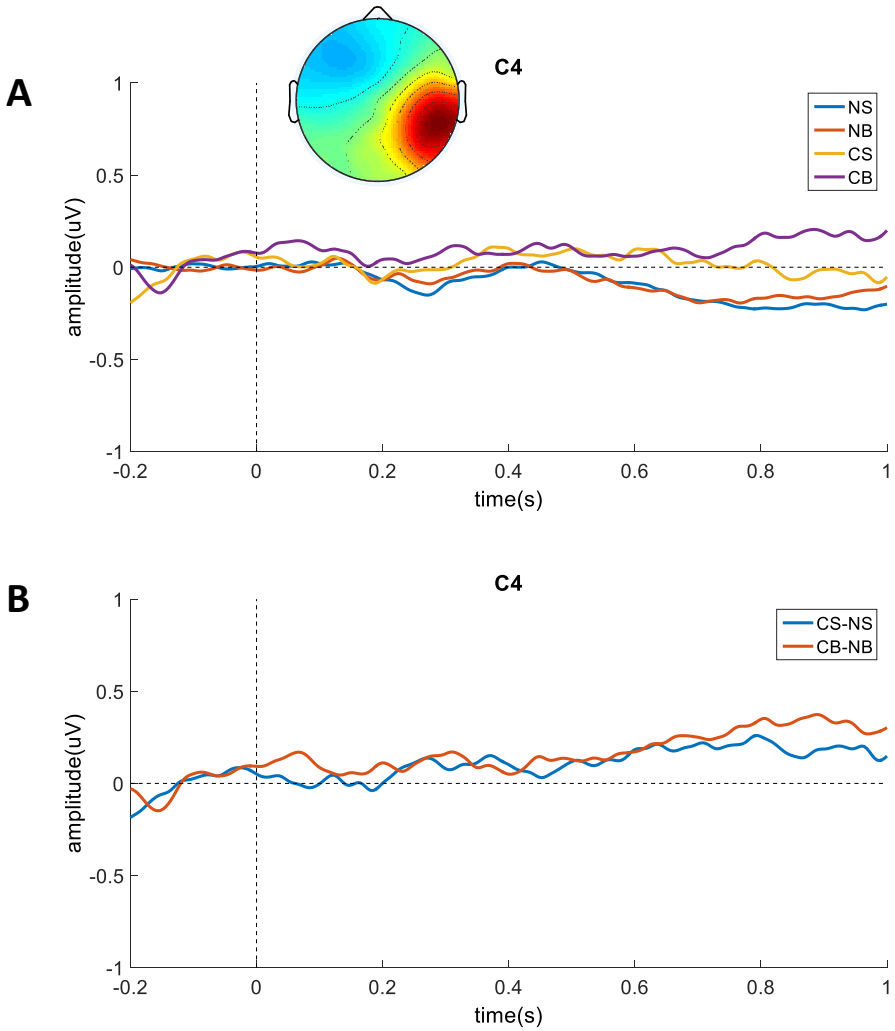


Figure 4-30 The ERP for SMC. A) ERP for left-SMC in all conditions, B) difference in ERP for left SMC in all conditions (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)



Ah Figure 4-31 ERP for SMC. A) ERP for right SMC in all conditions, B) difference in ERP for all conditions for right SMC (NS = normal condition for small cubes; NB = normal condition for large cubes; CS= conflict condition for small cubes; CB= conflict condition for large cubes)

As a control, ERP for left and right sensorimotor cortex (SMC) was evaluated. As shown in Figure 4-30, it can be seen that there was no statistically significant ($p > 0.05$) difference between different conditions of cube selection in PEN and Pe derived from the independent component of left motor regions and back-projected on C3. Similarly as shown in Ah Figure 4-31, it can be seen that there was also no statistically significant ($p > 0.05$) difference between different conditions of cube selection in PEN and Pe derived from the independent component of right motor regions and back-projected on C4 EEG electrode.

4.5. Summary

Based on the findings of the first experiment in Chapter 3, this experiment was carried out to understand the effect of velocity during the cognitive conflict task. The results indicate that velocity indeed modulates the PEN. Particularly, it was found that during the fast condition, the participant needs to be very careful at the end of the trajectory; therefore, this poses a higher level of cognitive conflict compared to the slow condition where the participants were already being careful from the beginning of trajectory. Furthermore, ACC and PCC also seem to be related to cognitive conflict and self-awareness, which was found to relate to the behavioral results of a realism, sense of agency and control of events in VR.

Chapter 5 : Closed-loop Brain-Computer Interface for Cognitive Conflict in Virtual Reality

This chapter focuses on the results from the design and development of the open and closed-loop brain-computer interface to continuously evaluate the level of cognitive conflict. First, an open loop system was designed to evaluate the feasibility of the system followed by a closed-loop BCI system. Figure 5-1 shows the schematic diagram of the closed-loop BCI system.

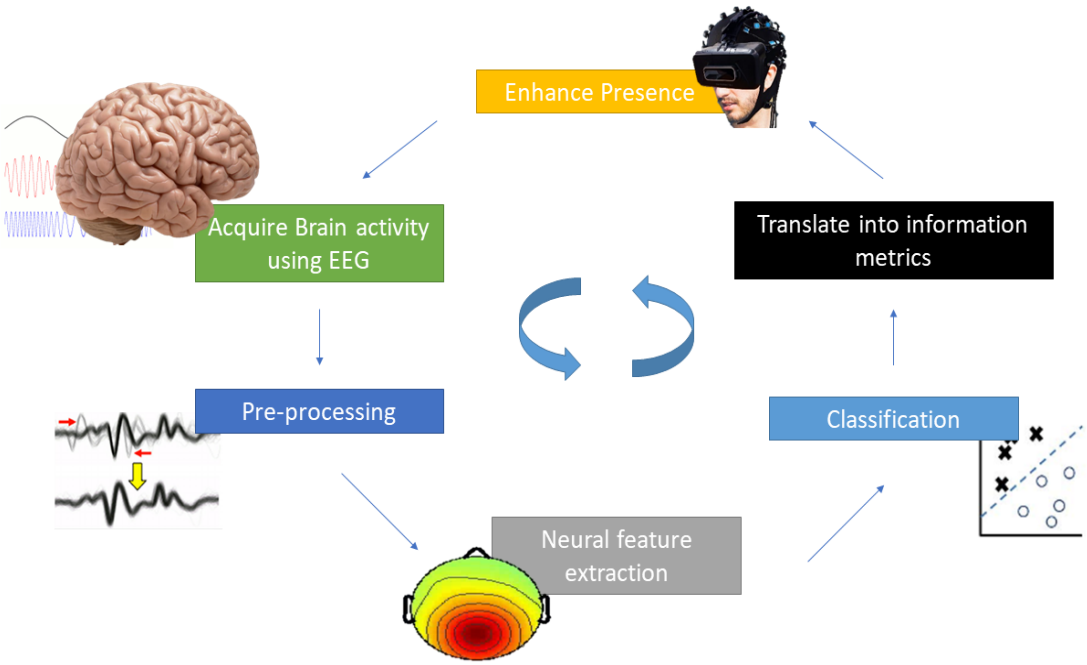


Figure 5-1 The schematic diagram for the closed-loop BCI system

5.1. Experiment

5.1.1. Participants and environment

EEG data were recorded from 10 participants (all males) to design and develop a closed-loop BCI system derived from the PEN to represent cognitive conflict. The mean age of the participants was 24 years, with a range of 18-30 years. Following an explanation of the experimental procedure, all participants provided informed consent

before participating in the study. This study obtained the approval of the Human Research Ethics Committee of the University of Technology Sydney, Australia and was conducted in a temperature-controlled room. None of the participants had a history of any psychological disorders, which could have affected the experiment results. Three participants were excluded from the experiment due to discrepancies in the data collection in the later stages of data analysis.

5.1.2. VR setup

This experiment uses the HTC Vive as the head-mounted display together with Leap Motion similar to the experimental setup described in 'VR setup' section of Chapters 3 and 4.

5.1.3. EEG setup

EEG data were recorded from 64 Ag/AgCl electrodes, which were referenced to the electrode between Cz and CPz with the extended 10% system (Chatrian, Lettich & Nelson 1985). Contact impedance was maintained below 5kΩ. The EEG recordings were collected using a Curry 8 SynAmps2 Express system (Compumedics Ltd., VIC, Australia). The EEG recordings were digitally sampled at 1 kHz with a 16-bit resolution.

The EEG cap setup with VR and Leap Motion was similar to the experiment described in 'EEG setup' section of Chapters 3 and 4. To have a better experience in VR, the table was kept similar to the experimental setup described in Chapter 4.

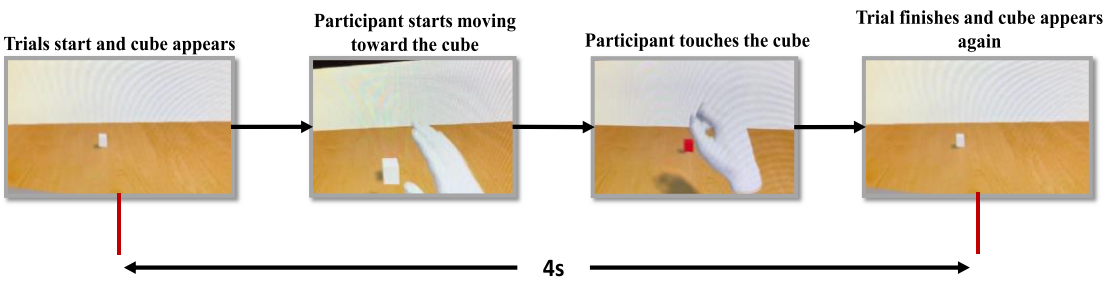


Figure 5-2 Experimental scenario for one trial

5.2. Experiment Scenario

The participants were required to perform the 3D object selection task with their dominant hand tracked by the Leap Motion controller in VR. Figure 5-2 displays the scenario for a single trial. The aim of this experiment scenario was to demonstrate how the PEN can be used to improve the participant's experience in VR. This experiment

scenario is similar to the previous two experiments described in Chapters 3 and 4, but it is based on an open- and closed-loop BCI settings. In both the open- and closed-loop setup, the participants were required to touch the cube with their dominant hand and the cube changes color from white to red as selection confirmation feedback to the participant. The scenario starts with the instructions and the cube appears as soon as the participant presses any button. The trial starts with the cube appearing on the table and the participant was instructed to reach out and select (touch) the cube, similar to the previous experiments. The participant was expected to finish the task within 4 seconds.

The selection distance of the cube change in every trial with +300% (large), 0% (medium), and -300% (small) compared to the default size of the selection radius of the cube (See Figure 5-3). The position of the cube on the table also slightly varies by about 30% to the left and right randomly from the center to create variety in the participants' hand movements and to keep the participants engaged.

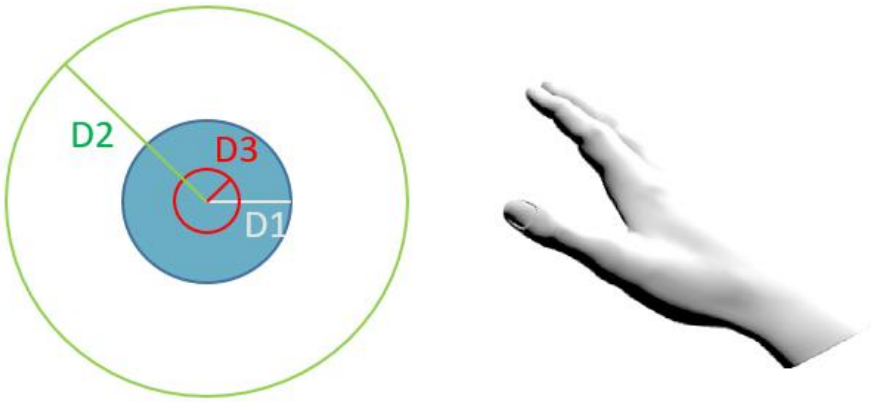


Figure 5-3 Selection radius representation where D1 is the normal radius, D2 is a radius larger than normal, and D3 is the radius smaller than normal

When the experiments had been completed, the participants were presented with a modified version of the IPQ questionnaire. The questionnaire asked the participant to give a subjective rating of the different parameters of realism, experience and controlling event as well as their past experience of game playing / VR on a seven-point Likert scale to rate the overall experience of the 3D object selection task.

5.3. Data Analysis and Classification

5.3.1. EEG data analysis

The EEG data were processed offline (open-loop) and online (closed-loop) using the EEGLab (Delorme & Makeig 2004) and BCILab (Delorme et al. 2011) toolbox in MATLAB 2016 (MathWorks Inc, USA).

For the offline analysis, the EEG signals were filtered using a 0.1-Hz high-pass and 40-Hz low-pass FIR filter. Subsequently, the data were downsampled to 250 Hz. The resultant data were inspected to detect and remove the noisy electrodes using the Kurtosis methods followed by an ICA (Makeig et al. 1996). The resultant ICs were further processed to detect artifact-related ICs using the SASICA plugin (Chaumon, Bishop & Busch 2015) which uses different autocorrelation, focals ICs, eye blink, and information from the ADJUST (Mognon et al. 2011) plugin to mark the possible noisy artifacts. These artifacts were marked and excluded from the resultant data.

The resultant data were epoched from 500 ms from the onset of the touching event for the cube to 1000 ms after the response for all conditions. The cleaned epoched EEG data were further analyzed for PEN and Pe.

For the online analysis, the EEG signals were filtered using a 0.1-Hz high-pass and 15-Hz low-pass FIR filter followed by being downsampled to 250 Hz. The resultant data were epoched from 0 ms from the onset of the touching event for the cube to 600 ms after the response for all conditions. The cleaned EEG signals were further processed to extract the PEN and Pe.

Figure 5-4 represents the pipeline used to process open EEG data for BCI system.

5.3.1. Closed-loop cognitive conflict classification

The different version of machine learning methods was applied with the help of the meta-learning-based voting method to find the best machine learning approach to detect the different levels of cognitive conflict with the lowest possible misclassification rate and to build a model. As per results from EEG analysis in Chapter 4, it was found that delta, theta, alpha spectral range plays an important role, therefore 100 ms windows with 0.1 to 15 Hz spectral selection were used for 6s long epoch after the selection of the cube as a feature for the selected machine learning method. The input data were selected from

Fz, FCz, and Cz electrodes which were decided from the findings from the results of experiment 1 and 2.

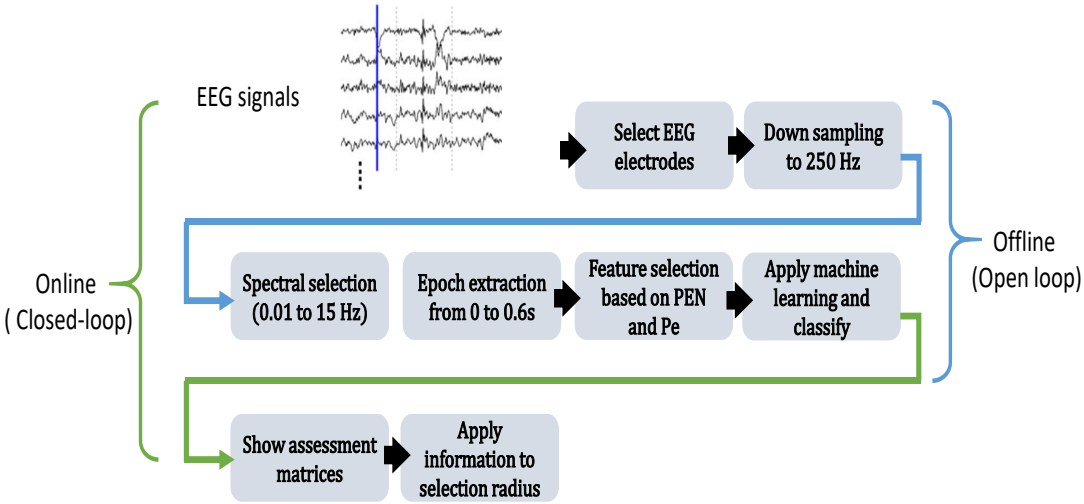


Figure 5-4 Data processing pipeline for the open and closed-loop BCI system

5.4. Results

5.4.1. Behavioral results

The results from the questionnaire clearly show (Table 5-1) that four participants (SN#1, 3, 6, and 7) have a higher level of realism (> 35) compared to the other participants (< 35) which also relates to a higher possibility to act, a higher quality of the interface, and a better evaluation of their performance. These four participants also showed more experience of playing video games or interacting with VR compared to the other participants. The score of these four participants is equivalent to the average mean score of the whole population of participants (see Figure 5-5).

Table 5-1 Questionaire results for all the participants

SN	Realism	Possibility to act	Quality of interface	Self-evaluation of performance	Interaction activity in a week (days)
1	37	22	8	12	3
2	30	20	14	9	1
3	36	19	13	11	3
4	26	16	12	8	2
5	31	19	11	14	6
6	41	24	9	13	6
7	42	27	10	14	4

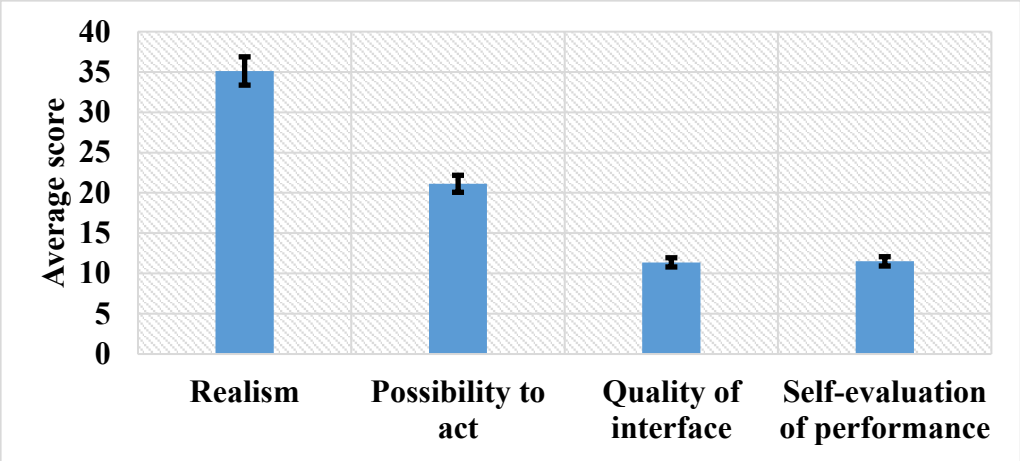


Figure 5-5 Averaged questionnaire results

5.4.2. EEG results

The EEG data were analyzed in the open-loop setup for the individual participants to determine their optimal selection radius, which induces the lowest level of cognitive conflict measured by PEN. As seen in Figure 5-6, different participants have different preferences for the three selection radii in the 3D object selection task. However, the medium radius dominates in term of the highest level of cognitive conflict, but the smallest and largest selection radii vary among participants. Two participants have a level of cognitive conflict which was statistically significant ($p < 0.05$) higher for large selection radius while four participants have a level of cognitive conflict which was statistically significant ($p < 0.05$) high for small selection radius. Interestingly, these four participants also have a higher level of realism. One participant has no statistically significant difference ($p > 0.05$) in conflict condition (normal vs cognitive conflict) for the large or small radius. One participant has a higher level of cognitive conflict for a large radius compared to the other conditions for the radius. Table 5-2 shows the amplitudes derived from PEN and Pe for each participant.

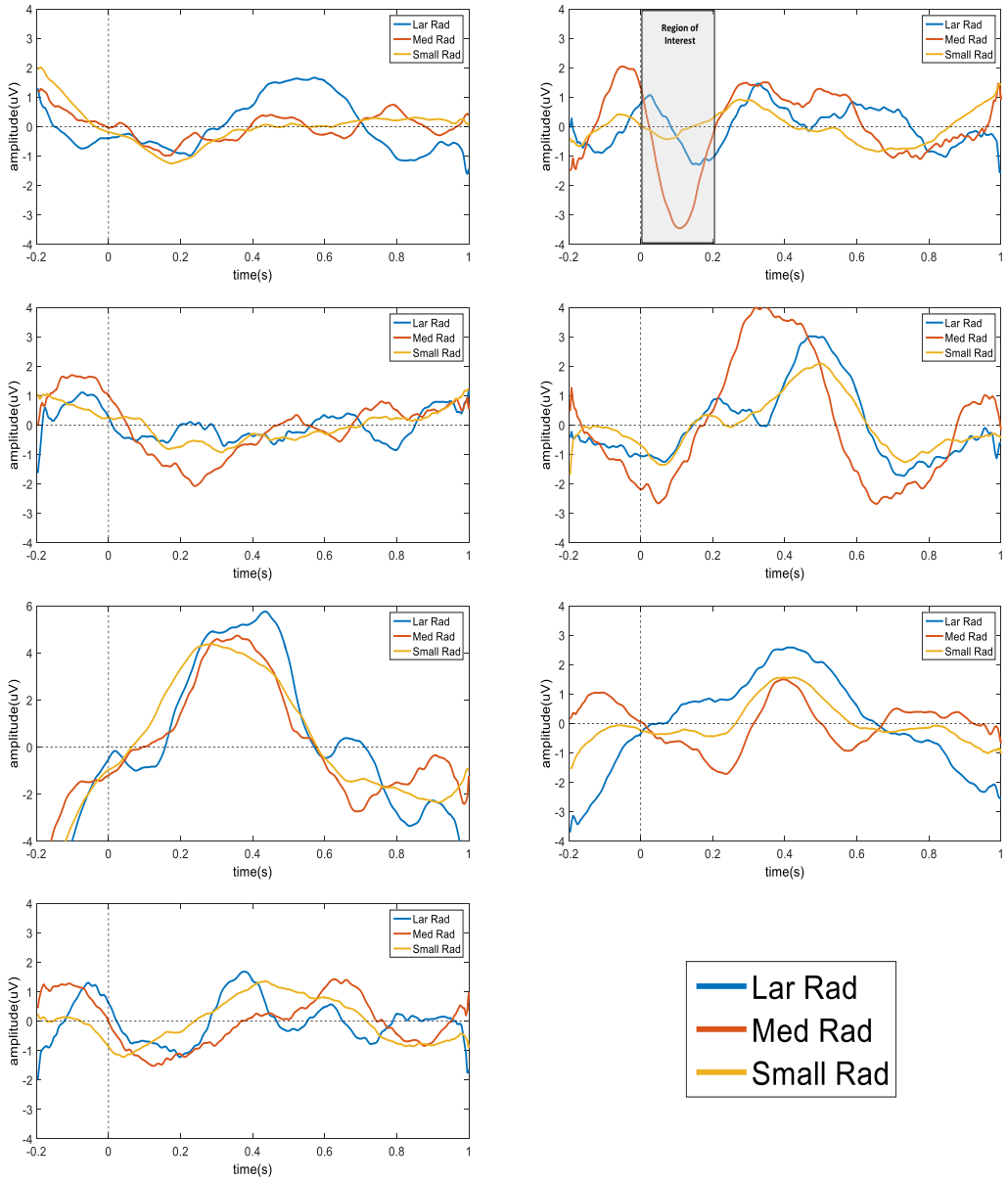


Figure 5-6 ERP for all participants individually over FCz (Lar Rad is a radius larger than the normal radius, Med Rad is equal to the normal radius, and Small Rad is the radius smaller than normal)

Table 5-2 PEN and Pe amplitude for all participants for the three conditions of the selection radius (Lar Rad is a radius larger than the normal radius, Med Rad is equal to the normal radius, and Small Rad is the radius smaller than normal)

PEN			Pe		
Lar Radius	***Med Radius***	***Small Radius***	***Lar Radius***	***Med Radius***	***Small Radius***
-0.685	-0.950	**-1.150**	-0.565	-0.226	-0.810
-1.260	-3.440	-0.425	0.119	1.000	0.780
-0.539	-1.380	**-0.715**	0.073	-1.330	-0.532
-1.230	-2.630	-1.340	0.887	2.220	0.341
-0.982	-0.384	-0.248	4.160	3.390	4.270
0.005	-0.877	**-0.355**	0.839	-0.920	-0.159
-0.880	-1.500	**-1.150**	-0.746	-0.926	0.119

The average results for all the participants were evaluated to see any visual difference in ERP for three conditions. As seen from Figure 5-7 (A), all three selection radii of the cube were statistically significant different ($p < 0.05$) around 50-150 ms time window from each other. This part of ERP was also defined as PEN in the previous experiment.

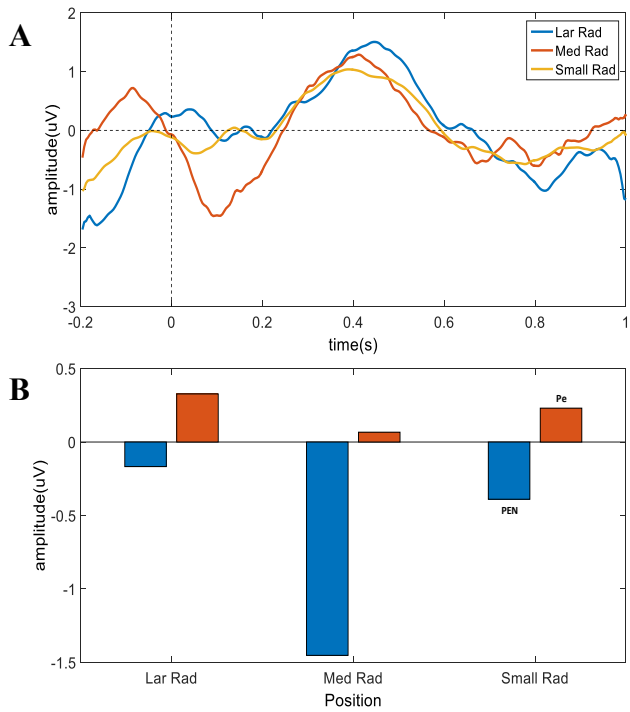


Figure 5-7 A) Averaged ERP for all participants; B) extracted PEN and Pe amplitudes (Lar Rad is a radius larger than the normal radius, Med Rad is the equal to the normal radius, and Small Rad is the radius smaller than normal)

To determine if there was any difference for the cognitive conflict-related biomarker, PEN and Pe amplitude were extracted and shown in Figure 5-7 (B). It can be seen clearly

that PEN has the highest negativity for the medium radius, followed by the large, and small. All these PEN were statistically significant different ($p < 0.05$) from each other. Similarly, a small radius has the largest significant Pe ($p < 0.05$) while for the other three radii, no significant difference ($p > 0.05$) was found.

5.4.3. Classification results

The classification was performed during the open and closed-loop setup using PEN and Pe to find the optimal choice of machine learning techniques. It can be seen from Table 5-3 that logistic regression was highly stable and incurs less computation cost in the five-fold cross-validation analysis for a single trial. It also shows the highest precision for classification for different conditions. After further evaluation of the reliability of the method and other parameters such as the null error rate and Cohen's Kappa, logistic regression seems to be the best choice for closed-loop classification for cognitive conflict.

Table 5-3 Classification results based on different machine learning methods

Algorithm	Misclassification rate	Time to compute (seconds)
Logreg	0.2411	1.9721
LDA	0.6987	2.8192
QDA	0.2455	1.4560
Dal	0.2411	260.4595
Gauss	0.7601	1.4336
GMM	0.2444	1.7691
SVM	0.2411	2.379e+03

5.5. Summary

The findings from the closed-loop experiment show that reducing cognitive conflict improves the overall experience of a participant in the VR object selection task. The findings also show that there was quite an individual difference among participants, which is highly correlated with their experience with VR and game playing as well as their realism, sense of agency, and ability to control events.

Chapter 6 : Discussion and Limitations

6.1. Modulating Factors of Cognitive Conflict

An experiment was conducted to develop a novel scenario of 3D object selection by applying the concept of cognitive conflict to evaluate the effect of visual appearance in VR. It was hypothesized that:

Hypothesis 1: A different visual appearance will affect the user's response toward cognitive conflict.

Hypothesis 2: A different task completion times will modulate the cognitive conflict.

Figure 6-1 Visual appearance of hand styles used in the first experiment

As hypothesized in hypothesis 1, the results showed a larger amplitude of PEN / Pe components in response to H1 than to H2 and H3 (shown in Figure 6-1). The results agree with the mismatch theory (Bernstein, Scheffers & Coles 1995; Coles, Scheffers & Holroyd 2001), which argues that the negative component amplitude correlates with the degree of mismatch between correct and erroneous responses. More specifically, the results showed that H1 gave participants a higher level of body ownership and, thus, a stronger expectation regarding when the virtual hand should reach cube 2. Thus, false feedback evoked a larger negative amplitude.

This result echoes the uncanny valley theory (Mori, MacDorman & Kageki 2012), which states that as a robot approaches, but fails to attain a likable human-like appearance, there will be a point where users find even the slightest imperfection unpleasant. In this work, as the virtual hand became more realistic, the participants also became more aware of the errors. In a related vein, the absence of the PEN component in the least realistic hand style (H3) condition seemed to imply that participants felt less body ownership and were, thus, more tolerant of or less sensitive to incorrect feedback. This finding suggests that, depending on the goals of the interaction and the hardware

capability, a higher rendering quality might not always be the best. For example, if the tracking precision is likely to be compromised or the display quality of an HMD is not ideal, then using a less realistic rendering style might be helpful. Only if the nature of the task and the available hardware permits, the users' preferred human-looking virtual body should be used.

The results also suggest that there is a correlation between BIS scores and the amplitude of the PEN, but it applies only to H1 as the realistic hand. In contrast, for the low BIS group, Pe might be a more effective ERP feature. The correlations between BIS scores and the PEN / Pe amplitudes also concur with the results of previous studies (Carver & White 1994b; Santesso, Dzyundzyak & Segalowitz 2011) that functionally linked these components with flexible behavioral adaptation (see Table 6-1).

Table 6-1 Correlation matrix for high and low BIS scores with PEN and Pe amplitude for H1, H2, and H3. Bold-highlighted cells represent that a correlation is significant

Correlation	Hand style	High BIS score	Low BIS score
PEN	**H1**	**-0.9833***	**0.8386***
	H2	-0.3142	0.2319
	H3	-0.0488	0.1177
Pe	**H1**	-0.1782	**0.6100***
	H2	-0.3678	0.2633
	H3	-0.0604	-0.2143

The BIS scale has been used to measure punishment sensitivity. The central implication of the BIS is that individuals with higher punishment sensitivities are more sensitive to negative outcomes or to errors in prediction than individuals with lower punishment sensitivities.

In the context of the current experiment, it seemed that participants with higher BIS scores were sensitive enough to detect the error of cube 2 turning red before they touched it, thus, generating a larger PEN and a negative correlation between BIS scores and the PEN amplitude. On the other hand, the participants with lower BIS scores were less sensitive to the error and, thus, ignored or tolerated the selection distance change and showed a small PEN amplitude.

The positive correlation between the low BIS group and the PEN/Pe amplitude in response to H1 was surprising. Due to the positive direction of the correlation, it was suspected that Pe was the main ERP component, which modulates for conflict condition. A potential explanation could be that the participants with lower BIS scores were less sensitive to the error and, thus, were more tolerant of the change in the selection distance, which resulted in a small PEN amplitude. This also implied that more weight is put into the visual feedback system, which evokes the Pe component.

As put forward in hypothesis 2, the results demonstrate that PEN amplitudes and the following Pe amplitudes were statistically significant larger when participants had more time to process and integrate visual and proprioceptive feedback (i.e., during long completion trials) as compared to fast trials with short completion times. This result concurs with previous results that associated reaction time with the amplitude of different ERP components such as ERN (Mayr et al. 2006). The result showed no correlation between the latency of the PEN and task completion times, suggesting that comparable cognitive processes took place in all trials. It is believed that the observed correlation between PEN amplitude and trial completion times for conflict trials can be attributed to the integration of sensory feedback that may require different processing times.

It was noted that PEN and Pe appeared in both normal and conflict conditions, which seems to suggest that users were expecting more sensory feedback, e.g. haptics feedback, than the perceived visual feedback of the object selection in VR. This result might be interpreted as reflecting a general conflict in the sense that participants perceived the object selection in VR differently from a natural object selection in the real world. Despite the realistic finger and hand tracking through the Leap Motion Controller, the participants might still have expected haptic feedback when touching the cube and an impact of their action on the virtual object, e.g. moving the boxes by touching them. Nevertheless, the PEN amplitude in both conflict and non-conflict trials were both modulated by the task completion times supporting the hypothesis on the correlation between amplitude and task completion time.

Prediction errors arise when there is a discrepancy between the users' observation and their expectation. In the given 3D object selection scenario, the participants computed their prediction depending on the time it took to reach the cube by integrating information from the visual, motor, and the proprioception system (Genewein et al. 2015; Körding &

Wolpert 2006). This prediction is then compared against the actual visual feedback received in the VR environment, i.e. the cube changing color from white to red when the participant touches it. It was assumed that in long completion trials, slower movement allowed for more time to integrate all the available sensory inputs with motor efferences, resulting in a more precise and confident prediction. This, in turn, resulted in the detection of a clear conflict between sensory and motor information in conflict trials, leading to a more pronounced PEN component. In the context of auditory negative priming, (Mayr et al. 2006) also observed a larger negative priming effect in trials with long reaction time. Mayr et al. provided an episodic retrieval explanation, arguing that a long reaction time allows for a higher probability of successful prime retrieval. The results from this experiment and Mayr et al.'s share a similar conclusion that a long task completion time allows a complete development of the stimulus evaluation and stronger negativity if a mismatch or error is detected.

Another potential explanation for the reduction in PEN amplitude in faster trials is that the participants' might have sacrificed accuracy for speed in those trials and developed a larger tolerance to the conflict condition, i.e. a larger selection radius. Previous work on object selection (Soukoreff & MacKenzie 2004) has shown that in relation to trials of the same difficulty, the movement endpoint spread is larger for those with a shorter task completion time compared to those with a longer task completion time, i.e. the participants favored speed over accuracy. One potential explanation for such a phenomenon is that precise object selection requires engagement of attentional and executive control mechanisms, and over time, the participants might sacrifice precision to reduce mental fatigue and workload or to simply finish the experiment faster. In the context of this experiment, participants might also have chosen speed over accuracy in the fast completion trials, and thus became less aware of the conflict condition where the cube changed color before being selected.

6.2. Movement Velocity and its Implications

The experiment was conducted to understand the effect of movement velocity on cognitive conflict and how it affects users' behavior toward the VR with the following hypotheses:

Hypothesis 3: Different hand movement's velocity will affect the user's response to cognitive conflict.

Hypothesis 4: Visual and proprioceptive feedback will be modulated by hand movement velocity and correlates with the user's behavior toward the virtual reality environment.

The second experiment was performed with the modified version of the 3D object selection task from experiment 1. The experiment was designed in such a way that it produces the two distinct hand movement velocity profiles due to different ID based on Fitt's law (Soukoreff & MacKenzie 2004). The small cubes posed higher ID compare to large cubes, therefore; small cubes required the participant to be careful while selecting cubes compare to large cubes. According to Meyer's optimized initial pulse model (Meyer et al. 1988), the fast velocity due to easy target selection required more correction and adjustments in the trajectory of the corrective phase. Similarly, the slow velocity due to difficult target selection required less correction in trajectory in the corrective phase. The corrective phase of the hand movement trajectory with higher correction is also required a higher integration of visual and proprioceptive feedback, therefore, resulted in higher PEN compared to a hand movement trajectory with less correction. As hypothesized in *Hypothesis 3*, it was found that PEN amplitude was modulated differently for velocity profiles of the participants as expected. The results from correlation analysis clearly show a positive correlation for large cubes' conditions and a negative correlation for small cubes' conditions. It happened because the corrective phase of the hand movement trajectory for the easier target (large cubes) required continuous proprioceptive feedback in short time until the target has been selected as compared to the difficult target (small cubes). Simply, it was wrong to say that the PEN was modulated due to the different difficulty of targets selection. Interestingly, the modulation of PEN was only found in the ACC region of the brain but not in SMC regions of the brain. These results clearly indicate that ACC is an important hub behind handling cognitive conflict situations which are aligned with existing research related to cognitive conflict (Carter et al. 1998; Umemoto, Inzlicht & Holroyd 2018), and probably also instructs motor control to act in bottom-up fashion (Rauss & Pourtois 2013).

On the behavior side, it was found that task completion time did not affect the PEN amplitude and was highly dependent on individual differences in terms of game playing and/or VR-related experiences. The participants with more experience were able to control things around them in a short time compared to those with less experience but no

relationship was found between task completion time and PEN. It may be possible that the participants took different task completion time for the same kind of conditions without being affected by velocity or strategy on normal and conflict conditions. This led to another possibility with the peak latency with PEN and Pe. The peak latency in error-related potential and positivity is known to represent the cognitive process changes of memory, workload (Portella et al. 2014), and attention (Horimoto et al. 2002). Interestingly, there was no relationship found between peak latency for PEN/Pe and its amplitude. These results contradict with the work of Donchin et al. (Donchin & Coles 2010). The potential reason could be the nature of the task in 3D object section task. This task is one of first of such kind known in the field of neuroscience which requires the active motor control and falls under the category of mobile-brain body imaging (MoBI) (Jungnickel & Gramann 2016) and is completely different from a traditional experiment with passive movement usually limited to key press or controller.

Several existing studies (Carter et al. 1998; Devinsky, Morrell & Vogt 1995; van Veen et al. 2001) demonstrate that event-related errors originated in ACC. The localization of EEG data with ICA (Makeig et al. 1996) and dipole fit (Scherg 1990) received from all participants show that ACC was found to be activated among 70% of participants during the 3D object selection task. The PEN and Pe extracted from ACC shown to have higher modulation compared to the normal condition that suggests that ACC indeed involves in the cognitive process, which is required for action control. These findings align with the theory of action monitoring (Botvinick et al. 2001), observational error (van Schie et al. 2004), and prediction error (Ozkan & Pezzetta 2018; Singh et al. 2018).

The results also showed that the frontal theta was modulated by the cognitive conflict response of the participants, which also aligns with the existing theory of frontal theta modulation during a cognitive involvement task (Arrighi et al. 2016; Zhang et al. 2018). Interestingly, the results showed that there was a significant difference just after the response onset for the large cubes compared to the small cubes. This difference in frontal theta appeared earlier for the large cubes because the participants had to correct their trajectory during the corrective phase of hand movement which happened just before the selection of cubes. On the other hand, for the smaller cubes, the participants were already careful from the beginning, and thus they did not require a lot of adjustments in their hand

movement trajectory. This again serves as an extended proof of the Meyer theory of trajectory movement (Meyer et al. 1988) in the 3D object selection task (Argelaguet & Andujar 2013) in a VR.

Several researchers (van Driel, Ridderinkhof & Cohen 2012) also argued that alpha modulation could be different in nature depending on various kinds of errors. This modulation could be results of attention and perception (Den Ouden, Kok & De Lange 2012), self-awareness (Devinsky, Morrell & Vogt 1995), and observer's relationship with the person-performing task (Kang, Hirsh & Chasteen 2010). In line with this research, modulation also has been found in the lower alpha band in ACC and assumed to be highly related to the attentional process (Pfurtscheller 2003). Alpha modulation was seen more in the small cubes due to the requirement of higher attention from the beginning of hand movement compared to large cubes.

In some of the existing work (Brewer, Garrison & Whitfield-Gabrieli 2013; Lou, Changeux & Rosenstand 2017), PCC region of the brain was found to be correlated with the self-awareness in human. It was shown to be activated and modulated for self-awareness conditions (Brewer et al. 2011). In current work, PCC region was found to be modulated for the small and large cubes conditions. The modulation in PCC was higher for the small cubes compared to the large cubes, because the participants were highly aware of the controlling hand movement to select a target. In general, it was not wrong to say that the participant felt highly self-aware in the case of the slow-movement induced condition compared to the fast-movement induced condition in 3D object selection task. PCC region of the brain can also be used to assess the sense of agency which reflects initiating, executing, and controlling one's own volitional actions in the 3D world (Jeannerod 2003).

As shown in the past (Balconi & Crivelli 2010; Devinsky, Morrell & Vogt 1995), the participant experience was found to be highly related to their interactions with the environment and how the environment affects behavior. A previous experiment of this thesis (Singh et al. 2018) shown that visual appearance affected cognitive conflict and was related to the level of realism (Argelaguet et al. 2016) and the behavior inhibition score (Carver & White 1994b). As hypothesized in *Hypothesis 4*, the results of the experiment of different velocity profiles revealed that the participants' level of realism was highly correlated with PEN amplitude. These results are aligned with the existing

findings in the previous experiment of this thesis. As expected, it was also found that the level of sense of agency was positively correlated with PEN. Given these finding, it can be speculated that a higher realism with a higher sense of agency poses higher PEN. This explains why some participants felt a higher cognitive conflict compared to others. These results partially explain the individual behavior of participants who felt more in control of events and their actions in VR compared to those who did not. This higher control over actions also enabled the participant to adjust the trajectory in the corrective phase accurately and therefore, this again concurs with the finding of PEN with Meyer's model (Meyer et al. 1988). These results support *Hypothesis 4*, where it is speculated that cognitive conflict affects the behavior of participants in VR.

Overall, the results from experiment 2 clearly show that the movement profile affects the participant's sense of agency, self-awareness, immersiveness and modulates the level of cognitive conflict.

6.3. Closed-loop Brain-Computer Interface

The experiment was conducted to design and develop a closed loop BCI system to assess and evaluate cognitive conflict with the following hypotheses:

Hypothesis 5: 3D object selection behavior modulates cognitive conflict differently among individuals.

The cognitive conflict has several direct and indirect implications on the experience of the participants' feelings towards VR. The results from experiments 1 and 2 clearly showed that cognitive conflict was affected by visual appearance and individual feelings of inhibition (Singh et al. 2018), task completion time and more importantly, hand movement velocity while interacting in the 3D object selection task. It was also found in the first two experiments that cognitive conflict was correlated with the subjective feeling of realism and sense of agency as well as objectively measurement in ACC and PCC regions of the brain. Cognitive conflict requires higher brain resources than non-conflict conditions. Cognitive conflict also disrupts the ongoing feeling of sense of agency (Sidarus & Haggard 2016; Sidarus, Vuorre & Haggard 2017; Villa et al. 2018), induces mental workload (Berka et al. 2007), frustration (Octavia, Raymaekers & Coninx 2011), and mental fatigue (Boksem, Meijman & Lorist 2006) compared to interaction involving less cognitive conflict. In line of this research, a BCI system (open and closed loop) was designed. In the open-loop BCI system, participants perform the 3D object selection task

in an environment where the radius of the cube continuously changes, thereby inducing different levels of cognitive conflict. The results showed that the PEN amplitude was correlated with realism and a sense of agency which concurs with the findings from the first two experiments. Interestingly, as hypothesized in *Hypothesis 5* in this experiment, different participants had slightly different preferences toward cognitive conflict measured by PEN. For about 60% of the participants, PEN was higher in the D1 condition but for the other 40%, it was higher in the D2 condition (see Figure 5-6 in Chapter 5). This difference probably arises due to the participants' previous experience with the VR environment. Participants with less experience show a higher sense of realism and sense of agency in VR compared to experienced participants.

In a follow-up experiment, a closed-loop BCI system was designed based on the detection of the PEN level representing cognitive conflict. The system was successfully able to evaluate and visualize the cognitive conflict among participants in real time. These results of different levels of cognitive conflict with respect to different selection radius were aligned with the findings on the sense of agency (Sidarus & Haggard 2016; Sidarus, Vuorre & Haggard 2017; Villa et al. 2018), immersiveness (Bowman & McMahan 2007; Slater & Sanchez-Vives 2016), and frustration (Octavia, Raymaekers & Coninx 2011). The closed-loop system demonstrates that it is possible to evaluate cognitive conflict in real time and can be further used to improve the overall experience of the participant. Such online evaluation matrices can be applied to a wide variety of interaction tasks for the purpose of evaluation. Further, this work leveraging the PEN to evaluate the level of cognitive conflict can also be applied in the complex environment of VR and Augmented Reality (AR).

6.4. Limitation of this Work

Although the findings of this work can be applied to a wide area of research and applications, it still has several limitations as follows:

- The current setup used the Scan SynAmps2 Express system, and the recorded EEGs were analyzed offline. Due to its long setup time, this device is only suitable for an initial investigation in a lab environment. It could be possible to reproduce the results using portable EEG devices and to process the data in real time (Girouard, Solovey & Jacob 2013; Lin et al. 2018; Vi & Subramanian 2012).

- During the experiments, the belt of the HMD was adjusted manually to avoid contact with the sensors on the EEG cap. This might not be possible if caps with higher sensor densities are used. The integration of the EEG cap with the HMD is a natural one and it is to be expected that commercial products will be developed by companies and will be available on the market soon.
- The participants in the experiment were 20-30 years old and therefore do not represent the whole population. In future work, participants from a broader age population should be recruited for such experiments to study how ages will influence conflict perception in virtual reality.
- Synchronization is also a challenging issue for hardware integration, especially if specific components, such as the PEN or Pe, are being targeted. Leap Motion introduces a 30 ms delay (Understanding Latency: Part 1), and both Vive and Leap Motion have a potential tracking precision error. Additionally, the event generated from Unity 3D[5] is limited by the rendering frame rate (60 FPS). There is also another system delay for the communication between Unity and the parallel port of Scan (EEG system). It was estimated that the latency to summate to approximately 100 to 150 ms might cause some delay in the ERP. For future works that focus on specific ERPs, such as PEN or Pe, dedicated synchronization hardware should be used.
- Closed-loop BCI is also challenging due to the requirement of synchronization of the system to record, analyze and run scenario simultaneously while communicating in parallel to make changes in the scenario, and to return results in machine learning algorithm. The current closed-loop BCI used offline data to analyze and play-back to simulate real-time recording. In future work, a dedicated setup should be used with real-time EEG data acquired from participant to perform closed-loop BCI.
- Finally, for well-defined tasks, such as 3D object selection in VR, cognitive conflict is most undesirable and might harm an individual's sense of presence. However, for tasks that are more complex or interactive, the cognitive conflict might not always diminish the sense of presence. For example, the cognitive conflict has long been used as a strategy for encouraging students to examine their

[5] https://unity3d.com/

previous knowledge and to aim for conceptual change (Limón 2001). Extending this framework to address such complex scenarios is an exciting future research direction.

Chapter 7 : Conclusions and Future Work

This chapter presents the overall summary of all the findings of the research presented in this thesis. This chapter also proposes how this work can be further extended with the ongoing research and potential application in human and robot interaction.

7.1. Conclusions

Experiment 1 (Chapter 3): Evoking the cognitive conflict in virtual reality and evaluating visual appearance as modulating factors

The effect of different visual styles on the behavioral and cognitive processes of users in VR was investigated. An EEG-based experiment was conducted to evaluate how the rendering style of the users' avatar hand affected user behavior and electrophysiological responses towards a prediction error during object selection with direct 3D input in VR. The results suggested that the more realistic the virtual environment was, the more sensitive the users become to subtle errors, such as tracking inaccuracies, which concurs with the uncanny valley theory.

Following this, the effect of visual appearance on the cognitive conflict of participants was evaluated. Further investigations were performed to evaluate the role of intra-individual and inter-individual task completion times on the PEN and Pe in a virtual 3D object selection task. The intra-individual analysis was performed by dividing trials of each individual participant into short (fast) completion time and long (slow) completion time groups while inter-individual analysis was performed by dividing the participants into short (fast) and long (slow) trials. The regression analysis has been performed on these trials from intra-and inter-individual with PEN and Pe. The results both from intra- and inter analysis show that PEN and Pe were statistically significant modulated in slow trials compared to fast trials while Pe was modulated statistically significant in fast trials. These results clearly indicate that different visual and proprioceptive systems require different temporal integration to detect a cognitive conflict.

Experiment 2 (Chapter 4): Movement velocity and its implications

In this study, the role of movement-velocity on the PEN and Pe in a virtual 3D object selection task were investigated. An experimental scenario has been designed to invoke

the different velocity profile during object selection. Regression analysis was performed to investigate the relationship between fast and slow velocities with PEN and Pe, and the participants' responses with IPQ scores. The results showed that PEN/Pe was found to be modulated in slow corrective phase in fast trials while only Pe was found to be modulated in fast corrective phase in slow trials. The results also showed that PEN was originated in ACC due to cognitive conflict while the sense of awareness was reflected by PCC. On the other hand, the subjective measurement of the users' perception of realism and sense of agency showed to be statistically significantly correlated with PEN/Pe. It was also found that participant with the experience in gaming/VR might develop stronger sense toward slighter changes in the environment.

Experiment 3 (Chapter 5): Closed-loop brain-computer interface for cognitive conflict in VR

Based on the results from experiments 1 and 2, it is clear that PEN was modulated by several factors including visual appearance, completion time, movement velocity, and of course participants' past experience and perception toward VR. A BCI system has been designed and developed to assess and evaluate the cognitive conflict. The BCI system demonstrated that the participants' level of conflict could be evaluated while performing the 3D object selection task. It was also found that for some participants, the equivalent selection radius as cube radius is not necessarily the most suitable option during the 3D object selection task. Such case could still invoke the cognitive conflict compared to those where selection radius smaller or bigger than cube radius and thus clearly indicated the dependency on individual preferences and which should be taken care by VR content developers.

7.2. Future Work

A standard approach to evaluating cognitive conflict opens several applications and methodologies for the investigation of other important questions:

7.2.1. Evaluating the importance of different factors for 3D object selection

Researchers have long been curious about the relationship between levels of immersion and presence (Bowman & McMahan 2007). There have been many inspiring works in recent years that aimed to add different sensory feedback into VR and interaction design (Obrist et al. 2016). For example, Impacto (Lopes, Ion & Baudisch 2015) rendered haptic feedback with both solenoid and electrical muscle stimulation, Level-Ups

(Schmidt et al. 2015) adds a self-contained vertical actuator to the bottom of the foot, and HapticTurk (Cheng et al. 2014) replaces the motion platform with actual human motion. Most of these works relied on questionnaires and interviews to evaluate the effect of the feedback. However, most of them have a clear event, e.g., the time when the haptic feedback or motion feedback is applied, and the ERP associated with this cognitive conflict will be a useful tool for providing continuous user feedback to the system (Czigler, Balazs & Winkler 2002).

7.2.2. Manipulating sense

The proposed experimental methodology and its findings can also be used to evaluate the effectiveness and the range of recent works that manipulate the senses to overcome the constraints of physics, such as a limited number of props (Azmandian et al. 2016), limited space (Sun, Wei & Kaufman 2016), and cybersickness (Fernandes & Feiner 2016). Again, in these cases, by controlling the sources of the conflict, e.g., visual warping, it can estimate a reasonable range for subtle sense manipulation without being noticed or causing discomfort.

Appendix A: Tools Used

Appendix Table 1 provides a summary of software used throughout the experiments and data analysis.

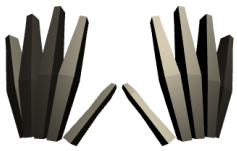
Appendix Table 1 Summary for software used during experiment and analysis

SN	Software name	Version	Purpose
1	MATLAB	R2014b (8.5); R2018b (9.5)	For EEG data analysis, graph plotting
2	EEGLab	12, 13 and 14	EEG analysis toolbox provided by Swartz Center for Computational Neuroscience (SCCN) to use with MATLAB
3	Unity	Unity 5.3.4f1	The cross-platform game engine used to develop VR based scenarios
4	Oculus SDK	SDK 0.8.0.0	Software development kit (SDK) is used to develop a VR scenario for Unity
5	Orion – Leap Motion	Orion 4.0.0	Orion is a Leap Motion SDK provide the support to develop and track immersive VR hands
6	IBM SPSS Statistics	Version 24	The software is used for statistical analysis
7	Parallel Port application	0.1	Customized in-home application to send event information from Unity based experimental scenario to Neuroscan device
8	Scan	2.0	Both of these software were used as an interface to record EEG data from 32 and 64 EEG electrodes
9	Curry	8	

Appendix B: Questionnaire for VR Testing

The following questionnaire was used in experiment 1 to evaluate the realism, suitability, dizziness, immersion, and cognitive conflict

1. Which hand style is more realistic (1 least realistic, 5 most realistic)

		
1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

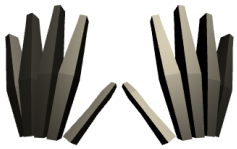
2. Which hand style is most suitable for target selection? (1 less suitable, 5 most suitable)

		
1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

3. Which hand style do you prefer for the given task? (1 less preferable, 5 highly preferable)

		
1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

4. We intentionally create a cognitive conflict by triggering the button “before” you touch the button. Please rank the **level of conflict** you feel for each hand style (1 means low level of conflict, 5 means high level of conflicts)

		
1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

5. Please rank the **level of dizziness** you feel for each hand style (1 means a low level of dizziness, 5 means a high level of dizziness)

1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

6. Please rank the **level of immersion** you feel for each hand style (1 means a low level of immersion, 5 means a high level of immersion

1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

Appendix C: BIS and BAS Questionnaire

The following questionnaire measured that BIS/BAS and has been used in experiment 1,

Each item of this questionnaire is a statement that a person may either agree with or disagree with. For each item, indicate how much you agree or disagree with what the item says. Please respond to all the items; do not leave any blank. Choose only one response to each statement. Please be as accurate and honest as you can be. Respond to each item as if it were the only item. That is, don't worry about being "consistent" in your responses. Choose from the following four response options:

1 = very true for me

2 = somewhat true for me

3 = somewhat false for me

4 = very false for me

1. A person's family is the most important thing in life.
2. Even if something bad is about to happen to me, I rarely experience fear or nervousness.
3. I go out of my way to get things I want.
4. When I'm doing well at something I love to keep at it.
5. I'm always willing to try something new if I think it will be fun.
6. How I dress is important to me.
7. When I get something I want, I feel excited and energized.
8. Criticism or scolding hurts me quite a bit.
9. When I want something I usually go all-out to get it.
10. I will often do things for no other reason than that they might be fun.

11. It's hard for me to find the time to do things such as get a haircut.
12. If I see a chance to get something I want I move on it right away.
13. I feel pretty worried or upset when I think or know somebody is angry at me.
14. When I see an opportunity for something I like I get excited right away.
15. I often act on the spur of the moment.
16. If I think something unpleasant is going to happen I usually get pretty "worked up."
17. I often wonder why people act the way they do.
18. When good things happen to me, it affects me strongly.
19. I feel worried when I think I have done poorly at something important.
20. I crave excitement and new sensations.
21. When I go after something I use a "no holds barred" approach.
22. I have very few fears compared to my friends.
23. It would excite me to win a contest.
24. I worry about making mistakes.

Appendix E: Presence Questionnaire

This questionnaire was designed to understand the participants' behavior in the VR environment and used in experiment 2 and 3.

Please answer all question only with reference to one single episode of interaction with a virtual environment

* Required

1. Participation ID *

_____

2. Name *

_____

3. Age *

_____

4. Gender * *Mark only one oval.*

- Female
- Male

5. Do you play video games at all? (whether online or offline) * *Mark only one oval.*

- Yes
- No

6. What type of game ? * *Mark only one oval.*

- Console Game
- PC Games
- VR Games
- All the above
- Not applicable

7. How many days of the week do you play video games? *Mark only one oval.*

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- Not applicable

8. On average, How many hours do you play video games per day? *Mark only one oval.*

- 1 or less
- 2 to 3
- 4 to 5
- 6 or more
- Not applicable

Characterise your experience in the environment, by marking the appropriate box of the 7-point scale, in accordance with the question content and descriptive labels. Please consider the entire scale when making your responses, as the intermediate levels may apply. Answer the questions independently in the order that they appear.

Do not skip questions or return to a previous question to change your answer.

9. How much were you able to control events? * *Mark only one oval.*

not at all completely

-3 -2 -1 0 +1 +2 +3

10. How responsive was the environment to actions that you initiated (or performed)? * *Mark only one oval.*

not responsive completely responsive

-3 -2 -1 0 +1 +2 +3

11. How natural did your interactions with the environment seem? * *Mark only one oval.*

extremely artificial completely natural

-3 -2 -1 0 +1 +2 +3

12. How much did the visual aspects of the environment involve you? * Mark only one oval.

not at all completely

-3 -2 -1 0 +1 +2 +3

13. How natural was the mechanism which controlled movement through the environment? * *Mark only one oval.*

extremely artificial completely natural

-3 -2 -1 0 +1 +2 +3

14. How compelling was your sense of objects moving through space? * *Mark only one oval.*

not at all very compelling

-3 -2 -1 0 +1 +2 +3

15. How much did your experiences in the virtual environment seem consistent with your real world experiences? * *Mark only one oval.*

not consistent very consistent

-3 -2 -1 0 +1 +2 +3

16. Were you able to anticipate what would happen next in response to the actions that you performed? *Mark only one oval.*

not at all completely

-3 -2 -1 0 +1 +2 +3

17. How completely were you able to actively survey or search the environment using vision? * *Mark only one oval.*

not at all completely

-3 -2 -1 0 +1 +2 +3

18. How compelling was your sense of moving around inside the virtual environment? * *Mark only one oval.*

Not compelling very compelling

-3 -2 -1 0 +1 +2 +3

How closely were you able to examine objects? * Mark only one oval.

not at all very closely

-3 -2 -1 0 +1 +2 +3

20. How well could you examine objects from multiple viewpoints? * *Mark only one oval.*

not at all extensively

-3 -2 -1 0 +1 +2 +3

21. How involved were you in the virtual environment experience? * *Mark only one oval.*

not involved completely engrossed

-3 -2 -1 0 +1 +2 +3

22. How much delay did you experience between your actions and expected outcomes? * *Mark only one oval.*

no delays long delays

-3 -2 -1 0 +1 +2 +3

23. How quickly did you adjust to the virtual environment experience? *
Mark only one oval.

not at all -3 -2 -1 0 +1 +2 +3 less than a minute

24. How proficient in moving and interacting with the virtual environment did you feel at the end of the experience? * *Mark only one oval.*

not proficient -3 -2 -1 0 +1 +2 +3 very proficient

25. How much did the visual display quality interfere or distract you from performing assigned tasks or required activities? * *Mark only one oval.*

not at all -3 -2 -1 0 +1 +2 +3 prevented task performance

26. How much did the control devices interfere with the performance of assigned tasks or with other activities? * Mark only one oval.

not at all -3 -2 -1 0 +1 +2 +3 completely

27. How well could you concentrate on the assigned tasks or required activities rather than on the mechanisms used to perform those tasks or activities? * Mark only one oval.

not at all -3 -2 -1 0 +1 +2 +3 completely

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