The Impact of Hand Movement Velocity on Cognitive Conflict Processing in a 3D Object Selection Task

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Abstract

Detecting and correcting incorrect body movements is an essential part of everyday interaction with one's environment. The human brain has a constant monitoring system that controls and adjusts our actions according to our surroundings. However, when our brain's predictions about a planned action do not match the sensory inputs resulting from that action, cognitive conflict occurs. Much is known about cognitive conflict in 1D/2D environments; however, less is known about the role of movement characteristics on cognitive conflict in 3D environment. Hence, we devised an object selection task in a virtual reality environment to test how the velocity of hand movements impact a number of brain responses. From a series of analyses of EEG recordings synchronized with motion capture, we found that the velocity of the participants' hand movements modulated the brain's proprioception during the task and induced prediction error negativity. Additionally, prediction error negativity originates in the anterior cingulate cortex and is itself modulated by the ballistic phase of the hand's movement. These findings suggest that velocity is an essential component of integrating hand movements with visual and proprioceptive information during interactions with real and virtual objects.

Keywords – virtual reality, EEG, cognitive conflict, PEN, Pe, velocity

Introduction

Several mechanisms are involved when a human interacts with their environment, each making use of information from different sensing modalities, such as visual cues and proprioception (Scheidt, Conditt, Secco, & Mussa-Ivaldi, 2005). These sensory modalities serve the brain's monitoring system, which instructs, plans, and executes interactions (Ozkan & Pezzetta, 2018). Importantly, this monitoring is constant to ensure one's perceptions of their surroundings are continually updated to match reality (Padrao, Gonzalez-Franco, Sanchez-Vives, Slater, & Rodriguez-Fornells, 2016). Should a change occur 'mid-strategy', i.e., during the process of planning and executing an interaction, the result is a mismatch

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response known as cognitive conflict (Fan, Flombaum, McCandliss, Thomas, & Posner, 2003; Singh et al., 2018). The human brain makes predictions about the outcome of an interaction, continuously comparing perceived information to that prediction, and when the prediction fails to hold, conflict occurs.

Cognitive conflict was first discussed in an article by Donchin et al. (1988) and republished in Donchin & Coles (2010). While there was no specific mention of event-related potential (ERP) related to an error, the work of Donchin and colleagues described P300 amplitude modulations due to changes in the environment. Later, Coull & Nobre (1998) show that cognitive conflict causes one to redirect attention and reconfigure their initial plan, causing higher cognitive resources than non-conflict. In subsequent years, an experimental task was devised, known as the bimanual choice reaction task, which revealed that cognitive conflict causes a sequence of two types of ERP. First, the erroneous response causes error-related negativity (ERN or Ne), which is a negative ERP typically peaking at around 50–150 ms (M. Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991; William J. Gehring, Goss, Coles, Meyer, & Donchin, 1993). This is followed by error-related positivity (Pe) after the erroneous response begins, which typically peaks at around 200–400 ms. Since this discovery, several experimental scenarios have been developed to test and demonstrate ERN and Pe. These scenarios include tasks like the Eriksen flanker task (Eriksen & Eriksen, 1974; Kopp, Rist, & Mattler, 1996), the oddball task (Halgren, Marinkovic, & Chauvel, 1998; Squires, Squires, & Hillyard, 1975), and the Stroop task (Stroop, 1935; West & Alain, 1999). Some other variants of ERN include feedback-related negativity (FRN) (Holroyd & Coles, 2002), and observational error, due to a person observing another person making an error (van Schie, Mars, Coles, & Bekkering, 2004).

However, most of the experiments, protocols, and findings described above only pertain to passive one-dimensional (1D) or two-dimensional (2D) stimuli and cannot necessarily be generalized to a three-dimensional (3D) world. A realistic 3D input, for example, grasping a bottle on a table in front of you, adds significant complexity to an interaction task given the computations need to move one's body parts through space.

At the same time, realistic 3D interactions provide a window of opportunity to understand better the brain's monitoring function and how it conducts complex monitoring of the real world (Jungnickel & Gramann, 2016). One of the most basic 3D interactions is object selection task (Argelaguet & Andujar, 2013). To grasp an object in the 3D world using the hand, the user is required to perform a set of complex movements that involves positioning their palm and fingers over the object. Our previous work with a 3D object selection task demonstrated that changing the selection radius of a virtual cube could lead to a mismatch between the visual and the proprioceptive feedback, invoking cognitive conflict (Gehrke et al., 2019; Singh et al., 2018). We found the conflict reflected a form of prediction error negativity (PEN) that seems to belong to the same class of ERP as the ERN and FRN found in the studies mentioned above. Additionally, the results indicate that sensory integration plays an essential role in monitoring and producing ongoing actions, particularly for 3D object selection. Our findings also suggest that visual feedback dominated proprioceptive feedback in participants who completed the task in a short amount of time. We conclude that proprioceptive feedback is more important for slower movements. However, limitations in the data did not allow us to analyze hand movement velocity and its role in integrating visual and proprioceptive information.

To overcome the limitations of our previous studies and to further investigate the role of movement velocity on the electrocortical responses to cognitive conflict, we manipulated hand movement velocity. Our intuition is that the velocity at which a hand moves does impact cognitive conflict processing in 3D object selection tasks. Hence, to test this hypothesis, we devised a task to measure hand movement velocity in tandem with electrocortical responses to cognitive conflict. The methods, results, and findings from this experiment are presented in this paper.

Materials and methods

Participants

To determine the effect of movement velocity on the amplitude of PEN, we recorded EEG data from 20 participants (2 females and 18 males). The mean age of the participants was 23.3 years, with a range of 18-30 years. The velocity of the hand's movement was deemed to have an effect on PEN at more than 0.99 ($F(1,17) = 89.454$, $p < .001$) – a large effect, according to Green et al. (1997). Before participating in the study, each participant was given a full explanation of the experimental procedure, and each provided informed consent. Ethics approval was issued by the Human Research Ethics Committee of the University of Technology Sydney, Australia. The experiment 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.

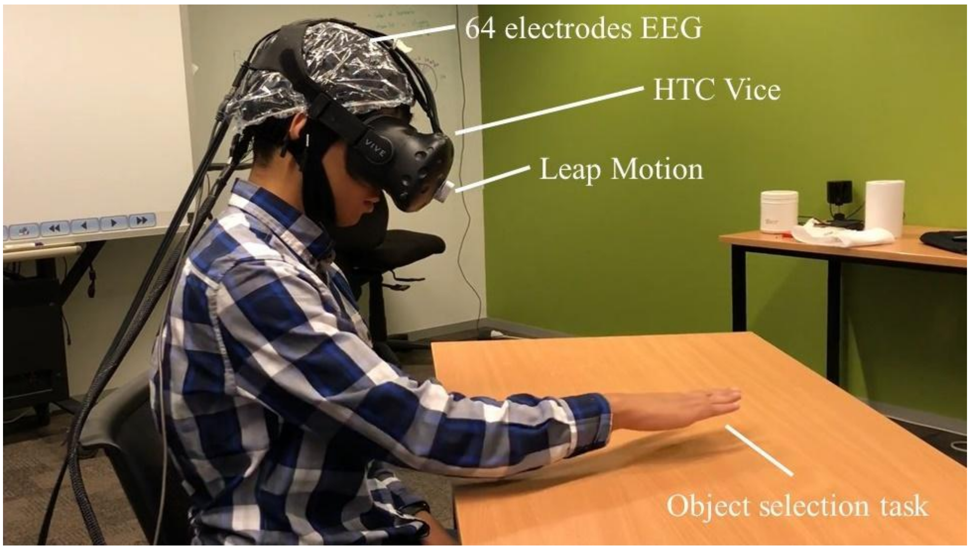

Figure 1. A participant performs the 3D object selection task with an HTC Vive head-mounted display and a Leap Motion controller while wearing the 64-electrode EEG cap

VR setup

The VR environment was provided through an HTC Vive head-mounted OLED display with a resolution of 2160 x 1200 and a refresh rate of 90 Hz (HTC Corp., Taiwan). The participants' head positions were tracked with embedded IMUs, while an external Lighthouse tracking system cleared the common tracking drift with a 60 Hz update rate.

Hand motions were recorded with a Leap Motion controller (Leap Motion Inc., USA) attached to the front of the HTC Vive that 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, Bachmann, Rudak, & Fisseler, 2013), and the latency has been reported to be approximately 30 milliseconds (Bedikian, 2013).

EEG setup

The EEG data were recorded from 64 Ag/AgCl electrodes, which were referenced to an electrode placed between locations Cz and CPz. The placement of the EEG electrodes was consistent 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) with a digital sample rate of 1 kHz in 16-bit resolution.

First, the participants were equipped with an EEG cap and an additional separator cap (a plastic shower cap) to reduce electrolytes polluting the VR equipment. The head-mounted display was placed on top of the separator cap (see Figure 1). To ensure the participants had a better VR experience, we installed a table similar to the one used in the VR environment. The height of the table in both worlds was the same so participants were not able to distinguish between the real and the virtual environment.

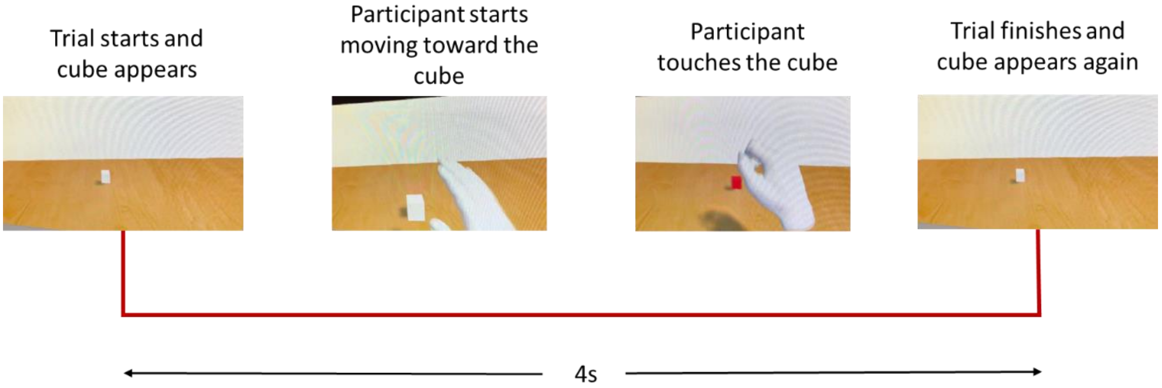

Figure 2 Experiment scenario for a single trial

The experiment scenario

Each participant performed the 3D object selection task with their dominant hand tracked. Figure 2 displays a scenario for a single trial. Each trial was four seconds long. The scenario starts with instructions about the task, and the experiment starts once the participant confirms they have understood the instructions. As the task begins, a cube appears on the table, which the participants must reach out and touch. The cube turns red when touched as a feedback signal. Participants were expected to finish the task within 4 seconds; otherwise, the trial was marked as incomplete.

The experiment was designed with two degrees of difficulty – a small cube (*d*) and a big cube (*D*) – which each produce a distinct velocity profile based on Fitts's law (Soukoreff & MacKenzie, 2004). Selecting a small cube is more difficult than selecting a big cube as the endpoint of the movement requires more finely-grained motor adjustments; the result is a slower velocity.

The selection distance of the cubes, defining the collision between endpoint of the moving hand to the cube, changed in 25% of the trials, such that 75% of the trials used distance D1/d1 and the remaining trials used distance D2/d2. The cube was also placed in three positions: center, 30° to the left at the same radius and 30° to the right. This created variety in the velocity profiles and kept the participants engaged. See Figure 3 for details.

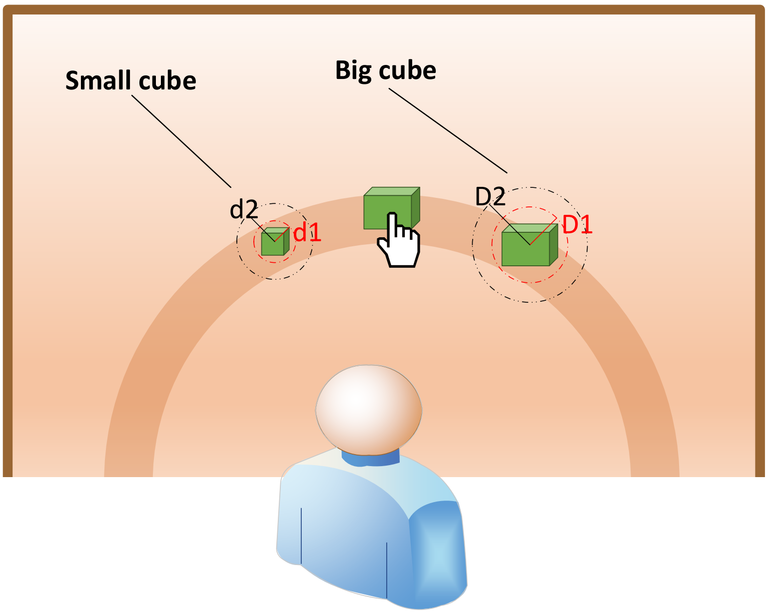

Figure 3. A schematic representation of the 3D object selection task. A small or a big cube randomly appears at one of three possible locations equidistant from the participant. D1 and d1 are the radii for the cube placement in the no-conflict trials. D2 and d2 are the radii for the cube placement in the conflict trials.

While there is no standard method for measuring the presence in immersive virtual environments, most researchers use questionnaires to assess self-reports from users. In the current experiment, a modified version of Igroup presence questionnaire i.e., IPQ (Schubert, 2003), together with the participant's experience of game playing, was used to measure the presence of participants. The questionnaire comprised a total of 24 questions to be answered on a seven-point Likert scale. At the end of the experiment, each participant completed a 24-item IPQ asking them to rate different parameters of the experiment on a 7-point Likert scale, such as realism, experience and controlling events, to yield a possible result of between 7 and 98. Additionally, the IPQ included a space asking them to state their previous experiences with game playing to help assess their overall proficiency with VR scenarios.

The experiment design was based on a 2 X 2 repeated measures with two factors: a) the conditions – no-conflict and conflict; and b) the size of cubes – small and big. The experiment was conducted over two sessions, each session comprising 250 trials over a duration of about 16 minutes. The full experiment for each participant took about 1.5 hours, including the initial setup of the EEG cap and head-mounted display, the trials, and completing the questionnaire.

Data Analysis

EEG data analysis

We used EEGLAB toolbox (Delorme & Makeig, 2004) in MATLAB 2016 (MathWorks Inc, USA) to process the EEG data. The raw EEG signals were filtered using a 0.1-Hz high-pass and 40-Hz low-pass FIR filter and subsequently downsampled to 250 Hz. The resulting data were inspected to identify and remove noisy electrodes using the Kurtosis method, followed by an ICA (Makeig, Bell, Jung, & Sejnowski, 1996) and equivalent dipole model fitting based on the scalp topographies of individual independent components (ICs) (Scherg, 1990). The resultant ICs were further processed to detect artifact-related ICs using the SASICA plugin (Chaumon, Bishop, & Busch, 2015), which uses autocorrelation, focal ICs, eye blinks, and information from the ADJUST plugin (Mognon, Jovicich, Bruzzone, & Buiatti, 2011) to identify ICs representing artifacts. These ICs were marked and excluded from the final data. On average, 19.80 ± 8.82 ICs were removed, and the data was back-projected to the sensor level. The back-projected data were epoched from 500 ms prior to touching the cube to 1000 ms after the touch event for all conditions, as well as being inspected again for artifacts using the Kurtosis method. On average, $19.84 \pm 10.04\%$ epochs were removed.

The components of all the participants were clustered using k-means based on their similarity with respect to the ERP, power spectrum, and ERSP, plus the component scalp maps, their equivalent dipole and corresponding dipole locations for each participant. Our more in-depth analysis focuses on clusters with IC components located in or near the cingulate cortex. It is well-known that the anterior cingulate cortex (ACC) plays a significant role in cognitive conflict (Schlüter et al., 2018). The clustered components were further used to compute event-related spectral perturbations (ERSP) and to extract the PEN and Pe from the back-projected ERPs. PEN was calculated as the minimum amplitude in a search window of 50-150ms after the touch event calculated as the mean of the minimum ±2 adjacent sample points. Similarly, Pe was calculated as the mean of the maximum in a 250-350ms search window after the touch event, including ±2 adjacent sample points.

Behavior data analysis

Task completion time

Task completion time was calculated as the difference between the time the cube appeared until the cube changed color.

Hand motion trajectory data

Velocity, hand position (palm, finger, etc.), the number of frames in each VR scene, and the time required for each frame were recorded for each participant. The primary focus of this experiment was to understand how the velocity profile affects PEN. Therefore, the magnitude of velocity and acceleration were calculated for each trial. The hand movement velocity has been divided into two parts based on the maximum peak of the velocity over the trial. The velocity before the peak is known as the ballistic phase of hand-movement velocity. The velocity after the peak is known as the corrective phase of hand-movement velocity.

Statistical analysis

The statistical analyses were conducted using SPSS (IBM SPSS Inc Version 24). The analysis of variance (ANOVA) was computed 2 x 2 with the condition and cube size factors. Further, we conducted an analysis of covariance (ANCOVA) to check whether the task completion times for the small and big cubes affected the group difference between the no-conflict and conflict trials.

Regression analysis

The multiple linear regression was also conducted using SPSS (IBM SPSS Inc Version 24) for PEN and Pe w.r.t. the conflict/no-conflict condition. The entered variables were in the following order: the velocity of the hand's movement during the ballistic phase, the VR quality score (QVR), the VR quality self-evaluation score (SVR), realism, the possibility of action in VR (PAVR) score, and the task completion time. We also performed another regression analysis swapping the order of the ballistics velocity with the task completion time. The results of the second regression analysis have been reported in the supplementary materials.

Correlation analysis

We tested the relationship between the ERSP for the delta, theta, alpha, and beta power bands and the ballistic phase of the hand movement velocity with a Pearson's correlation analysis.

Results

Behavior results

Figure 4 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 2 (cube sizes) x 2 (conditions). There was a significant difference for both the conditions ($F(1, 18) = 191.074$, $p < .001$) and the cube sizes ($F(1, 18) = 302.815$, $p < .001$). The two main effects were qualified by their interaction cube sizes * conditions ($F(1, 18) = 5.358$, $p = .032$). Tukey post hoc tests revealed no significant difference in task completion time ($p = .178$) in the no-conflict trials with the small and big cubes. There was also no significant difference ($p = .085$) in task completion time for the conflict and no-conflict trials. However, there was a significant difference ($p < .001$) between the task completion time for the small and big cubes.

We also plotted the overall velocity pattern to see how it changed over time. Figure 5 (NS & NB) shows the hand's trajectory initially increased sharply for about 20-25 frames, which is known as the ballistic phase, then slowly decreased until a cube was selected. According to the optimized initial pulse model, this decrease is known as the corrective phase (Meyer, Abrams, Kornblum, Wright, & Smith, 1988). The trajectories for the small and big cubes in the no-conflict trials were quite similar. However, as can be seen from Figure 5 (CS & CB), with the small cubes, the participant steadily increased velocity until the ballistic phase then decreased pace during the corrective phase until the cube was selected. By contrast, with the big cubes, there was still a sharp increase in the ballistic phase, but the decrease in the corrective phase was very steady compared to the small cubes. This is likely because, with a big target, the participants were less precise with their hand movements in the ballistic phase, resulting in more corrective movements needed in the corrective phase, as opposed to the more careful approach from the outset with the smaller cubes.

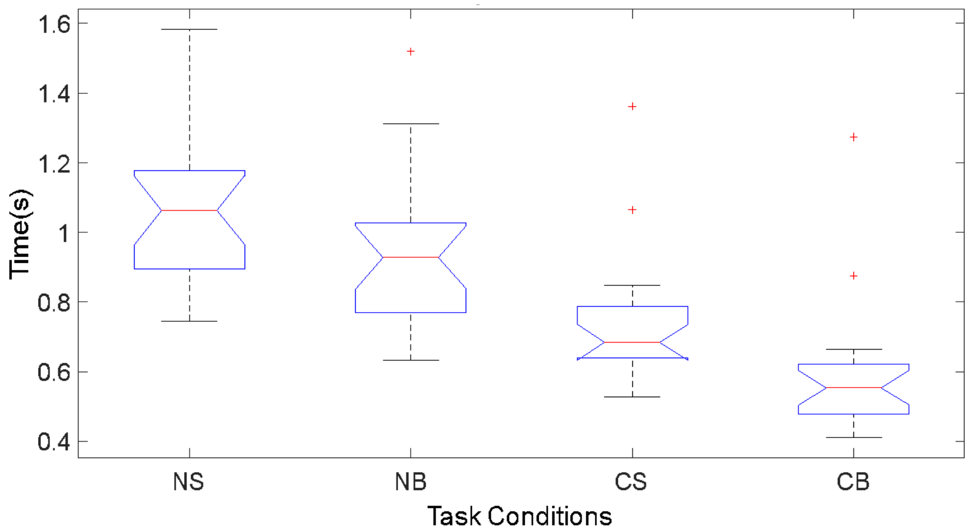

Figure 4. The task completion time for all conditions. NS) no conflict trials with small cubes; NB) no conflict trials with big cubes; CS) conflict trials with small cubes; CB) conflict trials with big cubes.

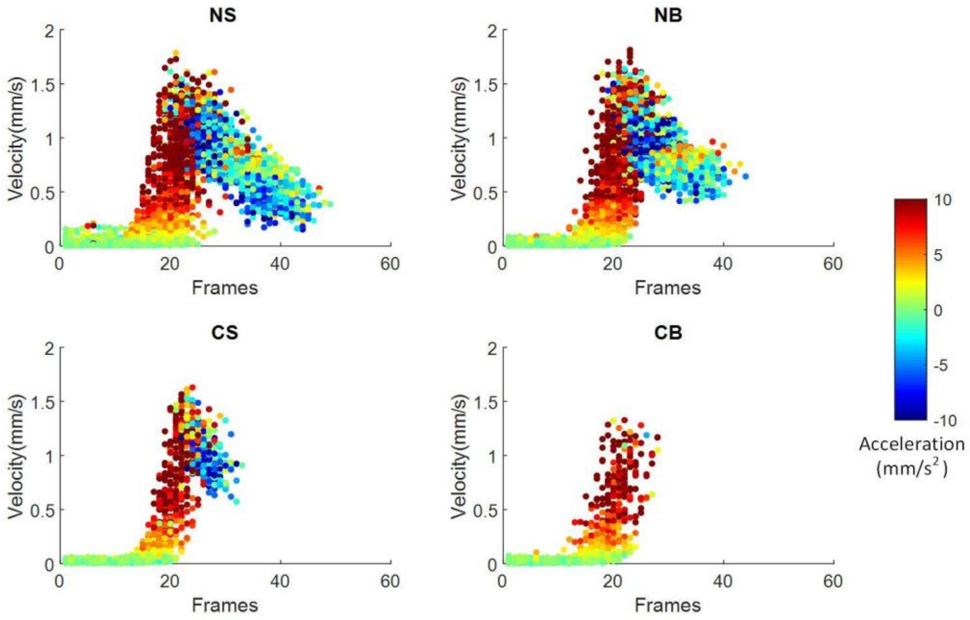

Figure 5. Hand movement trajectories for all conditions for one exemplary participant. NS) no conflict trials with small cubes; NB) no conflict trials with big cubes; CS) conflict trials with small cubes; CB) conflict trials with big cubes

EEG Results

Figures 6 and 7 show the topographical plots of the PEN and Pe, respectively. An independent samples t-test of the PEN component for both conditions indicate a significant difference in PEN at FCz in both the no-conflict and conflict trials with both the small cubes ($t(17) = -3.612$, $p = .002$) and the big cubes ($t(17) = -2.575$, $p = .020$). Similarly, there was a significant difference in Pe at channel FC6 in both the no-conflict and conflict trials with both the small cubes ($t(17) = 2.178$, $p = .044$) and the big cubes ($t(17) = -3.402$, $p = .003$).

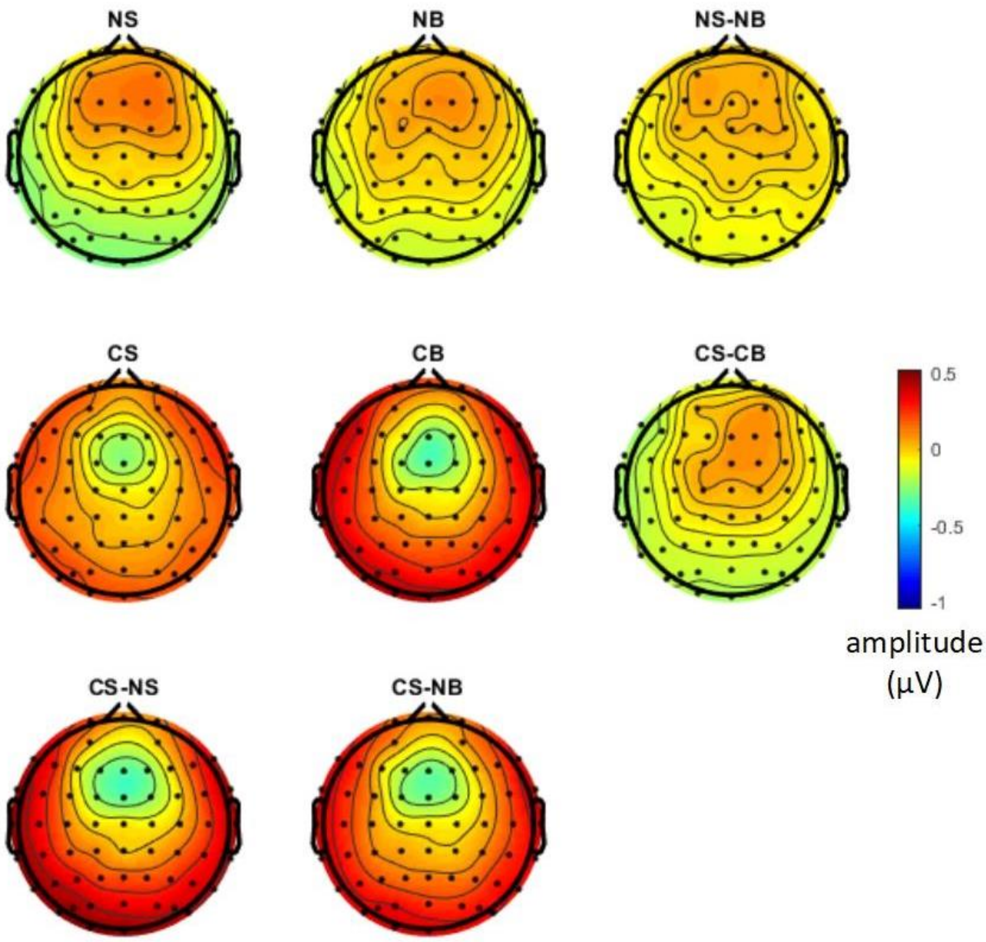

Figure 6. Topographical plots of PEN

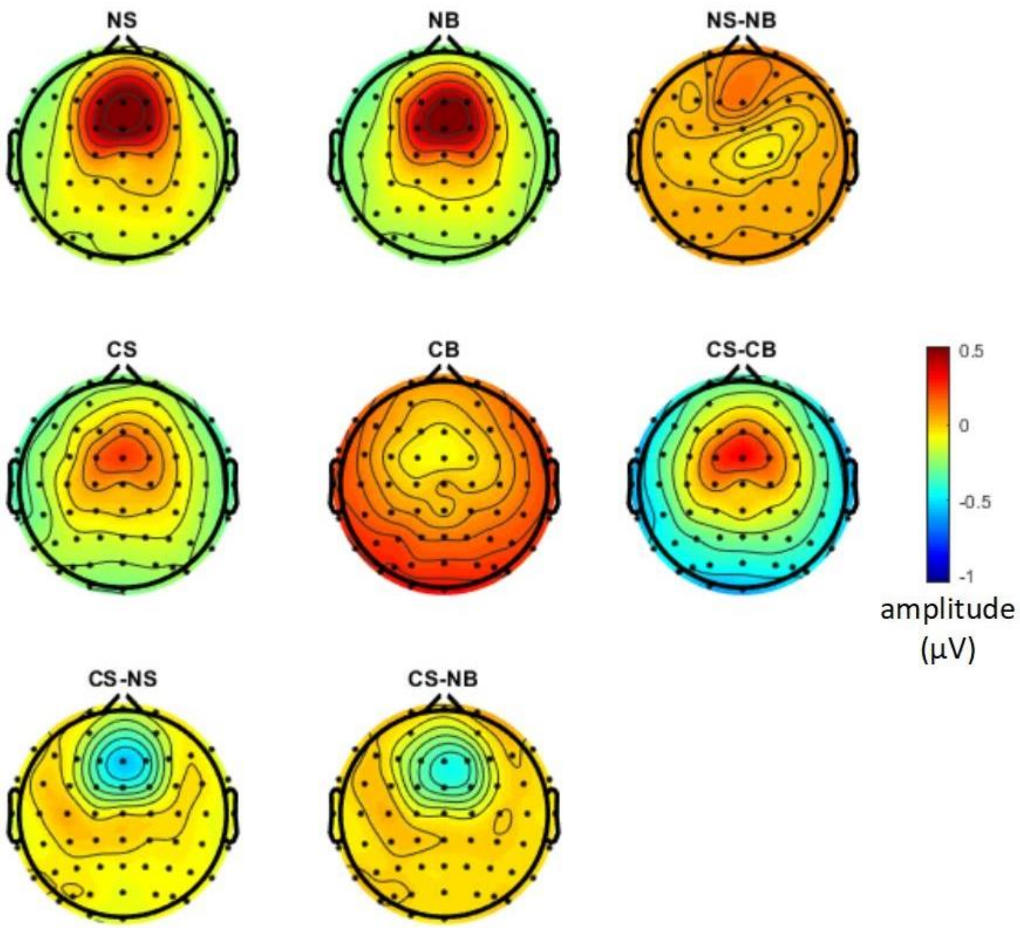

Figure 7. Topographical plots of Pe

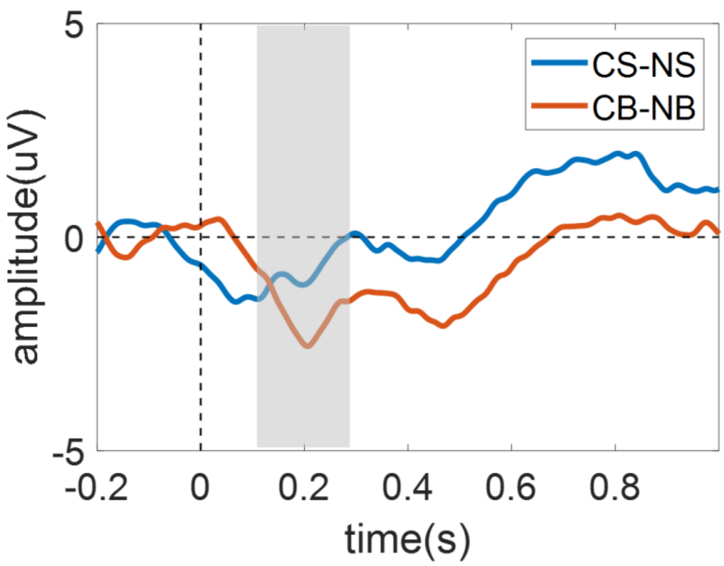

Figure 8. The difference in ERP between the no-conflict and conflict trials with the small and big cubes

As indicated from the topographical plots, the average ERP for all participants was evaluated for the frontocentral region at FCz. Figure 8 shows there was a significant difference in amplitude from 50 to 250ms between the no-conflict and conflict trials.

Further, to evaluate the potential source of the PEN, we performed dipole modeling over the individual ICs. Given every participant had a different set of ICs, we used a neural network-based clustering approach, implemented in EEGLab, to identify the most representative IC profile (Montgomery, Huang, & Assadi, 2005). Using features from the event-related spectral perturbations, inter-trial coherence, and event-related potential, the approach was able to cluster the components shared by approximately 70% of the participants. By inspecting the properties of the different clustered ICs in the frontocentral region, we were able to extract the clusters in the ACC with MNI coordinates of x=-6, y=10, and z= 24). This ACC cluster is shown in Figure 9.

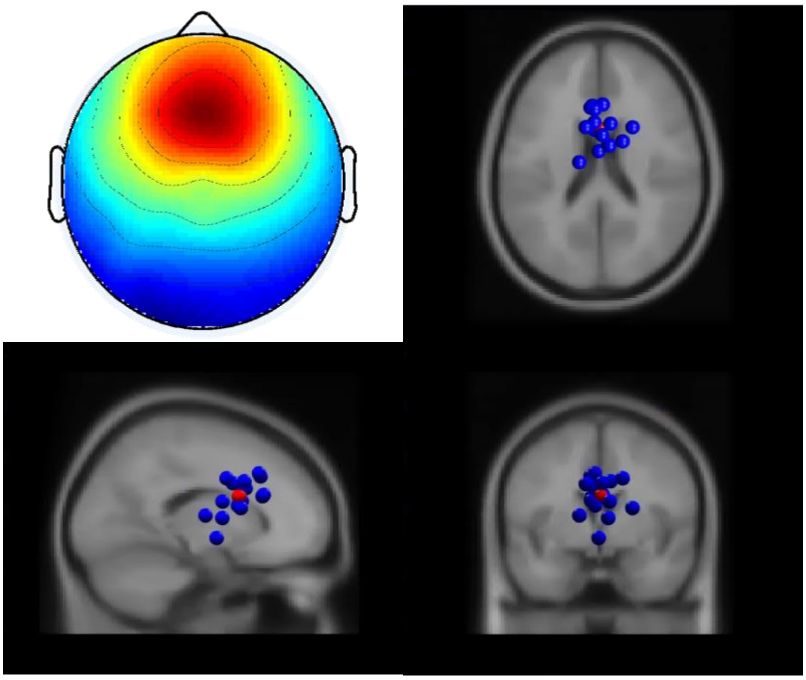

Figure 9. The anterior cingulate cortex and its dipole clusters from all participants (MNI coordinates x=-6, y=10, and z= 24)

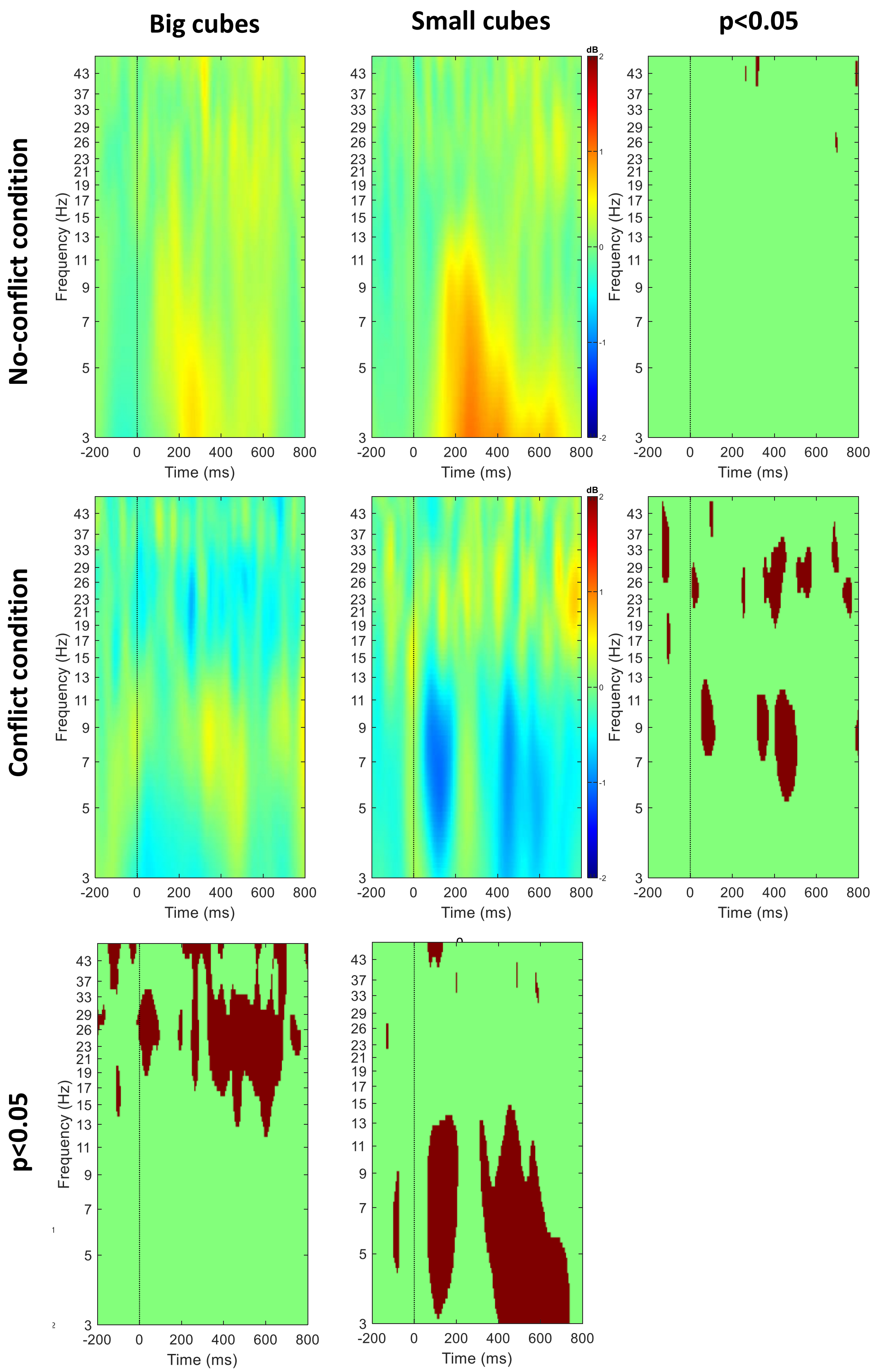

Figure 10. Event-related spectral perturbations and statistical results for the big/small cube and conflict/no-conflict conditions

To understand the effect of 3D object selection over time, we calculated the ERSP for the selected ACC component. As shown in Figure 10, in the conflict trials with the small cubes, there was substantial suppression in alpha band power between 50-150ms and in both the theta and alpha band at 400-700ms, which did not occur in the no-conflict trials. By contrast, in the conflict trials with the big cubes, there was suppression in beta band power at around 0-100ms and 300-600ms.

Analysis of covariates

This analysis was to determine whether task completion time had any effect on the PEN and Pe amplitudes for the different cube sizes. Based on an ANCOVA with task completion time as the covariate, we found no significant effect on PEN with the small or big cubes in either the conflict trials (F (1 , 34) = 2.188, p = .149) and the no-conflict trials (F (1 , 34) = 1.948, p = .172). The same was true for Pe (F (1, 34) = 0.019, p = .892) for the conflict trials and (F (1 , 34) = 0.997, p = .325) for the no-conflict trials.

Regression analysis

To understand the relationships between the subjective and behavioral data of the PEN and Pe amplitudes, we performed a regression analysis with the following results.

A linear regression established that the ballistic phase, together with the behavioral measures quality of virtual reality (QVR) and self-evaluation of virtual reality (SEVR), can predict PEN in conflict trials with small cubes (F (3, 17) = 4.455, p = .021). If realism, possibility to act in virtual reality (PAVR), and task completion time and the ballistic phase, QVR and SEVR can also predict PEN in conflict trials with small cubes (F (6, 17) = 3.248, p = .043). However, we observed no such covariation for Pe in conflict trials with small cubes (F (6, 17) = .937, p = .507). The ballistic phase, together with QVR and SEVR, accounted for 48.8% of the variance in PEN amplitude. Including realism, PAVR, and task completion time raised that level to 63.9% of the variance. The regression equation to predict the PEN with small cubes was as follows:

$$PEN_{small\ cube} = -3.481 - 6.195 * BV + 0.147 * QVR + 0.151 * SEVR$$

where BV = ballistic of hand movement velocity, QVR = quality of virtual reality scene, SEVR = self-evaluation of virtual reality scene.

Similarly, a linear regression established that the ballistic phase, together with the behavioral metrics taken from the IPQ, could predict the PEN amplitudes in the conflict trials with the big cubes at a statistically significant level (F (3, 17) = 3.880, p = .033). Again, when including realism, PAVR, task completion time, and the ballistic phase, QVR and SEVR could also generate an accurate prediction (F (6, 17) = 1.903, p = .043).

Notably, the ballistic phase alone was able to predict Pe amplitudes in conflict trials with big cubes at significant levels (F (1, 17) = 6.318, p = .023). The ballistic phase, together with the IPQ metrics, accounted for 45.4% variability in the PEN amplitude but only 28.3% for the Pe amplitude. The regression equation to predict PEN with big cubes was as follows:

$$PEN_{big\ cube} = -5.706 - 8.286 * BV - 0.132 * QVR + 0.307 * SEVR$$

where BV = ballistic velocity of the hand's movement, QVR = quality of virtual reality scene, SEVR = virtual reality scene self-evaluation

The regression equation to predict Pe with big cubes was as follows:

$$Pe_{big\ cube} = -0.966 + 8.112 * BV$$

where BV = ballistic velocity of the hand's movement

Correlation between velocity and spectral power

The Pearson's correlation between the spectral powers (delta, theta, alpha, and beta) and the ballistic phase in the no-conflict trials with small cubes suggests that the ballistic phase is significantly correlated with the alpha band (r = - .200, n = 185, p = .006) and the beta band (r = -.181, n = 185, p = .014). However, we found no significant correlation for the conflict trials with small cubes. Yet with big cubes and the conflict trials, we found a statistically significantly correlation between the ballistic phase and the delta band (r = - .254, n = 61, p = .048) plus the theta band (r = - .323, n = 61, p = .011). No correlation was found in the no-conflict trials with big cubes.

Discussion

We hypothesized that the velocity of the hand's movement impacts cognitive conflict processing in 3D object selection and, more specifically, PEN and Pe. To test this hypothesis, we designed a modified version of the 3D object selection task outlined in Singh et al. (2018) to produce two distinct hand movement velocity profiles based on different cube sizes and different collider radii to create cognitive conflict.

Hand movement velocity and its effect on PEN and Pe

The hand movement trajectories indeed showed that two distinct velocity profiles for the big and small cubes. Participants typically completed the task with the big cubes more quickly. In the no-conflict trials with cubes of both sizes, participants tended to initially accelerate their hand, followed by a deceleration before touching the cube. However, with the small cubes, both phases were steady, but with the big cubes, they were initially sharp before steadying as they approached the cube. This phenomenon supports Meyer et al.'s (1988) optimized initial pulse model (OIPM), suggesting that a hand's movement trajectory when interacting with a 3D object consists of a ballistic phase followed by a corrective phase. We found this phenomenon evident in all no-conflict trials with both small and big cubes and in conflict trials with small cubes only. (See Figure 5)

However, the conflict trials for the big cubes only had a ballistic phase. As shown in Figure 5, there was almost no corrective phase. This may be because the big cubes had a large selection radius to generate premature touch feedback, creating cognitive conflict. Therefore, there was not enough remaining execution space to correct the hand's trajectory. We also found higher theta power in these experiments and, as claimed by Kalfaoğlu, Stafford, & Milne (2018), uncorrected errors result in greater modulations in theta power than corrected errors. Therefore, our findings of higher theta power coupled with no corrective phase, i.e., uncorrected errors, support their argument.

The results from the conflict trials with big cubes showed a significant difference in higher theta and alpha powers just after the color change feedback, unlike the small cubes (see Figure 10). The difference appeared before 50ms, which meant the participants did not have a chance to correct their movements. However, the participants were more careful with the small cubes from the outset, which mean they did not require as many adjustments in the corrective stage. This again serves as extended proof that the OIPM model holds in the 3D object selection tasks (Meyer et al. 1988; Argelaguet & Andujar 2013).

Beyond the different velocity profiles, these different hand trajectories resulted in distinct PEN and Pe amplitudes in the ERP in the conflict trials but not in the no-conflict trials. Our results also show that PEN amplitude was significantly higher with the big cubes than small cubes. This is again in line with the OIPM model, which further suggests that easy target selection requires less correction and adjustment during the ballistic phase but more correction and adjustment in the corrective phase. Therefore, the higher PEN amplitude in the conflict trials with big cubes could be due to the lack of a corrective phase.

Another explanation could be the brain's cognitive control and information processing circuit (Gabriele, 2018). This circuit comprises a sensory and motor system that gathers information about the environment and monitors and control one's body to accommodate unexpected situations like cognitive conflict. As mentioned, in our object selection task, the participants spent less time selecting the big cubes compared to the small cubes in the conflict trials, as shown in Figure 4. Therefore, certain sensory information in the brain, particularly proprioceptive information, was not the same before touching the big cubes as compared to the small ones. This might be reflected in the ERP as a higher PEN with the big cubes than the small, as shown in Figure 8. By contrast, we found no significant difference in Pe between the big and small cubes. This may be due to the role of the visual sensory system, which was engaged continuously during the selection task and did not have a substantial impact on the time to completion (Polich, 2007).

Origin of cognitive conflict, event-related spectral perturbation, and its correlation with the hand's velocity

Several past studies have demonstrated that the cognitive conflict originates in ACC and is also a contributor to the family of event-related errors that includes PEN (Carter et al. 1998; Devinsky, Morrell

& Vogt 1995; van Veen et al. 2001). Our tests that localize EEG data with ICA (Makeig et al. 1996) and dipole fit (Scherg 1990) concur with those findings. ACC was found to be activated in most participants as they performed the 3D object selection task (see Figure 9). This strengthens proof that ACC is indeed involved in the cognitive process. ACC is the vital hub behind our ability to handle situations of cognitive conflict (Carter et al., 1998; Umemoto, Inzlicht, & Holroyd, 2018). ACC is also known to interact with motor controls in a bottom-up fashion (Rauss & Pourtois 2013). That cognitive conflict originates in ACC is also aligned with other related tasks, such as action monitoring (Botvinick et al. 2001), observational errors (van Schie et al. 2004), and prediction errors (Ozkan & Pezzetta 2018; Singh et al. 2018).

To further verify the origin of cognitive conflict, we looked at ERSP in ACC. The results show that frontal theta and alpha power are modulated by cognitive conflict responses in the participants (see Figure 10). Modulations in theta power accord with existing theories of frontal theta power variations during tasks that involve cognitive conflict (Arrighi et al. 2016; Zhang et al. 2018). However, we find one point of difference. Our results show that theta power decreases in situations of cognitive conflict while existing results show an increase – assumed to be the result of phase resetting over a sudden change in behavior, like cognitive conflict, which generates error-related negativity (Luu, Tucker, & Makeig, 2004; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010). We find evidence to dispute this claim in that phase resetting does not always generate ERN (Yeung, Bogacz, Holroyd, Nieuwenhuis, & Cohen, 2007). Hence, our result supports the Yueng et al. (2007) theory. It seems that the PEN evoked in our experiments was not the result of phase resetting in theta power given conflict conditions. Markedly, such arguments further raise a question about why theta power phase resetting did not occur. This requires further experimentation and investigation.

In addition to the theta power modulations discussed in the previous section, modulations in alpha power are also known to be related to errors (van Driel, Ridderinkhof & Cohen 2012). Several previous works suggest that the alpha power modulation could be results of attention and perception (Den Ouden, Kok & De Lange 2012), self-awareness (Devinsky, Morrell & Vogt 1995), and the observer's relationship with the person performing the task (Kang, Hirsh & Chasteen 2010). We found significantly more alpha power modulation in the conflict trials with the small cubes than the big cubes. This is potentially due to the higher attention requirements from the very beginning of hand movement, which is also in line with attentional process theory (Pfurtscheller 2003). Interestingly, the small cubes in the no-conflict trials also showed a significant correlation between the ballistic phase and alpha and beta power. Alpha and beta power are often associated with focused attention and motor inhibition (Foxe & Snyder, 2011; Horimoto, Inagaki, Yano, Sata, & Kaga, 2002; Neuper & Pfurtscheller, 2001), which were both required for our 3D object selection task. Nevertheless, there is still the question of why the same is not true for the conflict trials. The reason could be the dominance of theta power where cognitive conflict exists, which might dissipate the effects of other power bands.

We also found a correlation between delta power and the ballistic phase in the conflict trials with big cubes. The delta power band plays an essential role in the inhibition process, such as cognitive conflict (Harmony, 2013). Due to the lack of corrective phase, the participants may have needed to inhibit their actions over quite a short period, which would explain such a correlation.

Modeling the relationship between PEN, Pe and hand movement velocity, task completion time, and IPQ scores

The results from the regression analysis indicate that the ballistic phase has a major impact on PEN, while Pe only has a slight impact. Further, the ballistic phase with the behavior information from the IPQ (QVR and SEVR) is able to account for more than 48% of the variability in PEN for both small and big cubes. However, Pe is only a predictor with big cubes and even then, only accounts for 28% of the variability. We attribute this weak correlation to the hand movement trajectory. As mentioned, the hand movements with big cubes only had a ballistic phase, which is predominantly guided by combined proprioceptive and visual sensory information as feedback. Therefore, PEN found to be predicted. Although, including the realism and PAVR IPQ scores, along with the task completion time, increased the ability to predict PEN by more than 14%.

Interestingly, the IPQ score seems to play an essential role in modeling PEN and Pe. In past studies, the participants' experience was found to be highly related to their interactions with the environment and how the environment affects behavior (Balconi & Crivelli 2010; Devinsky, Morrell & Vogt 1995). A previous experiment by Singh et al. (2018) also shows that visual appearance affects cognitive conflict and is related to both the level of realism (Argelaguet et al. 2016) and the behavior inhibition score (Carver & White 1994b). Our findings are in-line with these studies and explain why the IPQ scores from the participants played such an influential role in predicting PEN and Pe with the ballistic phase and task completion time. The participant's interactive experience with VR, such as their control over the scene, its realism, etc. made it easier to translate their feelings toward the cognitive conflict. The more the experience the participants had with VR, the higher the PEN's amplitude in cognitive conflict conditions.

Overall, the results indicate that proprioceptive information plays an important role in handling cognitive conflicts. The results from behavior, EEG, regression, and correlation support the conclusion that the velocity of the hand's movement impacts cognitive conflict processing in 3D object selection tasks. Such a finding is only possible due to the nature of the task. This task is one of the first of its kind to involve active motor control in the field of neuroscience, falling into the category of mobile-brain/body imaging (MoBI) (Gramann et al., 2011). This finding has implications for our understanding of how proprioceptive and visual sensory information are integrated and together work toward cognitive control. These findings would be beneficial for enhancing user experiences in real and virtual environments with an adaptive system for therapeutic and entertainment purposes.

Conclusion

In this study, we investigated the impact of hand movement velocity on cognitive conflict processing. We designed an experimental scenario to invoke different velocity profiles during 3D object selection systematically. The participants were asked to grasp virtual cubes in a series of 2x2 factor trials: the first condition being the size of the cube – big or small; the second being the placement of the cube to induce a conflict/no-conflict situation. The results of regression analysis with PEN, Pe, and the participants' IPQ scores show that PEN is modulated in the ballistic phase and highly related to proprioceptive information. Additionally, previous experience with VR technology, as self-reported in the IPQ, also significantly impacts cognitive processing.

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