Intra-individual Completion Time Modulates the Prediction Error Negativity in a Virtual 3D Object Selection Task

Avinash Kumar Singh, *IEEE* Member, Hsiang-Ting Chen, Klaus Gramann and Chin-Teng Lin, *IEEE Fellow* Member

Abstract—**A prediction error negativity (PEN) can be observed in the human electroencephalogram when there is a mismatch between the predicted and the perceived changes in the environment. Our previous study using a virtual object selection task demonstrated an impact of the level of avatar realism on the PEN, reflecting a mismatch between visual and proprioceptive feedback about the object selection. To investigate the role of temporal integration of different sensory information on the PEN, this study investigated the impact of task completion times on the PEN amplitude, using the same virtual object selection task. Trials from each participant were divided into slow trials and fast trials based on the task completion time, and their associated PEN amplitudes were separately aggregated and analyzed. The result shows that PEN amplitudes are significantly more pronounced in slow trials than in fast trials. This finding suggests that task completion times modulate the PEN amplitude - a long task completion time allowed for a better integration of information from both visual and proprioceptive systems as the basis to detect a mismatch between the expected hand trajectory during a reaching motion and the perceived visual feedback in the virtual environment.**

Index Terms— **Virtual Reality, EEG, Cognitive Conflict, PEN, Pe, completion time**

I. Introduction

COGNITIVE conflict occurs when a person makes or perceives an error, which can be detected with the help of electroencephalogram (EEG) as an error-related potential [1-3]. It was first studied by Gehring et al [4] and Falkenstein et al [5] in a task known as bimanual choice reaction tasks, where the authors found two components of the 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) [2, 6], which is a negative event-related potential peaking around 50–100 ms, followed by a second component, which is known as the error-related positive potential (Pe), peaking around 200–400 ms [7]. Since the first description, several experimental scenarios have been tested demonstrating ERNs and Pes [8-10]. Due to the nature of difference experiment, other variants of conflict-related potential were also investigated. For example, error due to feedback during a reinforcement-learning task, known as a feedback-related negativity (FRN), can be measured fronto-centrally around 200–300 ms after the feedback [11]. The FRN seems to be related to, or can be seen as the same component as, the N200 [12]. Further, an error-related potential due to a person observing another person making an error, is commonly known as observation error [13]. It was also shown that an error could be measured through interaction [14]. Most of these protocols used discrete feedback mechanisms, but Krigolson and colleagues [15] have also investigated error-related potential in a continuous tracking task. They showed that an error due to a cognitive conflict can also be measured in a continuous task involving cursor movement [16].

In the current study, we evaluate the PEN that arises when there is a mismatch between the perceived and expected changes in the environment. We believe that PEN belongs to the same class of negativities as ERN because both components can be explained by the Error Comparator Theory [4]. Our recent work [17] demonstrated that a PEN can be evoked in a 3D object selection task in VR with an onset latency around 50-150 ms. The result showed that the level of realism of the virtual body part, i.e. hands, modulated the PEN amplitude. A larger PEN amplitude was observed when the participant's virtual hand was rendered with a realistic hand style, while no PEN was found when the participant's virtual hand was replaced with a 3D cursor. In the previous experiment, we also showed that the mismatch leading to the PEN was based on a conflict between the visual feedback and the proprioceptive feedback.

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Avinash K Singh is with Center of Artificial Intelligence, School of Computer Science, Faculty of Engineering and Information Technology, University of Technology Sydney, Australia (avinashsingh@outlook.com).

Hsiang-Ting Chen is with School of Computer Science, University of Adelaide, Australia (tim.chen@adelaide.edu.au).

Klaus Gramann is with chair of Biopsychology and Neuroergonomics at the Technische Universität Berlin, Germany and also with Center of Artificial Intelligence, School of Computer Science , Faculty of Engineering and Information Technology, University of Technology Sydney, Australia (klaus.gramann@tu-berlin.de).

Chin-Teng Lin is with Center of Artificial Intelligence, School of Computer Science , Faculty of Engineering and Information Technology, University of Technology Sydney, Australia (chin-teng.lin@uts.edu.au).

The present study extends our previous work [17] and evaluates what other factors might impact the PEN component. We hypothesized that task completion time is an important factor affecting PEN because previous error detector and comparator theory [4] have shown that it requires time to develop an expectation and recognize the error. During response execution, visual feedback about the consequences of one's action is compared with the proprioceptive feedback of the action. Thus, enough time is necessary to process a divergence in proprioceptive feedback during motor execution and visual feedback reflecting the motor consequences. Consequently, this follow-up study investigated how task completion time interacts with the amplitude and the latency of PEN in a 3D object selection task.

II. MATERIALS AND METHODS

This paper reports a new analysis of data published in our previous study [17]. In the previous study, we examined how the rendering fidelity of the avatar modulated the PEN amplitude. This paper presents new analysis results investigating the role of temporal integration of different sensory information on the PEN by examining the impact of task completion times on the PEN's amplitude.

A. Data Collection

The EEG data were collected using a Scan SynAmps2 Express system (Compumedics Ltd., VIC, Australia) with 32 Ag/AgCl electrodes from 33 right-handed participants, who performed the 3D object selection task. The task was performed in a virtual reality (VR) environment using HTC Vive [18], with hand tracking using a Leap Motion controller (LMC) [19].

B. Experiment Design

The conducted experiment used a mixed factorial design of a 2 by 2. This design contained two *selection distances for cubes* (equal and twice the size of the cube's collider radius) and two within-participants factors based on completion time. The selection distance was changed by changing the radius of the object collider [20] for the cube. Here, the first radius represented the actual object collider radius for a cube, while the second represented the radius, which was twice the size of the first. The overall experiment consisted of three sessions, each with 120 trials, for 360 trials in total. The order of these three sessions was randomized to avoid any bias. Note that our previous work [17] already investigated the independent variable of hand styles, and the analysis in this study focuses only on the first-hand style, i.e. a high-fidelity, realistic hand. To this end, the within-participant factor completion time was created by computing a median-split of all the trials for each participant and then grouping them into short completion times and long completion times (fast and slow group, respectively). Some participant trials overlapped between short and long completion times; therefore, we took the top 40% of trials as the short completion time group, and the bottom 40% of trials as the long completion time group, after median splitting the trials. The completion time for all participants for both normal and conflict trials was defined as the time from touching the first cube to touching the second cube. This resulted in one shorter completion time (fast) group with 1,284 trials (individual trial numbers varied with M = 76; SD = 15) and one long completion time (slow) group with 1,292 trials (individual trial numbers varied with M = 76; SD = 20). The distribution of individual trials to both groups were left-skewed (M = 85, IQR = 20.75 for the fast group; M = 83, IQR = 26.75 for the slow group).

(M = Mean; SD = Standard Deviation; IQR = Interquartile Range)

Please see details of the experimental design in the previous study [17], as well Figure 1 and Figure 2.

C. EEG Data Preprocessing

The collected raw EEG signals were first filtered using a 0.5-Hz high-pass and a 50-Hz low-pass finite impulse response filter, followed by a downsampling to 500 Hz for data reduction. The resultant EEG data were subjected to visual inspection for artifacts.

Independent Component Analysis (ICA) [21] was applied and independent components (ICs) reflecting eye movement and muscle activity from the temporalis were rejected. This resulted in 19 remaining ICs, on average, per participant (SD = 4). The resultant independent components were back-projected to the channel level and epochs were extracted from 200 ms before the onset of the visual feedback, indicating that the cube was touched to 800 ms after the feedback. A final artifact rejection was done on the epoched data through visual inspection. All remaining residual trials (total = 2,576, M = 76, SD = 17) were sorted into the short and long completion time groups, according to the median split.

The PEN and error positivity (Pe) [22] were extracted for each participant on a single trial level. To this end, we calculated the PEN-amplitude, defined as the minima mean negative deflection in the time window from 50 to 150 ms (±5 data points). Similarly, the Pe-amplitude was calculated as the maxima mean positive deflection in the time range 250-350 ms (±5 data points) after the visual feedback.

D. Amplitude and Completion Time Correlation

Statistical analyses were carried out using the SPSS Statistical tool (SPSS Inc Version 24). For each group, Pearson correlation coefficients between completion time and the PEN's and Pe's amplitude were evaluated. Our aim was to see if the amplitude for PEN and Pe are related to task completion time (fast and slow group).

E. Effect Size

The effect size for conflict condition was η_ρ^2 = .192 (i.e., a large effect [23]). The power to detect an effect in the slow and fast condition of the experiment was found to be 0.76, (F (1,32) = 7.623, p = 0.009, η_ρ^2 = .192). Thus, we can say that the number of participants was enough to detect an effect.

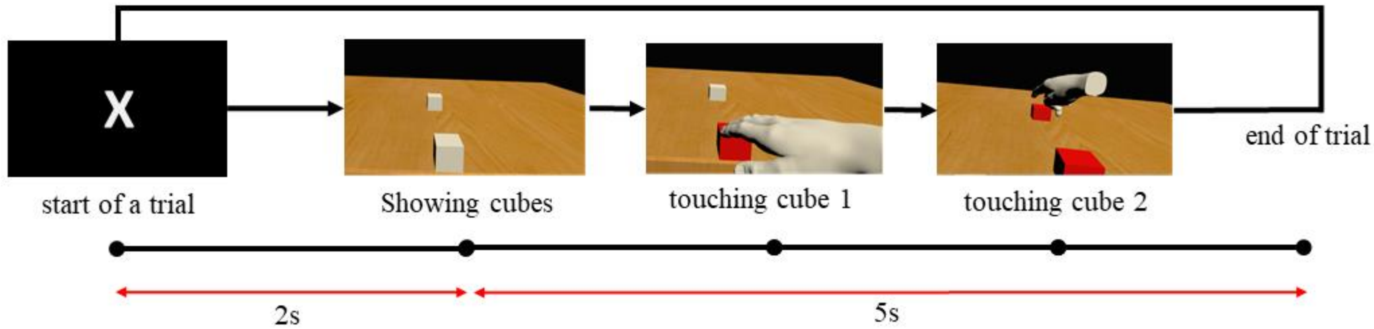

Figure 1. Experiment design: In the first two seconds, the participants looked at a fixation screen with both hands on their lap followed by two cubes shown on a table in VR then participant was instructed to reach and select (touch) cube 1, and then cube 2, and cubes would turn red as feedback on touched.

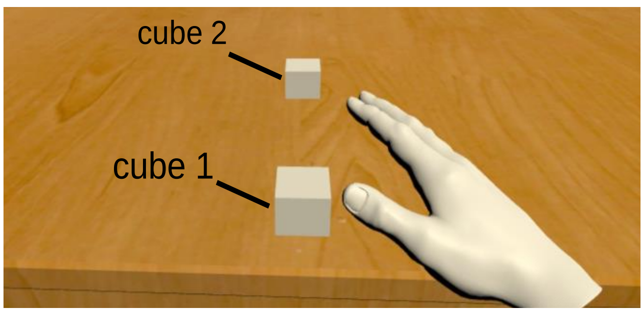

Figure 2. The scene of the experiment. Each participant was instructed to touch cube 1 and then reaches for cube 2.

III. RESULTS

A. *Behavioral Results*

Participants responded correctly in most trials, with only a small percentage of misses or incorrect trials (e.g., failing to touch the second cube). As expected, task completion times fluctuated for trials within participants; therefore, we sorted all trials from each participant and divided them into two groups (fast and slow groups), as mentioned in the methodology section. As per repeated ANOVA analysis, it was found that long and short trials were significantly different for normal condition ($F(1,32) = 37.028$, $p < 0.000$) and conflict condition ($F(1,32) = 67.476$, $p < 0.000$). (See Table 1 and Figure 3.)

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

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

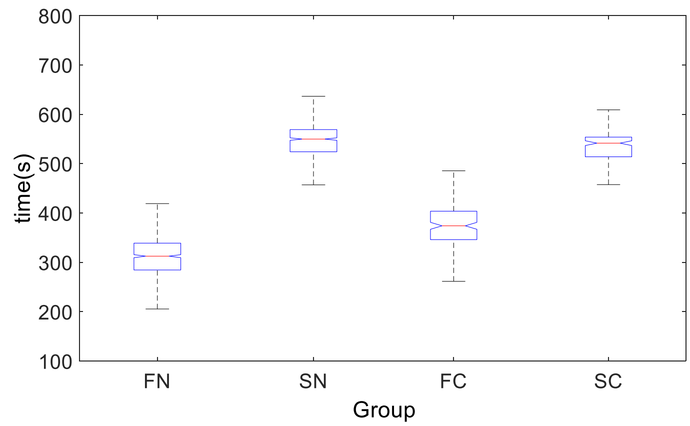

Figure 3. Boxplot for short (fast) and long (slow) completion time trials for the normal and conflict condition (FN= Fast with normal condition; SN = Slow with normal condition; FC= Fast with conflict condition; SC= Slow trials with Conflict Condition).

B. *EEG Results*

We evaluated if the task completion time played any role in participants' electrocortical response towards the conflict. We evaluated how completion time affected the amplitude of the PEN and the Pe using an ANOVA with repeated measures. We found that trials with fast completion times showed a clear Pe component with the onset of the visual feedback, while trials with slow completion times revealed a PEN, together with a subsequent Pe component, in the ERP (see Figure 4).

As can be seen in Figure 4, there was no significant difference ($F(1,32) = .017$, $p = .896$) between PEN amplitude for normal trials between the fast and slow group and also no significant difference ($F(1,32) = .449$, $p = .583$) for the Pe amplitude between fast and slow trials within the normal condition. On the other hand, in the conflict condition, there was a significant ($F(1,32) = 7.623$, $p = .009$) difference for the PEN amplitude for the fast and slow group, but no significant difference ($F(1,32) = 2.455$, $p = .127$) for Pe amplitudes. In the comparison between normal and conflict conditions for the fast and slow group, there was also no significant difference (fast group: $F(1,32) = .420$, $p = .522$; slow group: $F(1,32) = 1.745$, $p = .196$) found for PEN. Similarly, in the comparison between normal and conflict trials, there was no significant difference ($F(1,32) = .307$, $p = .583$) for Pe amplitudes for the fast group, but there was a significant difference ($F(1,32) = 7.623$, $p = .009$) for the slow group regarding Pe amplitudes.

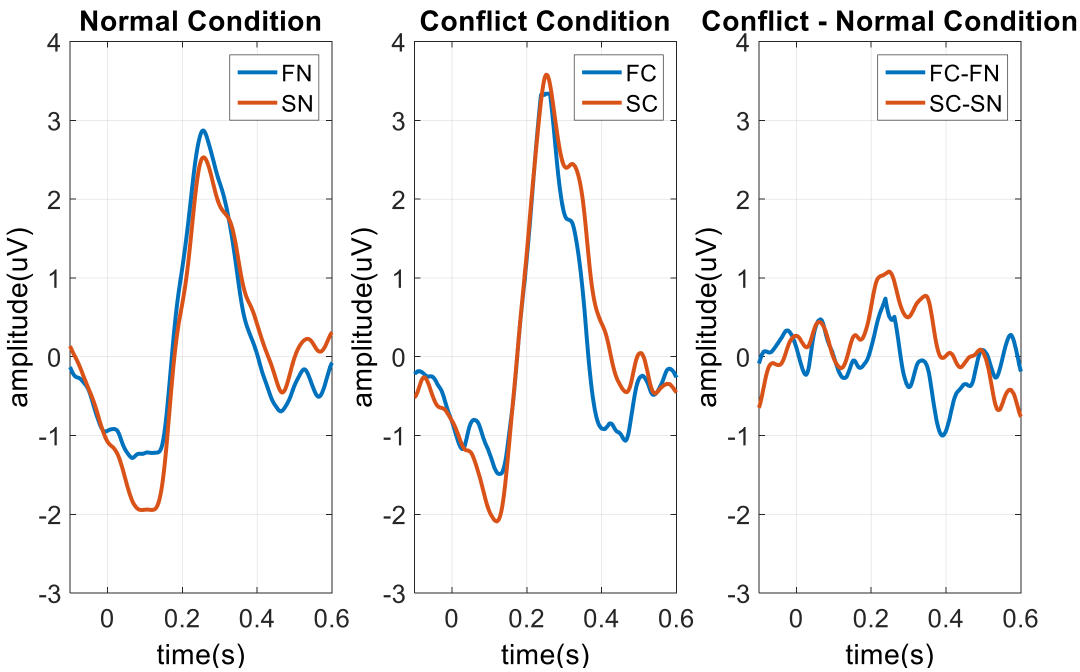

Figure 4. ERP for short (fast) and long (slow) completion time trials for normal and conflict conditions (SC= Slow with Conflict Condition; SN = Slow with normal condition; FC= Fast with conflict condition; FN= Fast with normal condition).

Overall, among all four conditions and two ERP components of interest, there was a significant difference on the PEN amplitude between slow and fast trials in the conflict condition.

We further evaluated the topographical distribution of the PEN and Pe component. Figure 5(A) shows that the PEN effect is more prominent over the fronto-central region of the brain; fast completion times showed less PEN compared to that of the slow group; and the same was not true for the normal condition.

Similarly, as per Figure 5(B), 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. Additionally, Pe seems more prominent in the slow group than in the fast group for the conflict condition.

It was also evaluated whether the chosen EEG channel was the optimal choice for PEN and Pe analysis. As per Figure 6, PEN amplitudes were most negative over the 'Cz' electrode, as compared to 'Fz' and 'FCz,' for all conditions. Similarly, the Pe amplitude revealed the largest amplitudes over the 'Cz' electrode, and decreasing amplitudes towards 'Fz' and 'FCz' for all conditions.

Further, as shown in Table 2 and Figure 7, for slow trials, PEN and Pe amplitude were significantly correlated (PEN: $r = -0.2280$, $p < 0.05$; Pe: $r = 0.2839$, $p < 0.000$) with completion time. On the other hand, PEN amplitudes for fast trials were not significantly correlated ($r = -0.0446$, $p = 0.611$) with completion time. Interestingly, Pe amplitudes demonstrated a significant positive correlation ($r = 0.2180$, $p < 0.05$) with completion time. Overall, slow trials and fast trials showed a negative correlation with PEN's amplitudes, while such a pattern was not observed for Pe's amplitudes, which demonstrated a positive correlation with completion time for the fast and slow groups.

Further ERP analysis has been performed for each participant. The result consistently shows larger PEN amplitudes at Fz, FCz, and Cz channels among trials in the conflict condition than those in the normal condition (Supplementary Figure 1-3). The result also shows that 54.5%, 57.6%, and 63.64% of participants have larger PEN amplitude among trials in the slow condition than those in the fast condition at Fz, FCz, and Cz channel respectively (Supplementary Figure 4-6).

IV. DISCUSSION

Our previous study reported a correlation between the fidelity of the visual appearance and the amplitude of the PEN [13]. The PEN is an ERP component evoked between 50-150 ms, followed by a positivity, the Pe component, around 250-350 ms over the fronto-central and central regions of the brain. Re-analyzing data from a virtual object selection task [13], this follow-up study investigated the role of the time taken to complete the 3D object selection on the amplitude of the PEN and Pe components. The results demonstrated that PEN amplitudes and the following Pe amplitudes were significantly 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 [24]. The result showed no correlation between the latency of the PEN and task completion times, suggesting that a comparable cognitive process took place in all trials. We believe 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 time (see Figure 7).

It was noted that PEN and Pe seem to appear in both normal and conflict conditions, which seems to suggest that users were

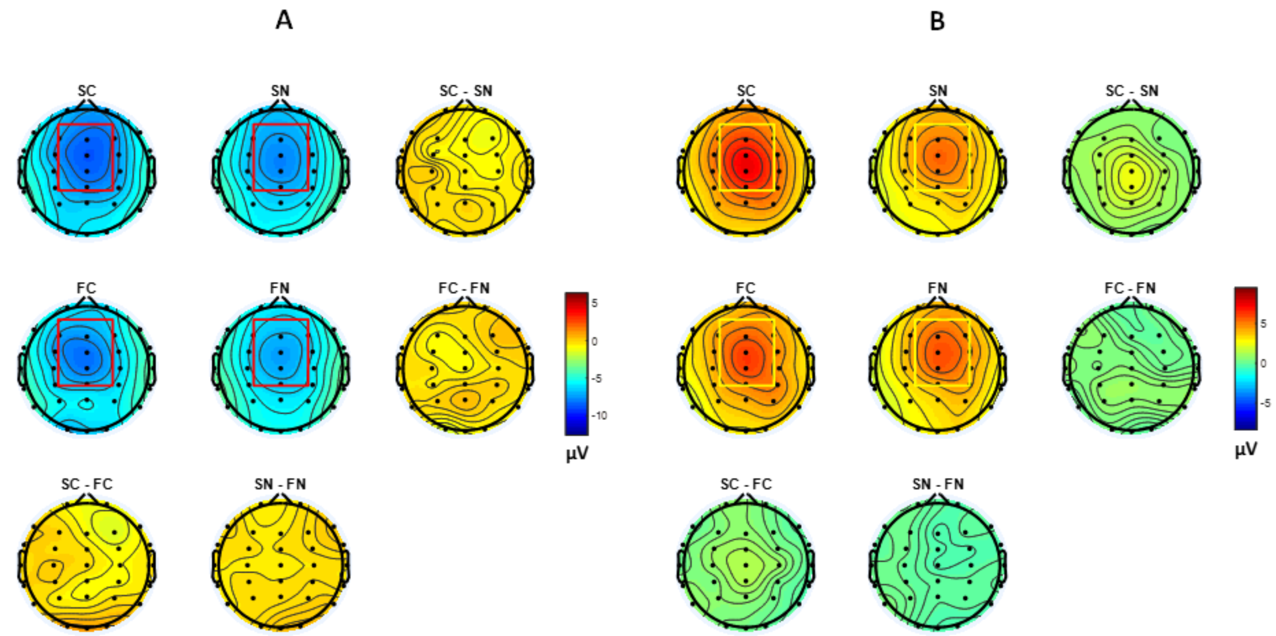

Figure 5. Topography plot. A. PEN component at 50-150ms for normal and conflict condition for short (fast) and long (slow) completion time trials; B. Pe at 250-350ms for normal and conflict condition for short (fast) and long (slow) completion time trials (SC= Slow with Conflict Condition; SN = Slow with normal condition; FC= Fast with conflict condition; FN= Fast with normal condition)

expecting more sensory feedbacks, 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 object selection in VR differently than object selection in the real world. Despite the realistic finger- and hand-tracking through the Leap Motion Controller, the participants might still have expected a haptic feedback when touching the cube and an impact of their action on the virtual object, e.g. moving the boxes by touching them.

The prediction error arises when there is a discrepancy between the users' observation and their expectation. In our 3D object selection scenario, the participants computed their prediction dependent on the time necessary to reach the cube by integrating information from the visual, motor, and proprioception systems [25, 26]. This prediction is then compared against the actual visual feedback received in the VR environment, i.e. the cube changing its color from white to red when the participant touches the cube. We assume that in long completion trials, the slower movement allowed for more time to integrate all 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 trails, leading to a more pronounced PEN component. In the context of auditory negative priming, Mayr et al. [24] also observed a larger negative priming effect in trials with long reaction time. Mayr et al. provided an episodic retrieval explanation, arguing that long reaction time allows for a higher probability of successful prime retrieval. Results from our experiment and Mayr et al. share the similar conclusion that a long task completion time allows a complete development of the stimulus evaluation and a stronger negativity if a mismatch or error is detected.

Another potential explanation of the reduction in PEN amplitude in faster trials is that participants might have sacrificed accuracy for speed in those trials and developed a larger tolerance to the designed conflict condition, i.e. a larger selection radius. Previous works on object selection task [27] have shown that, among trials of the same difficulty, the movement endpoint spread is larger for those with shorter task

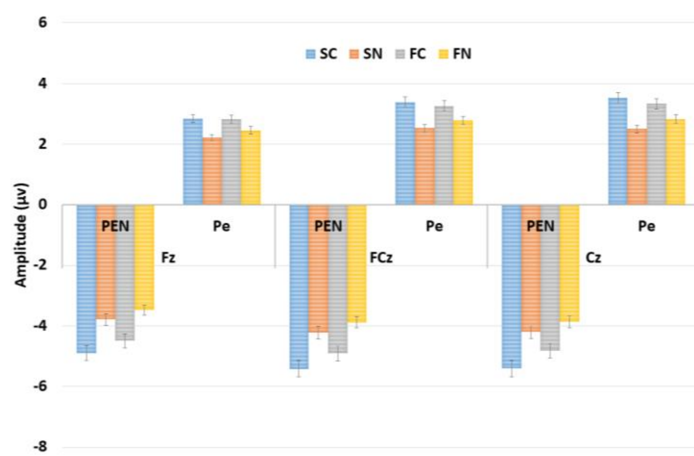

Figure 6. Grand average of PEN's and Pe's amplitude over Fz, FCz, and Cz for normal and conflict condition for short (fast) and long (slow) completion time trials for all participants (SC= Slow with Conflict Condition; SN = Slow with the normal condition; FC= Fast with conflict condition; FN= Fast with the normal condition)

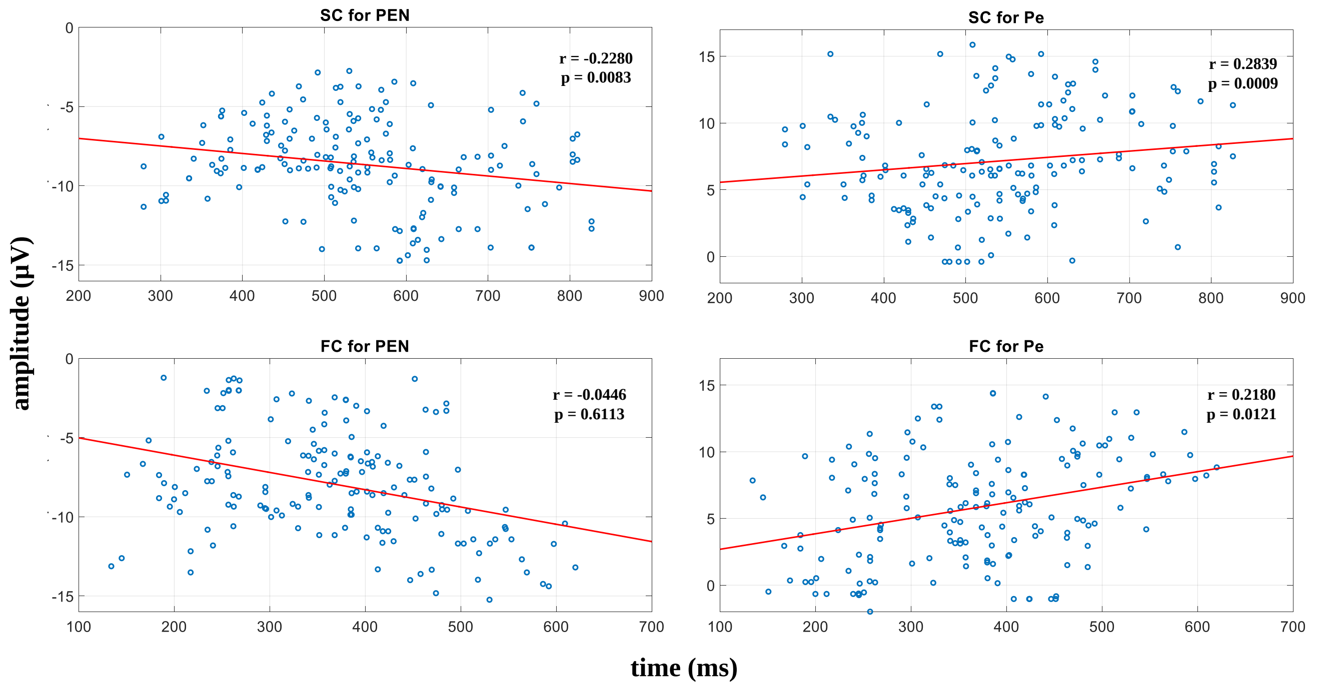

Figure 7. Regression analysis of short (fast) and long (slow) completion time with PEN's and Pe's amplitude (SC= Slow with Conflict Condition; SN = Slow with the normal condition; FC= Fast with conflict condition; FN= Fast with the normal condition)

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

Table 2. Correlation matrix between short (fast) and long (slow) completion time with PEN's and Pe's amplitude over Fz, FCz, and Cz (p<0.01 and *p<0.05)**

completion time as compared to those with long task completion time, i.e. the subjects favored speed over accuracy. One potential explanation toward such phenomena is that the precise object selection requires an 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 our experiment, participants might also have chosen speed over accuracy in the fast completion trials, and thus became less aware of the conflict condition, during which the cube changed its color before being selected.

The reduction of PEN could be also due to the participants. The total number of participants who took part in this study were 33 from the age group of 20-26 years old. However, our effect size analysis suggests a large effect size but larger population with varying age group represent better results. For future work, a broader age population will be recruited for such experiments to make sure that age does not influence conflict perception in virtual reality.

V. CONCLUSION

In this study, we have investigated the role of intra-individual completion time on the PEN and Pe amplitude in a Virtual 3D object selection task. We have evaluated this by dividing intra-individual trials into short (fast) completion time and long (slow) completion time groups and performed regression analysis with PEN and Pe amplitudes. Our results show that PEN's and Pe's amplitude significantly modulates in slow trials as compared to fast trials, while Pe's amplitude modulates significantly in fast trials. These results indicate that different sensory systems (i.e. visual and proprioceptive systems) require different temporal integration to detect a cognitive conflict.

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AVINASH KUMAR SINGH is received M.S degree in software systems from Birla Institute Technology & Science, Pilani, in 2013, and Ph.D. degree in computer science from University of Technology Sydney, Australia, in 2019. He is currently working as Postdoctoral Fellow at the Centre for Artificial Intelligence, School of Computer Science, Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, Australia. His current research interest are to integrate the artificial intelligence (Al) technologies with cognitive neuroscience knowledge for exploring the cognitive functions, discovering the relationships between brain dynamics, evaluated everyday interaction, decision making, and develop robust brain computer interface.

HSIANG-TING (TIM) CHEN received his Ph.D. degree in Computer Science from National Tsing Hua University, Taiwan in 2012. He then worked as a post-doc research fellow in the University of Tokyo and Hasso Plattner Institute, Germany from 2012 to 2015. In 2016, he joined the University of Technology Sydney as a lecturer in the Interaction Design Discipline. In 2020, he joined the University of Adelaide as a Senior Lecturer. Dr. Chen works in the field of Human-Computer Interaction and Computer Graphics. He is particularly interested in augmenting human perceptions with AI, wearables, and Augmented Reality.

KLAUS GRAMANN received a pre-diploma in psychology from Justus-Liebig-University Giessen, Germany, and a Diploma and Ph.D. degree in psychology from Rheinisch-Westfaelisch-Technical University Aachen in 1998 and 2002, respectively. He worked as an Assistant Professor at the Ludwig-Maximilians-University in Munich, Germany in the Department of Psychology from 2002 to 2007. From 2007 to 2011 he worked as Research Associate at the Swartz Center for Computational Neuroscience, University of California at San Diego. After spending half a year as a Visiting Professor at the Brain Research Center of National Chiao Tung University, Hsinchu, Taiwan, he worked as a Professor of Cognitive Psychology at the University Osnabruck, Germany. In 2012, he became the chair of Biopsychology and Neuroergonomics at the Technische Universität Berlin, Germany. Since 2017, he has also been also Professor at the School of Software at the University of Technology Sydney, Australia. His research covers the neural foundations of cognitive processes with a special focus on the brain dynamics of embodied cognitive processes. He works in the field of spatial cognition, visual attention and the development of a mobile brain imaging method to leverage the fundamental research results to applied neuroergonomics.

CHIN-TENG LIN received the B.S. degree from National Chiao-Tung University (NCTU), Taiwan in 1986, and the Master and Ph.D. degree in electrical engineering from Purdue University, USA in 1989 and 1992, respectively. He is currently the Distinguished Professor of Faculty of Engineering and Information Technology, and Co-Director of Center for Artificial Intelligence, University of Technology Sydney, Australia. He is also invited as Honorary Chair Professor of Electrical and Computer Engineering, NCTU, International Faculty of University of California at San-Diego (UCSD), and Honorary Professorship of University of Nottingham. Dr. Lin was elevated to be an IEEE Fellow for his contributions to biologically inspired information systems in 2005, and was elevated International Fuzzy Systems Association (IFSA) Fellow in 2012. Dr. Lin received the IEEE Fuzzy Systems Pioneer Awards in 2017. He served as the Editor-in-chief of IEEE Transactions on Fuzzy Systems from 2011 to 2016. He also served on the Board of Governors at IEEE Circuits and Systems (CAS) Society in 2005-2008, IEEE Systems, Man, Cybernetics (SMC) Society in 2003-2005, IEEE Computational Intelligence Society in 2008-2010, and Chair of IEEE Taipei Section in 2009-2010. Dr. Lin was the Distinguished Lecturer of IEEE CAS Society from 2003 to 2005 and CIS Society from 2015-2017. He serves as the Chair of IEEE CIS Distinguished Lecturer Program Committee in 2018~2019. He served as the Deputy Editor-in-Chief of IEEE Transactions on Circuits and Systems-II in 2006-2008. Dr. Lin was the Program Chair of IEEE International Conference on Systems, Man, and Cybernetics in 2005 and General Chair of 2011 IEEE International Conference on Fuzzy Systems. Dr. Lin is the coauthor of Neural Fuzzy Systems (Prentice-Hall), and the author of Neural Fuzzy Control Systems with Structure and Parameter Learning (World Scientific). He has published more than 330 journal papers (Total Citation: 22,778, H-index: 67, i10-index: 288) in the areas of neural networks, fuzzy systems, brain computer interface, multimedia information processing, and cognitive neuro-engineering, including about 125 IEEE journal papers