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Visual Appearance Modulates Prediction Error in Virtual Reality

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ABSTRACT Different rendering styles induce different levels of agency and user behaviors in virtual reality environments. We applied an electroencephalogram-based approach to investigate how the rendering style of the users' hands affects behavioral and cognitive responses. To this end, we introduced prediction errors due to cognitive conflicts during a 3-D object selection task by manipulating the selection distance of the target object. The results showed that, for participants with high behavioral inhibition scores, the amplitude of the negative event-related potential at approximately 50–250 ms correlated with the realism of the virtual hands. Concurring with the uncanny valley theory, these findings suggest that the more realistic the representation of the user's hand is, the more sensitive the user becomes toward subtle errors, such as tracking inaccuracies.

INDEX TERMS Virtual reality, cognitive conflict, prediction error, virtual hand illusion, EEG, body ownership.

I. INTRODUCTION

Recent advances in computer graphics hardware and rendering engines have enabled the creation of realistic virtual characters and environments in real time. However, a more realistic rendering style or a more immersive virtual environment does not always induce the preferred results or better user performance. For example, it is well known that near-human characters can produce negative audience reactions [1]. Schuchardt and Bowman [2] also found that the benefit of a more immersed virtual environment was only shown in a subset of spatial understanding tasks in their experiment. Choosing the right visual appearance is particularly important in therapeutic applications of VR, such as phobia treatment, so that the patient will experience the appropriate level of realistic experience without triggering a traumatic negative effect [3].

Researchers have been investigating the underlying psychological and neurological processes that induce different reactions towards different visual styles. Yuan and Steed [4] reproduced user responses in the classic rubber hand illusion experiment with immersive virtual reality and found that using an abstract hand style negated the illusion. González-Franco *et al.* [5] further identified a P450 potential and an event-related desynchronization of the mu rhythm in the motor cortex when a virtual threat was imposed on one realistically rendered virtual hand of the subject. Perani *et al.* [6] found that watching a video recording of the movements of realistic hands activated a visuospatial network, which included the right posterior parietal cortex. In contrast, watching an abstract-like hand elicited little engagement of right hemispheric structures. Similar activation of brain regions related to motor planning have been reported previously only in response to realistic rendering styles [7], [8]. Apart from changes in visual style stimuli, deviant changes in color [9], [10], image contrast [11] and spatial frequency [12] in stimuli are also known to create a visual mismatch negativity (MMN) [13]. The MMN reflects an important electrocortical mechanism to enable attention towards important changes in the environment. Some researcher also generalizes it as prediction error signal [14] which is the result of cognitive

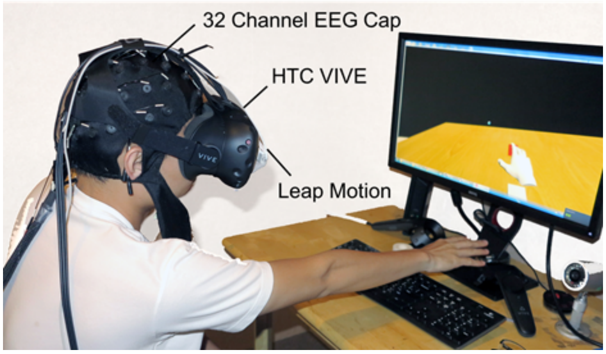

FIGURE 1. Our EEG-based experiment evaluated the interaction techniques in VR by measuring intentionally elicited cognitive conflict.

conflict when there is a mismatch between the perceived information and the required response [15], [16].

Building upon this line of research, we investigated how different rendering styles of a user's hand affect 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). To this end, we introduced a prediction error object-selection paradigm for VR environments by manipulating, on a subset of trials, the selection distance of a target object and providing incorrect visual feedback that was perceived too early (figure 1). The discrepancy between the user's prediction and the system's action results in prediction errors and an accompanying negative event related potential (ERP) component with a fronto-central scalp distribution at approximately 150-200 ms [17], [18]. Note that this error was not self-generated, and thus, the frontal negativity was different from the error-related negativity (ERN). Furthermore, since the virtual hand was synchronized to the participant's actual hand movements, ownership can be assumed. Thus, the resulting negativity is different from the observational error that peaks at approximately 300-400 ms [19].

The research goal of this paper was to investigate the feasibility of using cognitive conflict based on prediction errors to evaluate the interaction between rendering styles and the feeling of presence during a 3D object selection task in VR. We assumed that an increasing sense of presence in VR would be associated with more pronounced cognitive conflict in case of prediction errors. Under this context, we tested the following two hypotheses:

- Hypothesis 1: Different rendering styles will not affect behavioral measurements.
- Hypothesis 2: Different rendering styles will affect the users' response towards errors, which can be measured by the amplitude of the ERP negativity.

II. EXPERIMENT AND METHODOLOGY

A. PARTICIPANTS AND ENVIRONMENT

EEG data were recorded from 32 right-handed male participants to determine the prediction error effect for three different rendering style of hand conditions with 95% power based on G$*$Power [20]. 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.

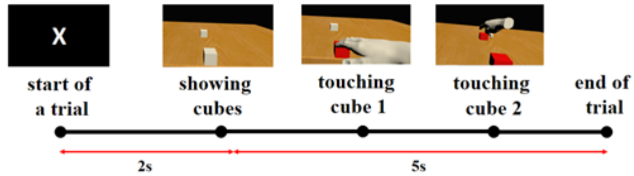

FIGURE 2. Experimental design.

B. VR SETUP

Our experiment used the HTC Vive [21] 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 [22], and the latency has been reported to be approximately 30 milliseconds [23]. (See figure 1.)

C. 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% system [24]. 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. We directly put the top belt of the HTC Vive on top of the central channel of the EEG cap. Interestingly, since the EEG channels were pressed firmly onto the scalp, they provided cleaner signals. However, participants also found these firmly pressed EEG channels uncomfortable. Thus, we manually adjusted the top belt of the Vive to avoid or reduce the pressure applied by the EEG channels. (See figure 1.)

Each participant performed the 3D object selection task with their dominant hand tracked by the Leap Motion controller in VR. Figure 2 displays the scenario for a single trial. Each trial was seven seconds long. In the first two seconds, each participant looked at a fixation screen with his right

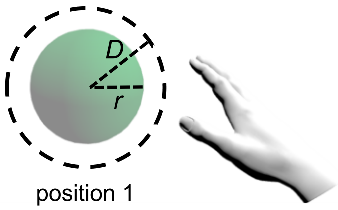

FIGURE 3. Change in the selection distance. 'r' is the normal radius, and 'D' is the changed radius that elicited the cognitive conflict.

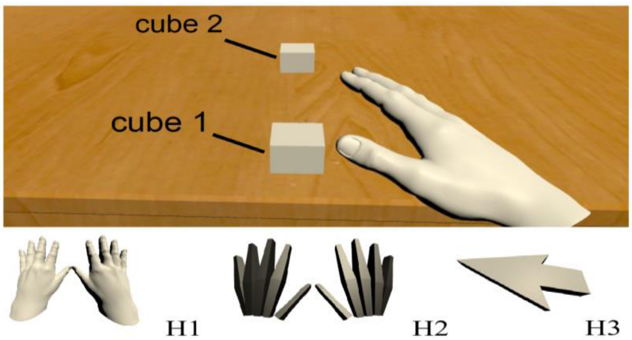

FIGURE 4. Top subfigure shows the scene of experiment 2. Each participant was instructed to touch cube 1 and then to reach for cube 2. The three subfigures at the bottom are the three hand styles used.

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.

The selection distance of the second cube changed in 25% of the trials, such that 75% of the trials used distance 'r' (D1) and the remaining trials used distance 'D' (D2) (See figure 3). Note that although we analyzed the ERP only for cube 2, the two-cube setup was designed to ensure that the participants approached the second cube with similar hand motions.

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 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 [25], 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 [26].

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

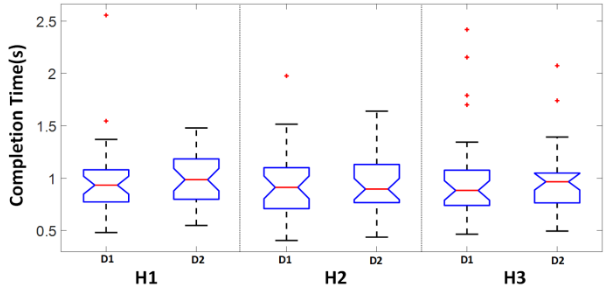

FIGURE 5. Average of task completion time (in sec) for all participants

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 questionnaires.

D. EEG 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 finite impulse response (FIR) filter. Subsequently, the data were downsampled to 500 Hz and subjected to the visual inspection of the artifacts.

Subsequently, an independent component analysis (ICA) was applied [27], and each epoch was extracted from 200 ms from the onset of the touching event for cube 2 to 800 ms after the response. A final artifact rejection was done on the epoched data by visual inspection. The EEG signals, without the components related to eye artifacts and muscle activity with a spectral peak above 20 Hz, were reconstructed using the back-projection method to selected channels to analyze the event-related potentials (ERPs).

Following [26], [28], [29], we calculated the amplitude of the **prediction error negativity (PEN)** by first extracting the negative peak value at the electrode location FCz between 50-250 ms for conditions D1 and D2, and we subsequently computed the difference wave by subtracting the ERPs with the onset of D1 from the ERPs with the onset of D2. Similarly, the P3 amplitudes were analyzed 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.

III. BEHAVIORAL RESULTS AND DISCUSSION

Figure 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 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 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 ($F(1, 30)=3.865$,

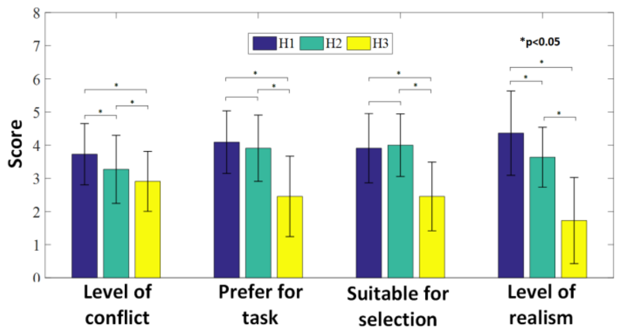

FIGURE 6. Questionnaire results for realistic level of the hand styles.

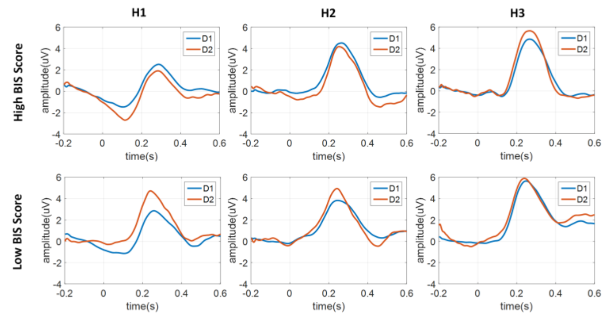

FIGURE 7. Average ERPs from all participants in response to hand style 1 (H1), hand style 2 (H2), and hand style 3 (H3) with the two conditions of the normal (D1) and conflict radii (D2) over FCz based on the high and low BIS score-based groups.

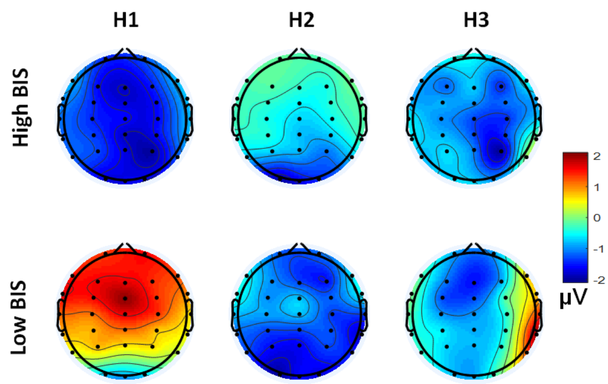

FIGURE 8. Average topoplots of the differences between the two conditions (change - normal) for participants with high (upper row) and low (lower row) BIS scores.

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 supported hypothesis 1 by demonstrating that different rendering styles did not lead to significantly different behaviors during the task [30].

As shown in Figure 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.

IV. ERP 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 continuous 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 lead 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 [31] 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 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 X high BIS interaction revealed a clear negative ERP component, while the low BIS group participants showed only a P300 component, which is commonly evoked by relevant changes in visual stimuli [32].

We also calculated the topoplots (see Figure 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 (P300) in response to H1 compared to H2 and H3.

The correlation analyses between the BIS group and both the PEN and the P300 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=0.000) (see Table 1). Low BIS scores were positively correlated (r=0.8386; p=0.000) with a change in the ERP negativity amplitude. Low BIS scores were further revealed to have a significant positive correlation with the P300 amplitudes in the realistic hand style (H1) condition. No significant

TABLE 1. Correlation matrix for high and low BIS with PEN and P300 amplitude for H1, H2, and H3. DARK-Highlighted cells represent THAT A correlation is significant.

Correlation	Hand style	High BIS score	Low BIS score
Prediction Error Negativity (PEN)	H1	**-0.9833***	**0.8386***
	H2	-0.3142	0.2319
	H3	-0.0488	0.1177
P300 amplitude	H1	-0.1782	**0.6100***
	H2	-0.3678	0.2633
	H3	-0.0604	-0.2143

correlation coefficients were observed for any of the other hand styles (all p's >0.05).

V. DISCUSSION ON THE ERP RESULTS

As hypothesized in hypothesis 2, the results showed a larger amplitude of the PEN / P300 components in response to H1 than to H2 and H3. The results agree with the mismatch theory [33], [34], which argues that the negative component amplitude correlates with the degree of mismatch between the correct and erroneous responses. More specifically, we believe 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 [35], 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 our case, 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' favored human-like looking of their virtual body should be realized.

The results also suggested that there is a correlation between BIS scores and the amplitude of the PEN, but it applies only to the H1 as the realistic hand. In contrast, for the low BIS group, P300 might be a more effective ERP feature. The correlations between BIS scores and the PEN / P300 amplitudes also concur with the results of previous studies [25], [36] that functionally linked these components with flexible behavioral adaptation.

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/P300 amplitude in response to H1 was surprising. Due to the positive direction of the correlation, we suspected P300 to be the main ERP component. A potential explanation could be that the participants with lower BIS scores were less sensitive to the error and, thus, tolerated the change in the selection distance more, which resulted in a small PEN amplitude. This also implied that more weighting is put into the visual feedback system, which evokes the P300 component.

VI. FUTURE WORKS

We believe the experimental procedure proposed in this paper can also be used to investigate other important questions:

A. EVALUATING THE IMPORTANCE OF DIFFERENT FACTORS FOR 3D OBJECT SELECTION

Researchers have long been curious about the relationship between levels of immersion and presence [37]. There have been many inspiring works in recent years that aimed to add different sensory feedback into VR and interaction design [38]. For example, Impacto [39] rendered haptic feedback with both solenoid and electrical muscle stimulation, Level-Ups [40] adds a self-contained vertical actuator to the bottom of the foot, and HapticTurk [41] 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 [9].

B. MANIPULATING SENSE

The proposed experimental methodology can also be used to evaluate the effectiveness and the range of recent works that manipulated the senses to overcome the constraints of physics, such as a limited number of props [42], limited space [43], and cybersickness [44]. Again, in these cases, by controlling the source of the conflicts, e.g., visual warping, we can estimate a reasonable range for subtle sense manipulation without being noticed or causing discomfort.

VII. LIMITATION

Our current setup used the Scan SynAmps2 Express system, and the recorded EEGs were analyzed off-line. Due to its long setup time, this device is only suitable for an initial investigation in a lab environment. We believe it should be possible to reproduce the results using off-the-shelf, portable EEG devices, and to process the data in real time [45]–[47].

During the experiment, we manually adjusted the belt of the HMD to avoid contact with the sensors on the EEG cap. This might not be possible if caps with higher sensor densities are used. We believe the integration of the EEG cap with the HMD is a natural one, and we expect to see commercial products from companies such as MindMaze to be available on the market soon.

Synchronization is also a challenging issue for hardware integration, especially if specific components, such as the N200 or P300, are being targeted. Leap Motion introduces a 30 ms delay [23], and both Vive and Leap Motion have a potential tracking precision error. Additionally, the event generated from Unity 3D 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 (our EEG system). We estimated the latency to summate to approximately 100 to 150 ms, which might cause some delay in the ERP (Figure 7). For future works that focus on specific ERPs, such as N200 or P300, dedicated synchronization hardware should be used.

The participants who took part in the experiment were 20-26 years old and did not represent the whole population. 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.

Finally, for well-defined tasks, such as the 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 previous knowledge and to aim for conceptual change [48]. We believe that extending this framework to address such complex scenarios is an exciting future research direction.

VIII. CONCLUSION

We investigated how different visual styles affect the behavioral and cognitive processes of users in VR. 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 is, the more sensitive the users become to subtle errors, such as tracking inaccuracies, which concurs with the uncanny valley theory.

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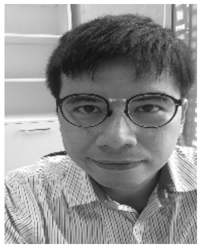

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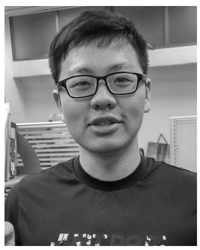

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