

# The Correlation Analysis Between Cybersickness and Postural Behavior in Immersive VR Experience

Ying Zhong<sup>\*1</sup>, Ke-Ao Zhao<sup>\*2</sup>, Leping Zhang<sup>\*3</sup>, Fangming Zhao<sup>\*4</sup>, Wentao Wei<sup>†</sup> Feilin Han<sup>\*✉</sup>

<sup>\*</sup>Department of Film and Television Technology, Beijing Film Academy, Beijing, China

<sup>†</sup> School of Design Arts and Media, Nanjing University of Science and Technology, Nanjing, China

**Abstract**—Cybersickness detection is one of the primary tasks in Virtual Reality (VR) content production. The existing subjective and objective studies on cybersickness give few guiding implications to VR content creators. To do experimental verification on previous hypotheses and propose design guidelines, this paper investigates the relationship between cybersickness and postural behavior, by analyzing the surface electromyography (sEMG) signals and hand movement videos. We conducted a user study to build the sEMG-video Cybersickness Benchmark Dataset (sEMG-CBD) and employed statistical analysis to summarize the regular pattern of participants' dizziness status under VR experiences. The results indicate that the fluctuations of cybersickness correlate positively with the extent of forearm sEMG signals and hand movements. The preliminary analysis implies the potentiality of sEMG-based cybersickness detection being used as one of the significant representations of VR viewing experience, which could contribute to VR content production.

**Index Terms**—cybersickness, sEMG, postural instability, VR content

## I. INTRODUCTION

With advanced head-mounted displays (HMDs) launched in recent years, the amount of VR stories is increasing gradually. Though these immersive and interactive artworks push the boundaries of storytelling and visual demonstration, VR content is still facing user experience issues. Cybersickness is one of the critical problems that keeps some users away from VR content, which has symptoms similar to motion sickness and sometimes linger on after exposure. To guarantee comfort, VR content creators need to analyze user experience to avoid elements triggering cybersickness.

Most cybersickness reasoning [1], [2] methods make it hard to continuously track the fluctuations during a complete narrative without any interference. An easy-to-use and impact-free measuring approach could offer VR content creators more intuitive and timely feedback on users' comfort and preferences. Inspired by the postural instability theory [1], which states that, when cybersickness occurs, postural perturbation appears, we analyzed the correlation between cybersickness and postural behavior, based on sEMG signals and hand movement videos.

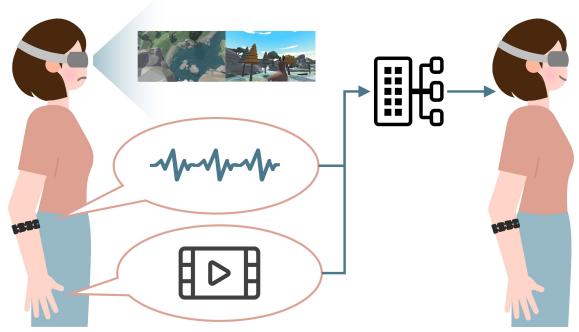


Fig. 1. The correlation analysis between cybersickness and postural behavior is based on sEMG signals and hand movement videos, offering VR content creators a measuring approach to intuitively track users' dizziness status.

In this paper, we conducted a user study to build the sEMG-video Cybersickness Benchmark Dataset (sEMG-CBD) and employed statistical analysis to summarize the regular pattern of participants' dizziness status under VR experiences. The experimental results demonstrate that the fluctuations of cybersickness correlate positively with the extent of forearm sEMG signals and hand movements, which indicates the potential of utilizing sEMG as a physiological metric of cybersickness. Our main contributions include:

- Investigate the correlation between cybersickness and postural behavior, by analyzing the forearm sEMG signals and hand movement videos.
- Experiments were designed to evidence the postural instability hypothesis, where the proposed method could continuously track the perturbation while user watching VR stories.
- Demonstrate the potential of sEMG signals being used as a physiological measure of cybersickness in VR content production.

## II. RELATED WORK

To detect cybersickness, previous studies proposed several subjective and objective measures. The typical subjective measurements are questionnaires and scales, such as Simulator Sickness Questionnaire (SSQ) [3], Fast Motion Sickness Scale (FMS) [4], Motion Sickness Susceptibility (MSSQ) [5] etc. Whereas they may have lag or possibly break the presence in VR. To continuously measure cybersickness, objective quantitative metrics are used, such as physiological measurements,

<sup>✉</sup>Corresponding author; email: hanfeilin@bfa.edu.cn

<sup>1</sup>email: zhongyingcw@mail.bfa.edu.cn

<sup>2</sup>email: zhaoke-ao@mail.bfa.edu.cn

<sup>3</sup>email: zhangleping@mail.bfa.edu.cn

<sup>4</sup>email: zhaofangming23@gmail.com

<sup>†</sup>email: weiwentao@njust.edu.cn

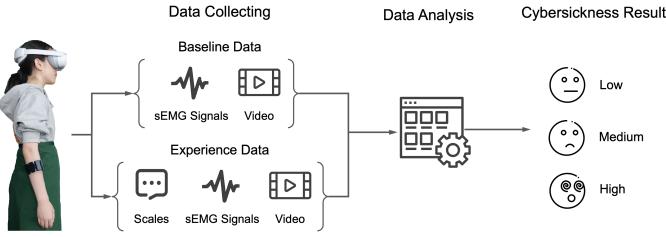


Fig. 2. sEMG armband and RGB camera were used to collect data and build the sEMG-CBD.

heart rate, breathing rate, galvanic skin response, etc [6], which have been verified that have correlations with cybersickness intensity.

Based on the postural instability theory, researchers measure participants' postural sway time [7] or analyse motion captured gait data [8] to infer their level of motion sickness. With the development of eye-gazing technology in HMDs, it has been validated that eye behavior, such as blinking and pupil position, relates to cybersickness [9]. Other electroencephalogram (EEG) related study shows that participants' brain activities are variable during cybersickness [8]. The HbO and HbR of frontal lobe functional near infra-red spectroscopy (fNIRS) significantly change when users suffer sickness [10]. HMD related properties, such as tracking data [11] and recorded images [12], are also prevalent objective measures, with deep neural network to interpret sickness severity.

Surface electromyography (sEMG) is a nonlinear and non-stationary physiological property representing muscular activity. Features extracted from data could be employed to observe the changes in sEMG signals. In time-domain amplitudes, Root Mean Square (RMS) and Mean Absolute Value (MAV) can describe the amplitude variation in time and estimate muscle fatigue. Frequency-domain features, such as median frequency (MDF) and mean frequency (MNF), can indicate muscle fatigue [13]. sEMG armband is a convenient forearm wearable device with multi-electrodes. Myo, as a wireless and non-invasive sEMG armband, released by the Thalmic in 2013, can be utilized for muscle fatigue detection [14] and gesture classification [13]. In this research, Myo is used to collect participants' forearm sEMG signals data during their immersive experience for cybersickness and postural behavior correlation analyses.

### III. METHOD

In this paper, we would like to analyze the forearm muscular variation and hand movements to predict when and where participants have cybersickness in an HMD-wearing immersive environment. The possibility of sEMG being used as a cybersickness measurement was also evaluated, meanwhile, user studies were designed to investigate the correlations between cybersickness and postural behaviors, considering about cinematography and individual differences.

#### A. Study Design

Experiments were designed as a within and between-subject study, using the cybersickness intensity, forearm muscular variation, and hand movement as dependent variables. The experiments had four sessions (one instruction session and three experience sessions) to collect physiological data and self-reported cybersickness intensity from participants. The overall data collecting and analysis process is shown as Figure 2 illustrated.

##### 1) Hardware

The user-study VR story was streaming to a Pico 4 pro, with  $2160 \times 2160$  pixels resolution per eye, 72Hz refresh rate, and 105 degrees field of view. The automatic Inter-pupillary Distance (IPD) adjustment equipped in Pico 4 pro ensured each participant experienced the content with matched IPD. The VR story was rendered on an Intel Core i9-10900X CPU and an NVIDIA GeForce RTX 3090 GPU. Myo armband was applied to collect forearm sEMG data at a sampling rate of 200Hz. Figure 3 (a) shows the placement of Myo's electrodes. Cameras were also used to record videos of participants' forearm and hand movements at a frame rate of 24fps.

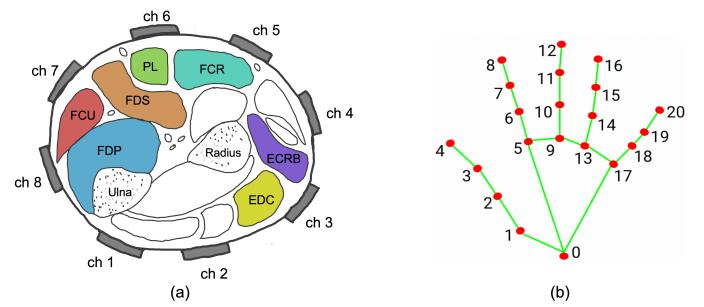


Fig. 3. Illustration of forearm muscle and hand structure. (a) shows the electrode placement of the Myo armband and the forearm cross-section. (b) shows the hand joints provided by Mediapipe [15].

##### 2) Individuals

When recruiting participants, MSSQ was used to measure their susceptibility to cybersickness and screen extremely non-susceptible users. In the experiment, researchers instructed participants (all right-handed) to wear Myo armbands on their right forearm to collect their sEMG data. Participants were allowed to turn their heads to observe the virtual environment, whereas they were required to maintain a standing pose with their arms down naturally and no unnecessary hand movements, to prevent other factors influencing forearm sEMG signal.

##### 3) Content

The first row images of Figure 4 illustrate the forest touring VR story designed to induce participants' cybersickness. To imitate common tour-based stories and provide immersion to participants, a low-poly forest asset was chosen as the background environment, and low-poly animals were placed along the touring route. The virtual camera followed a preset track consisting of turns and pedestals at a constant speed to produce an illusion of self-motion. With light music as the

background music, an AI-generated voice "please rate" was played every 15 seconds to remind participants to rate their scales. The 220-second VR story was presented once in each experience session. There was a 1-minute pause between two sessions for participants to rate the SSQ.

### B. Participants

34 participants (15 identified as female and 19 identified as male) were recruited to take part in our study, and each of them consented to their physiological properties being collected during the experiment. Every participant had a normal or corrected-to-normal vision (self-reported). All participants were permitted to discontinue the experiment when they were incapable of enduring the discomfort. Due to technical issues associated with the camera and Myo armband, three sessions of data from two participants were discarded. A male participant chose to terminate the experiment after finishing his first session due to severe cybersickness. Another male participant's data were removed because he reported no discomfort symptoms. The final dataset, therefore, contained 91 sessions data of from 33 participants (15 females, 18 males) with an average age of 21.36, standard deviation of 1.98 years, and MSSQ scores from 8.91 to 148.08 ( $M = 44.88$ ,  $SD = 36.74$ ). 5 participants had HMD experiences more than 15 times, and 29 participants experienced HMD less than 15 times. All participants had HMD-based VR viewing experiences before.

### C. Measurements

We employ 4 measurements to record the mentioned variables during and after the immersive experience. They are:

- FMS: To estimate the level of cybersickness, participants were required to rate the intensity of previous 15 seconds on the FMS scale when the AI-generated voice played. FMS scale ranged from 0 ("feel no sickness symptoms") to 10 ("unable to continue the experiment"). If the participant rated 8 or above, there would be an option to continue the experience or not. Five participants reached 8, but all finished the session. The FMS ratings split sessions into 14 clips.
- SSQ: Before the experience and after each session, participants verbally rated the items of SSQ. There were 4 SSQ for each participant:  $SSQ_0$ ,  $SSQ_1$ ,  $SSQ_2$ ,  $SSQ_3$ .
- sEMG: Forearm muscular activity was measured by Myo Armband. Both sEMG data during stimulation and before the experiment (using as baseline data) were collected.
- Video: A camera was used to record participants' right forearm and hand movements while viewing VR story.

### D. Procedure

All the participants were told the whole procedure and informed not to consume alcohol or medicines 24 hours before the experiment. In the experiment, first, the participant were asked to rate  $SSQ_0$ . Second, Myo armband was placed on the participant's right forearm and manually synced with the computer. We informed participant to relax their forearm and recorded the sEMG signals and video for 30 seconds as the

baseline data. Then, the participant had an instruction session including HMD interaction, IPD adjustment and controller mechanism. Third, the participant was asked to allow the streaming request from the computer and hand back the controller to keep hands empty and started experience sessions. During a experience session, participant gave FMS ratings verbally every 15 seconds. After each session, participant also rated SSQ verbally while staying in the virtual environment with the HMD (no camera locomotion) to maintain immersion. The experience session repeated three times in total. After finishing all sessions, HMD and Myo armband were removed from participant, and a semi-structured interview was conducted to learn whether participant was aware of physiological changes and how participant felt during the experience. It took 25 to 30 minutes to complete the procedure. All these data were collected to build the sEMG-CBD.

### E. Data Processing

SSQ questionnaire has a total score (TS) and three subscores: nausea (N), oculomotor (O), and disorientation (D) [3]. Total scores and subscores of SSQ questionnaires were calculated and conducted a Shapiro-Wilk test. The subscores O of  $SSQ_1$ ,  $SSQ_2$ , and  $SSQ_3$  were normally distributed while N, D, and TS were not. Then the Mann-Whitney U test was conducted between pre and post-experience SSQ scores ( $SSQ_0$  and  $SSQ_1$ ,  $SSQ_1$  and  $SSQ_2$ ,  $SSQ_2$  and  $SSQ_3$ ) to investigate the differences between them.

FMS scores were used to label sEMG and video data. As mentioned above, each FMS score denoted the sickness of all previous 15-second data. When the FMS rating of a clip was 3, the sEMG and video data in this clip all corresponded to a rating of 3. For data in the  $Clip_i$ , their rating would be  $FMS_i$ . The method proposed by Islam et al. [6] was applied to construct the ground-truth of the dataset. The FMS distribution was divided by quantile into three parts, each representing a cybersickness class: 1) Low (L), 2) Medium (M), and 3) High (H). The definition of cybersickness level  $CSL_i$  at  $Clip_i$  is:

$$CSL_i = \begin{cases} Low, & 0 \leq FMS_i \leq Q1 \\ Medium, & Q1 \leq FMS_i \leq Q2 \\ High, & FMS_i \geq Q2 \end{cases} \quad (1)$$

where  $Q1$  and  $Q2$  values were 1.0 and 2.0 respectively.

The raw data of the sEMG signal were filtered with a highpass filter with a cut-off frequency of 45 Hz to remove unwanted noise. The upper RMS envelope of the signal was also calculated from each window of size 150ms for better observation (see the second-row of Figure 4). To investigate the sEMG signals' power difference of three classes, the p-welch function of Matlab was applied to calculate the average power-spectrum density of each class. The power spectrum density was converted into decibel power.

*feature* was a group of features extracted from the filtered data. Four features were included in the group: MAV, RMS, MDF and MNF. *feature* were extracted from the data by setting the window size equal to the clip length. And *feature*

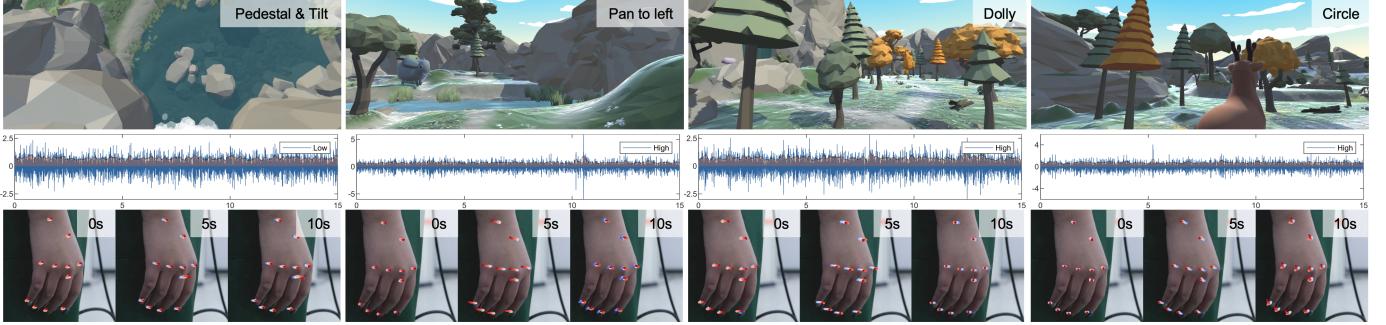


Fig. 4. First-row images are the simulation contents of 2nd, 10th, 13th, 14th 15-second. Second-row images show correspondent sEMG signals of channel 7 (muscles flex fingers) from Participant 26, whose cybersickness intensity was L, H, H, and H respectively. Third-row images show the trajectories of hand joint in y and z axis from Participant 26.

of 8 channels were conducted the Mann-Whitney U test every two cybersickness classes and the Spearman's rank correlation coefficient analysis with FMS ratings and three cybersickness classes respectively. In order to minimize the demographic error in the following analyses, the *feature* of baseline sEMG signals were also extracted and appended to correspondent features clips, and the data of the same participant were rescaled to the range of 0 to 1.

During the experiment, a 1 KHz audio signal was played at the beginning of each session for video and sEMG data synchronization. Videos were synchronized and edited to the same length as the simulation in DaVinci Resolve 18. 3D coordinates of each hand joint were obtained through the hand joints detection model bundle of MediaPipe [15]. 11 joints were selected for investigation: 0, 1, 4, 5, 8, 9, 12, 13, 16, 17 and 20 (see Figure 3). These joints represented the wrist, the carpometacarpal joint (CMC joint), and the tip of five fingers. The hand joint data of each session were also divided into 14 clips corresponding to the FMS ratings. The average value of x, y, and z axis coordinates for each joint in the clip was computed respectively. The total length of each joint in the clip varying on the x, y, and z axis was also calculated. To minimize the individual errors, the data of average and total length were normalized. The Mann-Whitney U test was conducted to average and length data of every two cybersickness classes. The averages and total length were also conducted with Spearman's rank correlation coefficient analysis with FMS ratings and classes.

#### IV. RESULTS

##### A. Cybersickness

The two-tailed p-values of the Mann-Whitney U test are given in Table I. There were notable differences in all four types of score of group-SSQ<sub>0</sub> & SSQ<sub>1</sub> and group-SSQ<sub>1</sub> & SSQ<sub>2</sub>. Whereas no significant differences were shown in four types of score of group-SSQ<sub>2</sub> & SSQ<sub>3</sub>.

The mean and standard deviation values of FMS ratings were computed. The higher peaks of average FMS ratings were the 2nd, 10th, 13th, and 14th 15-second in each session (see Figure 4). These peaks could be attributed to specific

TABLE I  
P-VALUES OF MANN-WHITNEY U TEST CONDUCTED TO SSQ.

	N	O	D	TS
SSQ <sub>0</sub> & SSQ <sub>1</sub>	<0.001	<0.001	<0.001	<0.001
SSQ <sub>1</sub> & SSQ <sub>2</sub>	<0.001	<0.001	<0.001	<0.001
SSQ <sub>2</sub> & SSQ <sub>3</sub>	0.334	0.172	0.707	0.668

VR content with intense camera movements (e.g., turning, pedestal) as demonstrated in Figure 4.

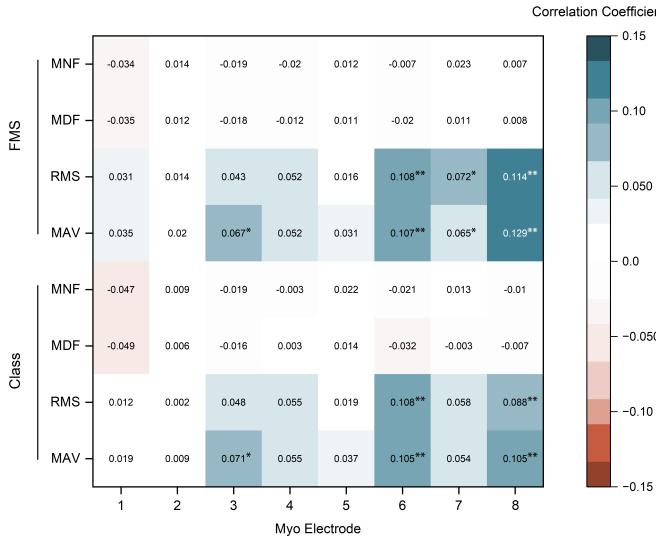
The SSQ and FMS data suggested that most of the participants had experienced sickness in the VR story. Greater FMS ratings were reported when participants experienced more drastic camera movements. Few differences of cybersickness severity were observed between experience session 2 and 3. The reason might be that the experiment duration was too short for symptoms accumulation.

In the semi-structured interview, participants reported they felt "weightless", "unsteady", and "weak at the knees" watching those intense camera movements. Participants whose hands were moving back and forth or whose fingers were shaking during these clips claimed that they had no awareness of hand posture changes.

##### B. sEMG Distributions and Hand Movements

Figure 4 presents the sEMG signals, envelope, and trajectories of hand joints from Participant 26 (P26) in the 4 content mentioned above. In these 4 clips, P26 had cybersickness intensity of L, H, H, and H respectively. Amplitude differences and peaks of sEMG signals and variations of hand movements can easily be observed.

The Mann-Whitney U test results of *feature* show that there are dissimilarities between class L and H and between class M and H in the MAV data of sEMG channel 3, 6, and 8 as well as the RMS data of channel 6 and 8. The correlation matrix of *feature* of 8 channels is shown in Figure 5. Both FMS ratings and classes significantly correlate with the MAV and RMS data of channel 6 and 8 ( $p < 0.001$ ). The MAV of channel 3 also has a correlation with FMS ratings and classes ( $p < 0.05$ ). The MAV and RMS of channel 7 correlate with FMS ratings ( $p < 0.05$ ). All correlated features mentioned



Note: \* indicates p-value < 0.05 and \*\* indicates p-value < 0.01.

Fig. 5. Correlation matrix of FMS ratings and classes and  $feature_{el}$  of 8 channels, which blue represents positive correlation coefficients and red represents negative coefficients.

have a positive correlation coefficient, which represents that the MAV and RMS values increase when participants feel greater sickness.

There are several muscles around these electrodes (shown in Figure 3). The PL and FCR are near channel 6. Channel 7 and 8 are located around FDP, FCU, and FDS. The channel 3 is placed around EDC and ECRB. PL, FCR, FCU, and EDC contribute to wrist movement (e.g., wrist flexion and extending). ECRB is responsible for the extension and stabilization of the wrist. FCU, FDP, and FDS flex the fingers. It is presumed that the activity of these muscles fluctuates with the increasing sickness, leading to finger and wrist movements. However, there is a subtle difference between the correlation coefficients of FMS ratings and classes. The reason possibly is that the categorization of L, M, and H rescaled the FMS ratings. The rescale led to different data distributions and thus different correlation coefficients.

The amplitude of sEMG signals fluctuates in the magnitude of participants' hand movement in the three classes. As the intensity of cybersickness increases, the sEMG signal has greater amplitude. The second row of Figure 4 shows the sEMG signals of P26 in L and H. The peaks of sEMG signals are significantly higher when they suffer severe levels of discomfort. Figure 6 shows the average power spectral density of channel 6 and 8 signals for the three classes of cybersickness. There is a power increase across frequencies for participants suffering greater cybersickness. The increases in the amplitude range and power spectral density indicate the enhancement of muscle activity, which is consistent with the correlation results mentioned above.

Table II shows the statistically significant results from the test conducted on hand joints. The data of joints represented fingertips have significant differences between class L and H

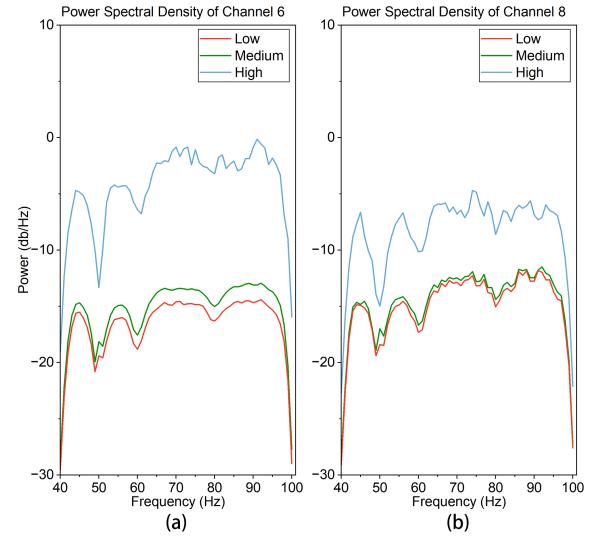


Fig. 6. Comparing the sEMG signals and power spectrum density of Low (red), Medium (green), High (blue). (a) and (b) shows the average power spectrum density of channel 6 and 8 respectively.

TABLE II  
THE RESULT OF MANN-WHITNEY U TEST AND CORRELATION ANALYSIS CONDUCTED TO JOINT MOVEMENT

	0Y	0Z	1Y	4Y	4Z	5Y	12Z	16Z	20Z
L&H	0.015	0.036	0.017	0.028	0.027	0.029	0.023	0.485	0.014
M&H	0.009	0.106	0.013	0.008	0.125	0.012	0.171	0.267	0.229

(a)

	0X	1X	5X	9X	12X	13X	16X	17X
L&H	0.007	0.016	0.021	0.006	0.031	0.015	0.064	0.008

(b)

	0Y	0Z	1Y	4Y	4Z	5Y	12Z	16Z	20Z
FMS	0.042	0.064*	0.044	0.044	-0.066*	0.040	-0.076**	-0.082**	-0.079**
Classes	0.063*	0.055*	0.063*	0.057*	-0.058*	-0.057*	-0.062*	-0.069*	-0.067*

(c)

	0X	1X	5X	9X	12X	13X	16X	17X
FMS	0.081**	0.064*	0.079**	0.091**	0.073**	0.079**	0.054*	0.080**
Classes	0.071**	0.064*	0.063*	0.075**	0.059*	0.068*	0.052	0.073**

(d)

Note: (a) and (b) shows the significant p-value of Mann-Whitney U test conducted to the averages and the total length, respectively. (c) and (d) shows the significant correlation coefficients of correlation analysis conducted to the averages the total length, respectively. \* indicates p-value < 0.05 and \*\* indicates p-value < 0.01.

in the y-axis and z-axis. Three fingertips (middle, ring, and pinky) have z-axis movement significantly correlated to the FMS ratings and classes, and their correlation coefficients are all negative. The movement of thumb fingertip correlates to classes in both the y-axis and z-axis. Its correlation coefficient of the y-axis is positive while the one of the z-axis is negative. The wrist movements on the z-axis also correlate to the FMS ratings and classes with a positive correlation coefficient.

It is presumed that participants' fingers tend to clench and the thumb may stretch outward when great sickness occurs. The total length data in the x-axis of wrist and all CMC joints are significantly different between L and H. Correlations are found between the wrist and CMC joint's total length data of the x-axis and FMS ratings and classes. Meanwhile, the

correlation coefficients are all positive, which indicates that participants may move their arms laterally from their bodies more frequently as the cybersickness increases. These results are in accordance with the sEMG signal analysis results.

## V. DISCUSSION

According to experimental results, the signals of specific sEMG channels, controlling specific hand movements, have features positively correlated with the severity of cybersickness, while the trajectory and position variations of hand joints show similar trend as the sickness gets severer; thus, sEMG signals and hand movements have consistency in changing when participants have dizzy feeling. Consequently, the correlation between cybersickness and postural behavior has been verified. Participants' forearm and hand movements do vary when they suffer cybersickness. As the sickness increases, participants may bend fingers or move wrists. The designed study suggests that sEMG could be able to detect cybersickness by measuring the muscle activities associated with finger bending and wrist movement. Therefore it is possible to utilize sEMG analysis as a user cybersickness measurement in the VR content production process without breaking the presence.

The experimental results on constructed sEMG-CBD show that the shifting sEMG signals represent the variation of participants' forearm muscle activity. The variation was correspondent to their changes of hand posture. Participants' unawareness of changes indicated that participants had less hand movement control while experiencing sickness, especially for those with shaking fingers. Based on postural instability theory, the uncontrolled variation represent "perturbations transmitted from high-mass segments" [1]. Comparing to the obvious body sway when experiencing cybersickness, the nuance of forearm sEMG signals is also consistent with the theory, which hands, fingers and forearms has relatively smaller effect as low-mass segments. As sickness increases, sEMG signals tend to have greater amplitude, in accordance with the theory that magnitude of instability is related to the intensity of sickness. Though the finding on the relationship between cybersickness and hand and forearm muscle activity is preliminary, it provide new support for the postural instability theory.

## VI. CONCLUSION

This study aims to explore the relationship between cybersickness and postural behaviors. We conducted a user study to build the sEMG-CBD and employed statistical analysis to summarize the regular pattern of participants' dizziness status under VR experiences. According to the presented findings of the study, forearm sEMG signals and hand movements significantly correlate with FMS ratings. Participants' forearm and hand movements intuitively reflect their cybersickness intensity. The study results demonstrate that sEMG signals could be employed as a cybersickness measurement in VR viewing experience analysis.

The proposed insights are a preliminary study of the correlation between cybersickness and sEMG signals. It presents the possibility to continuously measuring cybersickness during

user experience, which also demonstrates the necessity of further investigation into the origins and impacts of cybersickness. We believe that it will be worthwhile for VR content creators to utilize the sEMG-based cybersickness analysis to have a better understanding of their artwork in the future.

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