Predicting cybersickness based on user’s gaze behaviors in HMD-based virtual reality

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Abstract

Cybersickness refers to a group of uncomfortable symptoms experienced in virtual reality (VR). Among several theories of cybersickness, the subjective vertical mismatch (SVM) theory focuses on an individual’s internal model, which is created and updated through past experiences. Although previous studies have attempted to provide experimental evidence for the theory, most approaches are limited to subjective measures or body sway. In this study, we aimed to demonstrate the SVM theory on the basis of the participant’s eye movements and investigate whether the subjective level of cybersickness can be predicted using eye-related measures. 26 participants experienced roller coaster VR while wearing a head-mounted display with eye tracking. We designed four experimental conditions by changing the orientation of the VR scene (upright vs. inverted) or the controllability of the participant’s body (unrestrained vs. restrained body). The results indicated that participants reported more severe cybersickness when experiencing the upright VR content without controllability. Moreover, distinctive eye movements (e.g. fixation duration and distance between the eye gaze and the object position sequence) were observed according to the experimental conditions. On the basis of these results, we developed a regression model using eye-movement features and found that our model can explain 34.8% of the total variance of cybersickness, indicating a substantial improvement compared to the previous work (4.2%). This study provides empirical data for the SVM theory using both subjective and eye-related measures. In particular, the results suggest that participants’ eye movements can serve as a significant index for predicting cybersickness when considering natural gaze behaviors during a VR experience.

Keywords: cybersickness; virtual reality; eye-tracking, head-mounted display; subjective vertical mismatch theory; regression analysis

1. Introduction

Virtual reality (VR) and augmented reality (AR) technologies have been applied to not only entertainment but also various contexts such as education, manufacturing, and building design (Ceruti et al., 2019; Fukuda et al., 2019; Sun et al., 2019). During VR/AR interactions, some users can experience adverse side effects called cybersickness. Owing to the uncomfortable symptoms, the growth of the VR industry has been impeded. Several theories have tried to explain the cause of cybersickness (Reason & Brand, 1975; Stoffregen & Smart, 1998; Prothero et al., 1999). In particular, Bos et al. (2008) proposed the subjective vertical mismatch (SVM) theory, which considers the individual’s internal model for understanding the symptoms. According to the theory, an internal model, which is also called a neural store, can be...
created and updated based on one’s previous experiences. Several studies have tried to find experimental evidence for supporting the idea or interpret their results based on the SVM framework (Diels & Bos, 2016; Lubeck et al., 2016; Van Ombergen et al., 2016; Wada et al., 2018).

Earlier studies frequently used questionnaires or oral reports while manipulating the experimental conditions for the research hypothesis. However, this approach has a limitation in that it is difficult to reflect the user’s discomfort in real time. Several methods have been proposed wherein a user should report one’s state periodically (e.g., every minute) through a keyboard or a controller to compensate for this limitation (Fernandes & Feiner, 2016; McHugh et al., 2019). However, these methods still have a disadvantage in that they can interfere with the participants’ immersive VR experiences owing to their invasive way of measuring cybersickness.

Unlike with subjective measures, there has been an increasing interest in monitoring the level of cybersickness or presence in an objective approach (Kim et al., 2005; Soler-Domínguez et al., 2020). This approach can record the level of discomfort online while maintaining a high-quality VR interaction. According to a review by Chang et al. (2020), body sway, electroencephalogram, electrocardiogram, and eye-related index have been studied as promising objective measures for cybersickness. In particular, researchers have investigated the relationship between eye movements and cybersickness because the eyes are the primary organ for perceiving VR content (Diels et al., 2007; Yang & Sheedy, 2011). Moreover, it has been shown that users frequently reported eye-related discomfort when they experienced cybersickness. On the basis of these findings, it was expected that the response of the participant’s eyes during VR interaction might be directly related to the prediction of cybersickness.

Despite the growing interest in eye movements during VR interaction, limited studies have investigated cybersickness using an eye-tracking technique with a head-mounted display (HMD). Most of the previous studies have recorded the electrooculogram (EOG) signals of the participants while electrodes were attached around their eyes (Yang & Sheedy, 2011). Otherwise, eye movement was measured with an eye tracker attached to a monitor (Diels et al., 2007). Owing to methodological restrictions, participants usually experienced VR through the screen (e.g., a monitor) and were not allowed to move their bodies freely. Therefore, it was not clear whether the results of eye tracking could be applied to highly immersive VR interaction. Recently, Wibirama et al. (2020) recorded eye-tracking data while experiencing a racing VR with an HMD. The authors presented a multiple regression model for predicting cybersickness on the basis of well-known eye-related parameters (e.g., fixation duration, amount of fixation, and speed) and showed the possibility of predicting users’ discomfort through eye movement indicators.

This study aims to (1) provide empirical evidence for the SVM theory using both subjective and objective approaches and (2) develop a regression model for cybersickness. By changing the orientation of the VR scene and controllability of the user’s body, we intended to induce differences in updating a participant’s internal model. While experiencing VR, the psychophysiological responses of the participants were recorded using a simulator sickness questionnaire (SSQ; Kennedy et al., 1993) and an eye-tracking HMD. In particular, we focused on oculomotor responses that have not been fully understood in terms of the SVM theory. Based on these measures, we developed a multiple regression model to predict the level of cybersickness. In contrast to the previously suggested model, we selected a natural gaze behavior as one of the predictors and investigated whether this new approach can show a better result for cybersickness prediction.

2. Related Work

2.1. SVM theory

The SVM theory claims that cybersickness is caused by the difference between the perceived and expected sensory afferents (Bos et al., 2008). Accumulated past experiences in the real world develop an internal model in the brain, which serves as a neural store for predicting sensory information. Using VR technology, researchers have implemented various virtual scenes that can hardly be experienced in reality. They assumed that this manipulation can affect the building or updating of one’s internal model and can induce various responses, including cybersickness.

For example, several researchers manipulated the orientation of the moving virtual object and observed the changes in the level of discomfort. In the study of Bonato et al. (2008), participants reported greater discomfort when they were exposed to VR in the forward-moving direction than that in the backward-moving one. Similarly, cybersickness was exacerbated when they were in an upright VR scene compared with that when they were in an inverted scene (Golding et al., 2012). The authors interpreted these results according to the individual’s “neural expectancy” (Bonato et al., 2008) or “quarantine” (Golding et al., 2012). Since our brain is less likely to experience an unfamiliar moving environment such as a backward-moving direction or an inverted scene, the internal model would not expect any corresponding sensory information (especially the corresponding vestibular input). Therefore, users can experience less cybersickness in a virtual scene with an unfamiliar orientation.

According to the SVM theory, the user’s voluntary movement is one of the input elements that lead to an internal model update. A self-initiated action leads to an effector copy, which helps the brain to predict self-motion and achieve perceptual stability. Several studies have investigated whether the controllability of the user’s body can affect spatial perception and the level of cybersickness. Depending on the experimental condition, participants were instructed to move freely or maintain a fixed posture. The results have consistently shown that the level of discomfort increases when participants lose controllability of their body (Jaeger & Mourant, 2001; Sharples et al., 2008). The theory explains that a lack of voluntary movement restrains the update of the internal model, which fails perceptual stability and causes motion sickness.

Most previous studies have used subjective measures to quantify the participant’s reaction according to the changes in the internal model. However, the theory also underlines psychophysical responses due to internal model updates. To support empirical evidence, recent studies have tried to adopt both subjective and objective measures (Lubeck et al., 2016; Van Ombergen et al., 2016; Wada et al., 2018). Though some research focused on the user’s body sway during VR interaction (Lubeck et al., 2016; Van Ombergen et al., 2016), little is known about how users cope with specific VR conditions through the eyes. Since the SVM model hypothesized that eye movement is one of the physical responses caused by the internal model, more studies are needed to determine how individual internal models can change eye-related measures.
2.2. Eye-related measures

There has been a growing interest in measuring users’ physical responses due to cybersickness besides self-reporting. Previous studies investigated the identification of eye-related features for cybersickness (Kim et al., 2005; Diels et al., 2007; Yang & Sheedy, 2011). Eyeblink, variation in eye position, and vergence and accommodative responses have been examined as promising indices. Recently, HMD devices equipped with eye-tracking functions have facilitated the recording of the user’s natural eye movements in real time during VR experiences.

Several studies have recorded the EOG signals of participants to characterize eye movements. Kim et al. (2005) investigated whether there was a difference in the number of eyeblinks during VR interactions. The results indicated that participants showed more eyeblinks when experiencing higher cybersickness. Yang and Sheedy (2011) focused on the vergence and accommodative responses of users when viewing different types of depth images. According to the results, participants showed greater vergence and accommodation when they viewed a 3D movie. Moreover, they reported severe oculomotor-related discomfort compared with that when they watched a 2D movie.

Eye-tracking devices have facilitated the recording of natural eye movements during the VR experience. The study by Diels et al. (2007) revealed that participants reported more severe motion sickness when they were forced to gaze at an eccentric point. In addition, participants with high susceptibility to motion sickness tended to show more deviated eye movements from the center point as they experienced VR longer. Wibirama et al. (2020) implemented an immersive VR experiment using an HMD with eye-tracking techniques. While wearing the device, participants watched both first-person shooting and racing VR, and several eye movement indicators (e.g., amount of fixation, viewing duration, and average speed of eye movements) were measured. On the basis of the results, the authors performed a multiple regression analysis to predict the subjective level of cybersickness.

2.3. Regression model for cybersickness

Many researchers have tried to predict the level of cybersickness correctly. The psychophysiological responses or individual characteristics of users were selected as plausible predictors (Table 1). Kim et al. (2005) and Dennison et al. (2016) measured various bio-signals of users during VR interactions, derived promising indices of cybersickness, and developed a step-wise regression model for predicting user discomfort. The results indicated that various physiological variables can predict the severity of cybersickness. Nooij et al. (2017) considered vection-related factors as well as eye and head movements for the regression parameters. According to the results, an individual’s vection strength was a significant component of the regression model. However, the model only can explain the variance within subjects. Meanwhile, Weech et al. (2019) proposed a regression model using only the individual differences of each participant to perform a principal component regression analysis. The authors claimed that the combination of balance control measures of users could predict the level of discomfort. Despite these efforts, it was difficult to apply the previous prediction model to a practical VR environment. To acquire objective measures that showed a significant predictive coefficient (e.g., hear period and various brain wave features), users are required to equip additional devices for data recording, which has low accessibility to common users. In addition, the devices prefer limited body movement for the noiseless data acquisition, which can interrupt immersive VR experiences instead. For these reasons, there has been an increasing interest in a physical index that can be measured in a less invasive way as well as reliably reflect cybersickness. It is also noted that previous regression models considered at least one of the individual’s characteristic parameters for developing the models. These features were obtained through questionnaires or various preliminary user experiments, which might be challenging to apply to the end-user VR context. Meanwhile, several studies developed an objective assessment model for cybersickness considering spatio-temporal features of VR content (Jin et al., 2018; Hu et al., 2018; Kim et al., 2019a, b). Using up-to-date techniques such as convolutional neural network, researchers devised a computational model for cybersickness and showed that exceptional motion in a given VR scene can reliably predict the level of discomfort.

Recently, Wibirama et al. (2020) developed a prediction model based on various eye-movement features. The amount of fixation, viewing duration, and average speed of eye movements were selected as regression parameters. The model explained 4.2% of the total variance in participants’ oculomotor discomfort. This study contributed to the development of a regression model that only considers eye-related features, which can be measured with only minimal disturbance to the user’s immersive VR interaction. Although the result indicated a low coefficient of determination, the model can be improved by

| Reference | Regressor | Significant predictor | $R^2$ (adj. $R^2$) |
|-----------|-----------|-----------------------|---------------------|
| Kim et al. (2005) | SSQ$^1$ total | MSSQ$^2$ | 0.46 (NA) |
| Dennison et al. (2016) | SSQ total | Heart period | 0.37 (0.30) |
| Nooij et al. (2017) | FMS$^3$ | % Bradygastric activity | 0.78 (NA) |
| Weech et al. (2018) | SSQ total | Vection gain | 0.37 (0.27) |
| Wibirama et al. (2020) | SSQ oculomotor | Amount of fixation | NA (0.042) |

$^1$SSQ: simulator sickness questionnaire.
$^2$MSSQ: motion sickness susceptibility questionnaire.
$^3$FMS: fast motion sickness scale.
$^4$PC1: Principal component 1 (combination of MSSQ, vestibular thresholds, vection magnitudes, and total sway path length measures from the five balance conditions).
considering the user’s natural gaze behaviors while interacting with the VR content. Compared with the visual stimuli in earlier studies (e.g. simple rotating stripes or dots), recent studies have provided more realistic VR content to participants. Therefore, there has been a growing interest in identifying novel gaze behaviors during VR experiences (Piumsomboon et al., 2017; Hu et al., 2020), which can serve as reliable indicators for predicting cybersickness.

3. Method

3.1. Participants

26 undergraduate students at Korea University (mean age = 25.58 years, SD = 2.59; 13 females) participated in the experiment. All participants were healthy with normal or contact lens corrected-to-normal vision. The experiment was performed in accordance with the guidelines of the institutional review board of Korea University (1040548-KU-IRB-18-6-A-1). Before the experiment, written informed consent was obtained from all participants. They were also allowed to terminate the experiment whenever they wanted to. Three participants could not finish all experimental conditions owing to a severe level of cybersickness. Moreover, three participants were excluded owing to the malfunction of the eye-tracking recording.

3.2. Material

The specification of the PC used in the experiment was as follows: Intel Core i7-4790K CPU clocked @ 4.00 GHz and GeForce GTX1080 Ti AORUS Xtreme DSX 11GB. We adopted a VR roller coaster from “Animated Steel Coaster” (https://illusionloop.webflow.io/docs/animated-steel-coaster). Using the Unity engine [version 2018.1.8f1 (64-bit)], we customized the content to suit the user experiment. The VR scene included a roller coaster track and a series of carts moving on the rail. The total duration of the VR experience was about 3 min 27 s per ride.

A VR camera was located at the front of the first cart, giving the participant a roller coaster ride experience at the forefront. By manipulating the angle of the camera rotation, we provided two different orientations of the VR content: upright (x = 0, y = −180, z = 0) and inverted (x = 0, y = −180, z = −180) conditions (Fig. 1). The background of the content consisted only of a terrain and the sky to preserve the participant’s attention to the track. The field of view (FOV) of the content was 80°.

We used an Fove eye-tracking VR headset (FOVE, Inc.) for eye tracking while displaying the VR content. The sampling rate of the tracking was 70 frames per second, and the resolution was 2560 × 1440 pixels. The device provided a unit vector for each eye position in 3D space (Lohr et al., 2018). The value of (0, 0, 1) represents the participant’s eye looking straight forward, and each reference value of the vector is described in Fig. 2. Using the eye position vector of each frame, we converted the value into the x and y positions of the normalized device coordinate (NDC) space (see preprocessing and epoching).

Moreover, we used an SSQ to measure the subjective level of cybersickness. According to the scoring criteria of Kennedy et al. (1993), we calculated four types of SSQ scores: SSQ total, SSQ nausea (SSQ-N), SSQ oculomotor (SSQ-O), and SSQ disorientation (SSQ-D).

3.3. Procedure

We designed 2 × 2 experimental conditions by changing the orientation of the VR content and the controllability of the participant’s body. Depending on the camera orientation, participants watched an upright or inverted VR scene. The controllability of the participants’ body was manipulated by restraining their upper body. During a restrained condition, participants were instructed to pose with their head fixed using a chin rest. In an unrestrained condition, they were able to make a head or torso movement during the VR interaction.

Before performing the experiment, participants completed an eye-tracking calibration. Once a participant wore the Fove, the device provided the standardized calibration session ensuring the data accuracy. After the calibration, participants experienced four experimental conditions in a row: upright/unrestrained, upright/restrained, inverted/unrestrained, and inverted/restrained. To avoid the order effect, we randomly assigned the sequences of the experiments and counterbalanced them (Fig. 4).

Participants were required to report their SSQ scores before and after each VR experience (pre- and post-SSQ, respectively). Between each experience, there was a 10-min break to prevent a carryover effect. For the data analysis, relative scores between pre- and post-SSQ were used (i.e. △SSQ). Overall, it took an hour to complete the entire procedure of the experiment.

3.4. Data analysis

3.4.1. Preprocessing and epoching

Because the HMD device provides an eye position vector in 3D space, it was required to project the vector onto the 2D space. We transformed the value of a given position vector (x_p, y_p, z_p) to the point on the NDC plane (x_{ndc}, y_{ndc}, z_{ndc}) using the following equations (Ahn, 2021; Scratchapixel 2.0, 2021). Note that the focal length d = 1/tan(FOV/2):

\[ x_{ndc} = \frac{-d \cdot x_p}{z_p} \]

\[ y_{ndc} = \frac{-d \cdot y_p}{z_p} \]

\[ z_{ndc} = 1 \]

Figure 1: A VR scene of each orientation condition: (a) upright and (b) inverted.

Figure 2: An illustration of the eye position vector in 3D virtual space. We converted the vector into the x and y position on the NDC space.
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As the sequence \(\Delta t\) increases, the point moves farther away from the current cart position (i.e., Sequence 0). Note that these points are virtual objects for data analysis, which means they did not appear while participants experienced the roller coaster.

\[
y_{idec} = \frac{d \cdot y_p}{z_p}.
\]

After the conversion, the x- and y-axis locations of the point were preprocessed. Following the previous studies, we applied a weighted average filter with a time window of 300 ms (Kumar et al., 2008; Feit et al., 2017). After the filter, we performed a linear interpolation for the eye-blink data points (Wass et al., 2013; Hershman et al., 2018).

For analysing the gaze behaviors, we selected a specific course of the track considering both participant’s visual attention and level of discomfort. First, we chose the part of the scene where the upcoming track was mainly observed to the participant, ensuring that other distracting visual objects were not contained in the visual field. Therefore, we can assume that the participant focused on the track rather than any other visual stimuli. In addition, we selected the course including various rotational movements (e.g., pitch, yaw, and roll movement) where the previous results consistently showed higher cybersickness compared to the translational movement (Chen et al., 2011; Keshavarz & Hecht, 2011; Lubeck et al., 2015). By selecting the cybersickness-evoking course, we investigated whether the participant showed distinctive gaze behaviors during severe discomfort. Taken together, we selected the latter part of the VR ride, which took about 12 s in total. Also, the same data course was chosen for the analysis in each experimental condition.

3.4.2. Eye-related indices

**Fixation duration:** We calculated the participant’s fixation duration for each experimental condition. Following the study of Wibirama et al. (2020), we defined the participant’s eye movement as “fixation” when (s)he stared at a specific area (<10°) for more than 300 ms. In addition, nine areas of interest (AOIs) were assigned to investigate the spatial features of fixation (Fig. 5). Each AOI represented one of the 3 × 3 sections of the screen. We computed the fixation duration of each AOI among the participants and investigated the effect of experimental conditions on fixation duration.

**Deviation from the center point:** According to Diels et al. (2007), gazing at a specific point (e.g., fixation cross) can affect the level of cybersickness of users. Diels showed that the deviation from the eccentric gaze position differed between participants depending on their susceptibility to motion sickness. We set the center of the NDC space (i.e., \(x = 0, y = 0\)), which was a fixed point regardless of roller coaster riding and was not seen during VR interaction. Using the preprocessed eye-gaze point on the NDC space, we calculated how far the gaze point deviated from the center position at each frame (Fig. 6a) and then averaged it (Fig. 6b) using the following equation:

\[
\text{Mean deviation} = \frac{\sum_{i=1}^{n} \text{deviation}_i}{n}.
\]

As the value of the deviation increased, we assumed that the participant gazed away from the eccentric point during given \(n\) frames. We investigated whether the experimental condition could affect a participant’s eye movement in variation.

**Distance between the eye gaze and the moving point:** We investigated the pattern of the gaze trajectories while riding a roller coaster. According to the SVM model, an individual’s internal model can drive eye movements to make a better estimate of the expected sensory information. To demonstrate this claim, we calculated the distance between the participant’s gaze and a given point on the track and investigated whether participants accurately gazed where they expected to be located can associate with the level of cybersickness. We assumed that, if the distance became smaller, the participant tended to correctly follow one’s eye on the track. As the distance increased, on the other hand, the participant gazed away from the track.

For the analysis, we extracted the NDC position of five virtual points on the track where the participants might watch while experiencing the roller coaster. It is noted that these points were only used for calculating the distance, which did not appear during VR riding (Fig. 3). Each point represented a location on the track where the participants arrived after a given \(\Delta t\) (\(\Delta t = 0.5, 0.75, 1.0, 1.25, \text{and} 1.5\) s, respectively). As the time increased, the point on the track moved farther away from the current viewpoint (Fig. 3).

For the sake of simplicity, we named each point as a series of sequences. Sequence 1 represented a point on the upcoming path after 0.5 s and increased by 0.25 s as the sequence increased (Fig. 3). For each sequence, we calculated the distance between...
Using the following equation:

\[
\text{Mean distance} = \frac{\sum_{i=1}^{n} \text{distance}_i}{n}.
\]

This approach was attributed to the VR content of this study. While the previous study used stationary objects such as a fixation cross (Diels et al., 2007), our content did not include any fixed visual stimuli. This is intended for participants to watch any desired location on the rail to record natural gaze behavior in experiencing VR riding.

Thus, we first calculated the shortest distance between the eye and the object position on the NDC space (i.e. a point on the track) at each frame (Fig. 7a) and averaged it (Fig. 7b) using the following equation:

\[
\text{Mean distance} = \frac{\sum_{i=1}^{n} \text{distance}_i}{n}.
\]

4. Result

For the SSQ scores, data from 23 participants were used because three participants withdrew from the experiments. For the eye-tracking analysis, a total of 20 participants were used owing to malfunction in the data recording of three participants.

4.1. SSQ

We performed a Friedman test since the results of the Shapiro–Wilk test showed violations of the normal distribution in SSQ scores. Before we demonstrated the effects of orientation and controllability on cybersickness, we checked the carryover effect in each SSQ score. Although the participants had a 10-min break between each session, we investigated whether they reported higher SSQ scores as they repeatedly experienced the VR regardless of the experimental condition. The results of the Friedman test showed that there were no differences in the level of cybersickness according to the repetition; that is, the participants did not show more severe sickness in the fourth trial than the first trials. Post hoc analysis with Wilcoxon signed-rank tests showed differences between each session, we investigated whether they reported higher SSQ scores as they repeatedly experienced the VR regardless of the experimental condition. The results of the Friedman test showed that there were no differences in the level of cybersickness according to the repetition; that is, the participants did not show more severe sickness in the fourth trial than the first.}

\[
\chi^2(3) = 0.031, p = 0.999, \text{SSQ-N: } \chi^2(3) = 1.678, p = 0.643, \text{SSQ-O: } \chi^2(3) = 0.353, p = 0.950, \text{SSQ-D: } \chi^2(3) = 0.696, p = 0.874.
\]

However, the Friedman test showed that there was a significant difference in SSQ-N score depending on the type of experimental condition (\(\chi^2(3) = 9.258, p = 0.026\)). While participants showed the lowest level of nausea symptoms when they had controllability in the inverted VR condition, the level of SSQ-N was highest when watching the upright scene with fixed body posture.

Post hoc analysis with Wilcoxon signed-rank tests showed different levels of SSQ-N according to the orientation and controllability condition. Participants tended to report a lower level of nausea when watching the inverted VR than that when watching the upright VR (\(Z = -1.952, p = 0.051\)). Moreover, they
Table 2: SSQ scores for all experimental conditions (mean ± SD).

|                | SSQ total | SSQ-N | SSQ-O | SSQ-D |
|----------------|-----------|-------|-------|-------|
| **Unrestrained** |           |       |       |       |
| Upright        | 18.70 (±21.93) | 14.72 (±20.49) | 10.38 (±15.59) | 29.05 (±33.22) |
| Inverted       | 9.43 (±15.66)    | 7.05 (±16.58)    | 3.63 (±11.40)    | 18.16 (±28.29)  |
| **Restrained**  |           |       |       |       |
| Upright        | 21.63 (±21.28) | 22.61 (±23.02) | 9.39 (±13.99)  | 30.26 (±35.53)  |
| Inverted       | 15.45 (±15.96) | 12.44 (±12.68) | 9.23 (±14.63)  | 22.39 (±26.46)  |

Table 3: Mean deviations from the center point for all experimental conditions (mean ± SD).

|                | Unrestrained | Restrained |
|----------------|--------------|------------|
| Upright        | 0.249 (±0.116) | 0.243 (±0.091) |
| Inverted       | 0.221 (±0.070) | 0.254 (±0.062) |

**Fig. 8:** Fixation durations of each AOI according to each experimental condition. The results indicate significant main effects of orientation and controllability (*p < .05). Error bars represent SEM.

reported less SSQ-N when they were free to move (i.e. high controllability) (Z = −2.346, p = 0.019). However, other scores (i.e. SSQ total, SSQ-O, and SSQ-D) did not show statistical differences between experimental conditions. The mean (±SD) SSQ scores are shown in Table 2.

4.2. Eye-related indices

4.2.1. Fixation duration

The distribution of fixation duration violated the assumption of normality; we performed a Friedman test to determine a specific area where the participants mostly fixated their eyes. In accordance with the previous study of Wibirama et al. (2020), participants mostly fixated at the center part of the VR screen compared to other areas (χ²(8) = 136.907, p = 0.000).

Follow-up comparisons of fixation duration at AOI 5 showed significant differences between the experimental conditions (χ²(3) = 16.440, p = 0.001). The rank of fixation duration in each condition was restrained-inverted, unrestrained-inverted, restrained-upright, and unrestrained-upright, respectively. Post hoc analysis with Wilcoxon signed-rank tests showed that participants significantly spent more time fixating their eyes in the inverted scene compared to the upright one (Z = −2.837, p = 0.005). Besides, they showed significantly longer fixation duration when their body was restricted (Z = −3.248, p = 0.001) (Fig. 8).

4.2.2. Deviation from the center point

A 2 × 2 rmANOVA with orientation and controllability as factors was performed on the eye-gaze deviation from the center position. The results showed no significant differences between experimental conditions (Table 3).
Inverted 0.512 (±0.085) sequence. The results showed that there was a significant section. We assumed that, as the distance decreased, the participants gazed closer to the object position. The shortest distance between the eye gaze and the object position significantly predicted the total SSQ (i.e. upcoming path after 0.75 s) because the result of rmANOVA indicated the shortest mean distance at the second sequence. The overall model fit was significant and accounted for 34.8% of the variance in the total SSQ score. Fixation duration significantly predicted the level of discomfort ($\beta| = -0.477, p = 0.009$, partial $R^2 = 0.094$), indicating that a shorter fixation duration led to a greater level of cybersickness regardless of experimental conditions. Moreover, the interaction of orientation and distance between the eye gaze and the object position significantly predicted the total SSQ ($\beta| = 0.563, p = 0.000$, partial $R^2 = 0.252$).

According to the significance in prediction using the interaction term of orientation type and eye-gaze behavior, simple linear regressions on the total SSQ scores were performed for the post hoc analysis. For each upright and inverted condition, the distance between the eye gaze and the object position was added as a predictor variable. The distance significantly predicted the total SSQ score in the upright condition ($\beta| = 0.544, p = 0.000$, partial $R^2 = 0.296$) (Table 6). When the participants

### Table 4: Mean distances between the eye gaze and the moving point on each sequence (mean ± SD).

| Sequence | Upright | Inverted |
|----------|---------|----------|
| 1        | 0.259 (±0.094) | 0.512 (±0.112) |
| 2        | 0.212 (±0.058) | 0.429 (±0.085) |
| 3        | 0.253 (±0.067) | 0.430 (±0.058) |
| 4        | 0.323 (±0.072) | 0.471 (±0.036) |
| 5        | 0.408 (±0.076) | 0.536 (±0.027) |

### Table 6: Summary of a simple linear regression for predicting total SSQ score in the upright condition.

| Predictor | $\beta|$ | $t$  | $p$  | Partial $R^2$ |
|-----------|---------|------|------|---------------|
| Mean distance (seq. 2) | −0.404 | −1.777 | 0.080 | 0.044 |
| Orl. × mean distance (seq. 2) | 0.563 | 4.820 | 0.000 | 0.252 |

Note: $R^2 = 0.296$, adj. $R^2 = 0.277$, $F(1, 37) = 15.530, p = 0.000$. $\eta^2 = 0.380$]. Whereas the participants gazed close to the track in the upright VR condition, the eye movement trajectories deviated away from the track when they experienced the inverted roller coaster (Fig. 9). However, there were no significant differences in the distance according to either the controllability condition [$F(1, 19) = 0.347, p = 0.563, \eta^2 = 0.018$] or the interaction between the controllability and orientation [$F(1, 19) = 0.001, p = 0.973, \eta^2 = 0.000$].
predicted cybersickness based on user's gaze behaviors in HMD-based virtual reality

5. Discussion

The results of the SSQ scores indicate that the severity of cybersickness can be changed according to the orientation of the VR scene or the controllability of the user's body. Participants tended to report a lower level of discomfort while they watched the inverted VR scene. Moreover, those in the unrestrained condition (i.e. high controllability) experienced less cybersickness, the level of cybersickness decreased as eye movement trajectories deviated away from the track (β̂ = −0.331, p = 0.039, partial R² = 0.110) (Table 7 and Fig. 10b).

Table 7: Summary of a simple linear regression for predicting total SSQ score in the inverted condition.

| Predictor          | β̂   | t     | p      | Partial R² |
|--------------------|------|-------|--------|------------|
| Mean distance (seq. 2) | −0.331 | −2.137 | 0.039  | 0.110      |

Figure 10: A scatterplot of mean distance at sequence 2 (Δt = 0.75 s) and total SSQ scores. The plot indicates the opposite direction in predicting cybersickness according to the (a) upright and (b) inverted conditions. Shaded areas are 95% confidence intervals.

For the deviation from the center point, participants did not show a significant difference depending on the experimental conditions. According to Diels et al. (2007), participants were susceptible to motion sickness showed greater eye drift from the center, and this result was associated with the level of sickness. However, this study failed to reveal a correlation between SSQ scores and gaze deviation. This might have originated from the difference in the visual stimuli implemented in each study. Whereas Diels et al. (2007) used moving dots that simulated anterior–posterior oscillation, we adopted relatively high immersive VR including complex rotations and content scenarios (i.e. roller coaster riding). Thus, participants showed greater visual attention toward the center and had little room for focusing on the peripheral region. Further studies that implement slower moving content are required to clarify whether the deviation from the center can be a promising index for cybersickness.

Assuming that participants could anticipate the upcoming path, we examined where the participant usually gazed during the ride and whether such eye movements can be used to predict the level of cybersickness. The result indicated that the participants' gaze was found to be closest to a point on the track of the second sequence (i.e. the upcoming path after 0.75 s). This might be related to the characteristic of gaze behavior that people usually stare at the center of the screen (Carnegie & Rhee, 2015; Wibirama et al., 2020). Since the trajectory of the sequence 2 (Δt = 0.75 s) substantially covered the center part of the screen, the participant might naturally follow the moving point of the track in this sequence. Follow-up comparisons showed that participants viewed a wider part of the scene as well as the track when they watched the inverted VR compared to the upright orientation.
one. We suggest that this distinguished gaze behavior might be associated with the individual's internal model. When watching an unfamiliar orientation, participants hardly have an internal model of the scene, so they tend to focus on encoding broader visual information of a new environment along with following the path. On the other hand, in a familiar environment, participants already built neural expectancy for coherently perceiving the world, and the model might drive to minimize prediction errors by gazing at the upcoming path where the participants will arrive soon. Further studies using various types of scene orientation (e.g., forward-moving vs. backward-moving) are needed to support the idea that distinctive eye movements in VR orientation are related to the internal model.

Development of a regression model for cybersickness was attempted in previous studies (Kim et al., 2005; Dennison et al., 2016; Noojit et al., 2017; Weech et al., 2018; Wibirama et al., 2020). In accordance with the study by Wibirama et al. (2020), we combined various eye-related measures as predictors and found that fixation duration can effectively predict the level of user discomfort. The more participants fixated on the VR scene, the less cybersickness they likely experienced. This result can provide a plausible explanation for the previous approaches for reducing cybersickness. For example, it has been consistently observed that the level of discomfort decreases when users experience a narrower visual field in VR by reducing the FOV of the content (Fernandes & Feiner, 2016) or by implementing the dynamic depth of field (Carnegie & Rhee, 2015). These manipulations might cause the user to pay visual attention only to a limited area, to induce a longer fixation duration, and thereby result in decreasing cybersickness.

Besides fixation durations, we focused on natural gaze behaviors during immersive VR interaction. Considering the length of the entire VR experience, participants spent most of the time exploring the virtual world rather than fixating in a specific location. Thus, we assumed that including natural gaze behaviors as predictors would result in better performance in predicting cybersickness. The results indicated that our model could explain 34.8% of the total variance of cybersickness, which showed a substantial improvement in the coefficient of determination compared with that of a previous study (Wibirama et al., 2020). Interestingly, the result of multiple regression indicated that the interaction term (orientation × mean distance) significantly explained the 25% of the variance in SSQ total. This result implies that the mean distance between the eye and the object position in the second sequence can predict the total SSQ score but should be analysed separately depending on the orientation. As shown in Table 6 and Fig. 10a, there was a significant positive correlation ($\beta = 0.544$) between the mean distance and cybersickness in the upright condition; that is, participants who showed closer eye movement toward the upcoming track (i.e., shorter mean distance) could experience a lower level of discomfort if they watched the upright VR scene. However, a significant negative correlation ($\beta = -0.331$) was observed in the inverted condition (Table 7 and Fig. 10b). Thus, participants who gazed further away from the track tended to report a lower level of cybersickness. This result suggests that natural eye-gaze behavior might be a promising index for predicting cybersickness, but the index should be interpreted carefully depending on the orientation of the VR scene.

This study has several limitations. The VR content of this study was a roller coaster, which minimized visual elements other than the track for experimental purposes. Tracks are robust and explicit indicators that guide participants on what they will soon experience. Therefore, participants in this experiment were induced to focus their visual attention on the restricted space of the VR environment (i.e., the track). However, common types of VR content are more complex and consist of various visual objects. These types of VR can cause more dynamic eye movement depending on the content scenario or individual differences in visual attention. For this reason, the predictor variables in our regression model may be useful for a similar type of VR, such as racing or navigation. In future studies, various types of VR content are needed to choose the promising indices for improving the prediction model.

In addition, this study was unable to sufficiently evaluate the motion features of the VR content. Previous studies have shown that motion-related elements, such as speed or acceleration, can affect the level of cybersickness (Kim et al., 2019a, b). Further studies are required to investigate whether the current regression model can also successfully predict discomfort in varying degrees of motion situations. It is to be noted that we performed a multiple regression analysis for the prediction purpose. Therefore, it is not possible to interpret the relationship between oculomotor responses and cybersickness in a causal manner. More empirical data should be acquired to reveal the causal relationship between psychophysiological responses and cybersickness.

Owing to the low sampling rate of the eye-tracking device, limited approaches were adopted to investigate the distinctive eye movements. Other well-established indices, such as saccades and smooth eye pursuit, can be considered to clarify the relationship between eye movements and cybersickness. Lastly, recent techniques using a machine learning algorithm (Padmanaban et al., 2018; Kim et al., 2019a, b) or nonlinear regression analysis can improve the current prediction model.

6. Conclusion

Recent research on cybersickness has shown a growing interest in enjoying VR more safely. In this study, we investigated novel features of eye movements in VR while wearing an HMD with eye tracking. Using this device, we acquired natural gaze behaviors during the VR experience and examined whether these physical responses can be interpreted in terms of the individual's internal model. Moreover, we developed a regression model for cybersickness that only considers physical measures of participants.

The experimental results contribute new insights on (1) demonstrating the SVM theory using HMD eye-tracking data, (2) inducing changes in SSQ scores and eye movements by manipulating the internal model, and (3) developing a regression model for cybersickness using eye-related measures as predictors. The results indicated that the level of discomfort can change depending on the condition of the individual's internal model, suggesting that accumulated previous experiences in the real world and accessibility of update inputs can influence the severity of cybersickness. Furthermore, fixation duration and dynamic gaze behaviors can be affected by the internal model and its update.

On the basis of these results, we developed a regression model that only considers the eye-related measures as predictors. It is noted that these parameters were acquired without disturbing the user's immersive VR experience. Unlike the previous variables for predicting cybersickness (Kim et al., 2005; Noojit et al., 2017; Weech et al., 2018), eye movements can be recorded using an HMD-based eye tracker, which does not require additional devices for data recording. This advantage can facilitate to
develop a prediction model that is highly applicable to practical VR context. Besides, by considering natural eye-gaze behaviors, our model showed a clear improvement in predicting cybersickness compared to the previous study (Wirrama et al., 2020: 4.2%, our model: 34.8%). Taken together, this study provides empirical data for the SVM theory and suggests that eye movements can serve as a promising index for predicting cybersickness.

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**Conflict of interest statement**

None declared.

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