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Quality of Experience Comparison of Stereoscopic 3D Videos in Different Projection Devices: Flat Screen, Panoramic Screen and Virtual Reality Headset

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ABSTRACT The use of Stereoscopic 3D (S3D) videos has been popular in commercial markets with ongoing developments in the field of visual entertainment in recent years. A wide variety of projection methods of 3D video content is currently available, such as projection to a panoramic screen and projection of omnidirectional video content from head mounted displays using Virtual Reality (VR) technology. This article investigates the Quality of Experience (QoE) and associated Visually Induced Motion Sickness (VIMS) caused by the viewing of S3D videos. The investigations used three different projection screens: a 3D flat screen, a 3D panoramic screen in a hemispherical shaped room and a VR headset. Several assessment methods including a Simulator Sickness Questionnaire (SSQ), ElectroEncephaloGraphy (EEG), and measurement tools for eye blink rate detection were applied to measure the QoE experienced by viewers. The SSQ scores were also compared with the behavioral data such as attention and meditation levels and enjoyment ratings acquired from different video content and projection screens. The results indicate that the projection screen is a key factor affecting the level of visual fatigue, VIMS and QoE assessments, which are discussed in-depth in the article.

INDEX TERMS Stereoscopic video, omnidirectional content, virtual reality, quality of experience, electroencephalography, simulator sickness.

I. INTRODUCTION

The recent growth of Stereoscopic 3D (S3D) technology has led to the commercial production of 3D movies. However, research studies have found that people may experience visual fatigue after watching stereoscopic movies or images. The visual fatigue is usually accompanied by symptoms such as headaches, nausea, dizziness or eyestrain [1].

Quan *et al.* [2] studied the perception of 3D content and viewers' experiences. The authors suggested that the perception of 3D content could be differentiated from 2D content by viewers. Some studies proposed the perception of 3D content using a panoramic screen to achieve better visual attention. Wegner *et al.* [3] proposed a design specification for the projection of 3D videos on a circular panoramic screen; however, the design requires subjective quality experiments which have yet to be conducted. With the recent development of virtual reality (VR) and the production of powerful Head-Mounted Displays (HMDs), e.g. the HTC VIVE [4] and Facebook Oculus [5] product families, omnidirectional video content has become popular. These HMDs can process and display both 3D and 360° video content. Previous researchers have conducted a series of Quality of Experience (QoE) experiments with Visually Induced Motion Sickness (VIMS) caused by viewing S3D videos. Most of the previous research focused on the evaluation of the QoE in a viewing environment with a single projection screen but there is a lack of research that evaluates the QoE in different environments

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with more than one projection screen. Therefore, this article aims to identify the effects of VIMS and analyze 3D fatigue with three different projection screens, varying from an individual research-grade flat 3D screen, a consumer-grade VR headset and a 3D panoramic screen [6] with a series of objective and subjective tests. The subjective evaluation approach in this article invited participants to first view a set of S3D videos, during which time their ElectroEncephaloGraphy (EEG) and eye tracking biosignals were recorded. They then completed a survey to rate the enjoyment level and video quality, measuring their QoE. After performing these subjective tests, the EEG signals and QoE data were collected, analyzed and evaluated.

In the following, Section II discusses the background theory underpinning QoE and visual fatigue of 3D videos using various viewing screens. Section III and Section IV describe the experimental methodology used and explains the methods used with different projection screens. Section V discusses and analyzes the experimental results obtained, whilst Section VI concludes the article and proposes future directions for exploration. The main contributions of this article are to integrate three different subjective evaluation methods to evaluate the QoE of S3D videos in three different viewing environments, with a series of statistical analyses to assess whether their results correlate or not.

II. BACKGROUND

There is an existing body of research to discuss QoE experiments with different projection screens. These QoE experiments can generally be classified into three types: image quality assessment models, subjective evaluations among participants and adding stimulus for comparison. In [7], the authors conducted subjective evaluations on images displayed in an HMD environment. They suggested a testbed for conducting subjective tests on an omnidirectional environment using different projection schemes. Sun *et al.* [8] proposed a novel image quality assessment model for non-reference 360° images that were compared against other existing image quality assessment models on 360° databases. Narciso *et al.* [9] proposed a study using an HMD to measure the influence of video format and sound format on a user's sense of presence and cybersickness. A statistical analysis of their results failed to identify significant differences in the sense of presence and cybersickness observed between video and sound variables. A further study by Narciso *et al.* [10] proposed adding smell as an additional stimulus to measure the influence of presence, cybersickness and fatigue in VR environments. The results found no correlation between smell and other variables. Duan *et al.* [11] conducted a perceptual quality assessment of omnidirectional images through the collection of viewing directions, subjective quality scores and eye-tracking information into a database for omnidirectional image quality assessment. This database was compared with other existing image quality assessment databases. Singla *et al.* [12] compared the QoE of omnidirectional content viewed through different HMDs. Three categories of omnidirectional content with low, medium and high degrees of both camera and content motion were evaluated and it was found that there was a significant contribution of resolution and video content to the quality ratings. Anwar *et al*. [13], [14] compared high priority QoE factors of omnidirectional content in VR environments in terms of perceptual quality, presence and cybersickness. Also, two QoE factors for subjective evaluation: user's familiarity and user's interest in VR environments were evaluated by Absolute Category Rating (ACR) method. An artificial neural network (ANN) based QoE prediction model was also proposed to predict the impact of the three QoE factors under different stalling events on the cybersickness level of users.

Considering the quality assessment of S3D videos, Zhang *et al.* [15] conducted objective and subjective quality assessments of panoramic videos encoded at different bitrates and with the addition of noise at the same resolution. The results of the subjective quality assessments revealed that the subjective perception between normal videos and panoramic videos varied when the bitrate changed. Appina *et al.* [16] proposed novel subjective quality and objective quality prediction by using 288 test videos derived from 12 "pristine" S3D videos, where "pristine" video refers to uncompressed video with highest quality. The proposed pristine videos were chosen through subjective quality tests based on motion information, spatial information and disparity using a 6-point scale rating (scaled from 0 to 5). However, there was no further elaboration of QoE assessments.

Considering motion sickness and visual fatigue, Naqvi *et al.* [17] proposed measures to assess VIMS caused by the viewing of S3D videos and compared the ratio of low frequency to high frequency components in video content, where low frequency components were defined as less than 0.15 Hz, corresponding to sympathetic modulations, whereas the high frequency components were defined to be higher than 0.15 Hz, representing parasympathetic activities. Duan *et al.* [18] conducted an experiment to assess VIMS of immersive videos of real scenes by controlling visual oscillations. Wang *et al.* [19] compared the VIMS and eye fatigue caused by HMDs using Simulator Sickness Questionnaire (SSQ) scores and eye-tracking methods respectively. By analysis of the parameters in the eye tracker, new assessment models were proposed to assess eye fatigue of HMDs. Eye fatigue assessment models of [20] were proposed to assess eye fatigue based on eye movement data and eye blink data using an unobtrusive eye tracker.

Some researchers have used EEG signals to assess VIMS. The EEG signals included five waves, namely alpha (α), beta (β), delta (δ), theta (θ) and gamma (γ), each of which corresponds to different frequency ranges and which reflect different emotion states of viewers. The EEG components are divided into two types: temporal and oscillatory components. Table 1 shows the characteristics of the EEG components used in the cognitive neuro system. Oscillatory components reflect various neural states of participants [21]. Measurement of brain wave power in the different frequency bands corresponding to the α, β, δ, and θ waves can be used to detect fatigue by looking at the ratio between slow waves (δ and θ) and fast waves (α and β) as a function of time [22]. In cognitive neuroscience, by comparison of the behavior of temporal components before and after an event happens, mental fatigue can be measured. Also, different frequency bands reflect varying levels of alertness. The proportion of low frequency bands such as α, θ and δ waves tend to increase, whereas the proportion of high frequency bands such as γ and β waves decrease when the alertness declines [23]. Liu *et al.* [24] and Petrantonakis *et al.* [25] proposed using EEG signals to measure the bioelectrical activities and emotion recognition of humans. The emotions were classified into six classes: happiness, surprise, anger, fear, disgust and sadness. EEG can be recorded in temporal resolution so that the viewing experience of S3D video could be monitored in real-time. Li *et al.* [26] conducted 3D visual fatigue tests to measure biosignals by watching both 2D and 3D videos in a binocular parallax condition. The results found that measured EEG biosignals were significantly correlated with the subjective measurement of 3D visual fatigue. Choy *et al.* [27] proposed the adoption of the EEG method to conduct objective and subjective experiments to record signals [28]. The experiments included the comparison of 2D and S3D videos. Zou *et al.* [29] investigated the effectiveness of nine types of EEG indices and suggested that the alpha wave is the most promising indicator to detect stereoscopic visual fatigue. Hu *et al.* [30] utilized fMRI brain imaging to bridge low- level and high-level semantics for video classification. Oliveira *et al.* [31] studied EEG and other biosignals such as galvanic skin response, respiration rate and volume, skin temperature and heart rate, in relation to multimedia content and delivery based on user emotions. Liu *et al.* [24] proposed a method to recognize the dominance level of emotion interaction with the human brain using an EEG approach. However, this method used auditory stimuli only and did not consider visual stimuli.

To analyze EEG signals, some researchers adopted analysis of variance (ANOVA) statistical methods for their analysis. Li *et al.* [32] used ANOVA to compare and analyze EEG signals in order to find the responses of the brain when conducting acupuncture tests. Salami *et al.* [33] applied a common spatial pattern (CSP) algorithm via a brain computer interface (BCI) to identify the features of EEG signals. Unbalanced Factorial ANOVA was adopted to analyze the feature vectors of EEG signals using the F distribution parameter from an ANOVA table by linear regression. Mehmood *et al.* [34] conducted emotion recognition experiments to record EEG signals and processed Hjorth parameters such as activity, mobility and complexity [35]. A one-way ANOVA method was analyzed to select optimal EEG features from Hjorth parameters for different EEG frequency ranges.

In this work, EEG signals were measured and information such as attention, meditation, eye blinks and brain wave powers were obtained. The brain wave power equations from [29] were used to calculate the visual fatigue level. The evaluation of visual fatigue by EEG signals is thought to be a more accurate measure than a typical subjective rating. Secondly, VIMS was also evaluated by using a SSQ to correlate with the visual fatigue. Thirdly, the enjoyment level and video quality were obtained by typical subjective ratings.

TABLE 1. Characteristics of Major EEG Components

Component	Name	Frequency band	Reflection
Temporal	Delta (δ)	1 – 3 Hz	Deep sleep, unconsciousness of mind
Temporal	Theta (θ)	4 – 8 Hz	Light sleep, emotional stress
Oscillatory	Alpha (α)	9 – 14 Hz	Physical relaxation, meditation
Oscillatory	Beta (β)	15 – 30 Hz	Current emotional state
Oscillatory	Gamma (γ)	>30 Hz	Diagnose some brain illness

III. EXPERIMENTAL METHODOLOGY

In order to assess the response of viewing S3D videos, some measurement tools are proposed to assess visual fatigue as follows.

A. VISUALLY INDUCED MOTION SICKNESS (VIMS)

To conduct the subjective evaluation of QoE, a SSQ is the most common method to assess VIMS, proposed by Kennedy *et al.* [36]. Table 2 shows 16 symptoms to assess motion sickness, where each symptom item contains different ratings. The rating scheme of items is based on the data collection and analysis from the simulator sickness experienced by US pilots using ten different flight simulators [37]. The three sub-scales, Nausea (N), Oculomotor (O) and Disorientation (D), were based on the greatest varimax loading structure for identification. The symptom items of each sub-scale had at least a 0.3 varimax loading factor. Some items included more than one sub-scale factor, e.g., difficulty focusing, nausea, difficulty concentrating and blurred vision. Each symptom item was rated on four levels: none (0), slight (1), moderate (2) and severe (3). The Total Severity (TS) score was computed by the sum of three sub-scales based on the type of symptoms and the scoring level, with a particular multiplying factor. The N, O, D and TS scores were calculated as shown in Table 2.

Table 3 shows the potential score ranges of SSQ scores which shows the score ranges of each symptom level. For instance, when all participants have "slight" symptoms related to disorientation, the resulting D score is 97.4. The total SSQ score, which is also known as the TS score, can range from 0 to 235.6. The SSQ was used to assess motion sickness when participants were watching S3D videos. Kaufmann *et al.* [38] adopted the SSQ to assess the sickness for participants of handheld projector interaction. Solimini *et al.* [39] found that watching 3D movies might raise the potential risk of health problems. Choy *et al.* [27] noted that watching 3D movies may result in higher VIMS and viewers might experience higher visual fatigue.

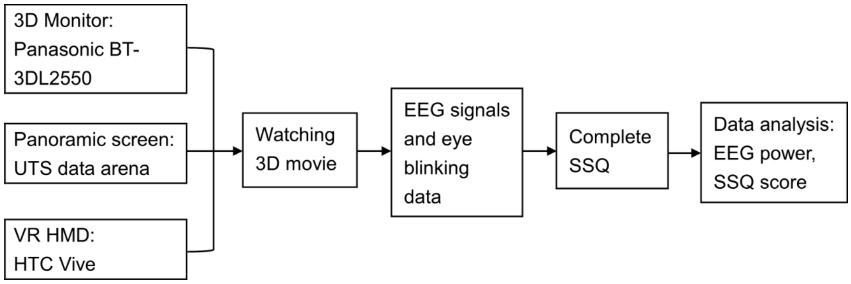

FIGURE 1. Block diagram of the experimental methodology.

TABLE 2. 16 SSQ Symptoms to Assess Motion Sickness

SSQ Symptoms	Weighting		
	N	O	D
General discomfort	1	1	
Fatigue		1	
Headache		1	
Eye strain		1	
Difficulty focusing		1	1
Increased salivation	1		
Sweating	1		
Nausea	1		1
Difficulty concentrating	1	1	
Fullness of head			1
Blurred vision		1	1
Dizzy (eyes open)			1
Dizzy (eyes closed)			1
Vertigo			1
Stomach awareness	1		
Burping	1		
Total	**[1]**	**[2]**	**[3]**

Computation of SSQ score and sub-scale scores:
Nausea = [1] × 9.54
Oculomotor = [2] × 7.58
Disorientation = [3] × 13.92
Total Severity Score = ([1] + [2] + [3]) × 3.74

TABLE 3. Potential Score Ranges of SSQ Scores

Symptom	Nausea	Oculomotor	Disorientation	SSQ Score
None	0	0	0	**0**
Slight	66.8	53.1	97.4	**78.5**
Moderate	133.6	106.1	194.9	**157.1**
Severe	200.3	159.2	292.3	**235.6**

B. ELECTROENCEPHALOGRAPHY (EEG)

Researchers have previously shown that analysis of EEG signals is a reliable technique for the detection of fatigue [40]. Different authors have used different algorithms of EEG signals to calculate a brain wave power ratio: Eoh *et al.* [41] used 1) $(\theta + \alpha)/\beta$ and 2) α/β to evaluate the fatigue level of drowsiness in simulated driving tasks, whilst Jap *et al.* [42] used 3) $(\theta + \alpha)/(\alpha + \beta)$ and 4) θ/β to evaluate the fatigue in monotonous driving simulator tasks. All algorithms show an increase with fatigue due to a decrease of beta waves. Li *et al.* [43] applied all algorithms and proposed an evaluation model for driver fatigue detection.

Chen *et al.* [44] suggested test methods to examine fatigue measurement of 3DTV by adopting all four algorithms above.

The results showed that brain wave power ratios may help to indicate fatigue whilst viewing 3DTV. In this work, the ratio of brain wave powers was computed using equations (1) and (2) to determine the fatigue level of 3D video. A previous 3D fatigue experiment conducted by Choy *et al.* [27] found that the fatigue level was typically higher than 0.05 when participants were watching 3D videos, while the fatigue level was lower than 0.05 when watching 2D videos. The result revealed that the typical 3D fatigue level is normally higher than 0.05.

$$Power\ Ratio_1 = \frac{\theta + \alpha}{\beta} \tag{1}$$

$$Power\ Ratio_2 = \frac{\theta + \alpha}{\alpha + \beta} \tag{2}$$

IV. METHODS

The experiment was divided into three parts in order to compare three different viewing environments created by different devices: 1) a flat screen, 2) a panoramic screen, and 3) a VR headset device.

A. EXPERIMENTAL PROCEDURES

All participants completed a short S3D vision test based on the ITU-R BT 2021 standard [45] before participating in the experiment. Figure1 illustrates the methodology of the experiment. Every participant was required to watch 5 sets of S3D video sequences, each about 1-minute duration, with each device. To prevent bias, the video sequences were played in a random order, generated by the Stat Trek Random Number Generator [46]. After watching each video sequence, the participants were required to complete the SSQ to rate the enjoyment level and video quality. Each participant participated in 3 sessions, with a 10-minute viewing break between each session (30 minutes at most) in order to minimize the motion sickness and fatigue. Participants were free to discontinue the test at any time if suffering from motion sickness, physical sickness or dizziness. The average duration of the whole experiment for each participant was 1.5 hours, including all viewing breaks to minimize VIMS and fatigue.

B. EXPERIMENTAL DEVICES

1) DEVICE 1: FLAT 3D SCREEN

A 25.5" Panasonic BT-3D L2550 Full HD (1920 × 1080) LCD 3D screen was used to play all S3D video sequences. In accordance to the specifications of the THX Cinema Certification [47], participants were required to sit in front of the 3D screen at a 0.9m viewing distance with a 36° viewing angle to watch 3D movies.

FIGURE 2. A participant wearing the Mindwave EEG headset and active shutter glasses to watch 3D movies in the Data Arena.

2) DEVICE 2: 3D VIDEO PROJECTION IN PANORAMIC SCREEN

The panoramic screen is a 10m diameter hemispherical room, known as the Data Arena at the University of Technology Sydney [6]. In the Data Arena, six 3D-stereo projectors arranged in circular position and a large panoramic screen were used to project S3D videos. The specifications of the Data Arena are shown in Table 4. Participants wore active shutter 3D glasses and stood in the middle of the panoramic screen to view stereoscopic videos, as shown in Figure 2. A high-performance computer graphics system drove the six S3D video projectors and the video walls were edge-blended to produce a seamless 3D panorama. Software tools including MeshLab [48] and FFMPEG [49] were used for graphic computation, rendering and re-construction of 3D images, and consistent projection from the six projectors. Algorithms were implemented to present S3D videos at a high level of resolution. In this experiment, the six projectors projected three identical, edge-blended 1920 × 1080 pixels S3D video sequences to fill the 360° surround panoramic screen.

TABLE 4. Specifications of the Data Arena

Dimension	Hemisphere Diameter: 10 m Height: 4 m from the floor to projectors
Screen Dimension	Height: 3.5 m, panoramic
Resolution of video projector	1920×1200

3) DEVICE 3: 3D VIDEO ON 360° IN VIRTUAL REALITY

Participants were required to wear a HMD to view the 360° scene. HTC Vive equipment was used in this experiment. The refresh rate, field of view and resolution of HTC Vive are 90 Hz, 110° and 2160×1200 pixels respectively. To minimize possible issues related to the synchronicity of the stimuli, participants were required to sit down to watch the video sequences in order to restrict body movements while they could turn their heads for different viewing positions. Before the experiment, all participants were briefed on how to use the HMD and its controller, and the 3D video player.

C. EEG DEVICES

When viewing 3D videos with the different devices, participants were required to wear a NeuroSky Mindwave brainwave headset shown in Figure 3. The headset contained 2 sensors that connected with the ear and forehead, respectively. Whilst a participant viewed a series of S3D videos, EEG signals and eye blink rates were captured by brainwave software from the Mindwave equipment to measure the fatigue level and track the eye blink frequency during the experiment.

FIGURE 3. NeuroSky Mindwave brainwave dataset.

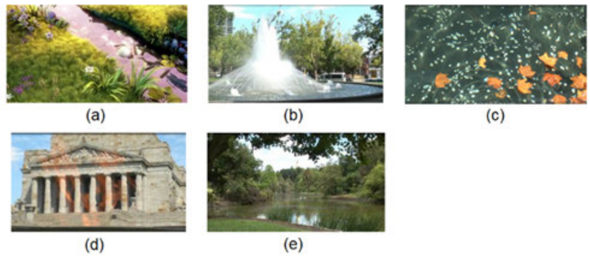

FIGURE 4. 5 video sequences extracted from Big Buck Bunny and RMIT3DV databases: (a) Big Buck Bunny, (b) Water fountain, (c) Wishing well, (d) Flame, (e) Garden.

D. VIDEO STIMULUS AND METRICS

The video sequences were extracted from Big Buck Bunny [50] and RMIT3DV [51] databases, as shown in Figure 4. The characteristics of the video sequences are summarized in Table 5. The selection criteria of the video sequences were based on the variety of 3D effects and the comparison of 3D video experiences between animation and outdoor scenes in different viewing environments.

For the subjective assessment of the video quality of S3D videos, an ACR method was adopted according to the ITU-T P.910 document recommendation [52]. The participants were asked to rate the video quality on a five-level scale according to the enjoyment of the video experience (5: very enjoyable, 1: not enjoyable at all). All captured EEG data, QoE evaluation metrics by using ACR method and SSQ scores were then analyzed to compute the fatigue level, total SSQ scores, and total eye blink frequency for each video sequence. ANOVA was also analyzed to identify the significance of QoE factors for the three different devices and five sets of video sequences.

V. RESULTS AND DISCUSSION

A total of 15 participants (11 males and 4 females) ranging in age from 18 to 46 years old (mean: 29.1 years, s.d.: 8.67

TABLE 5. Characteristics of Video Sequence

Name of Movie	Type	Description	3D effect
(a) BBB	Animation	Cartoon characters with the garden background	Weak
(b) Water Fountain	Outdoor Scene	Water, trees	Moderate, water fountain
(c) Wishing Well	Outdoor Scene	Warped water movement	Strong, warped water movement
(d) Flame	Outdoor Scene	Chaotic flame	Moderate at chaotic flame
(e) Garden	Outdoor Scene	Lake, birds, trees	Weak

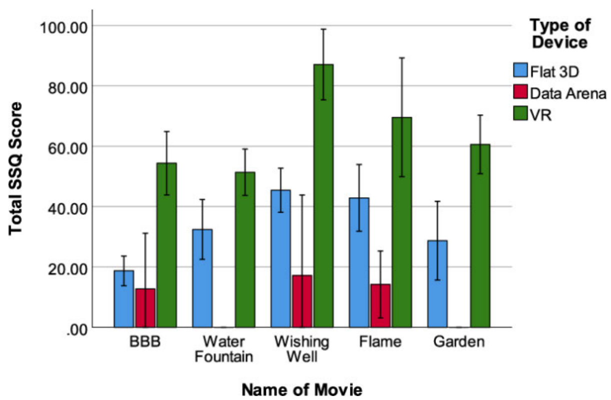

FIGURE 5. Total SSQ scores.

years) participated in the experiment. All participants were asked about their fatigue level to ensure that they were not in a fatigued condition before undertaking the test.

A. SIMULATOR SICKNESS QUESTIONNAIRE (SSQ)

Figure 5 and Figure 6 show the total SSQ scores and total SSQ scores with 3 sub-scales of each video sequence for the 3 different viewing devices respectively. Error bars across all participants are presented to indicate the 95% confidence interval. For all videos, the total SSQ scores of the VR device was more than 50 whereas that of the panoramic screen was lower than 20. The results suggest that VR devices may lead to more serious VIMS whereas VIMS may be less serious with the panoramic screen. The total SSQ scores with a panoramic screen was the lowest, especially for the "Water fountain" and "Garden" video sequences. No participants experienced the motion sickness symptoms. The results revealed that the viewing distance and the synchronization of the projection of video sequences in the Data Arena may contribute to less visual fatigue, resulting in lower total SSQ scores. On the other hand, the SSQ scores of both the "Wishing well" and "Flame" video sequences from all projection screens were generally higher than both the "Water fountain" and "Garden" video sequences. The results suggest that the chaotic movement of the "Wishing well" and "Flame" video sequences may correlate with higher SSQ scores. A single-factor ANOVA of the SSQ score was conducted. The results showed that the device factor ($F = 2.78$, $p < 0.01$) was found to be significant.

B. EEG BRAIN ACTIVITY

Figure 7 shows the brain wave power ratios across the 5 video sequences for the 3 different devices respectively, where PR1 and PR2 represent the brain wave power ratios calculated from Equations (1) and (2) respectively. The average brain wave power ratios measured for all video sequences ranged between 0.05 and 0.09, which were higher than 0.05, representing a higher level of 3D fatigue for all participants [27]. It can be seen that the brain wave power ratios of VR devices ranging from 0.0623 to 0.0893 stimulated the highest levels of brain wave power ratios across all video sequences, whereas the brain wave power ratios caused by the flat 3D screen and panoramic screen were similar, ranging from 0.0572 to 0.0708 and from 0.0507 to 0.0683 respectively. Among the video sequences, "Wishing well" caused the highest fatigue level when the participant was viewing with the VR device (0.0893) or the flat 3D screen (0.0683). With the panoramic screen, "Water fountain" caused the highest fatigue level (0.0708) and "Wishing well" the second highest (0.0650). Participants recorded the most significant differences between the two brain wave power ratios when watching "Wishing well" with the VR device, potentially reflecting different emotional responses of the participants [53]. A single-factor ANOVA of the two brain wave power ratios was conducted. The results showed that the device factor from the two brain wave power ratios, ($F = 1.85$, $p < 0.01$) and ($F = 3.23$, $p < 0.01$), was found to be significant.

C. EYE BLINK FREQUENCY, ATTENTION AND MEDITATION LEVELS

Figure 8 shows the average eye blink frequency of participants when using different devices to watch the video sequences. Among all participants, the eye blink frequency over one minute duration when using the flat 3D screen was between 46.2 and 57.3 times per minute, which was greater than with the VR device, which ranged from 36.4 to 50.3 times per minute. Also, shown in both Figure 5 and Figure 7 respectively, are the SSQ scores and the brain wave power ratios using the flat 3D screen and panoramic screen, which were generally less than those in the VR device. The eye blink results correlate to SSQ scores and brain wave power ratios, indicating that the 3D screen may cause a lower level of visual fatigue than the VR device. Also, the eye blink frequency was greater with the flat 3D screen than the Data Arena except for the "BBB" video sequence, possibly reflecting a lower level of visual fatigue for the different scene content. The relatively large confidence intervals from Data Arena (at least more than ± 5 for each video sequence) may also affect the accuracy. On average, the "Wishing well" video sequence caused the lowest frequency of eye blink,

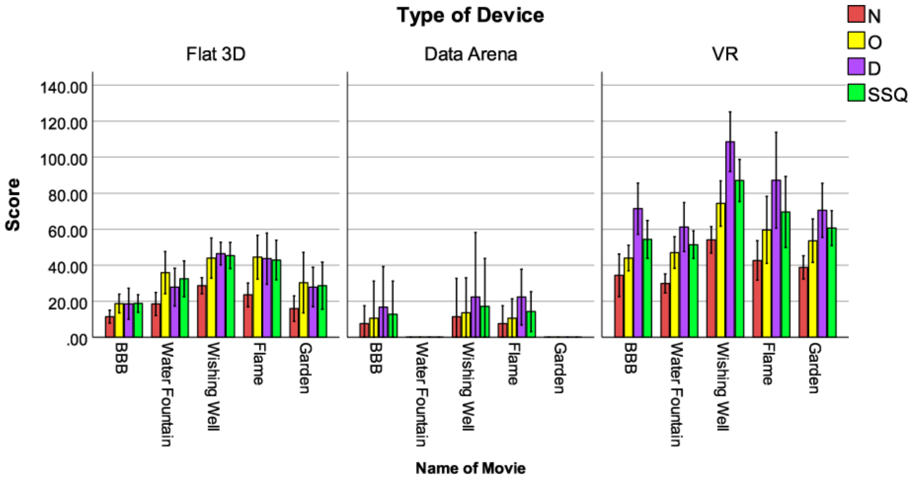

FIGURE 6. Total SSQ scores with 3 sub-scales: Nausea (N), Oculomotor (O) and Disorientation (D).

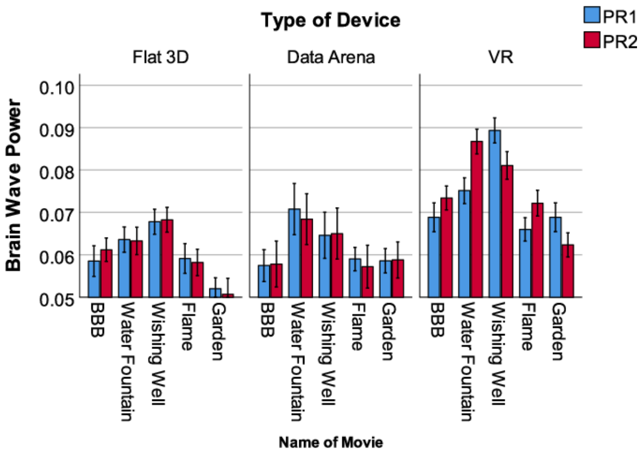

FIGURE 7. Measured brain wave power ratios for different viewing devices and 3D videos.

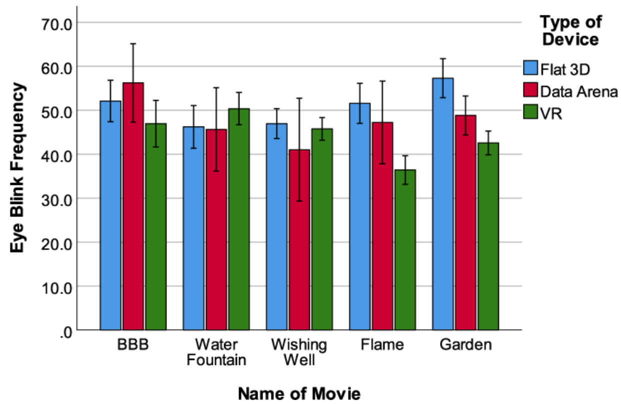

FIGURE 8. Eye blink frequency.

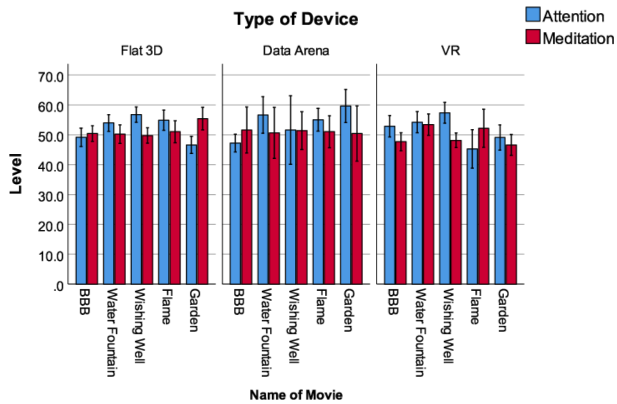

FIGURE 9. Attention and meditation levels.

which may be attributed to the movements of the objects under the water, the unstable water movements and natural lighting conditions. However, when participants were watching "Flame" with the VR device, the lowest frequency of eye blink, valued 36.4 times per minute, was recorded among the five video sequences, which may be a result of the main focus point, the flame, in the scene and the rapid movement of the flame. Previous researchers have investigated whether there is any implication of eye movements and eye blinks when viewing chaotic scenes, aiming at examining its nature in terms of non-linear dynamics [54] or changing the focus on an object when its distance varied in regards to the accommodative process [55]. These factors need to be further explored.

Figure 9 shows the attention and meditation levels of participants, as calculated by the Mindwave device, when they were watching each video sequence with the 3 different devices. According to the manufacturer's specification of the Mindwave equipment, both the attention (similar to concentration) and meditation (similar to relaxation) are reported by an "eSense" meter to characterize mental states. The eSense scale is between 1 and 100. A value between 40 and 60 is considered to be a neutral condition [56]. The results show that both the attention and meditation levels maintained an average level of 50 with the different devices, which may reveal a neutral neuro condition of the participants [57], [58]. Celia *et al.* [59] suggested that chaotic and fast audiovisuals increase attention scope but decrease conscious processing. The results show that the attention levels of "Wishing well" and "Flame" are the highest (at 56.7 and 54.9 respectively)

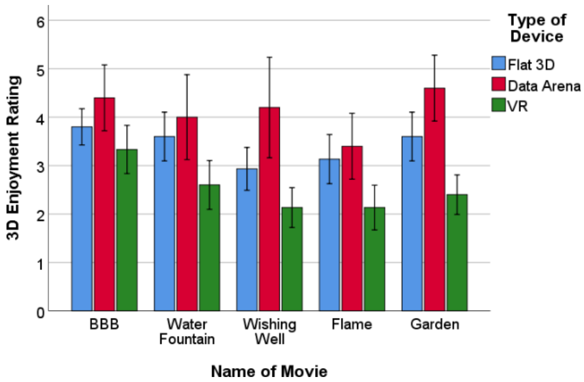

FIGURE 10. Enjoyment rating of participants.

with the flat 3D screen. However, this trend is not seen with the Data Arena and VR device. Projection devices may be a factor affecting the correlation between attention scope and conscious processing.

A single-factor ANOVA of eye blink frequency, attention and meditation levels were conducted. The results showed that both the device and video sequence factors were not significant. This may be because the attention and meditation levels obtained from participants might be in acceptable ranges because they can recognize the content [60].

D. ENJOYMENT RATING OF S3D VIDEO

Figure 10 shows the ACR enjoyment rating of participants. Generally, among all participants, the enjoyment rating of watching video sequences with the 3D screen ranged from 2.93 to 3.80 which was greater than with the VR device which ranged from 2.13 to 3.33. The results also reflect the fact that viewing the sequences with the panoramic screen lead to the highest enjoyment rating, valued between 3.40 and 4.60. This may be due to the longer viewing distance, larger viewing screen and the novelty of the unique immersive space in the Data Arena.

A single-factor ANOVA of enjoyment rating was conducted. The results showed that the device factor ($F = 12.2$, $p < 0.01$) was found to be significant.

E. STATISTICAL ANALYSIS OF QOE EXPERIMENTAL FACTORS

To statistically evaluate the impact of experimental factors, two-factor ANOVA within-subjects were carried out to find the correlation of the QoE assessment metrics of SSQ score, brain wave power ratios and eye blink frequency with the three different devices. The three major experimental factors (device, video sequence, ACR enjoyment rating) below were analyzed:

1) Device: 3 different devices refers to the corresponding 3 different viewing environments
2) Video sequence: 5 different S3D video sequences used in the experiments
3) Enjoyment rating: The level of enjoyment when participants were viewing S3D videos

As indicated in Table 6, Table 7 (A), Table 7 (B) and Table 8, the within-subjects ANOVA results showed significant correlations among total SSQ score, brain wave power ratios and eye blink frequency, respectively. Only p-values smaller than 0.05 are shown in the above mentioned tables. The effect of attention and meditation levels were not significant. The results indicate that both the device and video sequence factors have a significant impact ($p \leq 0.01$) among all QoE assessments. For the eye blink frequency, there was a significant cross-influence factor between device and video sequence ($p < 0.01$). The SSQ score was also found to be significant ($p < 0.01$) with the enjoyment rating. The statistical cross-influence analysis of the experimental factors in QoE found that:

1) Among all QoE assessments, the type of device used to view a S3D video is significant for most QoE parameters such as SSQ, brain wave power ratios and enjoyment rating. To extend this work, more projection screens can be tested with different video content with various 3D effects to further explore the correlation of QoE parameters.
2) One-factor ANOVA of individual factors such as eye blink frequency, attention and meditation level did not show a significant effect among the different types of devices. However, it was found that a two-factor ANOVA of eye blink frequency showed a significant difference with both the type of viewing device and the video content. The results revealed that eye blink frequency may be related to the nature of the video content and the stereoscopy of the added depth. Future

TABLE 6. Results From Within-Subjects ANOVA on SSQ

Factor	DF	Mean Square	F ratio	p-value
device	2	8260	22.7	<0.01
video sequence	4	1270	3.50	0.01
enjoyment rating	4	1910	5.26	<0.01

TABLE 7. (A) Results From Within-Subjects ANOVA on Power Ratio$_1$. (B) Results From Within-Subjects ANOVA on Power Ratio$_2$.

(A) RESULTS FROM WITHIN-SUBJECTS ANOVA ON POWER RATIO$_1$

Factor	DF	Mean Square	F ratio	p-value
device	2	0.001	38.6	<0.01
video sequence	4	0.001	25.1	<0.01
device × video sequence	8	0	3.48	<0.01

(B) RESULTS FROM WITHIN-SUBJECTS ANOVA ON POWER RATIO$_2$

Factor	DF	Mean Square	F ratio	p-value
device	2	0.002	64.8	<0.01
video sequence	4	0.001	28.5	<0.01

TABLE 8. Results From Within-Subjects ANOVA on Eye Blink Frequency

Factor	DF	Mean Square	F ratio	p-value
device	2	772	14.5	<0.01
video sequence	4	247	4.64	<0.01
device × video sequence	8	317	5.94	<0.01

work will be conducted to verify if there is any significant difference when using different video content for comparison such as the comparison from static to dynamic 3D video content.

3) It was found that the SSQ score significantly correlated with the enjoyment rating. The result revealed that subjective indicators, such as SSQ scores and the enjoyment rating, correlated with VIMS and the quality perception respectively. To explore the above correlations, future experiments will be conducted to investigate more video sequences for investigation.

VI. CONCLUSION

In this article, a series of experiments were conducted to investigate the occurrence of 3D fatigue of participants for three different viewing environments. Evaluation metrics used were Simulator Sickness Questionnaire (SSQ), EEG (brain wave) power in different brain wave frequency bands, eye blink detection, attention and meditation levels (as calculated by the EEG headset) and the Absolute Category Rating (ACR) enjoyment rating of watching video sequences. Across the five video sequences evaluated with a variety of content, experimental results indicated that participants watching Stereoscopic 3D (S3D) video sequences with a VR device exhibited higher SSQ scores, and therefore a higher visual fatigue than using other devices. The results also suggest that watching S3D videos with VR device may result in higher Visually Induced Motion Sickness (VIMS). Also, the lowest SSQ score and the highest enjoyment rating were recorded when participants watched S3D videos with the panoramic screen in the Data Arena facility at the university campus. The results suggest that the projection screen is a key factor affecting the level of visual fatigue, VIMS and QoE. The panoramic screen may be used to improve SSQ score and achieve higher enjoyment rating. Furthermore, both the projection screen and the content of video sequence are also key factors which affect the enjoyment rating when viewing S3D videos. The video content with chaotic movement may affect SSQ score, level of visual fatigue and enjoyment rating.

In future experiments, a larger sample of video sequences will be explored in order to further evaluate the correlation of ACR enjoyment rating with both SSQ scores and brain wave power ratios. In continuing this work, the findings of this research could help to extend the identification of quality factors to assess the stereoscopic visual fatigue and enhance the development of better quality experience (and measurement thereof) for 3D screens in different viewing environments. Also, this research may contribute to adapting the design of 3D video sequences to suit particular viewing environments. For example, the design of an optimum 3D video experience in a particular viewing environment, with the user preference of a typical S3D video content could be adapted to the 360° video content in a panoramic screen and the omnidirectional visual content in a VR environment. On the other hand, the Data Arena as a unique immersive multimedia facility on-campus can be used to further investigate the QoE assessments of 360° 2D videos, S3D videos and S3D videos with omnidirectional content respectively.

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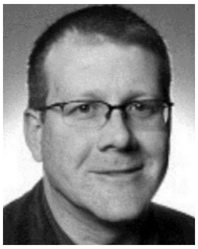

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