Using Biosignals for Objective Measurement of Presence in Virtual Reality Environments

M. Athif[1,3], B. L. K. Rathnayake [1,3], S. M. D. B. S. Nagahapitiya[1,3], S. A. D. A. K. Samarasinghe[1,3], P. S. Samaratunga[1,3], R. L. Peiris[2], A. C. De Siva[1] (MIEEE)

Abstract— The concept of 'presence' in the context of virtual reality (VR) refers to the experience of being in the virtual environment, even when one is physically situated in the real world. Therefore, it is a key parameter of assessing a VR system, based on which, improvements can be made to it. To overcome the limitations of existing methods that are based on standard questionnaires and behavioral analysis, this study proposes to investigate the suitability of biosignals of the user to derive an objective measure of presence. The proposed approach includes experiments conducted on 20 users, recording EEG, ECG and electrodermal activity (EDA) signals while experiencing custom designed VR scenarios with factors contributing to presence suppressed and unsuppressed. Mutual Information based feature selection and subsequent paired t-tests used to identify significant variations in biosignal features when each factor of presence is suppressed revealed significant ($p < 0.05$) differences in the mean values of EEG signal power and coherence within alpha, beta and gamma bands distributed in specific regions of the brain. Statistical features showed a significant variation with the suppression of realism factor. The variations of activity in the temporal region lead to the assumption of insula activation which may be related to the sense of presence. Therefore, the use of biosignals for an objective measurement of presence in VR systems indicates promise.

I. INTRODUCTION

The success of Virtual Reality (VR) systems depends on their capability of making the users feel present in the virtual environment. 'Presence' is thought of as the psychological perception of 'being in' or 'existing in' the virtual environment, even though physically situated in another [1]. Therefore, when developing a VR system, it is important to measure the level of presence of the user to evaluate the system. This creates a need for an objective, real-time and a quantifiable measurement of presence.

A. Measurement of presence

Questionnaires, behavioural and performance measures and biosignals are the three major modalities of evaluating the psychological responses of presence.

Currently, questionnaires are the benchmark method of evaluating presence where a feedback from the user is obtained post-VR experience. The Presence Questionnaire [1], the Immersive Tendencies Questionnaire [1] and the Slater-Usoh-Steed Presence Questionnaire [2] are commonly used for this purpose. However, this modality suffers from multiple drawbacks. Since questionnaires request an ordinal score for the VR experience, the scores calculated are highly subjective. This has led to a debate among the research community in selecting a suitable questionnaire [3]. In addition, since questionnaires are used post-VR scenario, real-time feedback is impossible to enhance the user experience and may not reflect the presence of the overall experience.

Biosignals on the contrary have gained a great interest in objectively evaluating psychological responses to VR scenarios in recent times. Electroencephalogram (EEG), heart rate variability (HRV) and electro-dermal activity (EDA) have been used in isolation and together to validate such responses. However, the use of biosignals to directly measure presence is not reported in the literature. Instead, these studies only focus on a specific VR environment, scenario or a psychological aspect [4]–[6] rather than considering presence in general.

The HRV [7], [8], and the mean heart rate [4] have been used to evaluate the level of engagement and presence respectively. Related to EDA, it has been reported that the phasic component has a correlation with presence and valence [8] while the tonic component showed a correlation with arousal [5]. Combining features of both the HRV and EDA, Farnsworth et. al. [9] has reported a case study quantifying levels of engagement in a VR environment.

Spectral power, coherence, spatial power distribution and event-related potentials (ERP) are the major features derived using EEG. Spectral power features are defined by the signal powers of EEG frequency bands. Many researchers have studied the correlation between these features and the different psychological responses of interest including the sense of agency [6], 3D vision [10], engagement and flow [11], attention level [12], game demand representing immersion [13], and attentional control [14]. Coherence represents the synchronization of the electrical activity of the brain between two regions thus may indicate complex psychological responses. Coherence has been used to evaluate presence [6], flow [11] and the effect of haptic feedback [10]. The spatial power distribution of EEG in the scalp has also been employed in evaluating psychological responses induced by presence [6], valence [14], arousal [14], and engagement [9], [13]. ERP are used to evaluate presence under

[1] Department of Electronic and Telecommunication Engineering, Uiversity of Moratuwa, Sri Lanka. {athifrm, lahiru.k.rathnayake, dickmendra, asankakosala23, pavansupul}@gmail.com, anju-lads.uom.lk
[2] Rochester Institute of Technology, USA roshan.peiris@rit.edu
[3] Contributed equally

the assumption that if a user responds to a stimulus unrelated to the VR environment reflected by eliciting an ERP, then the user is assumed easily distracted and hence is less immersed in the assigned task [14], [15].

In contrast to other modalities, biosignals are objective measurements and allow real-time measurements. Therefore, a general framework of using biosignals in quantifying presence is very useful. In the subsequent sections we proposes an experimental methodology to discover the correlations between biosignals and psychological variations of a user during VR scenarios with varying levels of presence, discuss results and further improvements.

II. Methods

A. Factors of presence

Factors contributing to the mental state of presence are well defined and taken as the basis for presence questionnaires. Witmer and Singer suggests that presence consist of 4 factors: control, sensory, distraction and realism and 17 sub factors [1]. By inverting this thinking, we hypothesized that the level of presence can be varied by suppressing one or more of these factors. Therefore, we developed VR scenarios with varying levels of presence by suppressing each of these factors which were then experienced by users while recording biosignals simultaneously.

B. Experiment Design

1) Scenario Development: A forest was chosen as the virtual environment because it can accommodate details that will keep the subject engaged without evoking unnecessary emotions such as fear, happiness, sadness and excitement which may overshadow the evaluation of presence (Fig. 1). Since presence can be thought to develop progressively in a VR user, scenarios were developed to allow the subjects to spend sufficient time (1.5 minutes) exploring the environment. To provide a sufficient level of engagement for the subject, a method of gamification was introduced by adding small mushrooms in the scenario at random locations and instructing the subject to follow them. This base scenario (scenario-6) included an audio playback of a forest environment, while providing an auditory feedback when mushrooms were collected. Five additional scenarios were developed by suppressing factors of presence [1] and were technically implemented by modifying the base scenario as shown in Table I. These virtual environments were developed in the Unity 3D game engine using assets available in the Unity assets store.

Fig. 1. VR environment: Forest scenario with mushrooms in random places

TABLE I

Developed VR scenarios

Scenario	Suppressed factor	Modifications in VR scenario	Modifications in real environment
1	All	All changes in scenarios 2, 3, 4 and 5	All changes in scenarios 2, 3, 4 and 5
2	Distraction		Flat screen display (no HMD)
3	Sensory	Removed: audio playback and feedback	
4	Realism	Removed: wind effect on tree leaves, shadows and ambient occlusion, Included: colour overlay (blue)	
5	Control	Introduced: Navigation lag	Subject instructed not to turn the head
6	None (base scenario)	No changes	No changes

C. Experiment procedure

Oculus Rift DK2 was used as the HMD to display scenarios $3-6$, while a 24 inch flat screen monitor was used to display scenarios 1 and 2. A ps4-ds4 controller was used as the navigation controller while the scenarios were played within the Unity game engine. EEG was recorded using the g.HIamp amplifier together with the g.GAMMAcap2 EEG cap and g.SCARABEO active electrodes. 32 channels were recorded with reference to the right earlobe lobe. ECG was recorded from the limbs and EDA electrodes were connected to the middle and ring finger in the dominant hand. The other hand was used to hold a controller to navigate the environment. Both these sensors were connected to an Arduino Mega 2560 board to read the analogue data using serial communication. Lab streaming layer [16] was used to record time synchronized data from multiple data acquisition devices.

Twenty male subjects with an age range of $20-36$ years voluntarily participated in the experiment. Biosignals were measured while the subjects were experiencing VR scenarios (Fig. 2). First, the subject was asked to sit comfortably while the written consent was collected. Then the biosignal recording hardware including the HMD was attached to them. At the beginning of each scenario, the subject was asked to focus on a black fixation cross on a white background for 10 seconds.

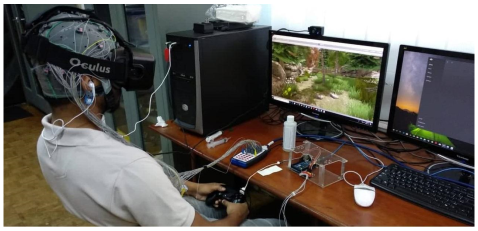

Fig. 2. Subject engages in a VR scenario while biosignals are measured

This served as a baseline for the subsequent signal measurements. Then, the subject was presented with all the VR scenarios listed in Table I in a random order to avoid any bias due to the order of trials.

D. Signal Processing

1) Pre-processing: A pipeline of signal pre-processing steps was used for EEG signal processing. A bandpass filter was initially applied with cutoffs at 0.1 and 45 Hz. Then, flat lines exceeding 20 seconds and channels with a correlation less than 0.6 with adjacent channels were removed and spherically interpolated using the good channels. To remove common mode noise, all the channels were then re-referenced to the global average. In order to avoid the rejection of an entire epoch due to isolated short burst of noise that appear in one (or few) channels, data portions whose variance is larger than a set threshold relative to the calibration data were reconstructed using the Automatic Subspace Reconstruction (ASR) algorithm [17]. Artefactual independent components such as eye movements, muscle movements, electrode noise were rejected following manual inspection and the output of the Multiple Artefact Removal Algorithm (MARA) [18] algorithm. ECG and EDA signals were bandlimited between 0.5-48 Hz and 1-10 Hz respectively.

2) Feature extraction: The pre-processed biosignals were then used to calculate features that have associations with psychological entities. A list of features extracted from each of the EEG, ECG and EDA signals are indicated in Table II. These features were extracted using MATLAB and the associated EDALAB [19] and EEGLAB [20] toolboxes. EDA signal was decomposed into tonic (skin conductance level (SCL)) and phasic (skin conductance responses (SCR)) for subsequent feature extraction.

To analyze EEG activity, we considered each of the EEG features with respect to the regions of the scalp and frequency bands. Band power features were computed in a combination of hierarchical levels shown in Fig. 3. According to this hierarchy, we obtained 191 features as a combination selecting a component in each level. Relative features were obtained as a ratio of the absolute features to total band power (or coherence) value of the respective region. For example, the delta band power of the left frontal region as a ratio of the total band power is one such feature.

TABLE II
Features extracted from EEG, ECG and EDA signals

EEG	
Feature	Definition
Statistical	Mean of EEG signal Standard Deviation of EEG signal
Entropy	Sample entropy
Band power	Signal power in delta(1-4Hz), theta(4-8Hz), alpha (8-13Hz), beta (16-30Hz) and gamma (30-45Hz) bands $\sum x^2$
Asymmetry	$\frac{Left hemispheric power}{Right hemispheric power}$
Coherence	$\frac{P_{xy}(f)}{2P_{xx}(f)P_{yy}(f)}$. P_{xy} is the power spectral density
EDA	
SCRn	Number of Skin SCRs within response window
SCRsum	Sum of SCR amplitudes of significant SCRs
SCRmean	Average SCR
SCRmax	Maximum of SCR amplitudes of significant SCRs
SCLmean	Average SCL
Globalmean	Average overall skin conductance
Globalmax	Maximum overall skin conductance
ECG	
Heart rate	Mean Standard Deviation
LF	Power of heart rate variability signal (0.01 Hz - 0.1 Hz)
HF	Power of heart rate variability signal (0.4 Hz - 0.5 Hz)

In addition, 20 combined features were calculated from statistical measures from the EEG signal as shown in the hierarchy in Fig. 4. Five asymmetry features were obtained from the 5 regions of the brain. Similarly, for entropy, 10 features were calculated for the 5 brain regions considering each hemisphere as shown in Fig. 6a.

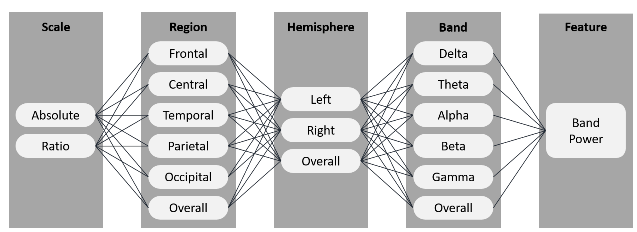

Fig. 3. Hierarchy of EEG band power feature extraction

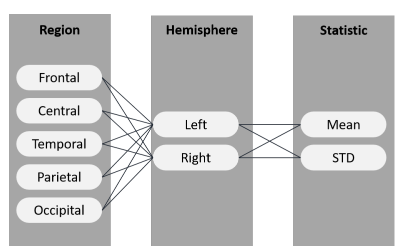

Fig. 4. Hierarchy of statistical EEG feature extraction

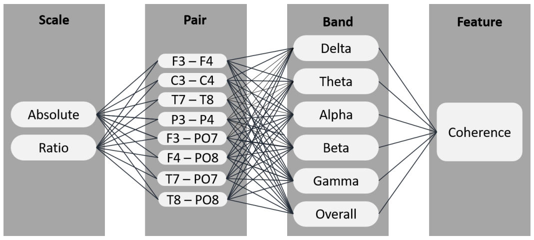

Fig. 5. Hierarchy of EEG coherence feature extraction

Eight pairs of locations were defined to extract meaningful coherence features: trans-callosal coherence (F3-F4, C3-C4, P3-P4), fascicle coherence (F3-PO7, F4-PO8) and visual coherence (T7-PO7, T8-PO8) [21] as shown in Fig. 6b. Similar to the other features, the hierarchy shown in Fig. 5 was used to obtain 88 coherence features.

E. Analysis

A total of 325 features were extracted from the EEG, ECG and EDA signals from 20 subjects for all 6 scenarios. Five sets of scenario pairs (1 vs 6, 2 vs 6, 3 vs 6, 4 vs 6, 5 vs 6) were considered for the analysis using biosignals. To find out the features that vary significantly between each pair, first, features showing the least variance and the least entropy were eliminated (unsupervised) to reduce the feature space to 80% of the original. Next, mutual information based feature selection (supervised) was performed for each of the five pairs selecting the 30 top most features for each. Finally, paired t-test was conducted for each of the 30 features to identify features having significantly different mean values with a statistical confidence of 95%.

III. Results and Discussion

Biosignal features that showed significant changes with the suppression of factors of presence are shown in Table III. Features in bold showed a significantly higher value when each of the factors was suppressed, while the other features showed a significantly lower value.

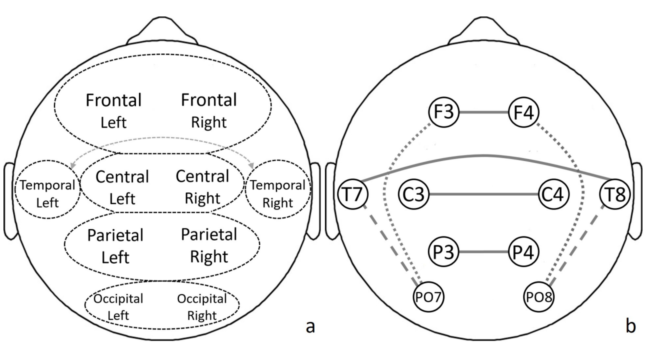

Fig. 6. a: The 5 regions of the brain, in the left and the right hemispheres. b: Electrode combinations for coherence measurement; solid lines: Trans-callosal coherence, dotted lines: Fascicle coherence, dash lines: Visual coherence

TABLE III
Significant Features

Factors suppressed	Significant features	
	Relative	Absolute
All	Coherence	
	Beta Temporal left - Occipital left	
Distraction	Band power	
	Beta Temporal left Gamma Temporal left Delta Occipital right	Alpha Parietal right Beta Parietal left Theta Parietal
Sensory	Coherence	
	Theta Temporal Right Temporal left	
Realism	Band power	
		Theta Occipital
	Coherence	
		Theta Parietal right - Parietal left
	Statistical	
	Standard Deviation Parietal right	
Control	Band power	
	Beta Temporal Delta Temporal right	Overall Frontal Frontal left
	Coherence	
	Beta Frontal right - Occipital right	Theta Parietal Right - Parietal Left

Observations from the results suggest that when all factors are suppressed, the relative coherence feature between temporal left and occipital left region in beta frequency range decreased.

When the distraction factor is suppressed (i.e. the VR scenario is shown on the flat-screen monitor instead of the HMD, thus allowing external distractions from the field of view), relative beta and gamma powers in temporal left region increased in comparison to the scenario where the HMD was used. In addition, some significant reductions of power were observed in the parietal region of bands alpha (parietal right), beta (parietal left) and theta (entire parietal region).

When the sensory factor was suppressed (no sound), only the relative coherence feature between temporal right and temporal left region in theta band increased compared to the scenario with sound.

The effect of suppressing the realism factor is reflected by significant changes in power, coherence and statistical features of the theta band.

Significant band power variations were observed in frontal and temporal region when the control factor was suppressed (navigation lag). Considering the frequency range from $1-45$ Hz, the total band power in the frontal and frontal left regions were decreased. Additionally, the relative beta power and relative delta power shows a significant increase in temporal and temporal right regions respectively. Also, two significant coherence features in the frontal, occipital and parietal regions can be observed when the control factor was suppressed.

In general, the activity in the temporal region consistently showed a significant relationship in multiple frequency bands when distraction, sensory and control factors are suppressed. A possible explanation for this observation could be the activation in the insula due to the processing of sensory stimuli while being in the virtual environment [22]. In a controlled environment, a subject may make many assumptions and decisions which could lead to variations in the sense of presence.

IV. Conclusion and Future Work

We have presented a framework for an experimental design to evaluating biosignal correlates of presence in VR. This framework comprises of; custom developed VR scenarios, a methodology to vary levels of presence, well-defined protocols for conducting experiments and a pipeline for signal procssing and feature analysis. This design was then trialed with 20 volunteers acquiring biosignals (EEG, ECG and EDA) while they experiencing the scenario.

To further improve the proposed framework, following suggestions are proposed: The experimental method could be replicated for a wide range of VR environments including different modalities and interfaces. The statistically significant features observed in our analysis could be further explored by developing interactive VR scenarios which measure presence and provides feedback to the VR environment.

ACKNOWLEDGMENT

The authors would like to thank personnel at the Bionics Lab, University of Moratuwa, Sri Lanka (UoM) for the technical support, Machine Vision Lab, UoM & Prof. Arjuna Madanayake, Akron University, USA for the HMD and the Department of Mathematics, UoM for the guidance on statistical analysis.

References

[1] B. G. Witmer and M. J. Singer, “Measuring presence in virtual environments: A presence questionnaire,” Presence: Teleoperators and Virtual Environments, vol. 7, no. 3, pp. 225–240, 1998.

[2] M. Slater, M. Usoh, and A. Steed, “Depth of presence in virtual environments,” Presence: Teleoperators and Virtual Environments, vol. 3, no. 2, pp. 130–144, Jan. 1994.

[3] M. Usoh, E. Catena, S. Arman, and M. Slater, “Using presence questionnaires in reality,” Presence: Teleoperators and Virtual Environments, vol. 9, no. 5, pp. 497–503, 2000.

[4] Meehan. M, “Physiological reaction as an objective measure of presence in virtual environments,” Doctoral Dissertation, University of North Carolina at Chapel Hill, 2001.

[5] A. Felnhofer, O. D. Kothgassner, M. Schmidt, A. K. Heinzle, L. Beutl, H. Hlavacs, and I. Kryspin-Exner, “Is virtual reality emotionally arousing? investigating five emotion inducing virtual park scenarios,” International Journal of Human Computer Studies, vol. 82, pp. 48–56, 2015.

[6] S. E. Kober, J. Kurzmann, and C. Neuper, “Cortical correlate of spatial presence in 2d and 3d interactive virtual reality: An eeg study,” International Journal of Psychophysiology, vol. 83, no. 3, pp. 365–374, 2012.

[7] D. Mestre and J.-L. Vercher, “Immersion and presence,” Virtual Reality: Concepts and Technologies, pp. 81–96, 2011.

[8] J. L. Higuera-Trujillo, J. López-Tarruella Maldonado, and C. Llinares Millán, “Psychological and physiological human responses to simulated and real environments: A comparison between photographs, 360 panoramas, and virtual reality,” Applied Ergonomics, vol. 65, pp. 398–409, 2017.

[9] Bryn Farnsworth, “Measuring the power of virtual reality immersion [a case study],” 2017.

[10] C. L. Lin, F. Z. Shaw, K. Y. Young, C. T. Lin, and T. P. Jung, “Eeg correlates of haptic feedback in a visuomotor tracking task,” NeuroImage, vol. 60, no. 4, pp. 2258–2273, 2012.

[11] R. Berta, F. Bellotti, A. De Gloria, D. Pranantha, and C. Schatten, “Electroencephalogram and physiological signal analysis for assessing flow in games,” IEEE Transactions on Computational Intelligence and AI in Games, vol. 5, no. 2, pp. 164–175, 2013.

[12] O. H. Cho and W. H. Lee, “Bci sensor based environment changing system for immersion of 3d game,” International Journal of Distributed Sensor Networks, vol. 2014, 2014.

[13] T. McMahan, I. Parberry, and T. D. Parsons, “Modality specific assessment of video game player’s experience using the emotiv,” Entertainment Computing, vol. 7, pp. 1–6, 2015.

[14] J. Frey, M. Daniel, J. Castet, M. Hachet, and F. Lotte, “Framework for electroencephalography-based evaluation of user experience,” in Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, ser. CHI ’16. New York, NY, USA: Association for Computing Machinery, 2016, p. 2283–2294. [Online]. Available: https://doi.org/10.1145/2858036.2858525

[15] C. G. Burns and S. H. Fairclough, “Use of auditory event-related potentials to measure immersion during a computer game,” International Journal of Human Computer Studies, vol. 73, pp. 107–114, 2015.

[16] Sccn, “Lab streaming layer,” Jan 2020. [Online]. Available: https://github.com/sccn/labstreaminglayer

[17] C. Chang, S. Hsu, L. Pion-Tonachini, and T. Jung, “Evaluation of artifact subspace reconstruction for automatic eeg artifact removal,” in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), July 2018, pp. 1242–1245.

[18] I. Winkler, S. Haufe, and M. Tangermann, “Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals,” Behavioral and Brain Functions, vol. 7, no. 1, p. 30, 2011.

[19] M. Benedek and C. Kaernbach, “Decomposition of skin conductance data by means of nonnegative deconvolution,” Psychophysiology, vol. 47, no. 4, pp. 647–658, Mar. 2010.

[20] A. Delorme and S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” Journal of Neuroscience Methods, vol. 134, no. 1, pp. 9–21, mar 2004.

[21] I. Cook and A. Leuchter, “Synaptic dysfunction in Alzheimer’s disease: clinical assessment using quantitative EEG,” Behavioural Brain Research, vol. 78, no. 1, pp. 15–23, jun 1996.

[22] M. Clemente, A. Rodríguez, B. Rey, and M. Alcañiz, “Measuring presence during the navigation in a virtual environment using EEG.” Studies in health technology and informatics, vol. 191, pp. 136–40, 2013.