An XR Experience to Collect Biosignals for Cybersickness Mitigation

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ABSTRACT

Cybersickness (CS) is one of the main obstacles to the use of Virtual Reality (VR), often caused by Head-mounted Displays (HMDs). Its symptoms, which can last from minutes to hours after exposure, include nausea, vertigo, eye strain, and headache. Researchers generally use subjective measures, such as the Virtual Reality Sickness Questionnaire, to assess CS. Studies indicate that CS significantly impacts physiological signals, but there is little research on the application of Symbolic Machine Learning to understand the causes of CS in VR games. This study investigates the use of biosignals to identify the causes of CS in VR. Our main hypothesis is that the combination of quantitative and subjective assessments, along with Symbolic Machine Learning techniques, allows for the creation of a ranking of the main causative or indicative factors of CS. To validate this hypothesis, software was developed to record the biosignals and self-reported symptoms of participants during experiments with two VR games. Physiological signals (ECG, EDA, and body movements extracted from an Accelerometer - ACC) and game data were collected. The results show a strong relationship between physiological changes and CS symptoms, with a model that includes biosignals achieving an AUC of 0.95. The rankings of the main factors, both for the model without and with the inclusion of biosignals, confirmed previous research described in the literature. As far as we know, our work is the first to use Symbolic Machine Learning models to detect the causes of CS.

CCS CONCEPTS

• **Human-centered computing → User studies**.

KEYWORDS

Virtual Reality, Cybersickness, Biosignals, HMD Devices, Symbolic Machine Learning, Decision Tree, Random Forest.

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1 INTRODUCTION

In recent years, Virtual Reality (VR) has become increasingly popular as a promising technology, enabling new forms of interaction between humans and computers [6, 11]. According to Jerald [4], VR is a "computer-generated digital environment that can be experienced and interacted with as if it were real." LaViola [6] states that prolonged exposure to virtual environments can result in a phenomenon called Cybersickness (CS). The symptoms associated with CS can vary from person to person and include nausea, vertigo, eye strain, and headache. The duration of these symptoms can range from a few minutes to hours after exposure to VR, depending on the individual. Recent advances in HMD technology can enhance immersion and realism but may also influence the occurrence of discomfort in Virtual Reality [10].

This study is based on the research by Porcino [7, 8], which addressed the classification of possible causes of Cybersickness (CS) in VR games using Symbolic Machine Learning (ML). However, in his research, Porcino did not use biosignals, relying solely on subjective measures and game data. In our research, the main hypothesis is that the combination of quantitative (biosignal and game data) and subjective assessments (data from the Cybersickness Profile Questionnaire (CSPQ)), using Symbolic ML techniques, is effective in identifying and classifying the causes of CS. For model training and evaluation, data from CSPQ questionnaires were used, along with game data and biosignals: Electrocardiogram (ECG), Electrodermal Activity (EDA), and Accelerometer (ACC). During the experiments, participants were immersed in two VR games, one a car racing game and the other a flight simulation. In summary, our contributions include:

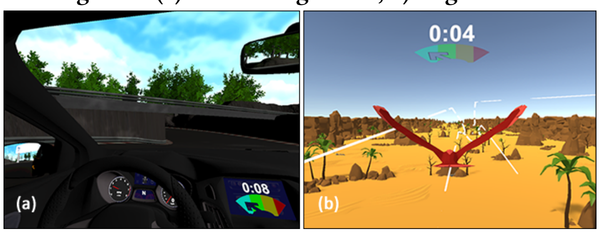
- Analyze the effectiveness of the Symbolic ML models used in this study in identifying the causes of CS (both without and with the inclusion of ECG, EDA, and ACC biosignals);
- Examine the potential significant correlation between the levels of CS reported by users and the recorded biosignals;

- Propose a dataset of physiological data obtained through ECG, EDA, and ACC;
- Develop a tool for acquiring biosignals and self-reports of users' CS levels.

2 METHOD

The qualitative data was collected during the use of the game software, as shown in Figure 1. This data was gathered from the CSPQ questionnaires [7, 8] and VRSQ [5]. During the experiment, the game data was recorded continuously, capturing a data instance every second, which includes information such as speed, acceleration, rotations, region of interest, among others.

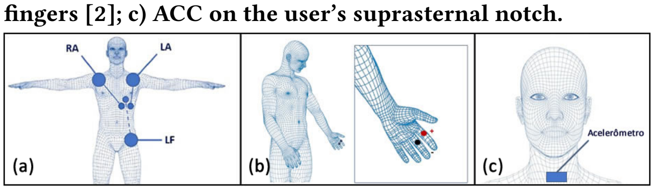
Figure 1: (a) Car Racing Game; b) Flight Game



EDA data were collected at a sampling rate of 100Hz. Its unit of measurement is micro-siemens (μS), typically ranging from 5 to 50 [9]. Participants' body movements were recorded using an Accelerometer (ACC), which can measure in two main units: g-force (g) and meters per second squared (m/s^2) [3]. ECG data were originally sampled at a rate of 100Hz. The normal heart rate range is 60 to 100 beats per minute (bpm), corresponding to an RR interval of 0.6 to 1 second [9]. In this study, the RR interval was used as an input value every second in the dataset employed for the Symbolic ML model.

As illustrated in Figure 2, for the placement of electrodes related to the Einthoven lead of the ECG, the IN+ (red) and IN- (black) electrodes were placed on the clavicles, and the REF (white) electrode was placed on the iliac crest. The EDA electrodes were attached to the fingers, while the ACC sensor was positioned on the participant's suprasternal notch using adhesive tape.

Figure 2: a) Electrode Attachment (ECG) [1]; b) EDA in the fingers [2]; c) ACC on the user's suprasternal notch.



The Biosignal Collector (BC) software developed in this study aimed to ensure more efficient control in the acquisition of biosignals and to enable participants to report the different possible levels of CS during the experiments.

The simulation was conducted using an HTC-Vive HMD, which features a screen resolution of 1080 x 1200 pixels per eye, a refresh rate of 90Hz, and a field of view of 110 degrees. The operating system for the simulation was Windows 10 Pro (x64), running on a computer with an Intel Core i7 processor, 16 GB of RAM, and an NVIDIA GeForce GTX 1050 Ti graphics card. Biosignals were acquired using the BITalino (r)evolution Plugged. This board supports sampling rates of 1, 10, 100, or 1000Hz and offers communication via Bluetooth/BLE.

3 CONCLUSION

The results of the VRSQ indicated that, in the Car Game, men experienced more discomfort than women, while in the Flight Game, women reported higher discomfort scores. The t-tests confirmed significant differences in the mean biosignal data between the resting state and during CS symptoms. We used the Random Forest algorithm to clarify the model's decisions and establish a ranking of the main factors causing or indicating CS. By combining game data, user profiles, and biosignals, our model achieved the best performance. This result demonstrates that the inclusion of physiological signals was highly significant in predicting CS. Compared to other studies that also used biosignals to predict CS, our performance was superior. For the Car Game, the most important factors were movements detected by the ACC, Exposure Time, EDA, and ECG RR intervals, while for the Flight Game, the most relevant attributes for predicting CS were Exposure Time, EDA, and Y Rotation.

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