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Intelligent Virtual Platform for Real-time Cybersickness Detection and Adaptation*

1st Azadeh Hadadi*
Institute for Information Management in Engineering
Karlsruhe Institute of Technology
Karlsruhe, Germany
Arts et Metiers Institute of Technology, LISPEN
HESAM Université, UBFC
Chalon-sur-Saône, France
azadeh.hadadi@kit.edu

2nd Jean-Rémy Chardonnet
Arts et Metiers Institute of Technology, LISPEN
HESAM Université, UBFC
Chalon-sur-Saône, France
jean-remy.chardonnet@ensam.eu

3rd Christophe Guillet
Université de Bourgogne, LISPEN
UBFC
Chalon-sur-Saône, France
christophe.guillet@u-bourgogne.fr

4th Jivka Ovtcharova
Institute for Information Management in Engineering
Karlsruhe Institute of Technology
Karlsruhe, Germany
jivka.ovtcharova@kit.edu

***Abstract*—This paper is a novel research endeavor focused on addressing cybersickness in virtual reality (VR) experiences. Traditional approaches to cybersickness prediction and detection rely on generalized artificial intelligence models and extensive data collection. However, there has been a lack of research exploring user-specific intelligence. This paper introduces an intelligent platform designed to adapt to individual users in real-time for cybersickness detection. By dynamically adjusting its behavior and interactions, this platform aims to mitigate cybersickness and enhance the VR user experience. The platform's effectiveness was evaluated using physiological data, including electrodermal activity (EDA) and eye movement signals. The results demonstrated the efficacy of our system in reducing cybersickness symptoms.**

***Index Terms*—Virtual reality, artificial intelligence, automated cybersickness detection and reduction, auto-adaptation.**

I. Introduction

Virtual Reality (VR) has experienced notable advancements, offering opportunities and challenges [1]. Among these challenges, cybersickness stands out as a major obstacle in VR technology [2]. Also known as visually induced motion sickness (VIMS) [3] or simulation sickness, cybersickness resembles motion sickness and can occur during VR navigation. Symptoms include nausea, oculomotor discomfort, and disorientation, negatively impacting the usability of VR technology, especially in critical domains.

Researchers employ both subjective and objective evaluation methods to assess cybersickness [4]. Subjective evaluation entails participants completing surveys before and after engaging in VR tasks, utilizing questionnaires such as Simulator Sickness Questionnaire (SSQ) [5] and Fast Motion Sickness Scale (FMS) [6]. Objective evaluation involves monitoring physiological and behavioral measurements, including postural sway [7], electrodermal activity (EDA) [8], electroencephalogram (EEG) [9], and electrocardiogram (ECG) [10], to analyze the occurrence and severity of cybersickness.

The ability to predict cybersickness in VR enhances user enjoyment and safety. Accurate prediction enables developers to optimize VR design, creating more comfortable experiences. This capability is crucial in preventing accidents and injuries caused by cybersickness.

Artificial Intelligence (AI) plays a vital role in effectively detecting cybersickness [11] [12] [13] [14] [15] [16]. With its ability to process large amounts of data and identify patterns, AI is well-suited for analyzing user behavior, physiological signals, and environmental factors to detect early signs of cybersickness. AI-powered systems can then trigger interventions to mitigate its impact. Moreover, these systems can adapt and personalize their responses based on individual user profiles, improving the effectiveness of cybersickness prevention and management. By leveraging its advanced data processing capabilities and adaptive nature, AI significantly enhances the user experience and overall safety in virtual and augmented reality environments.

Recent research has primarily focused on offline training of general AI models using subjective measurements for the detection and prediction of cybersickness. Studies by Garcia-Agundez et al. [10] and Martin et al. [15] utilized bio-signals and game parameters to predict VR sickness levels. EEG data has also been effectively used by researchers like Kim et al. [9], Liao et al. [14], and Jeong et al. [17] using convolutional and deep neural network algorithms. Most studies focus on

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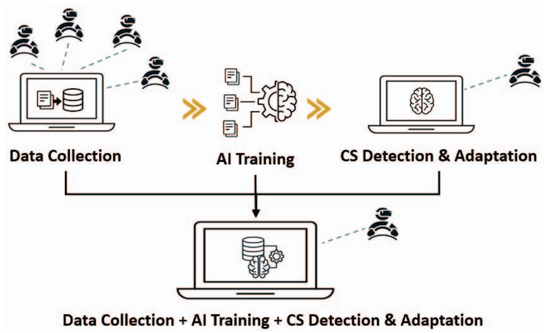

Fig. 1. Overview of the auto-adaptive VR for cybersickness (CS) detection and adaptation. Integrating three separate stages into a real-time closed loop.

detection and lack interventions to enhance the user experience. Nevertheless, one closely related research endeavor was conducted by Islam et al. [18]. They introduced CyberSense, an automated framework designed to detect the severity of cybersickness during immersive experiences. However, this approach requires extensive data collection and the utilization of pre-trained models to identify cybersickness instances among user groups and apply suitable solutions. Offline training for cybersickness detection has limitations such as lack of individualization, potential data bias, and difficulty in adapting to new users or scenarios. To address these shortcomings, real-time, personalized adaptation approaches are essential. These approaches enhance the accuracy and effectiveness of cybersickness detection and prediction in VR experiences.

A. Contributions

Our research focuses on the development of an auto-adapted VR platform that seamlessly integrates AI technology to enhance cybersickness detection as demonstrated in Fig. 1. By analyzing real-time subjective and objective data, the AI system continuously trains itself, allowing for the dynamic adjustment of the VR simulation and detection of cybersickness onset. A key advantage of our approach is that it eliminates the need for extensive data collection from a diverse panel of users. Instead, the AI model is individually trained using minimal user-specific data, enabling personalized cybersickness detection and tailored reduction methods. The entire process, including data collection, training, cybersickness detection, and adaptation, operates within a closed-loop system, optimizing efficiency. This innovative integration of AI technology proactively addresses cybersickness concerns, revolutionizing the VR experience for each user.

II. Architecture

Fig. 2 provides a comprehensive overview of the system, highlighting its components and capabilities. The system is designed as a distributed (client-server) application, utilizing a TCP/IP socket for development. The client component is a Unity Package. The server component is developed in Python. This architecture ensures efficient communication and data exchange between the client and server. Given the real-time nature of the auto-adaptation system, a multi-threaded architecture has been adopted to facilitate simultaneous data recording and processing. This architecture incorporates multiple independent processes that operate concurrently, each functioning at pre-configured intervals (e.g., 1 minute) to serve specific purposes. By employing this concurrent approach, the platform can effectively handle the continuous flow of data, enabling accurate and timely processing.

A. Client Side

On the client side, two essential components contribute to the functionality of the system.

- **VR Application:** The VR Application is a driving simulation that captures eye tracker and head movement data during the experiment, providing insights into users' visual behavior and physical responses in the virtual environment.
- **E4 Streaming Server:** The Emaptica E4 wristband utilizes advanced sensors to measure diverse physiological parameters. The E4 Streaming Server establishes a Bluetooth connection with the wristband, enabling seamless communication and data streaming. By connecting to the wristband, the server efficiently transmits real-time physiological data for continuous monitoring and analysis during the VR experiment. These client-side components ensure effective operation and data collection within the system.

B. Server Side

The server side of the system incorporates multiple essential components that work together to ensure its functionality and performance.

- **Automatic Speech Recognition (ASR):** The Automatic Speech Recognition (ASR) component receives the user's voice, and converts speech into text for voice-based interactions and inputs. The Google Speech Recognition API was employed as the ASR component in our platform.
- **Data TCP Client:** The process receives eye tracker data and head movement data from the VR application, establishing a TCP connection for seamless transmission to the *Braint module* for further analysis.
- **E4 TCP Client:** The E4 TCP Client component establishes a TCP connection with the E4 Streaming Server to retrieve physiological data captured by the E4 wristband. This data is efficiently retrieved and made available for processing and integration into the system's analysis pipeline.
- **Brain Module:** The Brain Module acts as the central component on the server side, consisting of three submodules:
  - **Pre-Processing Component:**This component synchronizes time series data collected from various sensors in the system. The Empatica E4 wristband incorporates sensors with different sampling frequencies, and the component ensures consistency by preprocessing the

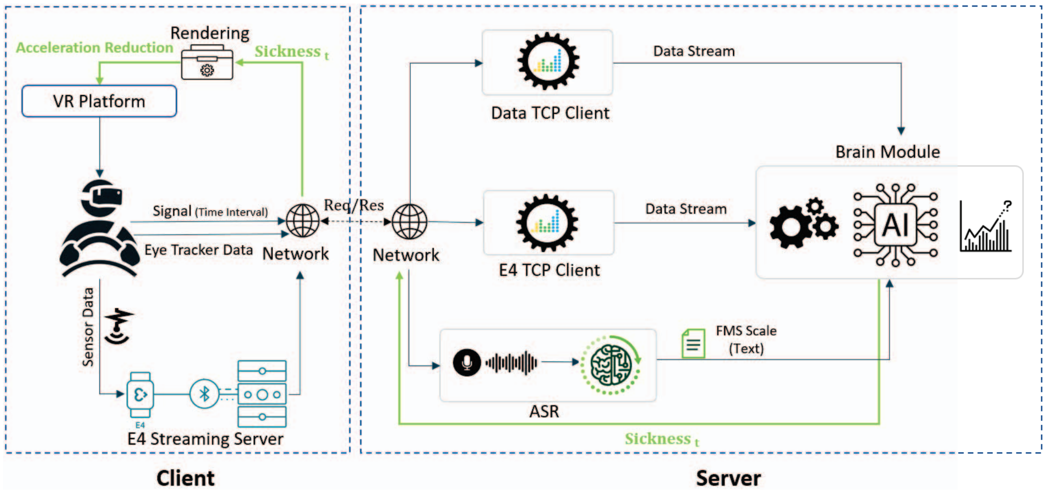

Fig. 2. Architecture design and data flow diagram of the implemented platform, a distributed system implemented across Client and Server.

data to a unified frequency of 4 Hz. This allows for the merging and analysis of data from different sources.

- **AI Component:**
  1) **Model:** Our architecture employs a Stream learning approach, also known as Online learning or Incremental learning [19]. Unlike batch learning, Stream learning trains the model incrementally on a continuous data stream, allowing the model to learn from individual observations or small groups of observations in a sequential manner. This approach is advantageous for real-time applications with rapid changes and limited computing resources. We utilized the River Library [20] for dynamic data streams and continual learning, defining a pipeline that includes a scaler transformer and a logistic regression model with stochastic gradient descent optimization with a learning rate of 0.01. This incremental learning update is fast and computationally efficient.
  2) **Classification Indicator:** We utilized the self-reported FMS scale as a classification indicator to categorize the data into sick and non-sick observations. We adjusted the original FMS scale, which originally ranged from 1 to 20, to a more concise scale of 0 to 3 (scale $=$ 0 :non-sick, scale≥ 1 : sick). This adjustment was necessary as the participants were unable to report their status with high-resolution accuracy.
- **Detection/Adaptation Component:** Once the AI model is sufficiently trained training, following the protocol (three minutes of reporting "sick"), and receives data from both the Data TCP client and the E4 TCP Client within a defined time interval, it identifies records indicative of sickness. The remaining records in that data packet are then halted for validation. Our approach focuses on reducing cybersickness by mitigating linear and rotational accelerations [8]. When a sickness-indicative record is identified, a signal is sent to the VR program to initiate a deceleration of the virtual car. This is achieved by reducing the engine power, specifically the main parameter controlling the car engine torque, by 70%.

Fig. 3. Experimental setup for the study with Meta Quest Pro head-mounted display (HMD) and Empatica E4 wristband attached to a participant.

III. Virtual Environment and Experiment

A virtual driving simulation was developed using Unity3D, where participants navigated through a city scene using Logitech-G25 driving tools. The route was standardized to ensure consistency among participants. Cybersickness assessment involved subjective questionnaires and objective measures, including head movement and eye tracker data. Physiological indicators were captured using an Empatica E4 wristband. Fig. 3 depicts the experimental setup. In the pre-study, a total of six participants, aged between 24 and 35 (Male:5, Female:1) were included in the study, and necessary introductions and consent procedures were conducted. The exposure time was flexible, transitioning to the adaptation phase based on participants' self-reporting. The experiment aimed to capture accurate data while considering participant well-being.

TABLE I
COMPARISON OF SLOPE COEFFICIENT OF THE EDA SIGNAL

Phase	EDA Slope Coeff. mean
Training	9.8e-3
Adaptation	6.0e-3

IV. RESULTS AND DISCUSSION

We calculated the average of the signals and performed a pre-study analysis on EDA [21] and eye movement signals [3]. Our objective was to compare the observed trends in these data during the training and adaptation phases, to investigate the impact of this platform on cybersickness control.

A. EDA Signal Analysis

Comparing the slopes of EDA signals between the training and adaptation phases yielded valuable insights into the AI's impact on cybersickness control (Fig. 4). Linear regression analyses were conducted on each signal, and the resulting slope coefficients were compared in Table I. The findings showed a significant 39% decrease in the mean slope coefficient of the EDA signal during the adaptation phase compared to the training phase. Analysis of covariance (ANCOVA) testing confirmed the hypothesis that the slope changes in the adaptation phase were significantly different from those in the training phase $(F(1, 5) = 1.95, p = 0.044)$. The accumulative effect of motion sickness typically leads to an increasing trend in signal changes over time [22]. However, our study results show a contrasting pattern during the adaptation phase, with a 39% decrease in the slope coefficient of EDA. This suggests that the application of the AI model in this phase mitigates the intensity of the EDA signal, potentially indicating lower emotional arousal and reduced cybersickness symptoms.

B. Eye Movement Analysis

Table II summarizes the findings of our eye movement analysis. During the adaptation phases, we observed a reduction in the variance of velocity and angular velocity for the left and right eyes, indicating variability in three directions (x, y, z). These findings were statistically supported by the Levene test (velocity $p = 1.3922e - 19$, angular velocity $p = 5.676e - 11$), providing significant evidence of a variance difference between the training and adaptation phases for both velocity and angular velocity data.

Furthermore, the average eye movement distance was examined by calculating the Euclidean distance based on the x, y, and z coordinates. The reduction suggests a more confined or localized eye movement pattern. The results were further analyzed using an independent t-test, which indicated that there is evidence to support the claim that the mean eye distance differs between the training phase and adaptation phase groups, with a $t - value = 2.81$ and a $p = 0.0049$. The reduction in average eye movement distance during the adaptation phase indicates participants exhibited focused and

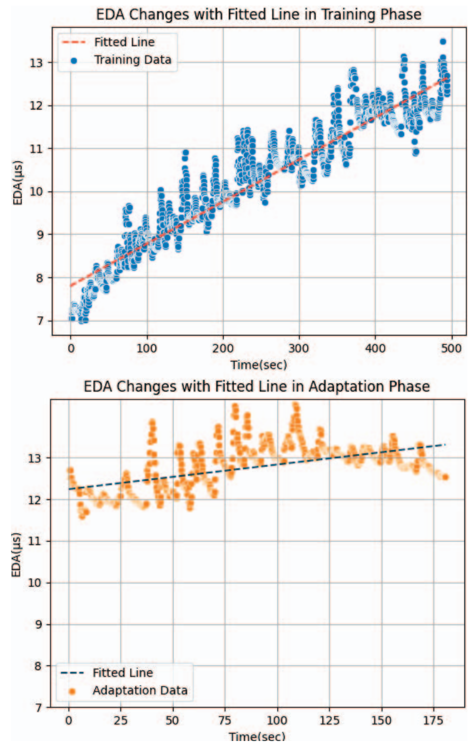

Fig. 4. Average of change trend of EDA and fitted line during the training and adaptation phases

TABLE II
COMPARISON OF EYE MOVEMENT SIGNAL

Phase	Velocity variance	Angular Velocity variance	Movement Distance mean
Training	1.47e-4	8.4e-3	6.3820e-2
Adaptation	3.06e-5	2.0e-3	6.3818e-02

stabilized visual experiences, contributing to decreased cybersickness symptoms. Analysis of eye angular velocity and eye velocity further supports the improved stability and consistency of eye movements in our system, enhancing interaction with the virtual environment. These positive effects can be attributed to the advanced technology, design, and intuitive control mechanisms of the platform, which reduce the need for excessive eye movements and provide a smoother visual experience, ultimately reducing cybersickness symptoms and enhancing user comfort.

C. Conclusion

This paper presents a novel platform, an intelligent auto-adapted system designed to enhance immersive simulations and reduce cybersickness. The platform utilizes data from physiological sensors and user-reported sickness levels to train in real-time, enabling automated cybersickness detection and adaptation of the virtual environment. Through analyzing electrodermal activity (EDA) and eye-tracking data, we observed a decrease in the accumulative effect of EDA and improved stability and consistency of eye movements during the adaptation phase, which correlated with cybersickness. The study aimed to compare objective data features between the training and adaptation phases, providing initial insights into the effectiveness of the proposed platform.

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