Beyond Subjective Reporting in VR Discomfort via Continuous Biological Assessment

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Abstract

During virtual reality experiences, users often encounter physical discomforts such as dizziness, nausea, and eye strain. Since this discomfort accumulates over time, intervening before users consciously perceive the symptoms is crucial. To overcome the limitations of post-experience subjective questionnaires, various biological signal measurements have been proposed. Unlike subjective reports, continuous biometric tracking records physical responses in real time and enables the system to dynamically adjust the virtual environment before the onset of perceived discomfort. Ultimately, developing systems that leverage real-time biological monitoring will be essential to ensure safe, prolonged, and highly immersive virtual experiences.

Keywords: Virtual Reality, VR discomfort, Cybersickness, Continuous Biometric Monitoring

1. Introduction

With the widespread expansion of Virtual Reality (VR), mitigating the physical discomfort of users, known as cybersickness or VR sickness, has emerged as a critical research priority. Diverse variables, including hardware configurations, content types, and human factors, heavily influence the severity of user discomfort (Chang, Eunhee and Kim, Hyun Taek and Yoo, Byounghyun, 2021). Consequently, detecting the nascent indicators of cybersickness prior to the manifestation of explicit and debilitating symptoms is paramount. Symptoms tend to accumulate as exposure duration increases, and once users consciously perceive discomfort, they often terminate the experience. Thus, early detection is imperative to facilitate timely and effective interventions.

2. Limitations of Retrospective Subjective Reporting

Traditionally, subjective assessment of cybersickness has relied on questionnaires, with the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) and the Fast Motion Sickness Scale (FMS) (Keshavarz & Hecht, 2011) serving as the primary benchmarks. Specifically, the SSQ categorizes symptoms into nausea, oculomotor disturbances, and disorientation to provide a comprehensive profile, whereas the FMS offers a rapid, single-item metric administered at brief intervals during the experience. While these retrospective instruments effectively establish a comprehensive baseline of user distress, they are primarily designed to evaluate cumulative experiences rather than immediate and fluid fluctuations in discomfort as they occur. Additionally, subjective metrics often exhibit notable inter-individual variability, as participants interpret rating scales based on differing personal thresholds. Consequently, establishing universal baseline thresholds or generalized mitigation protocols solely through subjective reporting can be challenging, suggesting the value of integrating complementary measurement approaches.

3. Continuous Biometric Monitoring as a Preemptive Measure

To address the shortcomings of subjective reporting, alternative measurement paradigms have been introduced, most notably utilizing physiological signals such as electroencephalogram (EEG), electrocardiogram, and respiration. These biological modalities offer distinct insights. For example, EEG captures cortical changes associated with subjective disorientation symptoms (Chang et al., 2022), heart rate reflects autonomic nervous system arousal, and respiration patterns signal systemic stress caused by motion sickness (Kim et al., 2005). However, to secure clean physiological signals and mitigate motion artifacts, earlier empirical setups strictly constrained user movement, predominantly employing sedentary experimental protocols. Such restrictions greatly compromise the ecological validity of these insights, given that actual VR deployment frequently involves unconstrained interaction depending on the immersive environments. Additionally, the requirement for cumbersome, multi-channel sensor arrays presents a significant barrier to practical implementation, rendering this approach intrusive and difficult to deploy for everyday consumer VR usage.

To bypass these hurdles, recent paradigms emphasize physical behavioral signals, such as eye-tracking metrics (e.g., gaze direction and pupillary responses) (Islam etal., 2022; Shogo et al., 2023) and embedded headset inertial measurement unit logs (Kundu et al., 2023), as non-intrusive alternatives that eliminate bulky external hardware and ensure high viability for standard consumer setups. Combining these tracking modalities has been shown to yield superior predictive performance by capturing the interaction between head and eye coordination (Kundu et al., 2023). Expanding on physical features,

Table 1 Summary of previous studies measuring biosignals and subjective cybersickness levels

Reference	Obj. Measures type	Signal Type	Sub. Measures	ML/DL Applied
Chang et al., 2022	Physiological	EEG, ECG	SSQ	No
Islam et al., 2022	Physiological, Physical	ECG, EDA, Head, Eye	SSQ, FMS	Yes
Shogo et al., 2023	Physical	Eye	Self-report	Yes
Kundu et al., 2023	Physiological, Physical	EDA, Head, Eye	FMS	Yes
Hua et al., 2023	Physiological	EEG	SSQ	Yes
Li et al., 2024	Physiological, Physical	ECG, PPG, Eye, Lower Face	FMS	Yes

Note: Obj. = Objective, Sub. = Subjective, EEG = Electroencephalogram, ECG = Electrocardiogram, EDA = Electrodermal Activity, PPG = Photoplethysmography, SSQ = Simulator Sickness Questionnaire, FMS = Fast Motion Sickness Scale, ML/DL = Machine Learning / Deep Learning.

recent work by Li et al. utilized lower face action units captured via built-in headset cameras to detect discomfort (Li et al., 2024). Rather than identifying autonomic reflexes like deep breathing, their study highlighted that users often externalize nauseogenic symptoms through negative facial expressions.

4. Discussion

In summary, establishing an objective, continuous measurement paradigm for cybersickness remains essential for the advancement of safe VR experiences. To capture the incremental, time-dependent nature of cybersickness progression, modern deep learning methods often deploy recurrent architectures like Long Short-Term Memory models (Hua et al., 2023). Nonetheless, current temporal sequence models frequently experience sharp performance drops when projecting over extended horizons, and their opaque "black-box" nature prevents granular interpretation of how individual biological streams shift over time. To overcome these limitations, future research is required to focus on hybrid architectures that pair sequence-modeling layers with spatial feature extractors, alongside dynamic multi-head attention mechanisms to quantify the specific contribution of each input stream. This will enable both long-term forecasting reliability and actionable interpretability for real-time adjustments.

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