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Affective Computing for Stress, Anxiety and Cybersickness Detection in Virtual Reality

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ABSTRACT

The prevalence of stress and anxiety has increased dramatically in recent decades, especially with the global COVID-19 pandemic. In parallel, effective ways of objectively assessing and quantifying these conditions have continued to be explored. Affective computing is one such technique that has gained popularity recently, using physiological signals to interpret, and infer human emotion. Additionally, virtual reality (VR) is a rapidly developing tool with promising advancements in the health sciences. Given the emergence of new unobtrusive wearables and biosensors-instrumented VR headsets, the combined use of VR and affective computing has enabled the development of new immersive applications to objectively evaluate stress and anxiety. In this paper, we examine various affective computing methods that have been combined with VR with the goal of quantitatively measuring stress and anxiety levels. Additionally, we explore how affective computing has been used in the assessment of cybersickness. In particular, we surveyed current VR studies and summarized the most common physiological measurements used to characterize stress, anxiety, and cybersickness. Methods monitoring heart rate, skin conductance, muscle movement, and brain activity are described. We highlight the current challenges and propose opportunities for future research directions.

Keywords: Stress, Anxiety, Affective computing, Physiological measurements, Virtual reality (VR), Cybersickness

INTRODUCTION

Affective computing refers to a computer's ability to recognize, interpret and infer human emotions, a skill that is a crucial aspect of human interaction, communication, and even evolutionary survival (Poria et al., 2017, p. 98). Given the complexity in the understanding of emotional manifestations through physiological and psychological signals, affective computing, with its potential to simplify this process, is emerging at the forefront of human behavioral research. Coupled with the vital role of affect in our everyday functioning, researchers are capitalizing on using machine learning to research psychopathology, learning, driver assistance, and so forth. This survey aims to expound on the current affective computing devices used in virtual reality to assess various physiological signals and cybersickness. We start by providing an overview of stress, anxiety, virtual reality, and cybersickness. We then elaborate on the physiological measures that were used in a virtual reality setting in the documents surveyed for this paper. We explain the measurements assessed, the devices used, their strengths and limitations. Finally, we discuss some future possibilities in this domain that current and future researchers can consider and implement.

BACKGROUND

Although stress has numerous definitions, it can be understood as body's non-specific response when a person is faced with a negative, uncontrolled condition that results in arousal (Fink 2016, p. 4-5). For instance, an individual may feel stress during an exam, as it is unpleasant and beyond their immediate means to change. The wide range of what is considered stress can be divided into categories of acute and chronic. Acute stress deals with recent pressures, while chronic stress encompasses long standing demands (Greene, Thapliyal and Caban-Holt 2016, p. 45). This survey, as with most studies, will focus on the measurements surrounding acute stress. As it is easier to elicit and observe, it is the choice of most experimenters in the field. Researchers have traditionally used questionnaires to measure stress and anxiety such as the Perceived Stress Scale (PSS) and Stress Appraisal Measure (SAM) (Andreou, 2011). Less subjective means, such as monitoring cortisol levels, have also been utilized, but traditional techniques often require very intrusive procedures to extract information (Greene, Thapliyal and Caban-Holt 2016, p. 46). As such, the need for objective, wearable, and safe assessments may be addressed by the physiological measurements of affective computing.

Virtual reality (VR) has existed for several decades, but recent advances in computer graphics and head-mounted display (HMD) technologies have revolutionized the way individuals interact with computer-simulated environments (Rangelova, Eckel and Andre, 2018). From games to infrastructure project visualization, VR has been rising in popularity in countless sectors (Linda et al., 2018). One such area of interest is the use of VR in healthcare. Methods such as exposure therapy have been shown to greatly improve outcomes (Carl et al., 2019). Similar findings have been seen in the treatment of anxiety and stress related disorders (Carl et al., 2019). Integrating affective computing physical measurements with VR therapies can help improve mental health procedures, as well as enable the real-time measurement of biomarkers to quantitatively monitor intervention outcomes.

Despite its promising advancements, VR is still heavily limited by the phenomenon of cybersickness. Cybersickness, also known as simulation sickness, is a subset of motion sickness that occurs within simulated environments (Ihemedu-Steinke et al., 2017). The biological basis surrounding the condition is not well defined within the scientific community and is a central point of research within its field (Miljković et al., 2019). The unpleasant occurrence leaves many users of VR in discomfort and hinders the ability of widespread engagement. As such, the means to accurately assess cybersickness is a primary goal of virtual environment innovation. Doing so allows for better management of the condition and increased quality of user experience. Although common measurement tools for cybersickness, such as the Simulator Sickness Questionnaire (SSQ), provide insight into the experience of VR, they are ultimately limited by their subjectivity. As such, more objective approaches based on affective computing have been used in recent years to gain a concrete understanding of the condition. Physiological measurements can produce consistent results across VR users and can serve as an anchor for further exploration into cybersickness.

RESULTS: PHYSIOLOGICAL MEASUREMENTS

Physiological measurements for affective computing involve two components: assessment of physiological signals associated with the central-autonomic activity and biochemical signals indicative of endocrine and immune activity. Amongst the various methods used to assess each of these two components, a few have been more prominent with VR. Brain activity, heart rate, skin conductance, and other techniques will be explored in the following sections.

Brain Activity

There are various ways to objectively measure and quantify brain activity. Due to its affordability, and higher temporal resolution, electroencephalography (EEG) is a preferred method of brain activity detection in VR experiments and will be the focus of this paper. EEG is a technique that measures the voltage variations from current flows within the neurons of the brain. EEG can be used to recognize mental workload, attention, emotions, amongst other mental states (Seo and Lee, 2010). The signals observed are commonly divided into five frequency bands, namely: delta (0.1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (greater than 30 Hz). Based on the different mental states associated with each frequency band, EEG can be used to recognize stress and anxiety. Pre-processing is commonly performed to remove noise and artifacts and bandpass filters from 4 - 45 Hz are commonly used (Arya, Singh and Kumar, 2021). Despite its higher temporal resolution advantage, EEG has a low spatial resolution and requires many electrodes to be placed on the scalp. For example, EEG recordings for stress measurement have been done using 128, 64, and 32 channels (Wang et al., 2019), but ongoing work suggests that acceptable performance can be achieved with as little as 5 channels (Parent et al., 2020).

EEG has also been frequently used as an assessment tool for cybersickness studies. Looking into the setup, important patterns emerge. The number of channels varied from as little as 5, to as many as 256 (Wang et al., 2019; Lim et al., 2021). Not all studies made use of an HMD, but those that did had various methods to maneuver EEG equipment around the gear. One paper used a BioSemi EEG cap in order for the piece to fit with the VR headset (Arafat, Ferdous and Quarles, 2018), while another chose a wireless EEG device: the Emotiv Epoc+ (Celikcan, 2019). The wireless option provides less obstruction with the HMD, but also removes limits of simulation motion of the participant (Celikcan, 2019). The studies that did not involve HMD used EEG caps as well, such as the HydroCel Geodesic Sensor Net (Lim et al., 2021). In these works, however, the relationship between SSQ trends and EEG has been weak. For example, in Lim et al.'s study (2021), no statistical correlation was found between the tested EEG parameters and SSQ scores and only a small relationship was found between the alpha band in the temporal area and SSQ scores. Future work within cybersickness prediction should focus on alternative feature representations beyond just simple subband frequency powers.

Heart Activity

Heart activity is another useful method to measure stress, anxiety, and cybersickness and metrics such as heart rate (HR) and heart rate variability (HRV) have emerged as the most popular. The former deals with the average number of beats in a given amount of time, while the latter deals with time differences in between beats (Ludwig et al., 2021). Fluctuations of these measurements are linked with the autonomous nervous system and correlate to certain conditions. For example, an increase in heart rate has been linked to stress and cybersickness, thus have been used in VR studies.

There are a few different methods to collect and interpret heart activity. One of the most common is electrocardiography (ECG), which monitors the excitation conduction of the heart. ECG is one of the most accurate ways to assess heart activity, but few wearable devices exist and only recently has it been integrated into a VR headset (Cassani et al., 2020). In the VR studies that looked at stress and anxiety, heart rate was measured using ECG sensors or with smartwatches/devices that rely on photoplethysmography (PPG). Electrodes were placed on the body of the participant, either on the chest area, or on the hands, legs or ankles. Some studies placed wireless straps on the chest wherein the heart rate data was transmitted via Bluetooth (Kamińska et al., 2020; Awada et al., 2021; Laforest et al., 2016; Poguntke, Wirth and Gradl, 2019). This permitted greater mobility among the participants. In one of the studies where researchers used a smartwatch to collect biodata, researchers faced some errors in recording data (Borgard, Hashemi and Yang, 2018). They noted that since smartwatches are intended for personal use, they might not be ideal for multi-person measurements which could compromise the data measurements. In cybersickness related VR studies, ECG medical sensors and wrist-based electrodes have been used to measure HR and HRV (Rangelova, Eckel and Andre, 2018; Yoshida, Kaneko and Yuda, 2020).

As mentioned above, other methods exist to measure heart activity, such as blood volume pulse (BVP) measurement from PPG sensors. BVP measures changes in vessel blood volume via changes in light absorption levels measured with PPG (Rangelova et al., 2019). Devices are typically attached to the tip of the ring finger with a cuff or velcro strap, or via a smart bracelet/watch form factor (e.g., the Empatica E4 device or the Fitbit Alta HR) (Rangelova et al., 2019). PPG sensors are usually less accurate than ECG but have been utilized in several studies of stress and anxiety (Yadav et al., 2019; Nunna et al., 2019, Zuniga Gonzalez, Richards and Bilgin, 2021; Crescentini et al., 2016). It is well recognized that PPG based systems can have some issues of replicability and reproducibility, as the technology can be sensitive to skin color, thickness, biobehavioral indices, and technological differences which can influence heart rate measurements.

In turn, BVP used in cybersickness studies have shown to produce correlations with SSQ scores. Its increased "wearability" compared to ECG systems make it a useful technology to be used with VR (Rangelova et al., 2019). In fact, one study showed that BVP sensors could measure heart activity that was more sensitive to cybersickness symptoms than the SSQ questionnaire, thus further motivating the use of BVP with VR (Preciado, Starrett and Ekstrom, 2020).

Skin Conductance

Skin conductance is known to be triggered in an unconscious manner to different emotional stimuli, as a natural reaction to changes in the sweat glands of the skin. Sweating is controlled by the sympathetic nervous system and high arousal states are known to increase skin conductance levels. Skin conductance is measured via the galvanic skin response (GSR), also known as electrodermal activity (EDA) (Wang et al., 2019). Changes in conductivity can be useful in determining stress, anxiety, and cybersickness levels of an individual. A higher GSR score is indicative of an increased stress response, which is measured in the unit micro-Siemens (μS) (Arafat, Ferdous and Quarles, 2018). Due to its ability to evaluate such reactions, GSR has been featured in several VR studies. Systems usually appear in wristband form factor, such as the Empatica E4 device, or more commonly, by attaching two electrodes to fingers in the non-dominant hand and applying a small current to allow for conductance measurements to be made.

In the surveyed papers, GSR was commonly used to measure levels of stress and anxiety in VR studies. Only one study employed a wrist mounted device (Empatica E4) to measure EDA (Yadav et al., 2019). Others relied on fingers-based sensors and relied on measures of skin conductance (Crescentini et al., 2016), most commonly using the ProComp Infiniti device from Thought Technology (Montreal, CA) (Martens et al., 2019). In cybersickness studies, in turn, GSR has shown varied levels of success. In some studies, skin conductance measurements showed some correspondence to SSQ reports (Wang et al., 2019) and results could also be replicated with individuals with multiple sclerosis (Arafat, Ferdous and Quarles, 2018), whereas other studies could not find any significant correlations (Rangelova, Eckel and Andre, 2018; Rangelova et al., 2019). This suggests that there is still ample room to explore the benefits of measuring skin conductance for VR applications.

Muscle Movements

Electromyography (EMG) relies on surface electrodes that are placed on certain muscles and measure electrical signals related to the muscle movement (Luca, 2006). As humans tend to contract their muscles under stressful conditions, most explored works relied on EMG sensors placed on the trapezius muscles to measure responses to different stressors (Rasmussen et al., 2006; Pourmohammadi and Maleki, 2020). One study used EMG to detect muscle co-contraction of agonist and antagonist muscles neighboring a joint (Kamińska et al., 2020). The researchers wanted to explore balance function and postural control as a function of anxiety. In another study, EMG was used to measure startle responses in response to an acoustic white noise burst while participants viewed combat-related stimuli (Norrholm et al., 2016). As with other electrical based systems, EMG is also susceptible to head movement and body movement artifacts, and thus requires signal pre-processing to enhance the signals. Additionally, it is hard to determine the appropriate sensitivity of the device because it depends on an individual's muscle structure (Martens et al., 2019). On the other hand, EMG has not been as widely used to assess cybersickness. One study looked at the use of electrogastrography (EGG) - gastric myoelectrical activity using electrodes placed on the abdominal skin over the stomach - to detect nausea in participants; a focal symptom of cybersickness (Miljković et al., 2019). It was found that VR did indeed impact gastric systems, regardless of nausea onset, and that EGG measures correlated with simple sickness questionnaire ratings. As such, EGG has potential to be a method of cybersickness evaluation but could be limited by electrode placement and the fact that wearable solutions do not yet exist in the marketplace.

Endocrinal Measures

The hypothalamic–pituitary–adrenal axis is known to react to stressful situations by increasing cortisol secretion in the body. In turn, cortisol is used as a measure for stress in laboratory settings. In fact, it is considered a gold standard for physiological stress measurement (Nath, Thapliyal and Caban-Holt., 2020). Cortisol is typically measured by saliva processing wherein saliva is collected using a swab that the participant places under their tongue and then transfers into a tube. In two of the studies surveyed, cortisol readings were used to measure stress levels of participants (Diemer et al., 2016, Shiban et al., 2016). On the other hand, cortisol might interact with hormones (such as DHEA) or hormone metabolites (such as allopregnanolone), thus could bias the readings and generate erroneous stress level correlates. Moreover, while in VR it could be more interesting to have real-time access to the user's stress levels, thus allowing for e.g., virtual environment changes. Readings based on cortisol do not allow for such real-time aspect, hence are seen as a major drawback of the method.

DISCUSSION

Integration of wearables and affective computing with VR is an area of burgeoning interest, especially within the healthcare space. The surveyed papers have looked at the use of different neuro-physiological signal monitoring devices and their use in measuring stress, anxiety and cybersickness levels when immersed in VR. It was found that across the many factors that contributed to the methods, the wearability of the assessment tools was the most important aspect in VR, hence motivating the development of new devices, such as the instrumented iHMD proposed in (Cassani et al., 2020) or the new

Galea system developed by openBCI (https://galea.co), where all the sensors are embedded directly into the VR HMD. Notwithstanding, while wearables allow for portable and real-time access to important neurophysiological data, such systems are known to be more prone to artifacts, especially due to movement. Papers that carefully integrated pre-processing and artifact removal algorithms tended to show improved results. Future work should not overlook sensor data quality issues and deploy state-of-the-art enhancement algorithms. Lastly, some papers emphasized the reduced naturalness of interacting with VR content when wearable devices were used, such as EMG/GSR sensors attached to fingers and shoulders. Size, weight and comfort of these devices were crucial for usability. Future work should pay special attention to these issues, as reduced usability may result in increased stress levels that are not necessarily due to the intervention per se, but to the comfort levels of the setup. Such confounds are to be avoided, especially with healthcare applications.

CONCLUSION

Surveying the current literature surrounding the objective assessment of stress, anxiety, and cybersickness has revealed numerous ways that VR can work in parallel with affective computing. This paper has summarized the key findings from the papers, has described the key biosignal modalities used and highlighted some key findings. The paper has also provided some suggestions on how future work should focus on portability, quality assessment, and usability to maximize the outcomes of VR-based healthcare interventions. It is hoped that this survey will help researchers working on VR and affective computing to build next-generation applications.

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