Real-time Emotion Regulation in Virtual Reality: An Adaptive Experience using Breathing Biofeedback

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Abstract

Virtual reality has increasingly been integrated with biofeedback systems for treating affective states such as depression and anxiety. The implementation of stress exposure therapies that adapt in real-time to individuals' physiological signals improves patients' ability to deal with real life stressors. This work evaluates the effect of a real-time adaptive closed-loop system using breathing rate as a biofeedback visual cue in an immersive, nature-based restorative virtual environment. Participants were divided into two groups and exposed to a baseline condition and different stressors: two Stroop Color-Word tests and a restorative virtual reality exploration task in the Virtual Levada. Their physiological signals (electrocardiography, electrodermal activity, and respiration) were recorded and subjective stress levels were annotated . The adaptive group received biofeedback based on their breathing rate, using the field of view as a representation of their stress levels, which was adapted using rule-based changes. Results revealed significant differences in physiological responses across experimental conditions. Specifically, the adaptive biofeedback group reported lower levels of stress during the immersive virtual reality task compared to the Stroop tests, highlighting the restorative effect of the Virtual Levada. These findings suggest that real-time adaptive biofeedback systems, when integrated with restorative elements, enhances users' ability to regulate their stress responses.

Keywords: Adaptive, Biofeedback, Breathing, Physiological Signals, Real-time, Stress, Virtual Reality

1 Introduction

Depression and anxiety disorders are closely related to a range of negative outcomes, which can negatively impact patients' mental health, often leading to an increase in stress levels and diminish quality of life (Dieleman et al, 2010; Ahmed et al, 2022). Individuals suffering from high levels of anxiety and stress, frequently struggle with daily life stressors, due to deficits in self-regulation skills (Bossenbroek et al, 2020). Consequently, the implementation of stress regulation techniques using biofeedback has the potential to enhance the ability of these individuals' to mitigate the impact of stressful situations (Brammer et al, 2021). Biofeedback-based stress regulation leverages users' physiological signals, which reflect a direct response of the autonomic nervous system, in response to an external stimuli (Kothgassner et al, 2022).

Physiological signals such as Electrocardiography (ECG), Electrodermal Activity (EDA) and Respiration (RESP), play an essential role in assessing and understanding stress responses (Ishaque et al, 2023; Lima et al, 2024; Bota et al, 2019). ECG signals provide insights into Heart Rate Variability (HRV), a reliable marker of stress that reflects the balance between the sympathetic and parasympathetic nervous systems (Shaffer and Ginsberg, 2017). EDA, directly influenced by the sympathetic nervous system activity, measures the electrical conductance of the skin, making it an indicator of stress, specifically, stress-related arousal (Boucsein, 2012). Additionally, RESP signals indicate stress changes through an increased breathing rate (BR) (Homma and Masaoka, 2008).

The integration of Virtual Reality (VR) therapies, particularly restorative VR that immerses users in calm and natural environments, when combined with biofeedback, represents a promising approach to stress management and emotional regulation. These VR environments are able to accurately simulate real-life stressors in a controlled and safe setting (Riva et al, 2016), allowing individuals to engage with and adapt to stressful situations. In contrast, restorative VR promotes relaxation and emotional recovery by immersing individuals in calming scenarios. By combining exposure to stressors with restorative VR environments, users can learn to regulate their emotional responses. Furthermore, real-time feedback on the users' physiological signals can help them practice stress regulation techniques, thereby increasing self-awareness regarding their emotional responses (Kothgassner et al, 2022). This immersive and personalized stress management approach, not only reflects real-life stressors, but also improves the patients' ability to deal with stress in their daily life, leading to better health outcomes.

This experiment had two main goals. First, we evaluated the impact of immersing users in a nature-based restorative VR environment with adaptive biofeedback on their physiological responses. Specifically, we evaluated how VR biofeedback influenced users' physiological signals when exposed to different stressors. Second, we aimed at developing a real-time closed-loop system. In previous work (Lima et al, 2024), we studied the users' physiological responses to emotional VR stimuli using an offline processing approach. In this experiment we aimed to implement the previously validated offline methodology with a real-time pipeline that receives, processes and extracts features from multiple streams of physiological data in real time. Then, we adapted the restorative VR environment, using the Flow Optimizer Framework (FOF) (Lobo et al, 2024) to create rule-based changes (see section 3.4.2). Finally, we assessed the overall user experience within the VR environment.

2 Background and Related Work

2.1 Physiological Signals and Stress

Physiological responses to stress involve both the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). These systems work together to maintain physiological balance, adapting to different stressors (Finseth et al, 2023). The SNS and the PNS have distinct roles in managing stress, with the SNS primarily responsible for activating the body's fight or flight response, whereas the PNS is responsible to calm down the effect of the stressors (Parnandi and Gutierrez-Osuna, 2017).

Previous research shows that individuals exhibit different physiological responses to identical stressors, due to the unique response and recovery times of each nervous system. These systems are triggered by specific stressors rather than their intensity (Bowers et al, 2008; van Dammen et al, 2022). To monitor and detect stress, several studies have used a multimodal sensor approach, using signals such as ECG, EDA and RESP (Lima et al, 2024; Ahmed et al, 2022; Cipresso et al, 2019).

The heart, regulated by both the SNS and PNS, provides valuable insights regarding stress levels, by measuring its electrical activity using ECG signals. Hence, HRV extracted from cardiac signals, reflects the balance between the SNS and PNS. The SNS tends to increase the heart rate (HR) during stress, in a flight or fight response, whereas the PNS tends to slow HR and promote relaxation (Jerritta et al, 2011).

Electrodermal activity is another metric to measure stress, as it measures skin conductance levels due to the activation of sweat glands, which are directly controlled by the SNS. Therefore, EDA is a reliable metric of physiological arousal when presented to an external stimuli (Parnandi and Gutierrez-Osuna, 2017). EDA response can be divided into two main components: the phasic component (SCR), which represents spontaneous peaks during a startle event, and the tonic component (SCL) which reflects the slow changing level of EDA over time (Boucsein, 2012; Bota et al, 2019). This work will focus only on the tonic component.

Respiration signals are also related to physiological responses to stress. Breathing signals are used to measure both the respiration rate and the depth of breathing. It is highly influenced by the PNS, as it encourages slower and deeper breathing to promote relaxation, while in situations of stress, the SNS induces rapid and shallow breathing patterns (Ishaque et al, 2023).

The combination of RESP alongside ECG and EDA signals, provides a comprehensive and detailed understanding of an individual's physiological response to stress.

2.2 Virtual Reality Biofeedback

Although physiological stress can be measured using a multimodal sensor approach, individuals are often unaware of their autonomic responses to stress, making it difficult for them to regulate these responses effectively (Price and Hooven, 2018). Hence, biofeedback has emerged as a promising tool to help individuals self-regulate their emotions and manage stress (Brammer et al, 2021).

Biofeedback has been increasingly applied in the field of stress-exposure therapy, to improve therapy outcomes for several affective states such as emotional self-regulation and anxiety (Lobel et al, 2016). Typically, during biofeedback stress-exposure therapies, visual cues are used to represent the biofeedback, which the user focuses on to regulate their emotional state. However, in more demanding and stressful situations, individuals may become distracted from the biofeedback target, leading to poor therapy outcomes.

To enhance the immersion and effectiveness of these therapies, VR has been used as an alternative method. VR offers highly immersive environments that can simulate real-life stressors in a controlled setting, making it suitable for exposure therapy to induce the target levels of stress and anxiety (Kothgassner et al, 2022). This immersive exposure (Gaggioli et al, 2014) allows more engaging therapies, reducing distractions and enhancing focus on the biofeedback visual cues (Suh and Prophet, 2018).

Furthermore, VR-based exposure therapy can be enhanced by integrating natural restorative VR environments. A restorative VR environment is designed to promote relaxation and reduce stress by immersing the user in nature-inspired settings (Spano et al, 2023; Mattila et al, 2020). These environments use visual and auditory elements, such as forests, beaches, mountains, rivers and ambient sounds (Franco et al, 2017; Mattila et al, 2020), which elicits a calm and relaxing response. By activating the parasympathetic nervous system, these natural elements help to reduce heart rate and stress levels (Masters et al, 2022), creating a sense of mental distance from high-stress settings, promoting a state of relaxation.

When combined with biofeedback, these restorative VR environments provide an adaptive, closed-loop and personalized experience. By continuously monitoring the user's physiological data, such as heart rate, skin conductance and respiration signals, the restorative VR environment can adjust visual and auditory elements in real-time, according to the user's stress levels (Spano et al, 2023). This adaptive approach allows individuals with stress disorders to improve emotional regulation by reinforcing relaxation responses within a safe and immersive environment. Thus, restorative VR environments, which replicate the calming effects of real-world nature, reinforce relaxation states and enable users to develop strategies for coping with stress and improving mental well-being.

2.3 Related Work

Adaptive closed-loop systems are increasingly being used in the treatment of mental health disorders(Bermudez et al, 2019; Wang et al, 2021). These systems continuously monitor the user's physiological state in real-time and adapt the virtual environment accordingly. By adapting to changes in the user's emotional state, they offer a high level of personalization, which is not achievable with static systems.

These systems integrate real-time physiological data such as HRV, EDA and RESP. By collecting and processing this data, they provide biofeedback and adjust the VR environment based on the user's emotional state, whether that involves the intensity of the stimuli, the difficulty of specific tasks or the type of feedback provided (Lima. et al, 2022; Jerčić and Sundstedt, 2019).

Despite their potential, adaptive closed-loop system still face several challenges. The primary concern is the complexity of accurately collecting and processing physiological data in real-time, and providing appropriate feedback regarding the user's emotional state (Brammer et al, 2021). Previous research has explored closed-loop adaptive systems using biofeedback and physiological signals in VR, to reduce the impact of stress and anxiety based on an individual's emotional state.

Two previous studies, in particular, have used breathing signals as biofeedback visual cue (Brammer et al, 2021; Van Rooij et al, 2016). Brammer et al. (Brammer et al, 2021) implemented a stress-exposure biofeedback training system in VR for police officers. In this system, the peripheral vision within the VR environment was adjusted based on the user's BR: a slower, calmer BR increased the field of view (FOV), while a faster BR decreased it, thereby inducing more stress. Similarly, Van Rooij et al. (Van Rooij et al, 2016) developed a biofeedback VR game called DEEP, where diaphragmatic breathing was promoted through biofeedback. In this game, users visualized their breathing phases, with inhalation and exhalation peaks represented as circles. The study showed that DEEP effectively reduce anxiety levels in children.

Wang et al. (Wang et al, 2021) developed a pipeline for real-time processing of electroencephalography (EEG) signals using LabStreamingLayer (LSL) and Python. This pipeline was used to monitor and adapt a virtual reality environment by providing implicit biofeedback based on the participant's state of anxiety. This work demonstrated that LSL is robust in signal acquisition, while Python is effective for real-time data processing.

To accurately monitor emotional states, a combination of physiological signals is often required. Gupta et al. (Gupta et al, 2021) used EEG, EDA and HRV signals to monitor participants' emotional states. This study developed a VR game called WizardOfVR, which provided real-time personalized biofeedback and adapted forest environmental factors, such as fog height and density, to enhance immersion in the virtual experience. Finally, Finseth et al. (Finseth et al, 2023) developed a personalized stress detection system for hazardous operations using different stressors. This system evaluated stress by measuring HRV, EDA, RESP and blood pressure, thus predicting stress responses in real-time through personalized machine learning models.

However, most of these studies focus on individual physiological signals rather than integrating multiple signals to create a more comprehensive approach. Therefore, the following methodology proposes a custom adaptive system that uses a multimodal physiological sensor approach to adapt an immersive VR environment in real-time, providing biofeedback based on the user's BR.

3 Methodology

3.1 Participants

Thirty healthy participants (15 male, 15 female) were recruited from a convenience sample of volunteer subjects, all adults with a mean age of 28.5 ± 7.32 years (19-46 years). Demographics included 28 participants from Portugal, 1 from Venezuela and 1 American, all fluent in Portuguese language. Participants were considered eligible if they were not color blind or had clinically diagnosed depression. Written informed consent was provided before collecting any type of data. The study ethical procedures were approved by the ethics committee of the University of Madeira.

3.2 Hardware

The hardware used in this study comprises the following components: An HTC Vive Pro Eye, a desktop, two laptops and a physiological wearable device.

The HTC Vive Pro Eye is a VR headset that incorporates eye-tracking technology, which allows more precise interactions and enhanced user insights. It has a 2880 x 1600 pixels resolution (1440 x 1600 per eye), 90 Hz refresh rate and a 110º field of view. The headset was connected to the desktop with Windows 10, an AMD Ryzen 7 7700 3.8 GHz processor with 32 GB of RAM and a NVIDIA Quadro P6000 graphics card.

Two laptops were also used in this study. The first laptop, an ASUS TUF, was powered by an Intel i7-11370H 3.30 GHz processor with 24 GB of RAM and a NVIDIA GeForce RTX 3060 graphics card. It was used to acquire physiological signals from the wearable device and to control the adaptive biofeedback loop (section 3.4.2). The second laptop was dedicated to the Real-time Loop System (section 3.4.1) and for saving all data for offline analysis. It was equiped with an Intel i7-1165G7 2.80 GHz processor with 16 GB of RAM and an Intel Iris Xe graphics card.

The wearable device was a biosignalsplux 8-channel device developed by PLUX (PLUX Wireless Biosignals, S.A.). This device allows wireless signal acquisition up to 8 simultaneous sensors. In this experiment, the following sensors were acquired at a sampling rate of 100 Hz: a piezo-electric chest band was used to acquire the RESP signal by measuring displacement variations in the thorax during the breathing cycle. ECG signals were acquired by placing three gelled electrodes on the participant's chest in the V2 configuration of Einthoven's triangle system. Finally, two gelled electrodes were placed on the middle phalanges of the second and third fingers of the non-dominant hand to measure EDA levels.

3.3 Software

Regarding the offline software, the acquisition of the physiological signals from the biosignalsplux wearable device was performed using the OpenSignals software (https://www.pluxbiosignals.com/collections/opensignals). This software allows real-time visualization and streaming, using LSL, of the physiological signals being monitored from all PLUX devices.

All the signals acquired during this experiment were synchronized using the LSL software (Christian Kothe et al, 2019). These synchronized signals were saved in a .xdf file for posterior offline analysis.

3.4 Real-time System

The Real-time system (Fig. 1) was developed to detect stress and predict the emotional state of the user in real-time. It comprises three modules: the Real-time Processing, the Adpative Biofeedback and the Virtual Environment.

3.4.1 Real-time Loop System

The Real-time processing module receives data from LSL streams provided by the physiological wearable device and event markers. This enables the real-time analysis and processing of the physiological signals (ECG, EDA and RESP). The signal processing algorithms used in the real-time system are the same as those applied in the offline processing pipeline developed by Lima et al. (Lima et al, 2024), ensuring the validity of the computed features.

The real-time system uses Python's parallel-based processing architecture to execute multiple processes simultaneously, minimizing delays. For each available data stream, a separate process is created to handle the data input (process #2 in Fig. 1). The data are then organized and synchronized into a single buffer containing the last 40 seconds of data, managed by another parallel process (process #3 in Fig. 1). This buffer is continuously updated with new data by process #2 and sent for feature extraction or machine learning prediction. Once the processing sub-module generates and outputs the target feature, the manager process (process #1 in Fig. 1) triggers the transmission of a new buffer containing the last 40

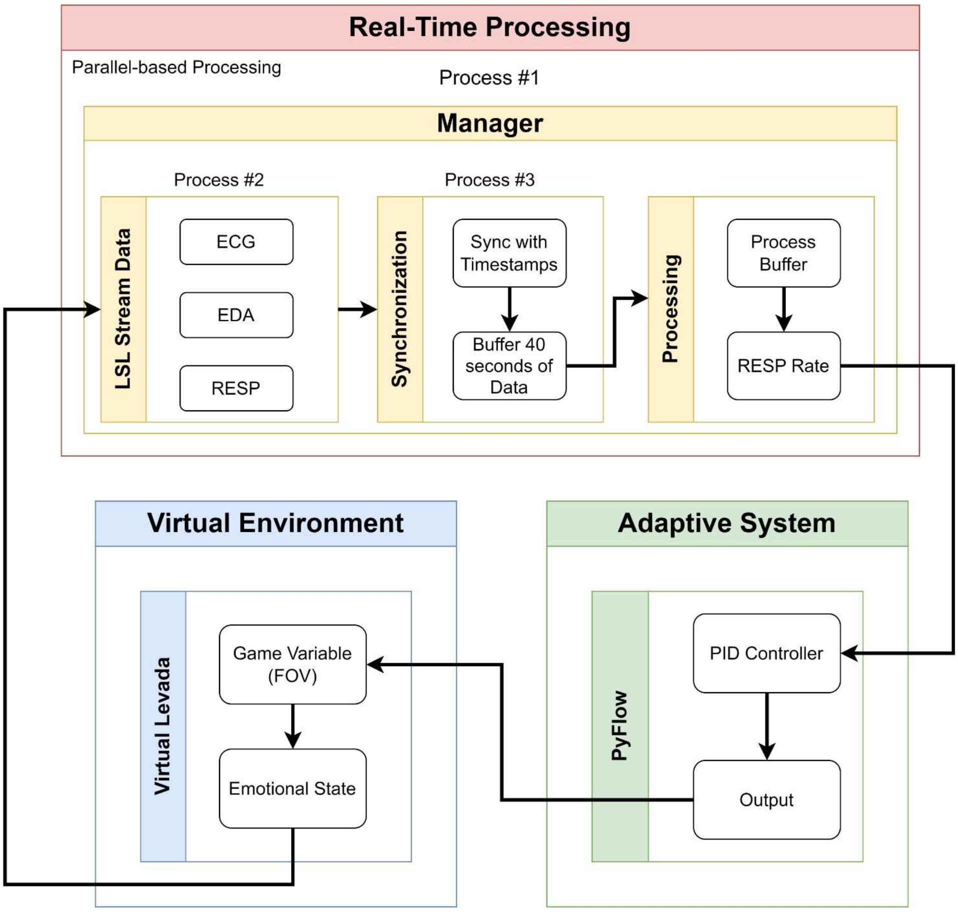

Fig. 1: Real-time Loop System overview, based on Python's parallel-based processing and the FOF framework for Unity3D.

seconds of data, from process #3 to the processing sub-module.

3.4.2 Adaptive Biofeedback

The Adaptive Biofeedback module is based on the FOF (Lobo et al, 2024), which integrates Unity3D, PyFlow (https://github.com/wonderworks-software/PyFlow) and LSL (https://github.com/sccn/labstreaminglayer), to enable real-time adaptation of a virtual reality game. This framework simplifies the process of adapting Unity3D applications by using PyFlow's visual-scripting, rule-based algorithms, while also enabling real-time visualization and monitoring of the user's physiological signals. To enable responsive adjustments, the PyFlow module within FOF was modified to include a Proportional-Integral-Derivative (PID) controller. The PID controller automatically adjusts a specific variable in response to changes in the user's BR. The Real-time processing module sends the BR via LSL to the PID controller, which automatically adjusts the target variable, aiming to set the BR at 10% lower from its baseline value, using the following weights: $k_p = 0.10$, $k_i = 0.25$, $k_d = 0.25$. The adjusted output is then sent back through LSL to the virtual environment, every 5 seconds, where it modifies the FOV (Fig. 2).

3.4.3 Virtual Environment

The virtual environment used in this study was the ”Virtual Levada” developed by Lima et al. (Lima. et al, 2022). It comprises four different naturalistic scenarios that mimic the hiking trails of Madeira Island (Fig. 3). The hiking trails included 3D nature objects, such as trees, mountains,

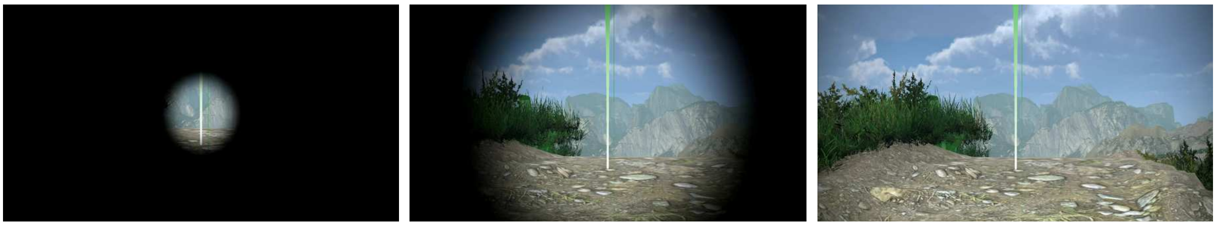

Fig. 2: Representation of the FOV biofeedback used in this study. The FOV ranges from 0.05 to 1.0 according to the BR. The lowest value of FOV (closed FOV) is related to a faster BR (more stress), whereas the highest value of FOV (open FOV) is related to a slower BR (less stress).

waterfalls, flowers, irrigation paths and tunnels created using Unity3D and Blender creation suite (Blender Foundation, Amsterdam, Netherlands). It also included naturistic sounds implemented using the *Ambient Sounds - Interactive Soundscapes* assets from the Unity Asset Store (Procedural Worlds), which included the sounds of forest, water, birds and wind.

Originally developed for the KAVE system (Ahmad et al, 2021), we adapted the Virtual Levada to work with the HTC Vive Pro Eye in this study. We implemented a teleportation locomotion system with designated anchor points, that enables users to teleport to fixed locations while consistently facing forward along the designated path. In this system, users controlled their movement by pointing a raycast from the remote controller to the desired destination. If the raycast indicator was green, users were able to teleport to the target positions; if the raycast was red, the target position was invalid, preventing teleportation. This system enhances user control and precision, maintaining immersion and reducing motion sickness in the virtual environment.

Furthermore, we adjusted this environment in real-time by selecting the FOV as the variable to provide biofeedback to users based on their BR. Therefore, by using the adaptive Unity module within the FOF, the virtual environment received updated FOV values via LSL, which induced changes in the participant's emotional state.

3.5 Instruments

3.5.1 Stroop Color-Word Test

The Stroop Color-Word Test (Stroop-CWT) is a widely used psychological assessment tool designed to measure cognitive control, attention, processing speed, and the ability to manage interference (Scarpina and Tagini, 2017; Stroop, 1935). Additionally, the Stroop-CWT is a well-established method to induce stress, as previous studies showed increases in HR, BR, EDA and feelings of anxiety during the test (Tulen et al, 1989). For this reason, the Stroop-CWT was used as a stressor in this study to evaluate the participants' physiological response to stress.

Fig. 3: Naturalistic scenarios of the Virtual Levada.

Participants completed a modified digital version of the Stroop-CWT using PsychoPy2 (Peirce et al, 2019), adapted for Portuguese population. This version included the words ”red”, ”blue” and ”green” (Fig. 4). In this test, participants were required to click on the square that matched the ink color of the text, rather than the word itself, as fast as they could. Instructions on how to perform the test were provided, along with

Fig. 4: Example of the modified digital version of the Stroop-CWT used in this experiment. In the congruent condition the word and ink color matched, whereas in the incongruent condition the word and ink color did not match.

ten practice trials to familiarize participants with the task before the actual test began. The test was then divided into two conditions, with a total duration of approximately 5 minutes: a congruent condition with 100 words, where the word and ink color matched (Fig. 4), followed by an incongruent condition with 100 words, where the word and ink color did not match (Fig. 4). The order of word presentation was randomized within both conditions.

3.5.2 STAI-Y1

The State-Trait Anixety Inventory (STAI) (Spielberger et al, 1983) is a psychological assessment tool used to evaluate a person's state and trait anxiety. It has two parallel versions: Form Y1 (STAI-Y1) and Form Y2 (STAI-Y2). In this study, an adapted version of the STAI-Y1, translated into Portuguese (Silva and Correia, 1997), was used to assess state anxiety at a specific given moment. The STAI-Y1 consists of 20-items that evaluates how the person feels right now, on a 4-point Likert scale, ranging from ”1 - Not at all” to ” 4 - Very much so”. Higher scores in the questionnaire indicates a higher level of anxiety.

3.5.3 Presence Questionnaire

The Presence Questionnaire (PQ) (Witmer and Singer, 1998) was used to measure the sense of presence in a virtual environment. In this study, the 21-item PQ validated for Portuguese population (Vasconcelos-Raposo et al, 2021), was used, which includes the following sub-scales: Involvement, Naturalness, Quality of Interface, Sensory Fidelity, and Immersion. The sub-scales for Sounds and Haptic were excluded from this study which reduced the questionnaire to 17 items. All questions were presented in a 5-point Likert scale, with higher scores indicating a higher sense of presence in the VR environment.

3.5.4 System Usability Scale (SUS)

The System Usability Scale (SUS) (Brooke, 1995) is a tool used to measure the usability of a system. It consists of a 10-item questionnaire, rated on a 5-point Likert scale, ranging from ”1 - Strongly Disagree” to ”5 - Strongly Agree”, that evaluates the user's perception of the system's ease of use, efficiency and overall satisfaction. The SUS scoring ranges from 0 to 100, with higher scores indicating better usability.

3.6 Experimental Protocol

This experiment was conducted in a single session lasting approximately 1 hour, using a between-subjects design. Participants were randomly assigned to one of the two groups: Non-Adaptive VR (NAVR) and Adaptive VR (AVR) group, with 15 participants in each. The AVR group received real-time feedback based on their BR, which adjusted the FOV in the VR environment, while the NAVR group had no feedback during the experiment. The diagram of the experimental protocol is shown in Fig. 5.

The session started with the placement of the physiological sensors (ECG, EDA and RESP). All these signals were visually inspected to ensure their quality. Participants were then asked to relax in a comfortable chair and look at a fixation cross placed at the center of the laptop screen for

5 minutes, while baseline signals were recorded. Next, participants performed the first round of the Stroop-CWT (Pre-Stroop), consisting of 100 congruent and 100 incongruent trials. Immediately after, participants answered the STAI-Y1 inventory to assess their stress level at that given moment.

Following this, participants performed the VR task, which involved exploring and finding hidden crystals along the four scenarios of the Virtual Levada, in randomized order, over a 15-minute period. Every minute, participants reported their arousal and valence levels using the Self-Assessment Manikin (SAM) scale displayed on the Head-Mounted Display (HMD). For the AVR group, the FOV during the VR task, was adjusted to their BR, every 5 seconds. All participants from both groups were naïve regarding the metric used for the biofeedback: the AVR group received instructions that the VR environment would adapt to their emotional state, whereas the NAVR group received instructions that the VR environment would remain constant. After the VR task, participants answered repeated the STAI-Y1 and completed another round of the Stroop-CWT (Post-Stroop). Finally, they answered the SUS and PQ questionnaires regarding their VR experience.

4 Results

In this experiment, we assessed the effect of providing real-time biofeedback based on BR to participants during a restorative nature VR exploration task. Users in the AVR group received the biofeedback protocol, while users in the NAVR group did not. We analyzed participants' physiological responses to stress, specifically BR, HR and EDA, during baseline, the VR task and two Stroop-CWT (Pre and Post) conditions, which served as stressors conditions. Additionally, we assessed the self-reported levels of stress using the STAI-Y1. User experience during the VR task was evaluated using the PQ and the SUS questionnaires.

4.1 Physiological Response to Stress

In terms of the physiological response of participants to stress, we evaluated the mean values for HR, EDA and BR, extracted offline, across the duration of each experimental condition (Baseline, Pre-Stroop, VR, and Post-Stroop), for both groups (AVR and NAVR). Hence, we conducted the Mixed ANOVA statistical test to assess the effect of biofeedback, on the physiological signals related to stress, measured across conditions. When the assumptions to perform the Mixed ANOVA were violated, the Friedman test and the Mann-Whitney U test, were applied, respectively, for the within-subjects and between-subjects factor.

Regarding the BR, the results of the Mixed ANOVA showed a significant main effect of Time (Baseline, Pre-Stroop, VR, Post-Stroop) on the average BR ($F(3, 84) = 21.88, p < 0.01, \eta^2 = 0.44$), suggesting that the BR changed significantly across the different time conditions. Post-hoc pairwise comparisons adjusted with Bonferroni correction were performed, and revealed that: the BR during Baseline ($M = 14.32 \pm 2.44$ bpm) was significantly lower than during both the Pre-Stroop ($M = 16.41 \pm 2.30$ bpm) ($p < 0.001$) and the Post-Stroop ($M = 16.94 \pm 2.34$ bpm) ($p < 0.001$); the BR during the VR task ($M = 14.64 \pm 1.72$ bpm) was also significantly lower than the Pre-Stroop ($M = 16.41 \pm 2.30$) ($p < 0.001$) and the Post-Stroop ($M = 16.94 \pm 2.34$ bpm) ($p < 0.001$). However, there was no significant effect for Group: AVR vs NAVR ($F(1, 28) = 1.34, p = 0.256, \eta^2 = 0.05$) or for the Time x Group interaction ($F(3, 84) = 0.40, p = 0.75, \eta^2 = 0.01$). Despite no significant difference was found between groups, Fig. 6 shows that the AVR group revealed, on average (blue and red lines in Fig. 6), a greater decrease in BR from the Pre-Stroop to the VR task ($\Delta BR = -2.0$ bpm) when compared to the NAVR group ($\Delta BR = -1.52$ bpm).

In terms of EDA levels, the results of the Mixed ANOVA also revealed a significant main effect of Time, on the average skin conductance level ($F(3, 84) = 36.13, p < 0.01, \eta^2 = 0.56$), suggesting a significant change in stress levels across the different time conditions. Post-hoc pairwise comparisons adjusted with Bonferroni correction were performed, and revealed that: the skin conductance levels during Baseline ($M = 4.03 \pm 1.95$ μS) were significantly lower than during the Pre-Stroop ($M = 6.25 \pm 3.06$ μS) ($p < 0.001$), VR task ($M = 5.32 \pm 3.01$ μS) (p < 0.001) and the Post-Stroop ($M = 6.95 \pm 3.35$ μS) ($p < 0.001$); the skin conductance level during the VR task

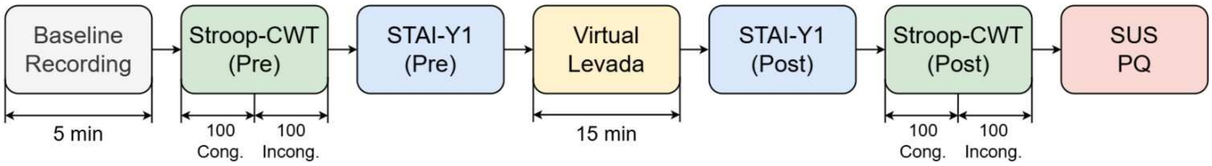

Fig. 5: Diagram of the experimental protocol.

($M = 5.32 \pm 3.01\ \mu$S) was also significantly lower than the Pre-Stroop ($M = 6.25 \pm 3.06\ \mu$S) ($p < 0.05$) and the Post-Stroop ($M = 6.95 \pm 3.35\ \mu$S) ($p < 0.001$). Nonetheless, no significant difference was found for Group ($F(1, 28) = 0.47, p = 0.497, \eta^2 = 0.02$) or for the interaction Time x Group ($F(3, 84) = 0.18, p = 0.913, \eta^2 = 0.006$). Similarly to the BR, Fig. 6 shows that the AVR group had a greater decrease in the skin conductance levels from the Pre-Stroop to the VR task ($\Delta EDA = -1.0\ \mu$S) when compared to the NAVR group ($\Delta EDA = -0.85\ \mu$S).

Finally, HR data revealed to violate the assumptions to perform the Mixed ANOVA. Hence, the Friedman test was performed to evaluate the effect of Time (Baseline, Pre-Stroop, VR, and Post-Stroop), and the Mann-Whitney U test to evaluate the effect of Group (AVR vs NAVR) on the average HR. The results from the Friedman test revealed a significant effect of Time on the average HR ($\chi^2(3, 30) = 36.68, p < 0.001$). Post-hoc pairwise comparisons using the Wilcoxon signed-rank test corrected with Bonferroni for multiple tests revealed that: the HR during Pre-Stroop ($M = 85.58 \pm 17.05$ bpm) was significantly higher than during Baseline ($M = 74.91 \pm 12.79$ bpm) ($p < 0.001$), VR task ($M = 76.65 \pm 13.26$ bpm) ($p < 0.001$), and Post-Stroop ($M = 79.12 \pm 16.72$ bpm) ($p = 0.002$). No significant difference was found between groups ($U = 1917.0, Z = 0.614, p = 0.539, r = 0.112$). However, Fig. 6 shows that the AVR group had a greater decrease in the average HR from the Pre-Stroop to the VR task ($\Delta HR = -10.53$ bpm) when compared to the NAVR group ($\Delta HR = -7.33$ bpm).

4.2 STAI-Y1

The STAI-Y1 questionnaire was used to evaluate the state anxiety of the participants, as higher scores indicates higher levels of anxiety. Hence, we conducted a Mixed ANOVA to assess the effect of the biofeedback: AVR vs NAVR (between-subjects factor), on the stress levels reported in the STAI-Y1, measured before (Pre) and after (Post) the VR task (within-subjects factor). The results of the Mixed ANOVA showed a significant main effect of Group (AVR vs NAVR) on the STAI-Y1 scores ($F(1, 28) = 11.54, p < 0.01, \eta^2 = 0.29$), with the AVR group reporting higher STAI-Y1 scores ($M = 49.10 \pm 2.16$) when compared to the NAVR group ($M = 47.43 \pm 1.94$). However, no significant effect was found for Time: Pre vs Post ($F(1, 29) = 2.07, p = 0.162, \eta^2 = 0.07$), and for the Time x Group interaction ($F(1, 58) = 0.70, p = 0.41, \eta^2 = 0.02$). Despite no significant effect was found, both groups decreased the STAI-Y1 score in the post VR task (see Table 1).

Table 1: STAI-Y1 scores for the AVR and NAVR groups, pre and post performing the VR task.

	Pre	**Post**
NAVR	48.07 ± 1.98	46.80 ± 1.74
AVR	49.27 ± 2.43	48.93 ± 1.91

4.3 Presence Questionnaire (PQ)

The overall experience and sense of presence in the VR environment were evaluated using the Presence Questionnaire (PQ). The results showed that both groups had a similar sense of presence inside the VR environment, as depicted in the sub-scales shown in Table 2. Specifically, the AVR group reported an average score of 63.33 ± 9.02, and the NAVR group reported an average score of 63.87 ± 9.46, out of a total score of 85. The Mann-Whitney U test revealed no significant difference between the two groups ($U = 108.0, Z = -0.187, p = 0.852, r = 0.03$).

4.4 System Usability Scale (SUS)

The usability of our VR environment was assessed using the SUS, with scores ranging from 0 to

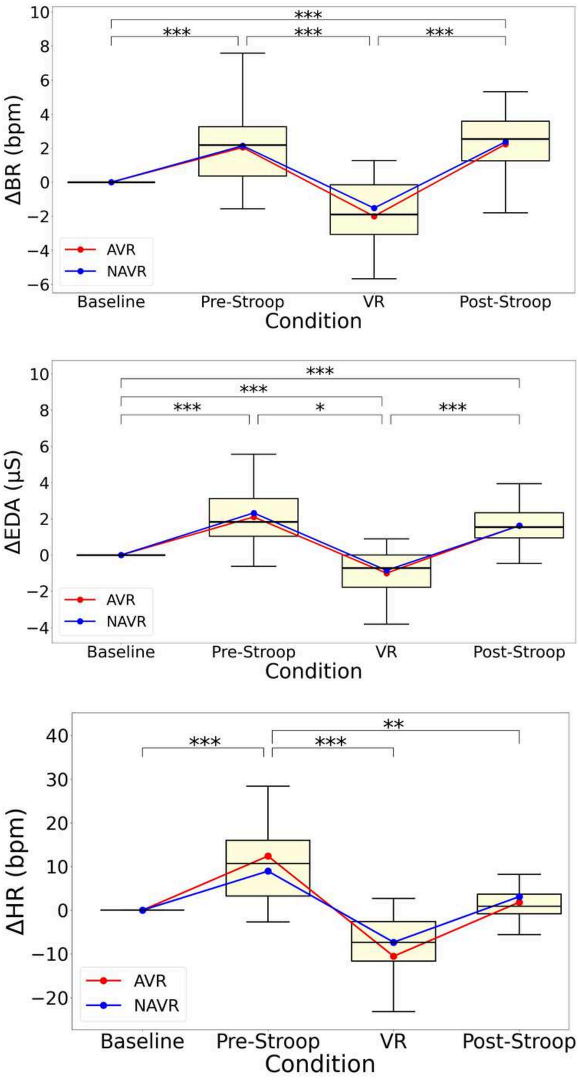

Fig. 6: Boxplots of the physiological signals represented as the difference in the average feature (BR, HR and EDA) from the current to the previous condition. The red line represents the mean difference in the AVR group and blue line represents the mean difference in the NAVR group. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

100, with higher scores indicating better usability. Typically, an average score above 68 is considered to be above average. The results from the Mann-Whitney U test, reveals that the NAVR group reported a significantly higher usability score ($M = 86.83 \pm 10.15$) when compared to the AVR group ($M = 79.17 \pm 8.80$) ($U = 61.0, Z = -2.15, p < 0.05, r = 0.39$).

Table 2: Comparison of the mean scores for the PQ total score and its sub-scales, between the AVR and NAVR groups. The maximum score of each sub-scale is shown inside parentheses.

Sub-Scale (Max)	NAVR	AVR
Involvement (25)	20.07 ± 2.94	20.07 ± 3.13
Natural (15)	8.47 ± 1.96	9.20 ± 1.82
Quality of Inteface (10)	7.87 ± 1.77	6.87 ± 1.92
Sensory Fidelity (10)	7.20 ± 1.86	6.93 ± 1.75
Immersion (25)	20.27 ± 2.69	20.27 ± 3.85
Total (85)	63.87 ± 9.46	63.33 ± 9.02

5 Discussion

The main goal of this study was to evaluate the effect of VR biofeedback on users' emotional response to stress by adapting a nature-based restorative VR environment based on their physiological signals. Additionally, user experience in the VR environment was measured using self-reported metrics from the PQ and the SUS.

The findings of this work provide insights into the effects of real-time biofeedback on physiological responses during a restorative VR task. We evaluated how biofeedback, based on the user's BR, influences both physiological responses (BR, EDA and HR) and subjective self-reported stress levels, measured by the STAI-Y1 questionnaire, under different stress-inducing conditions.

The results showed significant changes in the physiological signals (BR, HR and EDA) across the different experimental conditions (Baseline, Pre-Stroop, VR, and Post-Stroop). As expected, the highest levels for all these physiological signals were observed during the Pre-Stroop condition, since the Stroop-CWT was designed and used in this experiment, as a recognized stressor (Tulen et al, 1989). In contrast, during the restorative VR task, which was designed to immerse participants in a calming environment, physiological responses were significantly lower when compared to both the Pre-Stroop and Post-Stroop conditions. This indicates that the restorative VR task effectively provided a relaxing and calming environment, reducing stress levels for the participants.

However, no significant differences were found between the AVR group (biofeedback) and the NAVR group across all conditions and physiological signals. The lack of significance between the AVR and NAVR groups may stem from several factors, including a small sample size, which reduces statistical power, individual variability in stress regulation strategies, or the limited duration of the intervention. Additionally, the psychological signals measured may not have been sensitive enough to detect subtle effects, or participants may not have had sufficient time to master the biofeedack technique. Despite this, the AVR group exhibited a greater reduction in all physiological responses to stress during the VR task compared to the NAVR group. These findings suggests that biofeedback helped participants in the AVR group better regulate their breathing patterns under stress, thereby reducing their physiological stress responses. This highlights potential benefits that warrant further investigation.

The STAI-Y1 questionnaire results showed that both groups experienced a decrease in anxiety and stress levels after completing the restorative VR task, further supporting that the VR environment itself had a relaxing and calming effect. Nonetheless, while biofeedback appeared to have a beneficial effect on stress regulation, the AVR group reported higher anxiety levels before and after performing the restorative VR task compared to the NAVR group. These higher anxiety levels may be related to participants being naïve to the physiological signals used to control the biofeedback.

Regarding user experience, the results from the PQ showed that both the AVR and NAVR groups experienced a high level of immersion inside the VR environment (Meehan et al, 2002; Witmer and Singer, 1998). The AVR group had an average score of 61.47 out of 85, while the NAVR group had an average score of 60.27 out of 85. This difference between groups was not statistically significant, suggesting that the presence or absence of the FOV as a biofeedback visual cue did not affect immersion or user experience in the virtual environment.

However, significant differences were found in system usability, as reported by the SUS. On average, users in the AVR group reported significantly lower usability levels (79.17 out of 100) when compared to the NAVR group (86.83 out of 100). Although both groups presented high usability scores (scores higher than 68 are considered above average, and higher than 80 are considered excellent) (Brooke, 1995), this difference can be attributed to the influence of the FOV and its effect on the locomotion system within the virtual environment. Specifically, in the AVR group, the FOV increased when the user's BR was close to the target, which was a slower, more relaxed BR. If users could not achieve this goal, the reduced FOV made it more challenging and difficult to explore and move through the VR environment, thus affecting the system's usability.

In conclusion, while biofeedback is an effective tool for stress management, helping participants regulate their physiological responses, as indicated by the results obtained for BR, EDA and HR, its implementation requires further optimization to enhance the restorative nature of the VR environment. While receiving real-time biofeedback may increase the participants' awareness of their physiological state, it may also heighten their awareness of stress responses, potentially leading to higher feelings of anxiety. To better support relaxation and promote a calming experience, the biofeedback visual cue could be introduced gradually, allowing users to acclimate without becoming overwhelmed with the sudden changes. Additionally, providing physiological support could be provided to help participants manage the feedback without increasing their stress levels.

6 Limitations and Future Work

Some limitations can be pointed out in this work. First, the physiological responses to stress were evaluated across different experimental conditions with varying duration: the VR task lasted for fifteen minutes whereas each Stroop-CWT lasted approximately four to five minutes. A longer task like the VR task might allow for adaptation to the stressor, reducing physiological responses, whereas a shorter stressor (Stroop-CWT) may induce more acute stress responses. Additionally, during the VR task, participants were asked to report their levels of arousal and valence using the SAM, every minute, thereby introducing a pause in the exploration task. These interruptions may have attenuated the results of the physiological responses, by disrupting the immersive and restorative nature of the VR environment.

In future work, we aim to implement machine learning models to predict user's physiological responses in real-time, providing biofeedback on stress levels and adapting the VR environment accordingly. This approach will enable a more personalized and adaptive interaction between users and the VR system, allowing the system to respond to users' needs by adjusting visual cues to help reduce stress.

Abbreviations

AVR - Adaptive Virtual Reality
BR - Breathing Rate
ECG - Electrocardiography
EDA - Electrodermal Activity
EEG - Electroencephalography
FOF - Flow Optimizer Framework
FOV - Field of View
HMD - Head-Mounted Display
HR - Heart Rate
HRV - Heart Rate Variability
LSL - LabStreamingLayer
NAVR - Non-Adaptive Virtual Reality
PID - Proportional-Integral-Derivative Controller
PNS - Parasympathetic Nervous System
PQ - Presence Questionnaire
RESP - Respiration
SAM - Self-Assessment Manikin
SCL - Skin Conductance Level
SCR - Skin Conductance Response
SNS - Sympathetic Nervous System
STAI-Y1 - State-Trait Anxiety Inventory Form Y1
Stroop-CWT - Stroop Color-Word Test
SUS - System Usability Scale
VR - Virtual Reality

Declarations

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Competing interests

Author Hugo Gamboa is affiliated with PLUX Wireless Biosignals S.A., the company that produces the biosignalsplux acquisition device used in this work and also the OpenSignals software. The remaining authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval and consent

This study was approved by the Ethics Committee of University of Madeira (approved on the 13th of July of 2023 with Nº70/EUMA/2023) and conducted according to the guidelines of the Declaration of Helsinki. Participants were provided informed with a written informed consent to participate and for publication before enrollment in the study.

Availability of code, data and materials

The data that support the findings of this study are available from the authors upon reasonable request and with permission of the Data Protection Office of University of Madeira.

Authors' contributions

RL contributed to the Conceptualization, Data Curation, Visualization, Formal Analysis, Investigation, Methodology, Software and Writing - Original Draft. AC contributed to the Validation, Resources, Writing - Review & Editing. AG and HG contributed to the Project Administration, Supervision, Validation and Writing - Review & Editing. SBB contributed to the Conceptualization, Validation, Resources, Supervision, Project Administration and Writing - Review & Editing.

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