Open-Source Physiological Computing Framework using Heart Rate Variability in Mobile Virtual Reality Applications

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***Abstract*—Electronic and mobile health technologies are posed as a tool that can promote self-care and extend coverage to bridge the gap in accessibility to mental care services between low- and high-income communities. However, the current technology-based mental health interventions use systems that are either cumbersome, expensive or require specialized knowledge to be operated. This paper describes the open-source framework PARE-VR, which provides heart rate variability (HRV) analysis to mobile virtual reality (VR) applications. It further outlines the advantages of the presented architecture as an initial step to provide more scalable mental health therapies in comparison to current technical setups; and as an approach with the capability to merge physiological data and artificial intelligence agents to provide computing systems with user understanding and adaptive functionalities. Furthermore, PARE-VR is evaluated with a feasibility study using a specific relaxation exercise with slow-paced breathing. The aim of the study is to get insights of the system performance, its capability to detect HRV metrics in real-time, as well as to identify changes between normal and slow-paced breathing using the HRV data. Preliminary results of the study, with the participation of eleven volunteers, showed high engagement of users towards the VR activity, and demonstrated technical potentialities of the framework to create physiological computing systems using mobile VR and wearable smartwatches for scalable health interventions. Several insights and recommendations were concluded from the study for enhancing the HRV analysis in real-time and conducting future similar studies.**

***Index Terms*—Physiological Computing, Virtual Reality, Wearable, Heart Rate Variability, Biofeedback, Mobile, Open-Source, Framework.**

I. Introduction

Mental healthcare systems are facing major difficulties in meeting the challenges of a growing population and the increasing number of individuals suffering from mental conditions. It is estimated that between 15%-20% of the world population has suffered from some type of mental health disorder [1], and it is demonstrated that there are large inequalities in terms of accessibility to mental health services between high-income and low-income countries [2]. For this reason, The World Health Organization has recommended the "*promotion of self-care, for instance, through the use of electronic and mobile health technologies*" [3] as one of the approaches that would provide integrated and responsive mental healthcare services in community-based settings. Among the psychological treatments that are more suitable to evolve from expert-delivered interventions towards self-guided sessions are included conventional tools such as self-help books, but also basic exposure and non-specialist-delivered therapies [4].

The delivery of these basic self-managed therapies for mental care has been trying to leverage mobile technology as early as 1990s, but only the latest technological advancements have paved the way to ensure the presence of a therapist in every "pocket" through the development of low-cost, flexible, mobile solutions that use smartphones as digital lifelines [5][6].

An example of a technology that is being used for the benefit of a population's psychological well-being is Virtual Reality (VR). VR is a non-invasive technology that lets users experience a 3D computer-generated scenario and interact with the artificial environment through a head-mounted display (HMD) stimulating the feeling of being present in a real place, experience called first-person presence [7]. The capability of VR to digitally recreate reality under safe conditions also has the potential to transform the assessment, understanding, and treatment of mental health problems [8]. For instance, clinical psychology has used VR to help patients to cope with mental conditions [9], and it has now become the quintessential tool to deliver psychotherapies in the form of exposure therapy [10], with proven efficacy to treat phobias (e.g., spiders, heights, or flying), anxiety disorders, depression and post-traumatic stress disorder [11].

Despite the positivism and scientific evidence in using VR for mental healthcare, this new approach must address multiple challenges stemming from existing limitations of mental healthcare systems: (i) an extended technology adoption in healthcare institutions [12]; (ii) cumbersomeness and expensiveness of specialized VR equipment; (iii) content personalization and an appropriate balance between attractiveness (e.g., how compelling the simulation is) and effectiveness (e.g., how effective the simulation is to tackle the healthcare issues) [13]; (iv) standardization of measurable and quantifiable metrics

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to evaluate effectiveness. We believe that limitations (i) and (ii) can be addressed through novel mobile and standalone VR systems, while (iii) and (iv) can be solved through the inclusion of physiological signals to augment human-computer interaction (HCI) [14]. Thus, the combination of wireless VR systems with physiological computing systems has been proposed to be a game-changer methodology to extend the use of VR training in mental healthcare [15].

Similarly, the field of psychology often uses technological sensors to measure physiological variables of the users to collect data that may be significant to treat their disorders, being biofeedback one of the most extended techniques [16]. It consists of exercises that promote self-regulation of physiological responses by providing awareness of what is happening inside the body. A set of sensors is connected to the user and transformed into meaningful visual auditory cues that the subject can use to control these signals voluntarily, and produce responses that are more helpful for physical, emotional, and mental well-being [17]. Particularly, heart rate variability (HRV) biofeedback [18] has been associated with a reduction in self-reported stress and anxiety [19]. To calculate HRV, it is enough to record the peaks from the heart rate signal and get the time interval between subsequent peaks, also known as peak-to-peak interval (PPI). Nevertheless, more specific metrics are usually calculated in the time or frequency domain of the heart rate signal to get additional features about how the heart beats vary. For an extensive description of these features the reader may refer to [20].

Nonetheless, while the implementation of VR systems and physiological measurements for mental health is easier today than it was some years ago, there is still a **knowledge gap** regarding how these technologies can be used to provide scalable and self-directed mental health interventions. Some of the characteristics that hinder their broader and more extensive implementation are the use of non-portable devices, high cost of equipment, specialized knowledge required for physiological analysis, and need of specific complex laboratory setups to function. In consequence, the main **contributions** of this paper are to:

- **Introduce** PARE-VR *(Physiologically Adaptable Relaxation Experience through Virtual Reality)*, an open-source project that implements the five layers of a physiological computing system [21] using only *mobile technology*, which is *affordable* to facilitate *scalability* of mental health interventions.
- **Describe** the development of PARE-VR as a system that merges *wearable smartwatches and mobile VR* to provide HRV metrics that can be meaningful to deliver exposure therapy and biofeedback solutions in a *portable* way.
- **Evaluate** PARE-VR with an early-stage *feasibility* study in a relaxation scenario for self-regulation training, and analyzing HRV during slow-paced breathing exercises.
- **Present** potential applications of PARE-VR as a framework that can use the physiological data and artificial intelligence to deliver personalized adaptations in an autonomous way, based on the profile of each user.

The remainder of this paper is organized as follows: Section II presents the related work in the area of physiological computing systems for mental health, followed by the description of the proposed framework in Section III. Moreover, Section IV outlines the feasibility evaluation of the proposed solution using eleven participants, and Section V concludes the paper and provides directions for future work.

II. Related work

Physiological computing is considered a new paradigm of HCI, where computing systems can take physiological signals as inputs, analyze them in real-time, estimate a psychological context of the user and adapt their functionality to generate interactions tailored to the users [14]. Due to the wide variety of research projects that involve physiological signals, recent generic models have allowed the standardization of the different stages of the system according to its functionality. The **generic model** proposed by Kosunen [21] splits the pipeline into five layers: (i) signals: deals with raw physiological signals, (ii) metrics: quantifies features from the signals, (iii) indices: interpretation of features as psychological concepts, (iv) logic: defines how the indices are going to affect the system's functionality towards generating an "intelligent" behavior, and (v) application: implements the visuals of the physiological computing applications using the capabilities provided by the logic layer.

Using the aforementioned generic model as the basis of our study, we reviewed and compared the types of architectures used in other research projects employing physiological signals for mental health interventions. Our review was conducted looking for computing systems that were affordable, scalable and suitable to be used for mental health applications. The projects were categorized depending on whether: (a) they used wearable or wired sensors to measure physiological signals, (b) they used mobile phones or computers to process the signals in real-time, (c) they incorporated any type of real-time adaptation of the system based on the physiological data, (d) they displayed the applications using mobile-VR, desktop-VR, or non-VR devices.

The main finding is that, to the best of our knowledge, only one project (PhysioVR [22]) implements a technical architecture that is close to the requirements of a portable, affordable, easily-scalable, and using mobile-based technology with VR. Nonetheless, PhysioVR does not incorporate sufficient tools for extracting features from the physiological signals, which might be insightful for mental health interventions. Moreover, some projects employ wearable sensors connected to mobile devices to collect heart rate data for self-management of psychological stress [23], train respiratory paces that maximize relaxation [24], and evaluate the efficacy of games for biofeedback stress management [25] [26]. However, none of these approaches and frameworks considers the compatibility with VR systems to deliver interactive and immersive procedures. On the other hand, some research projects consider cardiac response measurements to deliver mental health interventions through VR systems in ways of home-based exposure therapies for arachnophobia [27] or social phobia[28], technological cognitive-behavioral therapies [29], or self emotional regulation [30]. Nonetheless, all of the reviewed projects utilize technological setups that need either tethered expensive body sensors or desktop computers to visualize the VR environments, which requires indoors laboratory settings and makes the accessibility to the technology more complex.

Some studies mention non-technical aspects that PARE-VR may address. For instance, the lack of inherent engagement in the normal relaxation therapies [26], which can be counteracted by using interactivity under VR environments [31]. Furthermore, a short study claims that scalability of stress and anxiety management interventions depends on the integration of mobile phones and wearables to provide biofeedback with physiological and psychological biomarkers simultaneously [25]. Finally, two studies propose as future work the inclusion of more advanced stress monitoring features based on HRV indexes [23] [32], just as we did. In conclusion, we claim that PARE-VR is relevant because the architecture addresses all the problems that have been detected in the related work.

III. PARE-VR: A Mobile VR-based Physiological Computing Framework

The PARE-VR framework for mobile physiological computing systems was developed based on the same five layers proposed by the generic model in [21]. The complete technical architecture of PARE-VR (see Fig. 1) is composed of three components that exchange and process data in real-time. The three modules are described next.

A. PPG Recorder

This component represents the “signals” layer of the generic model. The need of this application is raised by the fact that wearable manufacturers do not provide access to HRV data to be used outside their applications. Therefore, a custom application compatible with smartwatches running Tizen OS, was developed to read raw heart rate data in form of photoplethysmography (PPG) signals; which are used later to calculate peak-to-peak intervals and HRV. The application is responsible for acquiring the physiological signals from the sensor and broadcast the measured value to the application running on the mobile phone.

In order to guarantee the reliability of the time series representing the PPG signal, it is necessary to establish an adequate sampling frequency for proper detection of peak-to-peak intervals, but without affecting the duration of the battery in the smartwatch. Sampling frequency is set to 50Hz according to the minimum value suggested in [33] to extract reliable HRV metrics from wearable smartwatches.

The wireless communication between the wearable and the mobile phone is via Bluetooth using the proprietary Samsung Accessory Protocol (SAP). To facilitate data synchronization and offline data processing, each recorded sample is formatted, timestamped, and saved in a local log file in the smartwatch before transmission to the mobile device.

B. PhysioSense

The second component corresponds to the “metrics” and “indices” layers of the generic model. It is composed of an Android application responsible of receiving the physiological data and inferring psychological patterns from them. PhysioSense is based on the PhysioVR [22] framework, but it has been augmented with compatibility to smartwatches running Tizen OS, and, more importantly, the addition of a module to extract HRV features from the heart rate signal to provide more meaningful information for application systems aiming at using physiological adaptation.

PhysioSense contains a SAP receiver that collects the incoming Bluetooth packages originated from the smartwatch. Then, the data is represented as a buffered time series that is fed into the peak detector for calculating the time interval between peaks and constructing the HRV signal. The signal processing workflow is based on a part of the pseudo-algorithm proposed by Bhowmik et al.[34], where the reader may refer to for obtaining the mathematical steps necessary to calculate HRV from a PPG signal collected by a smartwatch. The original algorithm was designed to be employed offline, therefore it has been adapted to work in real-time using most of the parameters recommended by the original pseudo-algorithm; however, parameters like buffering space and Discrete Wavelet Transform (DWT) conversion were changed based on initial evaluation of the algorithm with synthetic data. The implemented HRV calculation algorithm processes the PPG signal in chunks of 1024 samples, using 5 DWT decompositions and a rectangular window that overlaps in 224 samples.

Once the HRV form is calculated per segment, it is recorded in a data log to facilitate data synchronization and offline processing. The HRV is timestamped and sent through UDP port 1111 to be analyzed by the physiological computing application that can adapt their functionality according to the HRV changes.

C. VR Game/Application

The third application symbolizes the “logic” and “application” layers of the generic model. This module comprises the mobile VR environment developed in Unity[1] to assist mental health interventions or any other interactive game or application to be adapted as a physiological computing system.

The VR application runs on the same mobile phone as PhysioSense; hence it is possible to exchange data packages between both via UDP communication. The framework includes a set of source codes that can be used on any Unity project to allow reception of physiological data from PhysioSense. Additionally, this module can use the features calculated in real-time from HRV data to feed *artificial intelligence* algorithms that modify the virtual environments according to the users’ patterns; for example, classifying users depending on detected level of emotional self-regulation and providing assistance or challenges to enhance the experience and mental health intervention.

[1]Game Development Engine: https://unity.com/

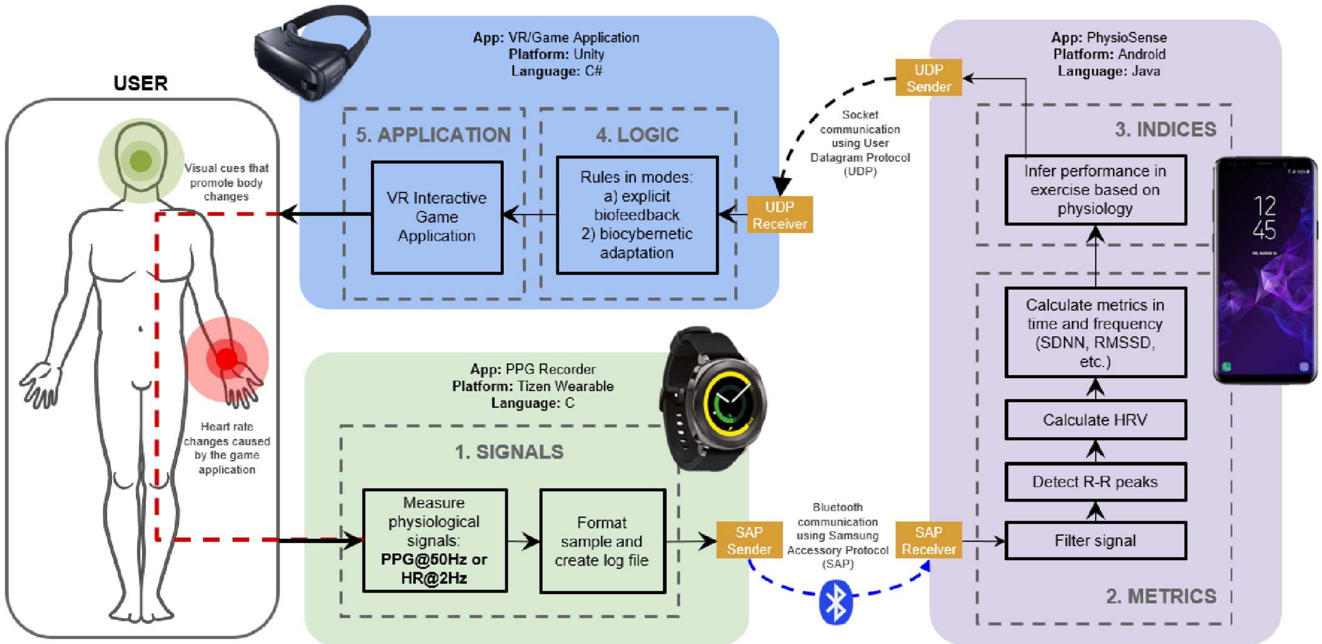

Fig. 1. Mobile-based Framework for Physiological Computing Systems. Implements the five-layers of the generic model [21] using three applications to provide real-time adaptation in mobile-VR applications based on features extracted from heart rate variability.

IV. Feasibility Study

To demonstrate the usefulness of the PARE-VR framework to integrate wearable physiological sensing technologies in mobile VR applications, we used an existing VR experience for relaxation called CalmPlace[2], and tried to integrate it with support for HRV analysis. The application is intended to support mental health, specifically anxiety and stress management, through a relaxation experience that includes meditation and respiration exercises.

The feasibility study considers a specific use-case scenario that focuses on the reported effects that slow-breathing has in the amplitude of the HRV signal. Controlled breathing is a common practice used as a complementary therapy for diseases that involve exerting a direct and conscious regulation of parameters, such as frequency, deepness, or inspiration/respiration ratio. While the average breathing frequency for most people is between 9 and 24 breaths per minute, recent studies suggest that there are some respiratory, circulatory, and *mental health benefits in slow-paced breathing* in 6 breaths per minute (equivalent to 0.1Hz) [35][36][37]. The most consistent finding in these studies is that slow-paced breathing generates a coupling between respiration rate, heart rate, and blood pressure; causing a maximization in the amplitude of the HRV signal [18].

Consequently, the **objective of the feasibility study** is threefold: (a) To get insights about the technical performance of PARE-VR in calculating HRV features in real-time using mobile systems; (b) to evaluate whether PARE-VR is capable of detecting significant changes in HRV metrics between normal breathing (experiment's baseline) and slow-paced breathing at 6 breaths per minute (experiment's intervention), (c) to analyze perceived relaxation level in both conditions according to self-reported results of the questionnaire.

EXPERIMENTAL SETUP

A. Physiological Sensing and VR System

The devices used to gather heart rate signals were: a smartwatch Samsung Gear Sport running the application PPG Recorder on Tizen OS, a mobile phone Samsung Galaxy S9 to run PhysioSense and the VR application CalmPlace executed through the headset Samsung Gear VR.

The VR application CalmPlace was adapted for the experiment including the scripts to receive physiological data, and dividing the normal relaxation experience into two parts: Baseline, where the participants breath at a normal pace while the HRV calculation is performed; and intervention, where a blue object appears in the middle of the virtual scene to guide the breathing exercise at a frequency of 6 breaths per minute.

B. Participants

For our study we employed non-probability convenience sampling for recruiting healthy volunteers that study in Stockholm. A sample of 11 volunteers was selected to be part of the experiment, aged between 23 and 32 years (i.e., 27 ± 3.24), out of which five were male and six were female. 10 participants reported previous experience with VR systems, and nobody reported any previous cardiovascular problems during the past 5 years that could affect the recorded heart-related measurements from the wrist.

[2]VR Experience CalmPlace: https://mimerse.com/products/calm-place/

Fig. 2. VR application CalmPlace, showing climate sequence going from dusk to noon under the two parts of the experiment. Left: Baseline with normal breathing. Right: Intervention in slow-paced breathing guided by the blue object.

C. Outcome Measurements

1) Perceived Engagement and Relaxation Levels: A customized questionnaire used a 5-point Likert scale to assess understanding of the instructions, perceived level of engagement with the virtual environment, and perceived level of relaxation during each of the two parts of the experiment.

2) Heart Rate Variability Analysis: The proposed framework logs specific data from the experiment to be used for offline analysis: (1) raw PPG signals gathered by the smartwatch, (2) HRV signal calculated in real-time and (3) log of events from PhysioSense, (4) timestamped data in the VR application used for packet synchronization based on the instant when each part of the experiment started.

The HRV metrics calculated were: SDRR, calculated as the standard deviation σ of the difference of subsequent peak-to-peak-intervals (PPI); RMSSD, as square root of mean μ of squared differences between subsequent PPI; and coefficient of variation (CV), calculated as σ/μ of PPI.

D. Experimental Protocol

The protocol followed a within-subject study design, where every participant was introduced to the experiment and signed an individual informed consent. The smartwatch was connected to the participant's wrist, and the PhysioSense application was started by the experimenter to verify reception of heart rate data in the mobile phone. Then, the VR application CalmPlace was executed and configured in the VR headset to present the experience. The presented scenario displayed different visual and auditory cues that tried to induce a relaxation state to the user, going from dusk with northern lights to vivid noon; a blue object appeared in the middle of the session to guide the slow-paced breathing exercise (see Fig. 2). After the session, the devices were removed and every participant filled out the questionnaire, and the experiment debriefing was conducted. The experiment lasted around 30 minutes per participant.

PRELIMINARY RESULTS

1) Perceived Engagement and Relaxation Levels: The distribution of the questionnaire's answers is presented in Fig. 3. All participants expressed clear understanding of the instructions and positive level of engagement, one participant presented "little dizziness comparable to motion sickness" but completed the whole experiment. Nobody reported difficulties to follow the respiration pattern at 6 breaths per minute, which gives basic reliability of the collected heart rate data. Regarding the perceived relaxation level, participants found normal breathing more relaxing than following the pattern to guide slow-breathing.

2) Heart Rate Variability Analysis: The HRV signal calculated with the system presented values that exceeded the normal heart rate range which is 40-150BPM. The cause for long peak-to-peak time intervals is presumed to be caused by two main reasons. First, the algorithm for real-time HRV peak detection divided the signal in data chunks of 4 seconds, but some segments were not returning valid peaks, thus making difference between two consecutive peaks to be in the order of several seconds. Second, when the algorithm collected the 1024 samples in the buffer to execute the HRV calculation, the system could not read samples at 50Hz, because the working thread was busy during the data analysis, causing some PPG signal peaks to be omitted.

As a consequence, **offline post-processing** of the collected HRV signal was performed and involved the next four stages: (a) clamp the signal with thresholds of 400ms-1500ms corresponding to normal heart rates, (b) use sliding windows of 10% of the signal length with 50% overlap to detect the values that were outside 2.5 standard deviations of the window, to discard values that imply any instantaneous increase or decrease of heart rate; (c) assigning to these positions the previous valid values to generate a difference between peaks of 0ms, and (d) filter out the outliers that could have affected the calculation of dispersion metrics. The post-processing affected between 3%-8% of the data, giving a reduction in the ranges of the HRV signal and increasing resolution to detect relevant changes for comparison between the two parts of the experiment.

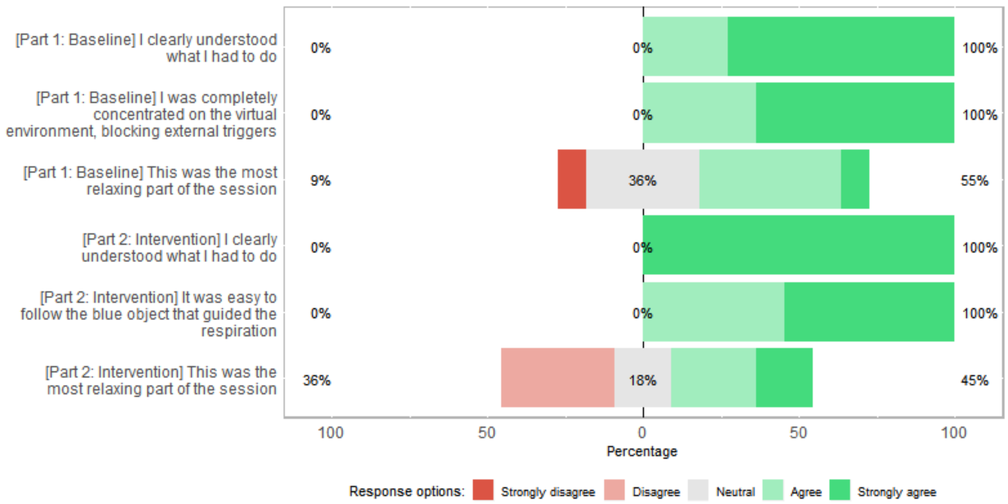

Fig. 3. Diverging stacked bar chart summarizing the results from the questionnaire administered post-experiment.

The performance analysis of the algorithm for real-time HRV calculation only considered 9 out of the 11 observations (participants). One was dismissed due to communication error between the smartwatch and the mobile phone, and the other was due to inadequate protocol by the experimenter.

The comparison of HRV between both parts of the experiment is summarized in the Fig. 4, and considers the metrics CV, RMSSD, and SDRR.

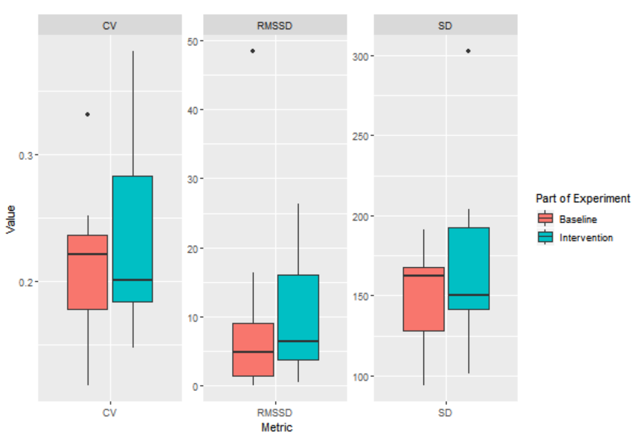

Fig. 4. Box plots showing the differences in HRV features between baseline (normal breathing) and intervention (slow-paced breathing). Slight HRV increase is perceived during slow-breathing intervention, although not statistically significant.

The critical value for the one-tailed Wilcoxon signed-ranked test is $W_{critical} = 8$, with significance level $\alpha = 5\%$ and sample size $N = 9$. The W statistics for each metric was: 15 for CV, 20 for RMSSD, and 17 for SDRR. All statistics were higher than $W_{critical}$, therefore there is not enough evidence to reject the null hypothesis assuming that HRV metrics during normal breathing are lower than or equal to ones during slow-paced breathing.

V. Discussion

In this paper we introduced PARE-VR, a physiological computing framework to aid the integration of HRV in VR applications targeting mental health applications. The major finding of this study is a proven technical feasibility of the construction of the proposed framework, which is entirely supported by wearable physiological monitors and mobile devices using the five-layer generic model of physiological computing [21] as a theoretical reference. Compared to previous studies, the main contribution of PARE-VR is the simplicity to augment mobile-based computer systems with the capability to use metrics from physiological signals in real-time; in this case, the use of HRV features from wearable smartwatch signals. These metrics can be an additional input to artificial intelligence agents that aim at understand users based on psychophysiology [38] and provide customized adaptive functionalities based on physiology.

From the technical standpoint, previous related projects on mental health either use wired sensors to collect data or computers for real-time data processing, or they do not use mobile VR to deliver the interventions. Conversely, PARE-VR leverages the use of wearable devices to collect physiological data, mobile phones to perform real-time processing, and mobile VR to deliver engaging experiences. These characteristics can potentially be the factors to conduct further research in technology-based medical therapies; specially leveraging from the enhanced the portability, scalability and affordability of the used technology. In addition, the compatibility of PARE-VR with the game engine Unity is key to facilitate the mass use of physiological signals in interactive solutions, given that Unity is widely utilized to build interactive serious games for physical and mental health interventions [39][40].

The Likert-type questionnaire was important to get hints about perceived level of engagement with the virtual environment, relaxation levels, and understanding of the experiment;

which revealed overall positive results. Particularly, the perceived relaxation was reported higher during the baseline in spontaneous breathing than during slow-breathing. A probable reason is associated with the required sustained attention to follow the breathing pattern in the second part of the experiment, since the first part did not have a specific task, it could have given a higher sense of calmness in the participants.

For HRV analysis, the post-processed data resulted in values within reasonable ranges for all the participants, demonstrating that the system gathered signals that are suitable to calculate HRV metrics. However, the offline processing pipeline described in the preliminary results needs to be built-in algorithm to enable accurate calculations in real-time. As shown in Fig. 4, HRV metrics show higher amplitude of HRV during slow-breathing than normal breathing in the sampled population, but not enough to produce statistically significant results.

Finally, we highlight the modularity and integrability of the PARE-VR framework, with a clear capability to use existing VR applications and transform them into novel physiologically responsive applications. Developers and researchers can use the PARE-VR framework to include HRV metrics in mobile VR applications without spending excessive time in the connectivity with the sensors and the integration with the game engine, thus streamlining the process.

Limitations

A new experimental protocol that shows the breathing object at two different respiration frequencies might reduce the bias induced by showing a guiding object just in one part of the experiment, it could also facilitate a more homogeneous way to measure the perceived relaxation level. Moreover, using longer exposure time to the application might allow participants develop strategies for producing desirable respiration patterns. Issues with the real-time algorithm were stressed during feasibility study and must be addressed for further studies. Additionally, the statistical analysis might be strengthened by repeating the feasibility study with a larger sample size and by calculating additional temporal and frequency-based features from the HRV signal, such as those described by Shaffer et al. [20]. The validity of the signal obtained by the smartwatch could be enhanced by comparing it with a reference point from specialized sensors that include information of HRV.

VI. Conclusion and Future Work

The current study aimed at designing and conducting a preliminary evaluation of the open-source PARE-VR framework as a tool to augment mobile computing systems with a layer of understanding of physiological signals to enhance the delivery of technology-based health interventions.

The initial feasibility study was performed using PARE-VR to support a basic mental health exercise in slow-paced breathing, thus giving a first step in the integration of wearable and mobile-VR technology to create self-guided physical and mental health therapies. These systems portable and portable solutions might support scalability and reach communities that lack these type of health services. The main contribution in comparison to earlier related work is the inclusion of HRV metrics calculated in real-time by only using a smartwatch and a mobile phone. These metrics can be meaningful in systems aiming clinical application via using artificial intelligent agents that build user profiles to adapt the functionality of a computing system to the specific user needs. Additionally, machine learning algorithms can be used to drive real-time adaptations based on detected cardiovascular states related with stress or workload.

Although the HRV analysis did not demonstrate any statistically significant differences between both breathing paces, it serves as a proof-of-concept for PARE-VR, as it is reasonably a feasible architecture for the mental health monitoring. Moreover, it provides technical and methodological considerations and insights for further studies in the area. A follow-up study will replicate the use-case of slow-breathing exercises solving the limitations in terms of real-time signal post-processing to enhance HRV accuracy, increasing the number of users and extracting more HRV features to improve and diversify the statistical analysis. In addition, the logic module might include machine learning algorithms to build models that automatically classify the two breathing states from the cardiac data captured with the smartwatch.

The open-source nature of the project facilitates the design of more applications in real-life settings and further development including compatibility to more sensors, physiological features, adaptation strategies and interactive virtual environments. More technical and medical research is encouraged in partnerships between research, healthcare and commercial actors. From the technical side, further projects could evaluate the performance of each stage of the deployed architecture in terms of robustness, stability, and computational speed of the algorithm. Additionally, they can assess peak detection accuracy compared to other heart rate monitors that include HRV, analyze different visual cues in the VR environment that could elicit higher perceived relaxation states in the users, and use the logic module to provide automatic adaptations in the environment. From the medical standpoint, future work can target the validation of the effects of automatic physiology-based adaptations under clinical conditions, and the assessment of ethical aspects regarding the use of self-guided therapies to provide evidence-based solutions. Finally, although other frameworks and software tools that integrate VR and physiological computing technologies have been proposed before, we believe PARE-VR provides a very specific, open-source, low-cost and integrative solution to combine HRV and mobile VR, aiming to be scalable in applications for mental healthcare.

PARE-VR repository: https://github.com/luiseduve/pare-vr/

Contributions

The framework and the study were designed by the authors LQ, JEM and PP; LQ developed the software and collected the information from volunteers.

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