Implementation of Mobile-based Real-time Heart Rate Variability Detection for Personalized Healthcare

Luis Quintero, Panagiotis Papapetrou, Uno Fors
Department of Computer and Systems Sciences
Stockholm University
Stockholm, Sweden
{*luis-eduardo, panagiotis, uno*}*@dsv.su.se*

John E. Muñoz
Systems Design and Engineering Department
University of Waterloo
Waterloo, Canada
john.munoz.hci@gmail.com

***Abstract*—The ubiquity of wearable devices together with areas like internet of things, big data and machine learning have promoted the development of solutions for personalized healthcare that use digital sensors. However, there is a lack of an implemented framework that is technically feasible, easily scalable and that provides meaningful variables to be used in applications for translational medicine. This paper describes the implementation and early evaluation of a physiological sensing tool that collects and processes photoplethysmography data from a wearable smartwatch to calculate heart rate variability in real-time. A technical open-source framework is outlined, involving mobile devices for collection of heart rate data, feature extraction and execution of data mining or machine learning algorithms that ultimately deliver mobile health interventions tailored to the users. Eleven volunteers participated in the empirical evaluation that was carried out using an existing mobile virtual reality application for mental health and under controlled slow-paced breathing exercises. The results validated the feasibility of implementation of the proposed framework in the stages of signal acquisition and real-time calculation of heart rate variability (HRV). The analysis of data regarding packet loss, peak detection and overall system performance provided considerations to enhance the real-time calculation of HRV features. Further studies are planned to validate all the stages of the proposed framework.**

***Keywords*-Heart rate variability, HRV, personalized health, framework, mobile, real-time, smartwatch.**

I. Introduction

The current speed of breakthroughs in digital technology comprises the so called Fourth Industrial Revolution that changes how people, government and institutions interact [1]. The healthcare field is not oblivious to this disruption, particularly due to the constant release of bands, garments, smartwatches and other types of miniaturized, portable and affordable sensors called wearables. The enhanced computing power of these devices allow them to collect and process physiological data that can be used to offer personalized and real-time feedback to the users [2]. The capability of wearables to monitor signals in a reliable and secure way has promoted their increasing popularity in medical research and medical industry; being used as physiological monitors that help both diagnosis and delivering of neurological, cardiovascular, pulmonary and mental treatments [3] at the same time that represent an affordable option for both institutions and patients [4].

The internet-of-things and the ubiquity of digital health sensors come with massive amounts of clinical data that is collected, stored and analyzed. The large datasets allow for the exploration of more medical hypothesis which would not have been possible using the traditional processes of observation and annotation of variables; on the other hand, data mining (DM) and machine learning (ML) algorithms transfer the burden of validating each hypothesis from the researchers to the computational systems, letting the researchers focus on the interpretation and applicability of results [5]. In the field of translational medicine (understood as the development of practical treatments, drugs, devices and policies supported by evidence-based knowledge), the use of DM and ML has facilitated data analytics to support more personalized healthcare and effective population health management by incorporating information from electronic health records and omic sciences [6].

A big share of current medical practice relies on scientific evidence and clinical guidelines that are manually reviewed to provide recommendations for large groups of patients, rather than personalized recommendations tailored to individual patients. Nevertheless, the widespread availability of mobile devices and mobile health applications offers an unprecedented possibility for customization of care based on individual health requirements, and has the potential to reduce costs of operations, improve the quality of care and assist decision making of professionals. Some potential roles of wearable devices and ML in personalized healthcare is diagnostic care in remote areas without direct access to qualified doctors, assistive care with technology-based interventions, and monitoring and alarming systems [7].

A relevant starting point to conduct research for providing personalized healthcare with wearable devices and ML methodologies is the use cardiovascular data. The easiness of access to data through wrist bands and smartwatches supports to widespread portable health interventions that are delivered outside clinical settings. The monitoring of simple variables like raw heart rate is relevant for daily-life activities like physical activity, but the clinical solutions require more specialized metrics like heart rate variability (HRV), which is the fluctuation in time intervals between

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subsequent heart beats and that can be calculated from the raw photoplethysmography (PPG) time series captured with a smartwatch. The heart is not a metronome that pumps at the same frequency, but it follows a set of complex and non-linear behaviors that are altered by different factors of the autonomous nervous system; and the features extracted from this signal are intensively used in research to profile a user in applications for mental and physical health [8].

According to market statistics[1], the sale of smartwatches is growing, being considered the largest product segment of consumer wearable devices. This gives a hint about the rapid adoption of these technologies in society, as well as its relevance as a platform that can set the foundations to advance healthcare through the delivery of scalable and customized services based on real-time acquisition of physiological data. However, the main technical limitation to the creation of solutions based on HRV is that commercial wearables that measure HRV do not provide access to the data, therefore it cannot be used outside their development environments, such as for medical or research applications.

The use of wearable to collect high quality physiological data should be fruitful for predictive analysis and follow-up of patients outside clinics. However, there is still the need to create frameworks that integrate data science paradigms and wearable systems within the spectrum of translational research, with solutions that are feasible, scientifically solid and that promote patient self-care [6]. As a solution to the problem, this paper outlines an open-source framework to deliver HRV-based personalized interventions. To increase accessibility for final users, it envisions easy scalability through compatibility with ML models and with interactive immersive applications for health.

The main **contributions** of this paper include: (1) the description of a mobile-based implementation of an algorithm that **calculates heart rate variability (HRV) in real-time** from photoplethysmography (PPG) signals collected with wearable smartwatches; (2) the presentation of an **scalable open-source framework** that encourages the use of HRV metrics with machine learning methods to provide **adaptation of mobile health applications** that **deliver personalized healthcare**.

II. Related work

Some investigations have proposed solutions to deliver personalized interventions to empower people in their self-management and enhance traditional procedures. For instance, one project [9] aims at offering clinical decision support and is connected to electronic health records; which grants access to a lot of data but does not enjoy the advantages of mobile-based systems. Other proposed frameworks include cloud services like [10] using mobile phones to connect and offer basic rule-based recommendations; or the projects UbeHealth[11] and MiningMinds[12] which are very complex frameworks that can analyze data using deep neural networks, use cellular networks for data transmission and other elaborated layers that enhance security and redundancy; but this complexity may also hinder the technical implementation in scale using physiological sensors.

As discussed in [13], the manufacturers of digital health sensors provide services where users can analyze their healthcare results from a wide spectrum of variables, and adjust lifestyle by implementing simple actions like physical activity, nutritional changes or other interventions. However, a drawback of these commercial platforms is the restriction in terms of accessibility to their data to be used in clinical or research settings.

Some other frameworks are rather conceptual models than easily implementable solutions. The JDC framework [14] is a valuable approach to create an agnostic model that can solve interoperability issues providing compatibility with several sensors, but the devices used to gather physiological measures do not provide the same mobility than wearable devices. The project HealthGuide [15] aims at deliver personalized guidance during patient visits but does not involve signal monitoring or adaptations. Similarly, the study from Jagadeeswari et al. [16] contains many conceptual architectures that describe how cloud computing, internet of things, big data and mobile systems can be incorporated in healthcare to improve quality; nonetheless, few of them are implemented using physical devices and none of them considers the use of cardiac metrics such as we do.

Real-time heart rate variability calculation has been implemented since the 1980s when Pan et al. [17] proposed the detection of QRS complexes of ECG signals. Since then, other methods have appeared to calculate HRV from PPG data captured through the camera of mobile phone [18] and via advanced portable ECG processors [19].

Nowadays, HRV features captured through wearables are commonly used in research projects for health. For instance, the data collected from a commercial smartwatch was used to detect mental fatigue in users and offer assistance while interacting with a robot [20], the classification was performed using a simple rule-based classifier using HRV values and processing the data in a computer. Another study [21] collected several physiological variables (galvanic skin response, peak-to-peak interval, body temperature) to detect mental stress using a 1-KNN classifier during daily life activities. The work in [22], used a smartwatch to provide an alertness score that trained an SVM model with 43 features extracted from HRV data.

To the best of our knowledge, the proposed framework is the first open-source implementation that calculates HRV in real-time from PPG captured through commercial smartwatches, and envisions its use in scale to offer personalized healthcare by implementing adaptations based on HRV metrics and processed through DM and ML algorithms.

[1]Online smartwatch unit sales worldwide from 2014 to 2018 in www.statista.com

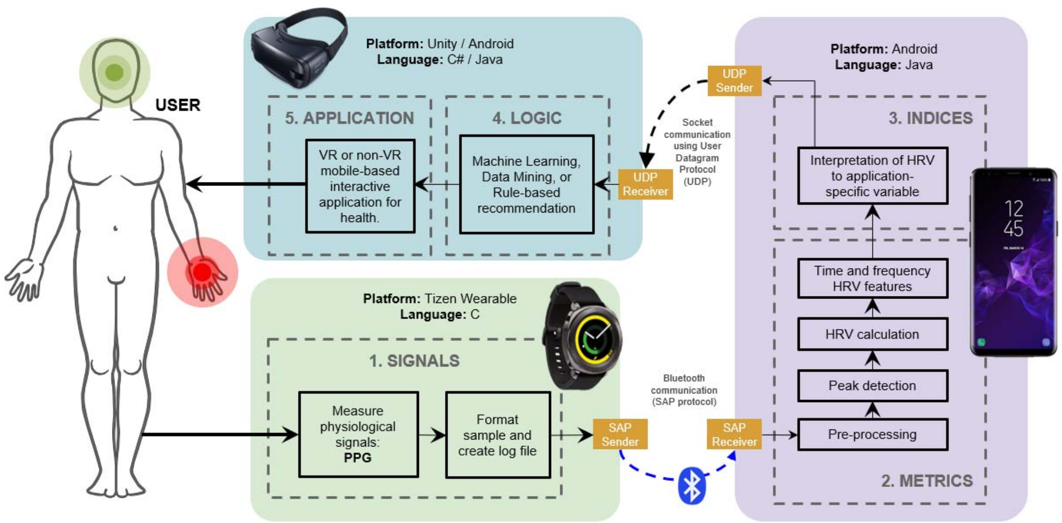

Figure 1. Mobile-based Framework for Physiological Computing Systems. Implements the five-layers of the generic model [23] using three applications to provide real-time adaptation in mobile-VR applications based on features extracted from heart rate variability.

III. Proposed Framework

The proposed architecture, shown in Fig. 1, is an open-source technical implementation of the conceptual model proposed by Kosunen [23] for computing systems that incorporate physiological signals as inputs. Namely, the model is divided into five layers; (1) signals: deals with raw physiological data, (2) metrics: quantifies features from the signals, (3) indices: interprets the numerical features as variables that are relevant for the specific application, (4) logic: defines how the system functionality changes according to specific input values, and (5) application: implements the visuals and mechanics of the computing application for health. The five-layer model is implemented using three independent software applications that run on commercial mobile devices (i.e., a smartphone and a smartwatch) and communicate via bluetooth and UDP protocols. The modules are responsible for acquiring raw heart rate data, calculating HRV in real-time, running machine learning and data mining algorithms and, ultimately, executing adaptations that offer personalized behavior to mobile applications for health.

A. Acquisition of Heart Rate Time Series

The first module belongs to the "signals" layer of the conceptual model and it is responsible for acquiring the raw heart rate data from the user. A custom application was developed to collect raw photoplethysmography (PPG) signals in real-time which allows to perform manual calculation of HRV, this is necessary because manufacturers of wearable wrist sensors that incorporate HRV analysis use proprietary software and do not allow to use HRV data in third-party solutions. The application is developed in C language and compatible with Samsung smartwatches running Tizen Wearable OS.

The time series representing the PPG signal must be reliable to guarantee an adequate calculation of HRV. A substantial element of signal reliability is the sampling frequency (f_s) used by the sensor, which needs to be chosen in such a way that maximizes battery life of the sensor without sacrificing data quality to guarantee appropriate detection of systolic peaks and subsequent estimation of peak-to-peak intervals.

The smartwatch connects via bluetooth with the mobile phone which processes the PPG signal. This connection is performed using the Samsung Accessory Protocol (SAP) that allows seamless streaming of data in real-time between both devices. Additionally, the application provides persistent storage of the PPG time series representation by formatting, timestamping, and saving a log file in the internal memory of the wearable sensor to be used in offline analysis.

B. Calculation of Heart Rate Variability

The second application corresponds to the "metrics" and "indices" layers of the conceptual model. The module is an Android application developed in Java that runs on the background of the operating system and is responsible for processing the PPG signal and calculating HRV. It is inspired by the open-source project developed by Muñoz et al.[25] but this version includes extended compatibility with smartwatches running Tizen OS, and it is enhanced with real-time extraction of HRV features that offer to computing systems more meaningful information to perform adaptations more tailored to the user.

The application receives data from the smartwatch through the bluetooth SAP receiver, then the data is sent through different stages that process the original time series to calculate HRV features; finally, the original HRV features are transmitted using socket communication through the UDP port 1111 to reach the mobile digital health application with

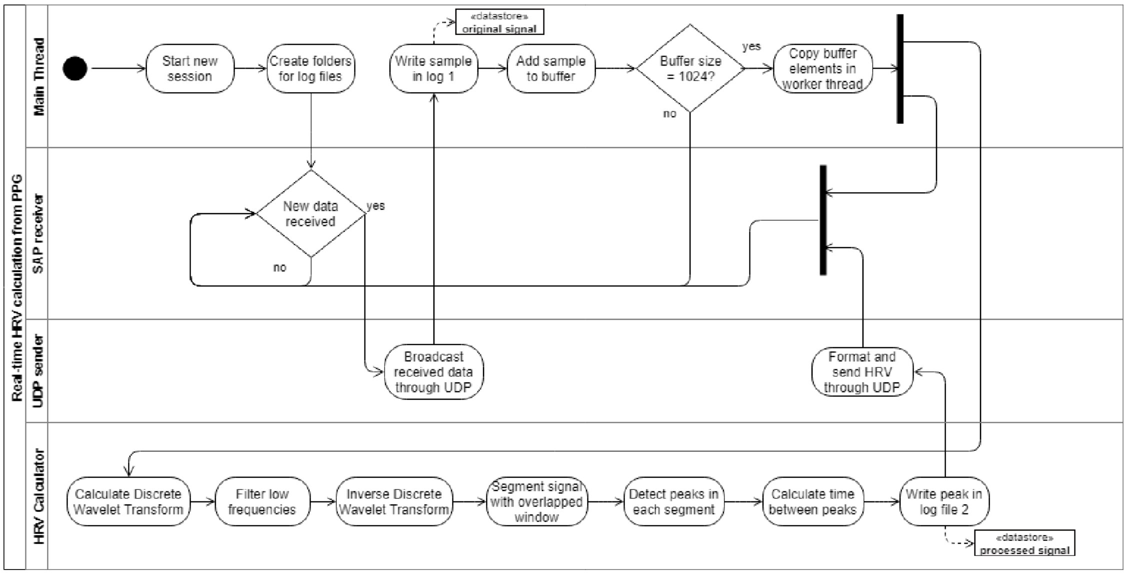

Figure 2. Activity diagram of the implemented algorithm to calculate HRV in real-time from PPG data. Based on the pseudo-algorithm described in [24].

which the end-user interacts.

The signal-processing workflow transforming the original PPG time series signal from the smartwatch into the HRV signal is largely based on the pseudo-algorithm proposed by Bhowmik et al.[24]. Nonetheless, since the original version was designed to be employed in offline processing, the mobile-based real-time implementation of the algorithm includes some modifications (see Fig. 2) described next.

Session preparation. Every set of recordings is organized by sessions, meaning that, although the smartwatch is continuously sending data to the mobile phone, it is the user who decides when to start the logging process, while the HRV detection is performed only when a session is active. The user interface of the application allows to define a customized name and start the session manually, a folder is created in the local storage to save four files: (a) original signal received from the smartwatch, (b) denoised signal, (c) position of the detected peaks with its corresponding peak-to-peak interval, and (d) debug file that logs all the warnings and stages from the process of HRV calculation.

Signal pre-processing/denoising. When a new packet is received from the sensor, it is recorded in the log files and broadcasted through UDP port 1111, as a result, all the applications running in the mobile device can also have access to the original time series of the PPG data to be plotted or analyzed independently.

In the mobile device, the PPG signal is processed to reduce any noise artifacts that were captured with the sensor and facilitate the peak detection. As shown in the figure 2, each signal packet is temporarily stored in a buffer of size L that triggers the denoising pipeline when is full. The procedure to denoise the signal starts with a Discrete Wavelet Transform (DWT) [26], which used a Daubechies 4 wavelet to perform 5 signal decompositions. Then, a filter is applied by setting to zero the coefficients of approximation L5 to remove the signal components in the band frequency between 0Hz and 0.78Hz. The inverse-DWT process reconstructs the signal without the baseline component, facilitating the identification of peaks.

Peak detection. The denoised signal may present some artifacts in the extremes, maximized by the DWT transformation. Hence, a rectangular overlapping window of size M and overlap P slides the reconstructed signal, creating segments that are processed independently and reducing the effects of the irregularities in the extremes. An $argmax$ function is applied over a subwindow of size N that moves each sample used to detect peaks along the time series.

Given that the PPG signal is considered quasi-periodical, the next stage involves the detection of a fundamental period T_f in the segment by finding two consequent peaks in the auto-correlation function of the segment; T_f in a segment is considered valid if the differences in the peaks lie within a range $T_f \pm \epsilon$ from the previous segment. Ultimately, the detected peaks in the denoised segment are considered valid only if they are within a maximum deviation of $T_f \pm \theta$.

Calculation of HRV. To calculate HRV, it is sufficient to use the peaks that were detected from the raw heart rate signal and get the time interval between subsequent peaks, also known as peak-to-peak interval. Fig. 3 depicts visually the process to calculate HRV from a set of peaks detected on a PPG signal. This process is performed by the application in the background and the result is also transmitted via UDP to be processed by applications running in the mobile phone.

Feature Extraction. HRV is used as an umbrella term to encompass other metrics that describe how the rhythm of the heart varies. The metrics can be calculated in time-domain or

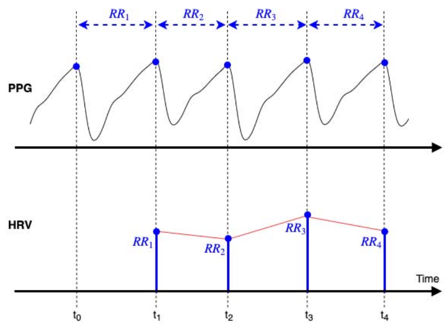

Figure 3. Visual representation of how HRV is calculated PPG.

frequency-domain, some examples of time-domain features are described as follows, and a complete list of features is provided in [8]:

- *SDRR:* Standard deviation of all peak-to-peak intervals. Calculated in ms. SDRR measures how these intervals vary over time.
- *RMSSD:* Root mean square of successive differences between normal heart beats. RMSSD is obtained by calculating each successive time difference between heart beats in ms. Then each value is squared and the result is averaged before the square root of the total is obtained. Reflects the beat-to-beat variance in HR.

C. Personalized System Adaptation

The third software comprises the "logic" layer of the conceptual model. The personalized system adaptation is an independent application running on the same mobile device as the previous application. The engine for personalized system adaptation is provided with a UDP receiver that sets up the connection to gather HRV data used as input to the algorithms in the logic layer.

The adaptation logic is an independent module because it allows to detach the stages of feature extraction and customized adaptations. In this way, two different use-cases can use the same source of physiological signals, calculate the same HRV features; but still differ in the implemented adaptations, which machine learning models are developed, or even use simple rule-based systems for the specific health intervention envisioned by the researchers.

The machine learning models that can involve decision trees, bayesian classifiers, regressions, SVM, or convolutional neural networks; using dozens of features that are extracted just from the HRV and the heart rate signals. Nevertheless, a main consideration is that the creation and training of these models require a large amount of data, hence the necessity to evaluate adequately the stages of data acquisition and HRV calculation in order to create a knowledge base that is reliable to be used in automatic adaptations for personalized healthcare.

D. Mobile-based Application for Health

The last software also includes the module "application" from the conceptual model. It displays the graphical user interface or interactive environment that is used to deliver the digital health interventions that could leverage from HRV analysis, such as biofeedback for mental health and sports [27][28]. Such scenarios can be developed as native Java/Kotlin Android applications or using development platforms like Unity[2] to build interactive environments for traditional mobile screens or virtual reality headsets.

IV. Empirical Evaluation

The feasibility of the framework to calculate HRV features in real-time using the mobile-based approach was assessed considering a specific use-case scenario. It was derived from the the reported effects that slow-paced breathing exerts over the amplitude of the HRV, controlled breathing is a practice where the user has direct regulation of respiration parameters like frequency, deepness or inspiration/expiration ratio. Some studies [29][30][31] consider that breathing at a rate of six breaths per minute has respiratory, circulatory, and mental benefits; and the most frequent finding is that it maximizes the amplitude of the HRV signal through a coupling between respiratory rate, heart rate and blood pressure [27].

As a result, the empirical evaluation involved a mobile virtual reality application for relaxation and stress management, which was adapted with the implementation of the first stages of the framework to collect HRV in real-time. The main objective is to assess the technical performance of the mobile-based architecture in detecting HRV features in real-time, verify the reliability of the calculated metrics, and profile a further usage of the whole framework as a system that can design personalized adaptations tailored to each user based on HRV information and supported on machine learning and data mining methods.

A. Participants

The study used a non-probability convenience sampling for recruiting 11 healthy volunteers who studied in Stockholm, aged between 23-32 years (i.e., 27 ± 3.24), six female. One participant had no experience using virtual reality applications and nobody reported cardiovascular complications that could affect the heart-related measurements.

B. Hardware and Framework Setup

The hardware devices used to collect heart rate data under the proposed architecture are: a smartwatch Samsung Gear Sport running the application for signal acquisition, a mobile phone Samsung Galaxy S9 for signal processing and a VR application executed through the headset Samsung Gear VR.

Regarding the configuration of the proposed framework, the sampling frequency f_s in the acquisition system is

[2] Unity3D is a cross-platform game engine.

defined relying on relevant literature [32], which asserts that the minimum sampling frequency to extract reliable HRV features from PPG captured through smartwatches is 20Hz. Since initial tests did not present significant battery drains, the chosen sampling frequency is set to $f_s = 50Hz$ to increase time resolution of the peak detector. The size of the buffer used for signal pre-processing is defined in $L = 1024$ samples because the DWT is executed faster in arrays with length equal to a power of two.

Similarly, for peak detection, the width of the rectangular window $M = 224$ samples with overlap $P = 48$ samples. These values allow the signal array of 1024 samples to be analyzed in four repetitions of signal processing, but only the middle 800 samples were used for peak detection and HRV calculation to avoid errors in the extreme of the signal, the last 224 samples were stored to be analyzed in the next activation of the algorithm. The thresholds for peak detection and validation of T_f were set in $\epsilon = 0.4s$ and $\theta = 0.4s$, and the width of the subwindow that uses $argmax$ to find peaks is set to $N = 11$.

C. Outcome Measurements

The empirical evaluation allows the technical evaluation of the framework in the stages of collection of physiological data and real-time calculation of HRV. It utilizes the stored log files from each application to compare variables of interest related to the following items:

- *Packet Loss:* Analysis of number of packets successfully sent along the architecture's pipeline, the calculation is conducted by comparing the number of signal packets that stored by each of the three applications.
- *Peak Detection:* Brief evaluation to check whether the algorithm is detecting peaks from the raw PPG signal collected from the smartwatch according to the provided parameters.
- *HRV Calculation:* Assessment of the reliability of the peak-to-peak time intervals estimated from the signal.
- *System Overall Performance:* Qualitative description of technical performance presented during the experiment and that are not related to previous categories.

D. Experimental Setup

The protocol follows a within-subject study design, where every participant signs an informed consent, the wearable smartwatch is connected to their wrist and the applications are started in sequence by the experimenter. The virtual reality scenario consisted on a nature relaxation environment that promotes two different breathing paces along the experience while the heart rate data is being collected and the HRV detection is performed in the background application. At the end of the session, the devices were disconnected and the experiment debriefing was conducted. The experiment lasted around 30 minutes per participant.

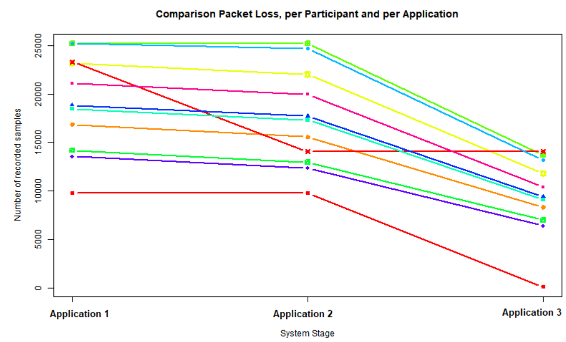

Figure 4. Parallel plot with number of received messages along physiological system stages per participant.

V. Preliminary Results

A. Packet Loss

Given the different transmitters and receivers used in the architecture, the analysis of packet loss provided insights about the performance of the system in handling real-time information at the specified sampling frequencies, and an overview of the computational workload of the algorithms and visualization processes. The three sources of data in the system were synchronized to take out the time window that corresponded only to the experimental session, the total packet loss was compared per participant and per application, as shown in Fig. 4.

Analyzing the data from the 11 participants, the packet loss in the bluetooth link between the smartwatch application and the mobile phone was $8.1\% \pm 10.9\%$; between the background application and the virtual reality environment was $47.3\% \pm 22.2\%$, and the total packet loss in the physiological computing system from end-to-end was $53.3\% \pm 15.6\%$. However, the two observations, drawn in red lines, had a differential behavior. When they were considered as outliers, performing the final calculation with the remaining 9 observations, the standard deviation in packet loss was reduced to $5.5\% \pm 2.9\%$ in the bluetooth link, $46.9 \pm 0.8\%$ in the UDP link, and $49.7\% \pm 2\%$ from end-to-end.

The two observations drawn with red color in Fig. 4 presented special conditions during the experiment, thus they were considered outliers. First, the uppermost red line corresponds to the participant in which the session was not properly set, causing the physiological data to be stored while the real-time HRV calculation not being active. This observation was the only one without packet loss in the UDP link, providing insights about the impact that the algorithm had in the data throughput. On the other hand, the lowermost red line corresponds to a session in which the smartwatch stopped recording data early in the experiment, resulting in a small number of recorded samples and incomplete HRV data to compare algorithm performance.

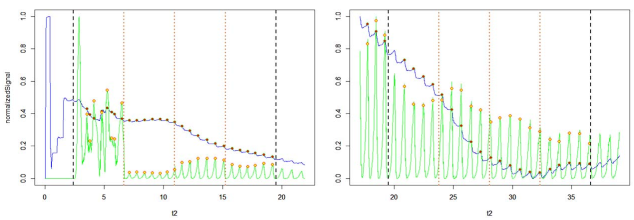

Figure 5. Result of peak detector in two subsequent segments with overlapping windows.

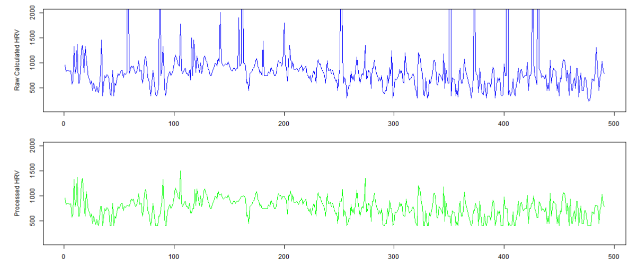

Figure 6. Example of one HRV signal before (top) and after (bottom) processing outlier values

B. Peak detection

The initial validation of the peak detection was performed on a test signal captured from the smartwatch before deployed on the final system. The Fig. 5 displays in yellow the peaks that were detected in real-time from one of the users.

C. HRV Calculation

The HRV curve calculated by the system presented values outside the normal range of 40-150BPM (time between peaks between 1500-400ms), therefore offline post-processing was necessary. Two reasons are assumed to cause long peak-to-peak time intervals. First, the algorithm for real-time HRV peak detection divided the signal in data chunks of 4 seconds, but some segments did not return valid fundamental periods T_f, hence omitting the peak detection process and causing peak intervals in the order of several seconds. Secondly, when the algorithm collected the 1024 samples in the buffer to execute the HRV calculation, the system could not keep reading samples at 50Hz, because the working thread was busy during the data analysis, causing some peaks in the PPG to be omitted and affecting final peak-to-peak intervals.

The offline post-processing of the HRV signal involved three stages: (1) clamping the window in the range 400ms-1500ms, (2) using 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, and (3) assigning to these positions the previous valid values to generate a difference between peaks of 0ms. The post-processing stage affected between 3%-8% of the collected data, and produced positive effects in the overall metrics of the signal by reducing the variation of the HRV signal and increasing signal resolution to detect relevant changes. Fig. 6 depicts an example of the HRV signal calculated by the framework (top) and after applying the offline post-processing (bottom).

As an example of the real-time nature of the implemented algorithm, Fig. 5 also depicts the detection of HRV in two subsequent segments. The blue line represents the original signal, the green line is the denoised signal, and the two vertical dashed black lines delimit the area where peak detection and HRV analysis are performed, omitting the edges of the signals to avoid the issues mentioned in the section III. In the left image, since it was the beginning of the session, the peak calculation is not executed in the first 112 samples of the session and this chunk is never processed. In the right image, the subsequent segment contains the overlap of 224 samples with some peaks detected in the previous execution. This same process was executed every time the data buffer was full; specifically every 16 seconds, the time needed to gather the remaining 800 samples at 50Hz.

D. System Overall Performance

The main technical issue of the whole physiological system was the stability of the Android application running in the background. It was stopped in the middle of the experiment in 9 out of the 11 sessions, affecting the data collection and stopping the calculation of HRV. This was due to the fact that the operating system detected that the battery was intensively used by a background application and forced the end of this process while the user still experimented the virtual reality environment. Fig. 7 depicts the time that the software was active for each experimental session; the first dashed line indicates the change in the breathing pace, and the second line shows the expected end of the experiment, only two participants had the system in the background running during the whole experiment.

The open-source repository with the implementation of the proposed framework is available on: https://github.com/luiseduve/pare-vr/

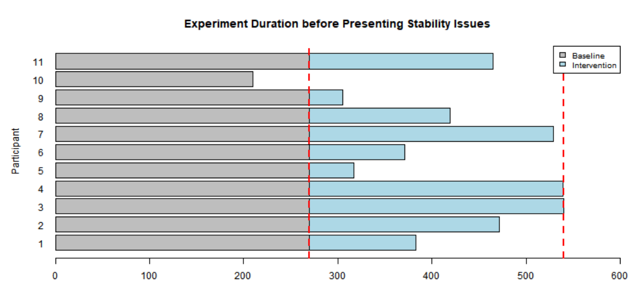

Figure 7. Duration of the experiment, per participant, before the background application was closed by the operating system.

VI. Discussion

Several technical generalities were identified from our experimental evaluation. First, the small packet loss presented in the bluetooth link indicates a proper functioning of the implemented wireless communication SAP protocol. However, the UDP link presented significant losses and the data gathered from the abnormal experiments served to detect the bottleneck generated in the the background application; it is hypothesized that the packet loss in the UDP link is caused by the execution of the algorithm for HRV calculation, which reduced the available computing resources needed for data reception. Secondly, the function and parameters used to detect peaks in the denoised signal were appropriate according to the analysis of the example signals. Thirdly, HRV was possible with the proposed algorithm but post-processing stages were needed to increase reliability and get values within reasonable ranges, it means that the real-time detector needs to incorporate the peak interpolation between segments to avoid the issue, such as described in [24], and amplitude clamping to avoid having undesired HRV values. Finally, the fact that the mobile operating system was shutting down the background application, implies that further validations are requirede to reduce the computational workload required by the HRV calculation; some evaluations varying the sampling frequency from the smartwatch, buffer size that triggers analysis and thread management might end up in an improved performance.

The major finding is related with the proven technical feasibility of construction of the proposed system based on available wearable health monitors and mobile devices. The validated stages of the proposed framework pave the way to validate a computing system implementing the five-layer framework and aiming at facilitating future technology-based interventions in research and medical settings.

The contribution of the paper in relation to the previous studies in the field is mainly the use of real-time metrics from physiological signals in computational systems, specifically the capability to use HRV features from smartwatch signals. These features extend the spectrum of metrics that can be used by a system to understand the users and provide intelligent adaptation based on machine learning and data science methodologies. Similar research projects presented either conceptual cloud-based frameworks without technical implementation, or used wired sensors to process the data in real-time, or cumbersome systems to deliver the interventions. Conversely, the presented architecture leverages from the use of wearable devices to collect physiological data, mobile phones to perform real-time processing, and use of mobile virtual reality or mobile screens for health interventions; thus enhancing the portability and scalability of this type of setup for projects aiming at conducting further research with HRV over personalized healthcare interventions, and allowing the creation of a public knowledge-base of data captured from wearables and suitable to be used for future decision support systems [9].

The interoperability for data transmission between peer technologies is still a challenge. The initial system uses specific sensors and operating system, and additional programming efforts are needed when trying to scale up the framework to be able to communicate every new device intended to be incorporated as a source of physiological signals. A standard that defines the transmission of physiological data in real-time over bluetooth networks could solve this hindrance.

Concerning ethical and legal issues, the solutions promoting the use of technology to bridge existing gaps in healthcare face different social challenges, e.g., patient confidentiality, accessibility and regulations [33], and technical challenges, such as data security, interoperability, data protection, and big data management [15]. Our artifact is not exempt from these issues, as the collection of physiological data using digital health sensors is sensitive if transferred to other devices and accessed by external people, and granting access to technology-based services might reduce human contact between medical practitioners and patients, eventually leading to patient isolation and risks for psychological complications caused by technology flaws or misuse.

VII. Conclusions and Future Work

The paper described a framework for collecting the PPG signal from a smartwatch and calculating HRV in real-time using mobile systems. It was shown that heart rate metrics can then be used to feed ML algorithms that calculate adaptations to offer personalized interactions to the users in applications for mental or physical health. The empirical evaluation tested the technical feasibility of the construction of the framework, based on principles from physiological computing systems and previous conceptual algorithms for PPG signal processing. The evaluation of the performance of the algorithm under the proposed framework provided valuable insights, showing that the system might be considered as a technical example in the use of interactive and cutting-edge technologies for personalized health interventions.

Future work includes conducting research solving the technical issues of the HRV calculation and evaluating the complete framework by including the temporal and frequency features from HRV (see, e.g., Shaffer et al. [8]). In addition, these features could be used to deploy ML algorithms to classify actions under the same slow-paced breathing scenario that was proposed in this study.

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