Real-Time Pervasive Monitoring System for Ambulatory Patients

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Abstract— **Personalization is becoming an evermore present concept in healthcare. The increasing amount of information it is possible to collect from a patient allows for the development of better and more targeted clinical and therapeutic approaches. With this in mind, a novel data acquisition and processing system is proposed, allowing to monitor patients inside and outside of hospital environment for long periods of time. It is completely generic concerning the sensors and variables it collects, and makes it possible for medical teams to monitor patients remotely and in real-time. The system was developed in collaboration with medical experts of Hospital de Santa Marta - CHLN, Lisbon and there was tested on patients with cardiac pathologies using a comercial product and a BITalino based device to monitor various physiological parameters.**

Keywords: Personalized Medicine, Pervasive Monitoring, Wearable sensors, Smart devices, Bio-signals

I. Introduction

In recent years, pervasive monitoring and personalized medicine, are two of the most common words when describing the future health-care, with agents being evermore eager to have better and more efficient treatments and approaches, that are tailor made to best fit each situation. At the same time, the continuous collection of information about one's activities, symptoms and physiological parameters, is becoming common, as sensors are being included into our daily lives. This easy access to information about a patient's status, activities and even preferences, may constitute a very useful tool when diagnosing, treating and tracking the evolution of one's condition.

This work describes a novel system, designed to pervasively monitor patients' physiological parameters for long periods of time, in and outside of the hospital. We build on previous work reported in [1], to which new features and functionalities were added, and experimentally validated. The system collects medically relevant data and displays it in real time through a web interface. This allows medical teams to permanently monitor patients and remotely access real-time and past values of the desired variables, creating the tools to detect patterns associated with certain diseases and monitor their progression or even check medication effectiveness. The system is designed to require as least maintenance as possible and, apart from charging the device's batteries, it can operate for up to two months without intervention.

The system is prepared to deal with any sensor that provides Bluetooth (BT) connectivity with minimal implementation cost. This is accomplished using a smartphone as a mobile hub for data collection, centralizing the information from the patient's designated sensors. The smartphone stores the information incoming from the sensors and, if necessary, processes it to produce more informative measures. Information is then relayed to a central server where it is permanently stored and displayed when required through a web interface. Physicians can specify which sensors should be active with each patient and which are the relevant variables to be measured and displayed. Besides data visualization, it is also possible to configure alarms and receive a notification when a certain event occurs e.g. heart rate (HR) is below 50bpm for more than 5 minutes.

The main aspects differentiating this system from others proposed are its versatility and its "final-product" approach. As it allows interaction with many different types of sensors, the system allows for a very personalized approach where physicians can define exactly which are the relevant parameters to be collected for each patient. Another aspect contributing to the novelty of the system, is the fact that it is ready for real life application context as it includes a fully functional and convenient interface for patients and medical teams to use, coupled with robust commercial devices, allowing the system to be used immediately and ensuring scalability.

In [2] some of the general requirements of this type of systems and the main challenges still presented when developing such a system are mentioned. The currently proposed system covers most of the mentioned requirements, such as data reliability and "comprehensive health monitoring", and solves some of the main challenges pointed including scalability, versatility and the delivery of processed and useful information to the medical teams in an easy to use interface and format. There are, in the literature, some examples of systems that implement pervasive monitoring, for example the ones proposed by [3] and [4]. Most of these systems use wireless technology to perform data transmissions from a custom hardware device to a central storage. However, very few of these systems tackle practical implementation problems like scalability, integration of new sensors or even interfaces designed specifically for medical teams. Other studies, like [3], propose systems that are quite comparable to the presented here with the main points of distinction being the medical personnel oriented interface that makes a significant difference when trying to integrate the system in a context as demanding as a hospital environment.

System tests took place with patients suffering from cardiac diseases at Hospital de Santa Marta - CHLC (HSM), where the main variables collected were HR and Metabolic Equivalent of Tasks (METs) [5]. These variables were indicated by the hospital's cardiology team as being commonly used in their practice to diagnose and track patients' conditions [6], [7]. Variables to be collected determined the type of sensors needed.

II. System Description

This system is based on two components: a smartphone, that is responsible for interacting with the remote sensors, connected via BT, and relaying information to a central server; and the server, that stores data and manages the interaction between the user interface, the database, and the smartphone. The system is completely versatile regarding what remote sensors are connected to the smartphone, as long as they are capable of sending their data as a stream of numerical values through BT. Figure 1 illustrates the connections between the various system components.

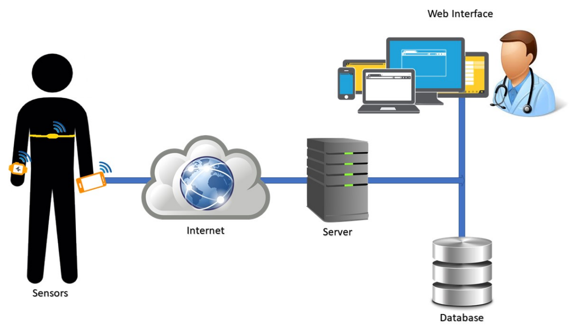


Fig. 1: System's architecture and connectivity of devices. BT connects the smartphone and remote sensors. The smartphone connects to the server through a mobile web connection.

Data acquisition starts with the medical personnel configuring, through the web server, acquisition parameters. Parameters that can be configured are:

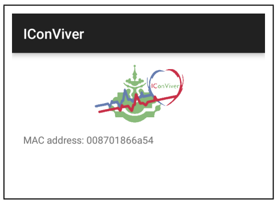
- The types of device currently available in the system (smartphone, smartwaches, etc...)
- What devices are to be given to each patient;
- What variables are to be collected from each device (e.g. electrocardiogram (ECG)), and with what frequency they should be sent to the central server;
- The variables that are expected to be received on the server (that may not be the ones collected, some processing can occur e.g. HR extracted from ECG) and how they should be visualized (color, range, etc...)
- Several alarms can be set defining what variable should be in what range for how long to trigger the alarm e.g. HR is below 50bpm for more than 5 minutes;

Each remote device is identified by a universally unique identifier (UUID), and each device is assigned as part of a type of devices e.g. smartphones. The number and identification of each family is completely configurable, but a single device of each type can be assigned to each patient simultaneously. Additionally it is also possible to introduce into the system all the patient's information, including current diagnostic and medication, allowing for the patient's informations to be centralized into a single platform. After this initial configuration, when turned on, the smartphone queries the server for this information and starts connecting to the designated remote sensors, if any configured, and acquisition starts. Until the end of the study data is continuously sent to the server from which the physician can analyze it in real time. Data flow between the smartphone and the remote sensors is made using BT and the connection between the smartphone and the central server is accomplished using a socket [8]. During and after the data acquisition, medical teams can monitor the patient's incoming data through the web interface. They can choose the time frame and the variables to be displayed in a static frame, or they can choose to see incoming data in real-time. Other type of information is also visible as events like connection to remote sensor lost, low battery detected or smartphone turned off.

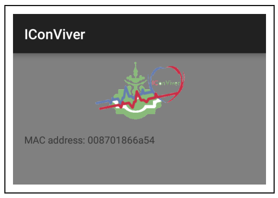
A. *Smartphone*

In this system, the smartphone acts as a central hub for collecting, storing, processing and relaying information between the various sensors and the central server, with all this being managed by a custom app. Incoming raw data from the sensors is stored into a local SD card; if necessary, data processing occurs, applying the adequate algorithms, according to the variables to be extracted; and finally, after processing, data is sent to the central sever in the form of more informative clinical variables, as per table I.

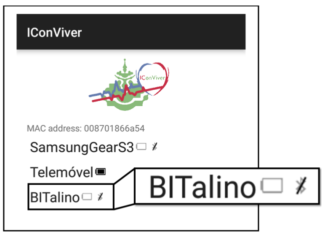
Raw data received through BT is buffered and every 10s it is compressed and stored in memory, and if necessary processed. As data samples are acquired at different rates from each device's sensors, a time stamp is associated with each sample to facilitate the time location of each one, and make easier temporal alignment of the overall signals.



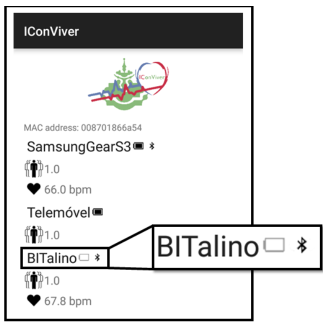
(a) Display at startup showing device's UUID.



(b) Screen when it was not possible to establish server connection. A sound notification also occurs in this event.



(c) Display after information from the server is received. BT symbols indicate there is still no connection with the other devices.



(d) Display after connection has been established and data from devices is received. Below each device's name there is the value resulting from processing the last 10s of data collected.

Fig. 2: Android app screens in various states of acquisition.

The app was implemented using Android Studio® 3.0.1.

All functions were designed to be as computationally efficient as possible to minimize loss of data and maximize battery life. The app was designed as a replacement for the android home screen, so, when the smartphone is turned on, the app will automatically initiate and shown on screen (fig. 2a), to facilitate the use of the device by patients.

Data coming from each type of sensor is acquired, processed and stored by an independent thread to avoid clogging the processor and BT reading buffers. This aspect also eases the inclusion of new sensors and devices, as it allows to completely isolate the implementation of communication protocols for different devices. All the threads are managed by a service running on the background that relays information between device threads and user interface (UI) service.

At the same time data is saved into files by each device's thread, and the result of processing that 10s window of data is sent to the UI thread to be displayed on screen. These threads also request battery status from the devices. This information is sent to the UI thread where a symbol indicates battery status of all devices.

Optionally, using the web interface, medical teams can request raw data in real time from a specific or all devices to be sent. This process is accomplished by a separate thread that receives each 10s block of data after it is written to files, further compresses and sends it through a socket to the server where data is stored. Further compression is needed as bandwidth and internet plafond are more restrictive than memory space. Data compression and sending occurs in a separate thread to ensure there is no delay in data acquisition.

B. *Server and Web Interface*

The central server is responsible for serving the web interface and storing all the data and settings into a database. It is also responsible for awaiting and establishing socket connection with the smartphones. Each remote device is uniquely identified byby its corresponding BT Media Access Control (MAC) address.

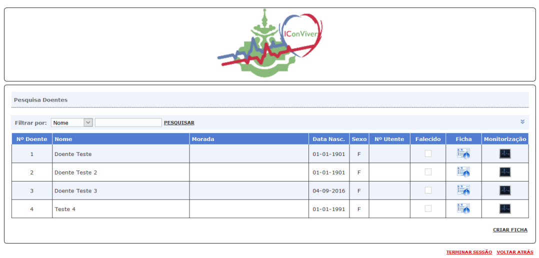


Fig. 3: Screen showing the patients enrolled in the system. From here one can access all the information and collected data from each patient.

The system works with three major components:

- **Web interface -** A website, built with ASP.NET, where user can configure all patient, device and acquisition parameters that are then stored into the database.
- **Socket -** This component has two subcomponents that ensure the communication between remote devices and the database.
  - One is constantly waiting for socket connections and sends acquisition parameters to remote devices. It also receives and stores data sent from the devices containing patient processed data, such as HR and METs values.
  - Another component, which is also constantly waiting for socket connections in a different port, is responsible for receiving and storing realtime raw data that may be sent by a remote device (only active if raw data is requested by the medical team).
- **Database -** This component is responsible for storing all data that comes from all other components.

Fig. 4: Data visualization screen where one can choose the variables to see and their time frame.

Medical teams can use the interface to configure which sensors should be used with each patients, which variables are to be extracted from raw data, the frequency at which they are sent to the server and also view and manage all the devices' and patients' information and collected data.

Figures 3 and 4 show some examples of the implemented web user interface.

C. *Privacy*

To ensure safety of patient's private data, the system features several security layers. The first layer is the necessity of a login and password to access the web interface, allowing for several types of permissions in the system, with the possibility to set which configurations and informations are visible for each user. Another layer is the anonymity of the patient in remote communications i.e. when a patient is registered into the platform a sequential number is given to that patient and when the server sends the acquisition parameters to the smartphone only the identification number is sent. In addition, the BT and socket communications are encrypted natively to both protocols, making it very difficult for data to be stolen. Also data in the server's database is stored anonymously further protecting patients' identity.

D. *Data Compression*

Raw data from all the sensors is stored into the smartphone's SD card as text files. There is a separate file created for each connected device and each sample of data is saved with the timestamp taken at the acquisition moment. Data vectors to be saved have the format [Timespamp, S1, S2, S3] where S1, S2 and S3 are samples from 3 sensors acquired simultaneously.

Given the limited memory, battery capacity and computational power of smartphones, the compression algorithm should be simple (and hence of fast computation), and lossless (in order to allow future reliable data processing). To do this, the following data compression algorithm was implemented: Data is saved into the files in 10s batches and the first value of each batch is stored as a raw value to make the recovery of the original data possible, and thus ensuring this method is lossless. The following samples are the time derivative of each sensor's values. To recover each sample from the file, one must integrate the saved values up to that sample according to eq. (2).

$$X_i^{coded} = \begin{cases} X_i^{original} & i = 0 \\ X_i^{original} - X_{i-1}^{original} & i \neq 0 \end{cases} \quad (1)$$

$$X_i^{decoded} = \sum_{j=0}^{i} X_j^{coded} \quad (2)$$

$X_i^{original} \rightarrow$ ith sensor's sample
$X_i^{coded} \rightarrow$ ith sample to be written to file
$X_i^{decoded} \rightarrow$ ith sensor's sample after decompression

An example of data from a 3-axial accelerometer saved in the described format would be:

```
#;1508325806082;8;268;5418
10;0;70;1774
10;-10;63;1129
...
```

Corresponding to the raw data:

```
1508325806082;8;268;5418
1508325806092;8;338;6592
1508325806102;-2;401;772
...
```

When real time raw data is being sent to the central server, further compression is needed to reduce data volume and to limit battery expenditure, as the constant relaying of information requires much energy. With this in mind, a simple Huffman coding [9] was implemented using a static code for all subjects, as statistical properties of data are approximately invariant with subject. This was concluded by determining Huffman code for different subjects in different activities, achieving very similar codes for all (only least common characters had some minor changes). This codding is performed after time-difference operation to encode each digit of the values obtained from the first step.

III. Real World Application Case Study

To test it, the system was used to monitor cardiac patients, and relevant variables indicated by the medical team of the cardiology department of HSM were HR and METs. To achieve this, alongside the smartphone, two other devices were used, a Samsung Gear S3 smartwatch [10] and a BITalino [11] based chest-band. Table I describes the variables collected by each device and what are the clinical indicators extracted from the data after processing. Figure 5 shows a patient wearing the system's sensors.

TABLE I: Variables acquired by each device and the corresponding information extracted. HR - Heart rate; CD - Chest Deflection; PA - Physical Activity (measured in METs); RR - Respiratory rate.

Device	Variables	Sampling Rate (Hz)	Clinical Variable
Smartwatch	PPG	25	HR
	HR	25	HR
	ACC	100	PA
BITalino	ECG	1000	HR
	ACC	1000	PA
	CD	1000	RR
Smartphone	ACC	100	PA

A. *Outpatient Devices and Sensors*

1) ***Smartwatch****:* The smartwatch was chosen for being a very convenient and comfortable package, as it can replace the watch many use daily, and, at the same time, includes many useful sensors described in[12]. In particular, this smartwatch can monitor the patient's HR using data collected from a photoplethysmography (PPG) sensor [13], that is processed using a manufacturer's algorithm in order to determine HR. Besides PPG it can also collect tri-axial accelerometry data, that can then be processed to estimate the patient's physical activity.

A custom app was implemented to extract the information from the sensors, using a manufacturer provided API [12], and send it via BT to the smartphone. The sampling rate varies with the type of sensor as per table I. Data is sent in packets containing 10s of data from the PPG and accelerometry sensors and also the value of HR determined by the manufacturer's algorithm.

Interactions with the user occur via vibratory and sound notifications triggered by a loss of BT communication with the smartphone or a low battery level which can be identified by the information visible in the smartphone screen.

2) ***BITalino****:* BITalino was used to collect various signals as mentioned in table I in the form of a chest band that collects various signals and sends them to the smartphone via BT. The choice of this device is justified by the very good ECG signal quality acquired [14], [15], [11], and for being a very versatile and customizable sensor platform, which can collect several clinically relevant variables.

A chest band was built in order to accommodate the sensors described in table I with a comfortable and practical form-factor. This was a major concern as patients comfort was very important to ensure success of the system as it was intended to be used for long periods of time.

The base to the chest band was a standard commercial product band from Polar® used for sports tracker devices that includes conductive pads that rest in skin contact acting as electrodes. The chest band ensures a good signal quality even when patient is moving as it is elastic and tight to the chest, minimizing the introduction of moment artifacts. Furthermore, the material of the electrodes, which is a rubber-like material has a certain adhesion to the skin that prevents slippage.

B. *Comfort and Usability*

Comfort and ease of use for patients and physicians were two major concerns when designing and choosing all hardware and software features.

Fig. 5: Subject wearing chest band and smartwatch used for data acquisition.

As the system is intended for long term and constant wearing, it is crucial to ensure the patient's comfort. Besides comfort, ease of use, is also a major requirement as many times patients are elders and without simple enough interfaces and battery charging procedures, it could become impossible for them to use the system. These conditions influenced the choice of devices and led to the inclusion of on screen battery information and sound notifications to notify the patient to charge the devices when needed (fig. 2). To ensure practicality and ease of use for physicians and medical staff, requisites were to have a simple web interface in what concerns patient enrollment into the platform, and data visualization.

All of these aspects were assessed along the design process and were put to test in hospital context. During the design process students were asked to wear the system and report on aspects to be improved relating with comfort and ease of use. The same was made in hospital context with medical teams using the system with patients, using a user guide for support. All of their feedback was then collected and used to improve the system.

C. Data Processing

System testing was performed in close collaboration with the medical team of HSM. As the clinical variables of interest were not the ones being collected by the chosen sensors, it was necessary to include some data processing and automatic data analysis methods.

*1) **Real Time Estimation of HR from ECG Data**:* Once the BITalino inside the chest band acquires ECG, data processing must occur as the target variable is HR.

To accomplish this, an algorithm was implemented to identify R-peaks (RP), a fiducial mark of the ECG wave morphology usually seen as a high amplitude peak in the ECG signal, and from them calculate the HR. This algorithm had to be as simple and reliable as possible in order to limit the exhaustion of the smartphone's battery, which would harm system's usability, and also to maintain reasonable computing time preventing delay in acquisition and loss of data. The proposed algorithm is based on the segmenter described in [16] although some modifications were implemented.

The ECG signal is processed in non-overlaping 10s windows, and the first stage consists of digital filtering using a 5-40Hz 5th order bandpass Butterworth filter , followed by adaptive amplitude thresholding for detecting R peaks locations. If a local maximum has an amplitude higher than this threshold, it is considered an RP, otherwise it is classified as a noise peak.

The computation of the dynamic threshold follows an initialization and iteration steps. It is initialized as defined by eq. (3) with a value corresponding to 98% of the cumulative probability function of the ECG amplitude over the first 10s window being an initial approximation of the peaks amplitude on that window.

The threshold value is then dynamically updated according to eq. (4).

If no peaks are found in a 2s segment, which would correspond to a HR below 30bpm, the search is backtracked and the threshold value is lowered to 90% of its current value. In an analogous way, if two peaks are found in less than 100ms (corresponding to 600bpm), the threshold is increased by 10%. These strategies allow to keep up with sudden changes in the ECG amplitude, reducing false positives and missed heart beats.

Initialization:

$$\begin{cases} THR = \arg_x \left(\frac{F_{ECG}(x)}{\lim\limits_{y \to +\infty} (F_{ECG}(y))} = 0.98 \right) \\ SP = THR \\ NP = 0.5 * THR \end{cases} \tag{3}$$

Iteration step:

$$\begin{cases} SP = 0.125 * P + 0.875 * SP & \text{if } P > THR \\ NP = 0.125 * P + 0.875 * NP & \text{if } P < THR \\ THR = SP - 0.25 * (SP - NP) \end{cases} \tag{4}$$

$THR \rightarrow$ decision boundary between RP's and noise
$P \rightarrow$ amplitude of the local maximum to be classified
$SP \rightarrow$ running estimate of the RP's amplitude
$NP \rightarrow$ running estimate of noise peaks' amplitude
$F_{\text{ECG}} \rightarrow$ ECG signal cumulative distribution function

Finally each pair of consecutive local maxima classified as RP in the 10s window is used to produce an estimate of instantaneous HR according to eq. (5). To improve robustness, instead of returning instantaneous HR, a single value is returned for the 10s window, meaning a 10Hz HR estimation is produced. To do this, the median of the various HR (calculated from each pair of RP's) is taken, improving performance based on the assumption of HR being relatively constant inside the 10s window.

$$HR_i = \frac{60 * f_s}{t_{R_{i+1}} - t_{R_i}} \tag{5}$$

$HR_i \rightarrow$ ith instantaneous HR
$f_s \rightarrow$ Sensor's sampling frequency in Hertz
$t_{R_i} \rightarrow$ sample number of the ith RP

If the final estimate falls outside the 30-220bpm range, the calculation is rejected and a special error value of -3bpm is returned.

*2) **Off-line Estimation of HR from ECG Data**:* In order to obtain a ground truth reference for HR calculated, the ECG collected by the chest band is processed off-line using an established segmenter [17] that detects the RP and allows to estimate patient's HR according to eq. (5). After this step, to eliminate errors of any wrongly detected RP, and to allow comparison with estimates made by other devices, data in sliced into 10s windows and the returned HR value is the median of the instantaneous HR values inside that 10s window. This approach offers great reliability and is computationally heavy, so it is used off-line to validate the estimates produced in real time by the on-line method.

*3) **Physical Activity METS estimation**:* METS were estimated using rules presented in [5] and refined in [18].

Counts estimation from accelerometry data was made according to 6.

$$Counts_{10s} = \sum_{i=1}^{10*f_s} |ACC_{i-1} - ACC_i| \qquad (6)$$

$ACC_i \rightarrow$ ith accelerometry sample
$f_s \quad \rightarrow$ Accelerometry sampling frequency in Hertz

This metric allows physicians to estimate physical activity of the patient.

D. Sensor Validation - HR Estimation from PPG data

In order to evaluate the accuracy of HR estimates given by Samsung Gear S3, the later was used to record HR in different situations with several subjects with and without cardiac pathologies. Simultaneously a BITalino [11] and a medical-grade certified device were used to determine the HR from ECG data and provide a reference for Gear's values.

*1) **Experimental Protocol**:* To validate HR values calculated by Gear S3 three experiments were conducted:

- E1 - Consisted on acquiring data for short periods of time with subjects performing a specific activity:
  - Resting state, moving as least as possible (2min)
  - Walking at a regular pace (5min)
  - One subject was asked to pedal on a stationary bike at moderate pace (5min)
  - One subject was asked to run at moderate pace (2min)

  Some of these acquisitions were repeated to verify reproducibility and infer on system robustness.
- E2 - On this experiment, data was recorded for periods between 1 and 2 hours while subjects performed their usual activities during their daily lifes.
- E3 - The experiment consisted on collecting data from 3 hospitalized patients with various cardiac diseases during a stress test, taking place at hospital. These tests consisted of patients walking on a treadmill, increasingly fast until they are not able to continue, followed by a rest period. Patients ECG and energy consumption are monitored while executing the task. The procedure was performed according to Bruce protocol [19].

Data was collected from two separate groups performing different activities. Stress tests (E3) were undertaken by 3 patients with various cardiac conditions and ages 42, 47 and 50 years old. The other experiments enumerated were performed by 3 healthy volunteers all 23 years old. In all following figures and tables Si denotes subject i and Tj denotes jth trial.

*2) **Test Equipment**:* Multiple devices were used to evaluate subjects' HR:

- Samsung Gear S3 Frontier where HR is calculated by the smartwatch from PPG data using manufacturer's algorithm.
- A BITalino based chest band, collecting one derivation ECG at 1000Hz, with HR estimation being made using a standard algorithm [17].
- For stress tests HR information is also collected by a Mortara XScribe 3.10.10 by Mortara Instrument [20] that collects 12 lead ECG, producing a very reliable HR estimate as it is a certified medical device.

*3) **Accuracy Measurement**:* The accuracy of the HR values produced by the smartwatch, and also the ones estimated from the ECG signal, was summarized as statistics of the absolute error (AE) e.g. mean absolute error (MAE) as defined in eq. (8).

$$AE_i = \left|HR_i^{true} - HR_i^{est}\right| \qquad (7)$$

$$MAE = \frac{1}{N}\sum_{i=0}^{N} \left|HR_i^{true} - HR_i^{est}\right| \qquad (8)$$

$N \quad \rightarrow$ nr. of HR values estimated for a subject
$HR_i^{true} \rightarrow$ Reference value of HR for ith 10s signal window
$HR_i^{est} \rightarrow$ Estimated value of HR for ith 10s signal window

This measurement was chosen as it provides an easy and fast interpretation quantity to be known and used by physicians when analyzing patient data. Furthermore, unlike other metrics like percent error, absolute error is completely independent from HR range.

E. Sensor Validation - HR Estimation from ECG data

As a way of validating the algorithm described in section III-C.1 running on the smartphone, that is being used to determine the HR from the ECG signal, a comparative analysis was made between the HR estimates based on the proposed algorithm and a standard one described in section III-C.2.

The main difference between algorithms is that one is a very simplified RP detector running in the smartphone in real-time while the other runs off-line with no complexity restrictions.

During E2, described in section III-D.1, ECG was collected by the chest band and was used to test the algorithm proposed in section III-C.1. At the same time, the raw signal was recorded and processed off-line by the standard algorithm described in section III-C.2. This allowed to isolate signal quality from the tests, as the same signal, divided in the same 10s windows was being processed by both algorithms and HR estimates were compared.

IV. Experimental Results and Validation

A. Data Compression

Applying the data compression framework described in section II-D to the raw data saved from the various experiments done during the course of this thesis, it was possible to determine its effectiveness.

Figure 6 represents the relative frequency of each character in the saved files. The count was extracted from real data collected from several subjects. The use of Huffman coding is favored as a very clear difference in character occurrence is present allowing for a great reduction in average character length.

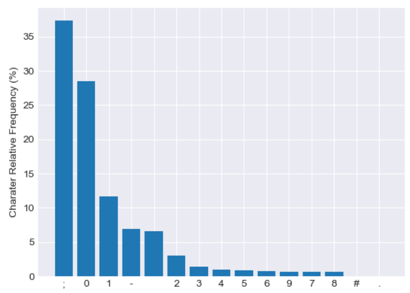


Fig. 6: Character relative frequency obtained from all the data collected from 4 different subjects for at least 30min each.

TABLE II: Codes determined for each character based on counts from fig. 6. [9]

Character	Code bits	Character	Code bits
';'	'0'	'5'	'1110010'
'0'	'10'	'6'	'11101011'
'1'	'1111'	'7'	'11101000'
'-'	'1101'	'8'	'111010101'
'\n'	'1100'	'9'	'11101001'
'2'	'111011'	'#'	'1110101001'
'3'	'111000'	'.'	'1110101000'
'4'	'1110011'		

Table III shows the compression ratios achieved. These ratios were estimated from data collected from several patients, and they clearly show the efficacy of the very simple techniques utilized. Taking into consideration the very light computional burden these methos imply, they allowed to compress data into a format almost 8 times smaller, making possible for the system to be used for longer periods without memory shortage, even storing all the raw data from all sensors.

B. Comfort and Usability

During the various experiments that we performed, Web, Android and Tizen interfaces were considered very convenient and simple to use. Battery life was one of the main aspects medical professionals referred as to be improved. This led to the introduction of a power bank for the smartphone and a bigger battery for the chest band to ensure battery life expectations were met, as well as many software optimizations. Despite efforts, table IV still depicts slightly shorter-than-optimal battery lifetimes.

Overall the system had very positive feedback by all participants, patients and medical teams. Interfaces were considered convenient, presenting useful information. On the patients' side there was an unexpected effect, besides considering the system comfortable to wear with minimum disturbance of their daily-life, patients reported to feel more accompanied and better taken care knowing that they are being monitored 24hr a day. This was not expected initially and may contribute to even better outcomes, as feeling more taken care of may improve patients' health status acting similarly to the placebo effect.

C. HR Estimation from PPG data

After data collection from subjects, the first observation of the PPG signal revealed the vast influence of motion artifacts (MA). This is depicted in fig. 7 and fig. 8. When the subject is completely immobile it is easy to find, even by inspection, a correlation between ECG and PPG signal peaks (fig. 7) corresponding to systolic peaks. The same is not true when the subject is moving, as signal corruption greatly affects PPG signal and correlation is no longer obvious and maybe not present at all (fig. 8).

TABLE III: Memory usage when data is stored as a raw sensor value, as time-differences and using Huffman coding.

Device	Memory Usage (MB/day)		
	Raw	Time difference	Huffman
Smartwatch	345.2	145.4	71.3
BITalino	3037.3	574.3	355.7
Smartphone	253.3	99.6	54.6
TOTAL	**3635.8**	**818.9**	**481.6**
Compression Ratio	—	**4.43**	**7.55**

TABLE IV: Battery lifetime of acquisition devices

Device	Conditions	Duration
Smartphone	Connected only to Smartwatch	13h 30min
	Connected to BITalino and Smartwatch	11h 30min
	Connected to BITalino, Smartwatch and power bank	16h 30min
BITalino	With 1300mAh battery	48h
Smartwatch	—	12h 30min

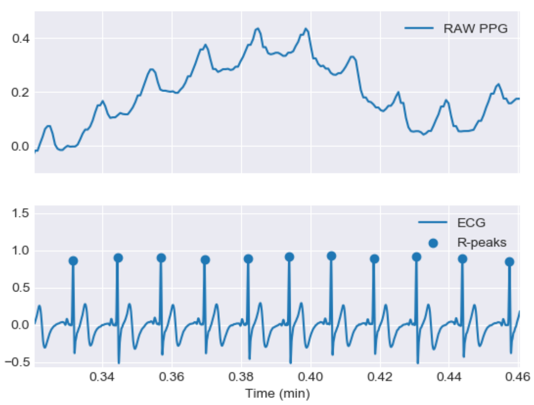


Fig. 7: Raw signal while completely immobile. HR calculated from PPG (first curve): 75bpm; HR calculated from ECG (second curve): 79bpm.

Observing fig. 11, it is visible that Gear S3 is not capable of keeping up with fast variations in HR and fig. 13 clearly illustrates the difficulty in determining HR accurately during movement, with a very large estimation error being present, until subject enters the resting phase of the stress test.

Short Acquisitions (E1) - When analyzing the absolute error of HR determined from the smartwatch's PPG data collected while subjects were performing specific activities, it is very obvious that motion highly corrupts sensor data and thus, greatly damages accuracy. In fig. 9 is very clear a tendency to error increase as subjects go from resting to cycling or running.

Another thing that can be noted in fig. 9 and table V is the relatively large difference in the error values between subjects and trials. This indicates low robustness of the device's measurements, as they are affected by sensor positioning, tightness and also by how the subjects move, as some individuals present accentuated arm movement which can further disrupt accuracy.

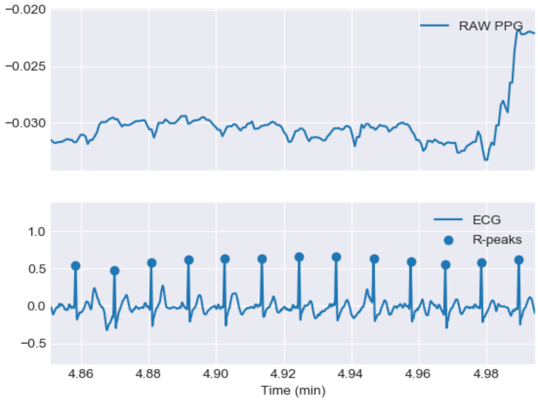


Fig. 8: Raw signal while walking. HR calculated from PPG (first curve): 52bpm; HR calculated from ECG (second curve): 81bpm

TABLE V: Mean Absolute Error (MAE) of each experiment and activity averages.

Activity	Subject	MAE	Average
Resting	S1	1.4	2.4
	S1T2	1.8	
	S2	1.3	
	S2T2	5.1	
	S3	2.2	
Walking	S1	10.8	21.2
	S1T2	35.3	
	S1T3	46.4	
	S2	17.7	
	S2T2	3.4	
	S3	3.3	
Cycling	S1	22.8	63.4
Running	S2	104.1	

Fig. 9: Absolute Error of HR while performing different activities: (left) resting; (middle) walking; right cycling and running.

Daily life (E2) - Figure 10 and table VI demonstrate clearly that during daily-life activities like walking or any activity that implies arm movement, Gear S3 has a poor performance as a sensor platform and, in certain occasions, it is not even possible to detect any type of signal trends. In a medical context, this could lead to gross errors rendering the pervasive monitoring inefficient or even counterproductive.

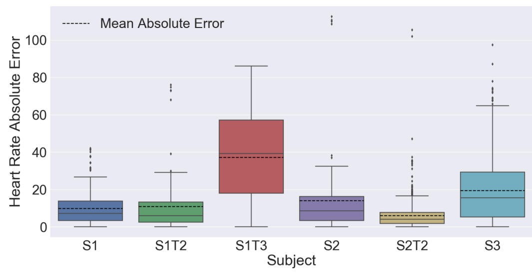


Fig. 10: Absolute Error of HR while subjects perform their usual life activities (office working, walking, eating, etc...).

TABLE VI: Mean Absolute Error (MAE) of each subject during daily life activities.

Activity	Subject	MAE	Average
Daily-life activities	S1	9.7	16.2
	S1T2	10.8	
	S1T3	37.1	
	S2	13.9	
	S2T2	6	
	S3	19.3	

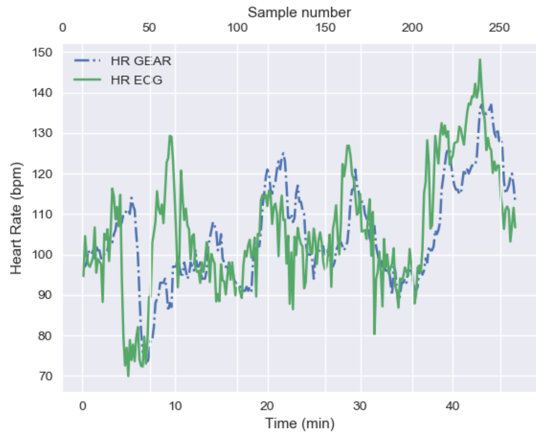


Fig. 11: Example of HR curves obtained during daily life activities.

Stress Test (E3) - As expected, during a stress test, where the subject is moving with some intensity, HR determination error is very large and as can be seen in fig. 13, error is specially large during the exercise phase of the stress test, supporting the hypothesis of MA corrupting the signal. Error during these tests reached over 100bpm wich renders this sensor platform completely unfit for this kind of context where precision is of utmost importance to avoid wrong diagnostics and treatments.

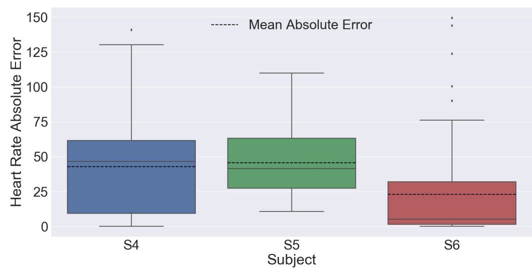


Fig. 12: Absolute Error of HR during stress test.

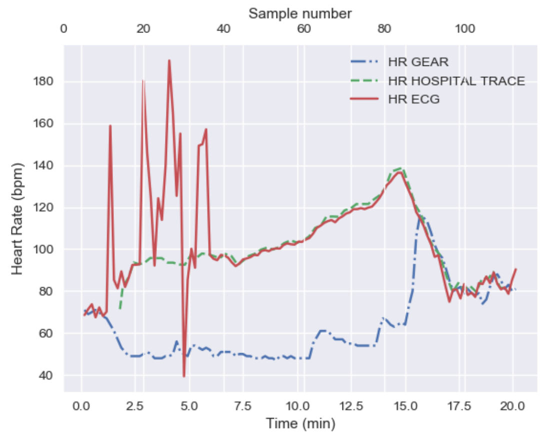


Fig. 13: Example of HR curve obtained during stress test.

*1) **Discussion**:* When observing the results obtained, the first conclusion that can be made is that the PPG signal collected with Samsung Gear S3 is very easily corrupted by motion artifacts. This corruption is present either during exercise or daily-life activities and even with very light movements, some corruption can be noticed. This means that very easily, the identification of systolic peaks in the signal cannot be made reliably, having a negative impact in the HR determination accuracy thus rendering this device unfit for pervasive monitoring in a medical context.

The main reasons for this low accuracy can be related with the sensor itself and also with the device as a whole. The sensor has only one green LED and one photodiode, while other sensors have two of each, with LEDs of different wavelengths. This apparent redundancy has a great impact as it allows for different signal processing approaches that can greatly improve the performance.

Concerning the weight of the smartwatch, it must be taken into account that this is a very complex device and all its functionalities and capabilities make the device heavier and lager, thus, making it harder to keep comfortably and tightly secure to the wrist without it having its own dynamics. This is a problem as the relative movement between the sensor and the subject is the sole cause for MA in the signal. In addition, the positioning of the sensor in an area with a relatively low SNR greatly increases the impact of MA.

Due to poor quality PPG signal acquired, several algorithms were used in an attempt to get better HR estimates. Algorithms used included adaptive filtering with and without Laguerre expansion [21], [22], signal separation by sparse signal reconstruction [23], [24] and onset detection [25]. A total of 8 algorithms were used to process the PPG and accelerometry data coming from S3 to produce estimates of HR. However, the results obtained were equally bad, or even worse, than Gear's algorithm and, for this reason, they were not considered. This clearly indicates that the error in Gear's HR estimations is probably related with a low quality signal and not with a poorly performing algorithm.

D. HR Estimation from ECG data

In fig. 14 the HR curves calculated by both the on-line and off-line algorithms can be seen. The calculations, for this particular subject, present an almost zero error, as the curves appear to be overlapping for almost all samples, and

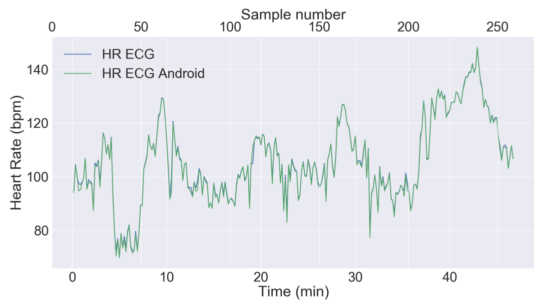


Fig. 14: Error of android segmenter.

with minor deviations in a few points.

Looking at fig. 15 it can be noticed that observations made from fig. 14 are in agreement with error values for most subjects.

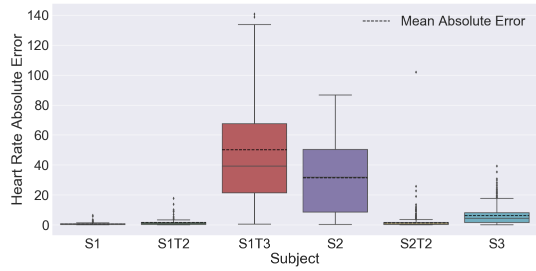


Fig. 15: Error of android segmenter.

*1) **Discussion**:* Analyzing fig. 14, it can be noticed that HR estimation made using the proposed algorithm and the reference algoritm [17] are rather small. This demonstrates that, even being computationally lightweight, it performs well during daily-life tasks. This is confirmed by fig. 15, where very small errors predominate with exception for two subjects S1T3 and S2. In this particular pair of acquisitions, the increase of error is probably due to the introduction of motion artifacts in the ECG signal, as subjects reported to be exercising.

Besides MA, the other major weakness of this algorithm is chest band placement. This occurs due to the nature of the algorithm, as it is based in amplitude, it is expected of the RP to have an amplitude much larger than other signal features, which is only true for certain ECG electrodes placement. In case of a patient misplacing the chest band, it may be that signal morphology is altered leading to great errors in the HR estimation. However, with careful teaching of each patient on how to operate the system, this problem can be reduced.

Overall, the algorithm performed well, specially when taking its simplicity into account. Robustness may be questionable when exercising, but for daily-life activities, it is very reliable, and improving the reliability would, probably, require a great increase in the computational burden of the algorithm, harming the smartphone's battery life and the general system's usability.

V. Conclusion

In this thesis, a remote monitoring system for clinical use was developed. It was designed to offer support for different sensors and to be capable of being used for extended periods of time with minimum maintenance requirements. The system was put to test at Hospital de Santa Marta (Lisbon), with sensor technology and overall interfaces receiving a very positive feedback from both medical staff and patients.

Versatility was the most prized feature as the easy inclusion of different sensors, make it suitable for potentially all fields of medicine and in some sense, also make it timeless, as the same system can be used as sensor technology evolves. This means the system itself is very low cost, comparing with other medical data collection systems, as the proposed architecture, being based on a smartphone app, allows for the interoperability of the devices with no need for a separate device for each type of monitoring context. Also the possibility of condensing all the information about the patient, regarding it's current and previous conditions, diagnostics and medications had a very positive feedback from medical teams.

A possible addition for this system could be an interface for family and caregivers, allowing them to also be informed about the health state of the patient and even receive notifications when a relevant event takes place e.g. when a patient falls. Another aspect that can be improved is the battery life time of the devices, in particular the smartwatch, which can be achieved with some software optimizations and the choice of a different device, more efficient and precise. Finally an useful feature that could improve this system is the inclusion of an interface so the self-reported health status can be collected, allowing for medical teams to monitor this very relevant indicator.

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