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Original Article

A Real-Time Remote Monitoring System for Cardiovascular Diseases

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Abstract - *Currently, real-time recording and bio-signal-based early diagnosis are feasible solutions thanks to increasing progress in monitoring device development technology, including self-monitoring devices, integrated electronic systems, the Internet of Things, and edge computing. The pandemic emergency of coronavirus disease 2019 (COVID-19) activated the remote monitoring era and highlighted the need for innovative digital approaches to managing cardiovascular disease. The scientific community and health organizations have considered this new era confirming that remote consultation and monitoring systems have become indispensable in cardiovascular healthcare circumstances to enhance patient healthcare and offer personalized treatment. The paper aims to introduce a real-time remote monitoring system for cardiovascular diseases and to describe the proposed system modules and the ECG signal processing algorithms. The described approach can monitor the patient's cardiac activity, allowing the specialist to control the electronic instruments remotely without leaving their office. Therefore, this system aims at all cardiopathic patients with objective motor difficulties either because they are bedridden or geographically located in places distant from the health facility of interest. Furthermore, considering the real-time monitoring approach of this system, a future application scenario in a global pandemic context can be hypothesized.*

Keywords - *Cardiovascular diseases, ECG signal processing, ECG monitoring system, Remote control, Sensors, Remote consultation.*

1. Introduction

Noncommunicable diseases (NCDs), which include heart disease, stroke, cancer, chronic respiratory diseases, and diabetes, are considered the leading cause of mortality globally [1]. More specifically, in the last decade, the number of deaths caused by chronic and cardiovascular diseases (CVDs) has grown significantly in all countries. The World Health Organization (WHO) documents 17.9 million deaths yearly, confirming CVDs as the number one cause of death globally [2].

Among the 2030 Agenda for Sustainable Development objectives, ensuring a healthy life and promoting healthy well-being for all ages stand out [36]. In this context, the need for developing health-monitoring systems (for hospitals, clinics, or home settings) that can detect and react to warning signals, thus providing efficient services to patients with cardiovascular diseases, is becoming increasingly important. In the contemporary healthcare scenario, continuous heart rate monitoring and real-time analysis of electrocardiogram (ECG) signals are the primary concerns. Indeed, scientific and experimental evidence has shown that these solutions could better diagnose, control, and prevent many CVDs [4-9], becoming a valuable tool to support clinical decisions. During the last few decades, ECG monitoring systems have been widely adopted in hospitals [10–13], homes [14–16], outpatient ambulatory settings [17–19], and in remote contexts [20] and have considerably evolved due to advances in sensor technology and communication infrastructure as well as to improvement in data processing and analytics algorithms. A recently published accurate and systematic review [21] proposed a comprehensive, expert-verified taxonomy of ECG monitoring systems, focusing on different and essential aspects: applicability, the technology used, architecture, lifecycle, classification, and challenges.

The pandemic emergency of the coronavirus disease 2019 (COVID-19) shed light on the need for remote monitoring systems [28] and other digital approaches to cardiovascular disease management across the world [22]. Indeed, during this health crisis, intending to reduce the infection from Covid-19 and replace (or at least support) the traditional face-to-face interaction between patients and doctors, remote consultation and monitoring systems have become indispensable [22].

Different typologies of stand-alone technologies can be adapted to easily collect data remotely from people with or at risk of cardiovascular disease [28]. The almost continuous streams of physiological variables (blood pressure, pulse rate and regularity, heart sounds, respiratory rate, electrocardiogram parameters, oxygen saturation, and sleep quality) and the adoption of traditional or machine learning algorithms can be handy tools to identify patients with, or at risk of, clinically important events.

The classification of existing context-aware ECG monitoring systems, proposed in [21], reported several categories of home-based, hospital-based, ambulatory-based, and remote-based ECG solutions. Each of these environments' applications can be the object of interest and in-depth analysis since it can give information on solved problems and current challenges. However, home ECG monitoring systems represent the context of most significant interest since they are conceived for patients with lifelong and chronic diseases or older people who need permanent assistance and monitoring [21]. They aim to involve patients in their daily health monitoring with the advantage of being comfortably at home, thus reducing the economic burden on hospitals and health facilities. Several studies in this context described solutions based on telemonitoring [32 - 35] since it represents an approach that can be easily integrated into home settings. Indeed, using ECG telemonitoring systems, it is possible to efficiently monitor patients' vital signs, identify cardiac abnormalities and irregular heart rhythms, and eventually treat them before they propagate to more severe issues.

To allow for early detection of atrial fibrillation (AF), a not-very recent work [32] presented the extension of their previous home monitoring system based on mobile phones and Near Field Communication technology (NFC) to enable patients to record their ECG patterns autonomously. Although the system's technical feasibility, usability, and patient compliance were evaluated in a clinical pilot trial, signal quality was limited by the used ECG recorder component and needed improvements for daily application.

In a recent study, Venkatesan et al. [33] used a mobile cloud computing approach to combine ECG telemonitoring and coronary heart disease (CHD) risk assessment. The authors tried to overcome the well-known challenge of continuous monitoring concerning the complex computational requirement and significant data processing.

Similarly, Wang et al. [34] presented a new hybrid mobile cloud-based electrocardiograph monitoring and analysis approach to enable more effective personalized medical monitoring. However, this study has limitations, especially concerning security, which must be addressed. Indeed, the high data exchange between the mobile and the cloud could expose users to higher security and privacy threats.

Benini et al. [35] proposed a user-friendly single-lead ECG device designed to be used by Chronic Heart Failure (CHF) affected people with complete autonomy. The device required a few basic actions to be operated and sent transparently the acquired ECG signals to the designated service center through a wirelessly connected network gateway.

Remaining in the home ECG monitoring context, a plethora of studies proposed systems that involved wearable continuous monitoring (see for details a review paper [37] focused on remote or long-term monitoring of cardiac functions [14, 16, 38, 61]).

A wireless ECG monitoring system, designed using flexible and dry capacitive electrodes, was proposed by Majumder et al. 2018 [61] for long-term monitoring of cardiovascular health. Considering the experimental results from three different healthy subjects, this ECG system reported a performance comparable to existing ECG monitoring systems, which are reviewed, compared, and critically discussed.

Particularly in a wearable health monitoring environment and under massive ECG data, traditional real-time diagnosis is a demanding task for healthcare staff because of the lack of expert resources for ECG diagnosis and excessive workload. For this reason, automatic identification of cardiac abnormalities using intelligent classification algorithms and sophisticated methods for self-diagnosing cardiovascular diseases are of great practical significance for economic and social development and people's health [39]. Several approaches have emerged in the scientific literature on heartbeat recognition. A widely accepted classification subdivides heartbeat recognition methods into supervised and unsupervised learning [47, 46]. The first category includes recognition algorithms that are constructed based on data with labels and counts as examples of convolutional neural networks (CNN) [41], neural networks [42], support vector machines (SVM) [43, 44], k-nearest neighbors (k-NN) and so on [50].

A recent study [39] proposed a sleep-monitoring model based on a single-channel electrocardiogram using a convolutional neural network (CNN). The proposed model could be used in portable devices to detect Obstructive Sleep Apnoea (OSA). However, as a limitation, the automated anomaly detection of ECG based on this CNN model and the discrimination ability of the method for normal (AEs) and abnormal epochs (NEs) need further improvements.

The second category does not need an input-label/reference pair for training the algorithm and includes the K-mean clustering algorithm [49], principal component analysis (PCA), hidden Markov model (HMM), and so on [46]. With the advent of deep learning, many research groups have begun to employ these algorithms to diagnose and analyze ECGs [56, 40, 60, 45]. An accurate example of this approach is reported in the study of Tseng et al. 2021 [62], which intended to present a suitable deep learning framework to improve the accuracy of ECG diagnoses with a mobile device. Furthermore, this work could be considered helpful to the cardiovascular disease (CVD) community to help monitor people's health. The main contributions of this work are the sliding segmentation and the Large Kernel Network (LKNet) methods, which can enhance the accuracy of the ECG diagnosis process.

Although current development in ECG monitoring systems is based on sophisticated technologies and accurate automatic diagnostic techniques, this has always been an open area of research [63]. Indeed, many challenges concerning device capabilities and reliability, ECG diagnostics overlapping patterns, security problems and privacy support, and other ECG signal-related issues throughout the system's lifecycle are still under discussion [21].

Heart disease management software, remote and continuous diagnostics, digital cardiovascular disease prevention, and digital care tools are urgently needed.

The solution to these challenges could be assembling small, inexpensive, convenient, and wearable sensors that can be connected to the Internet via data aggregators and then transmitting the information to the cloud for data processing and sending it back to the medical teams via alerts, warnings, or other notifications.

The aims of the paper are:

-to introduce a real-time remote monitoring system for cardiovascular diseases.

-to describe the proposed system modules and the ECG signal processing algorithms in detail.

-to hypothesize a future application scenario of this system in a global pandemic context.

The present ECG solution is an extension of one of the integrative nodes of a more sophisticated and secure medical platform, SIMpLE [54], described in detail in our previous works [30, 31].

SIMpLE is a mobile cloud-based monitoring system for patients affected by neurodegenerative diseases, such as ALS patients and the elderly [30, 31]. The SIMpLE platform can provide healthcare facilities and users with a complete system for small home cardiological monitoring.

The constitutive modules of the SIMpLE system are (i) data acquisition module (i.e., commercial sensors able to acquire physiological signals (EMG, ECG, and EEG)); (ii) SIMpLE mobile, a sort of hub which sends the acquired signals to the web-based system and (iii) the SIMpLE cloud-based system. The SIMpLE cloud-based module, of which the present system represents an extension, includes patient summary management services, remote control, the visualization and analysis of acquired signals, the management of patient diagnostic imaging, and teleconsultation.

The paper is organized as follows: Section 2 introduces ECG signal characteristics and acquisition procedure; Section 3 describes the architecture of the proposed monitoring system; Sections 4 and 5 present the main results and the discussions, respectively, whereas Section 6 concludes the paper.

2. ECG Signal Characteristics and Acquisition

Electrocardiography (ECG) involves recording, analyzing, and interpreting electrical phenomena in the heart during its activity. The ECG can be registered with electrodes placed on the cardiac or skin surface of the limbs or chest. The ECG, in its most complete form, consists of a series of waves (deflections) of different duration, amplitude, and signs: three of them are positive (P, R, T, and possibly U), and two are negative (Q and S)(see Figure 1). The waves express the depolarization and repolarization of the cells that make up the heart tissue.

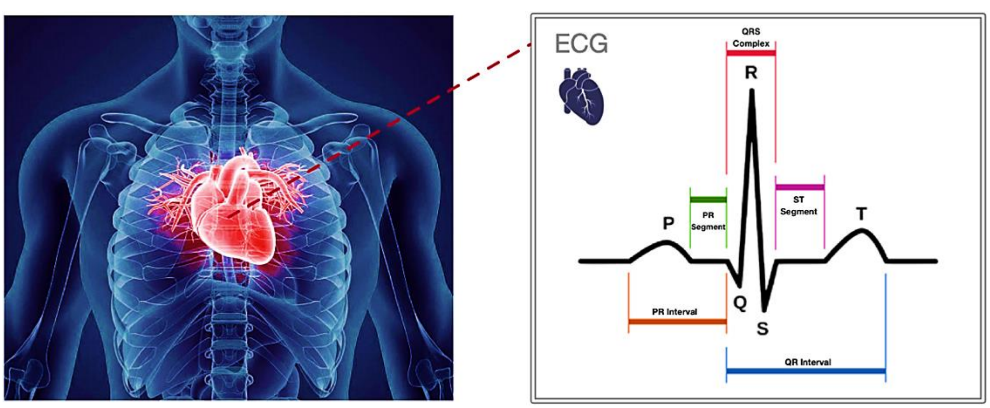

Fig. 1 ECG signal (Adapted from [29])

Table 1. ECG signal components

ECG components	Duration [ms]	Amplitude [mV]
P	60-100	0, 2- 0,4
PQ	120-200	-
QRS	60-110	1 – 2
ST	80-120	
T	160-200	<1
QT	280-370	

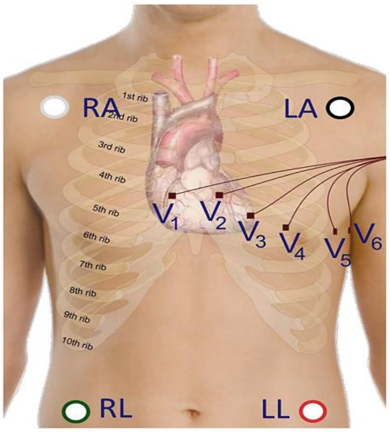

Fig. 2 ECG electrodes positioning.

The deflection sign indicates approaching (positive deflection) or moving away (negative deflection) of the excitation wave concerning the recording electrode. Table 1 reports the detailed features of ECG waves.

To record an ECG, it is necessary to position electrodes on the surface body to obtain derivations arranged in such a way as to analyze well the variations of the heart dipole vector. They are indicated as Einthoven's peripheral or bipolar leads, unipolar leads, and Wilson's precordial or thoracic derivations (Table 2). Bipolar leads are identified with the notations: RA for the right arm, LA for the left arm, LL for the left leg, and RL for the right leg, taken as a reference, connected to the ground (Figure 2).

Positioning the electrodes on the left and right wrists and the left ankle produces an equilateral triangle: the triangle of Einthoven, which has the heart at its center. The bipolar leads then record the cardiac electrical activity as these results from its projection on the side of the triangle. The three derivations obtain by taking the potential difference between the two electrodes, as indicated in Table 2: VI = VLA-VRA; VII = VLL-VRA; VIII = VLL-VLA.

Unipolar leads explore the frontal plane along the bisectors of the corners of Einthoven's triangle. Specifically, connecting the extremes of each derivation with two equal resistances and using the junction between them as a reference, respect at the electrode placed on the opposite vertex of the triangle, recording is obtained along with three other directions, corresponding precisely to the bisectors of the triangle itself. This, considering the junction of the two resistances, such as the reference electrode and the electrodes on the right and left arm and left leg as exploring electrodes, the three unipolar leads of the limbs are obtained. They are called aVF, aVR, and aVL (Table 2).

Wilson's precordial or thoracic derivations are used to identify and locate, in an exact way, the lesions that could escape with the use of other leads and to analyze the vector of cardiac depolarization on a plane other than the frontal one. Precordial derivations are defined in Table 2.

V1 and V2 record the events of the right ventricle, while V4, V5, and V6 are those of the left ventricle; V3 is called transitional. Thus, the twelve derivations allow a complete analysis of the heart's activity locally and generally.

Table 2. The standard placement of leads

Name of Lead	Electrode Placement]	
Einthoven's peripheral or bipolar leads.	*Reference (-) Electrode*	*Reference (+) Electrode*
I	RA	LA
II	RA	LL
III	LA	LL
Unipolar leads		
aVF	RA and LA	LL
aVR	LA and LL	RA
aVL	RA and LL	LA
Wilson's precordial or thoracic derivations		
V1		4th ICS, right of sternum
V2		4th ICS, left of sternum
V3		halfway between V2 and V4
V4		5th left ICS, mid-clavicular line
V5		5th left ICS, anterior axillary line
V6		5th left ICS, middle axillary line.

[1] *RA: right arm; LA: left arm; LL: left leg; RL: right leg; ICS: intercostal space.*

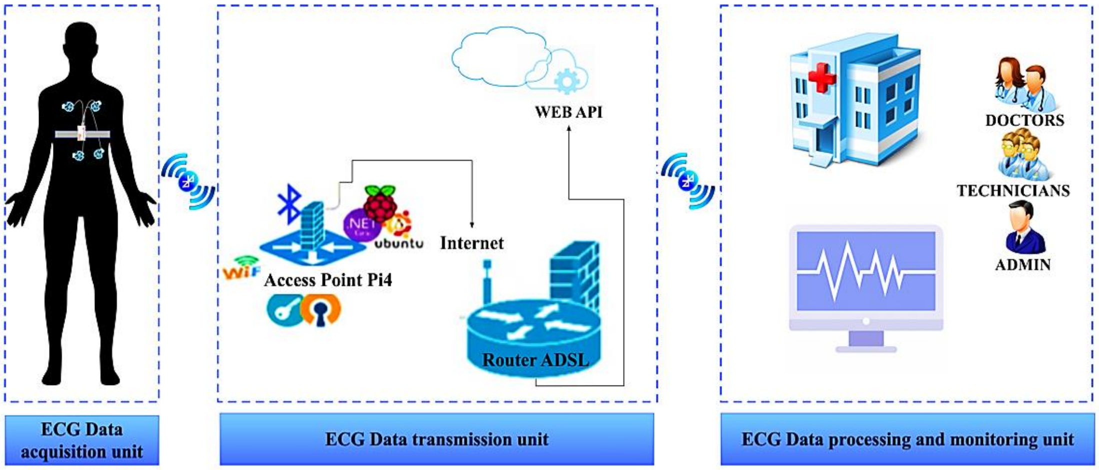

Fig. 3 ECG system monitoring architecture

3. System Description

The architecture of the ECG system, illustrated in Figure 3, consists of the following main block components:

- ECG Data acquisition unit acquires ECG signals in a non-invasive way. The module amplifies, preprocesses, and digitally converts ECG signals. Then, it transmits ECG data to the following unit through Bluetooth technology.
- ECG Data transmission unit manages ECG data transmission to the remote system through the Internet network.
- ECG Data processing unit processes and extracts significant ECG features to support the clinical decision.

3.1. Data Acquisition Unit

The ECG acquisition unit must be suitably designed for remote and real-time physiological monitoring to acquire user signals through wearable and non-invasive sensors and transmit them to a processing unit. Therefore, the Sensing Health with Intelligence, Modularity, Mobility and Experimental Reusability (SHIMMER) ECG unit [23, 51-52] has been chosen since it presents a configurable digital front-end optimized for measuring physiological signals for ECG. It provides sensors to record the pathway of electrical impulses through the heart muscle on resting, ambulatory subjects or during exercise. The Shimmer3 [51] is a wearable sensor platform with Bluetooth class 2 connectivity for data collection. It allows flexible wireless support and enables the user to control data acquisition in real-time for better interpretation, suitable for several application contexts. SHIMMER platform used an incorporated MSP430 microcontroller for processing. At the same time, for communication, the ChipCon CC2420 radio with Revering Network RN-42 has a communication range of up to 10 m, while the default baud rate (transmission rate) is up to 115 K bauds [52]. Figure 4 shows the internal block diagram of the ECG data acquisition unit. Biological signals are collected from the skin via five externally connected wires to the ECG Unit and attached to the ECG snap-on electrodes [24]. They feature a patented pre-gelled non-irritating adhesive side, specially developed to prevent allergic reactions, and are made of latex-free foam material suitable for every skin type. Specifically, it is possible to acquire the following leads:

- Bipolar leads:
  - Lead I (LA-RA) is output on the ExG1 Ch2 channel of the ECG unit.
  - Lead II (LL-RA) is output on the ExG1 channel Ch1 of the ECG unit.
  - Lead III (LL-LA) is obtained by subtracting Lead I from Lead II.
- Unipolar leads:
  - Vx-WCT is the ECG signal measured from the Wilson center terminal voltage (WCT) at the Vx position. Therefore, any unipolar Vx lead (i.e., V1, V2, V3, V4, V5, and V6) can be measured on the ExG2 Ch2 channel by placing the electrode at the Vx input (see Figure 4).

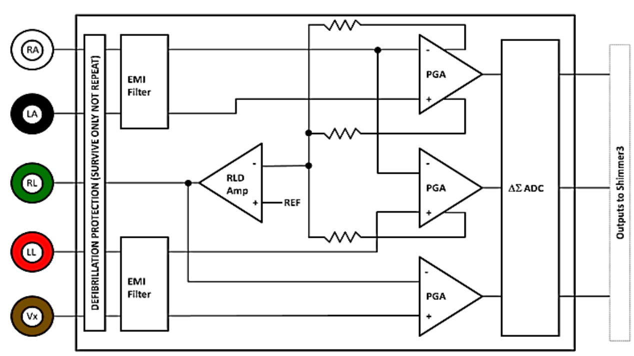

Fig. 4 Shimmer3 internal block diagram

Wilson's Central Terminal (WCT) represents the mean potential of the body and serves as a reference point against which the voltage difference for the unipolar leads is acquired. First, it is derived by averaging the voltage measured on the RA, LA, and LL electrodes. Then, the inverted WCT voltage is sent to the body via the RL electrode to create a negative feedback loop and achieve common-mode interference rejection. Each Shimmer3 ECG unit has two Texas Instruments ADS1292R chips; each has eleven bytes for configuration register settings. A data rate of at least 500 SPS to acquire ECG signals was selected. Moreover, for the ECG, a gain value of 4 is recommended.

3.2. Data Transmission Unit (hub)

The data acquired through the Shimmer sensors are sent over the network thanks to a hub device. The Raspberry PI4 device was selected for its economic and technical characteristics and immediate availability. The choice fell on this hardware not only for its cost but also for its ease of use.

Furthermore, the operating system can be installed on an external SD card; therefore, even a possible system replacement could be immediate and straightforward. The Ubuntu server 20.04.1 operating system has been installed inside the Raspberry Pi4 device (Figure 5).

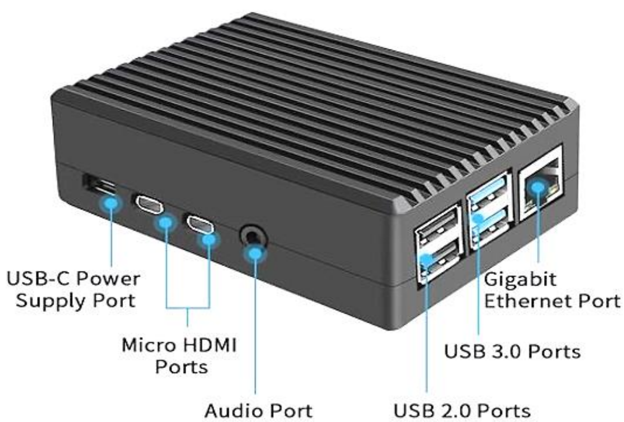

Fig. 5 Raspberry PI 4

The data is sent to the server through RESTful Web API calls. The data received is persistent to system crashes and the lack of Internet connection thanks to a local SQL database. The Raspberry Pi4 has been configured as a wi-fi access point and connects to the Internet via the ethernet cable. So, for example, it is possible to communicate with a tablet and then configure the system, check the parameters, and check the Bluetooth or the Internet connection through an application created specifically for these functions [30, 31].

3.3. ECG Data Processing and Monitoring Unit

The software control panel for acquiring and processing ECG signals was created using the National Instruments LabVIEW programming language (Laboratory Virtual Instrument Engineering Workbench-National Instruments, Inc, Austin, TX, USA). The Shimmer LabVIEW Instrument Driver Library [25] of LabVIEW VIs allows users to easily interact with the LabVIEW development environment offering several signal processing and analysis tools and providing the ability to solve and execute complex algorithms in real-time [59]. In addition to the acquisition of ECG signals, the control panel (described and illustrated in more detail in Section 4) also provides data processing through the implementation of high pass, low pass, and notch filters and several signal processing operations to define a complex scenario of derived functional parameters. Figure 6 illustrates the steps of ECG signal processing and analysis, described in detail in the following subsections.

3.3.1. ECG Pre-processing

Preprocessing is a crucial step because it aims to improve the signal-to-noise ratio of the ECG-acquired signals and enhance the analysis's accuracy. Specifically, the ECG signals can be corrupted by noise, such as baseline wander and powerline interference, electrode contact noise, electrode motion artifacts, and muscle contractions. Frequency filtering such as band-pass filters (with cut-off frequencies 0.05 – 150 Hz, Butterworth topology) and notch filters (50/60 Hz) have been implemented to attenuate low and high-frequency noise external to the ECG band (e.g., electromyographic artifacts due to muscle contractions) and power line interference, respectively.

Fig. 6 ECG data processing steps

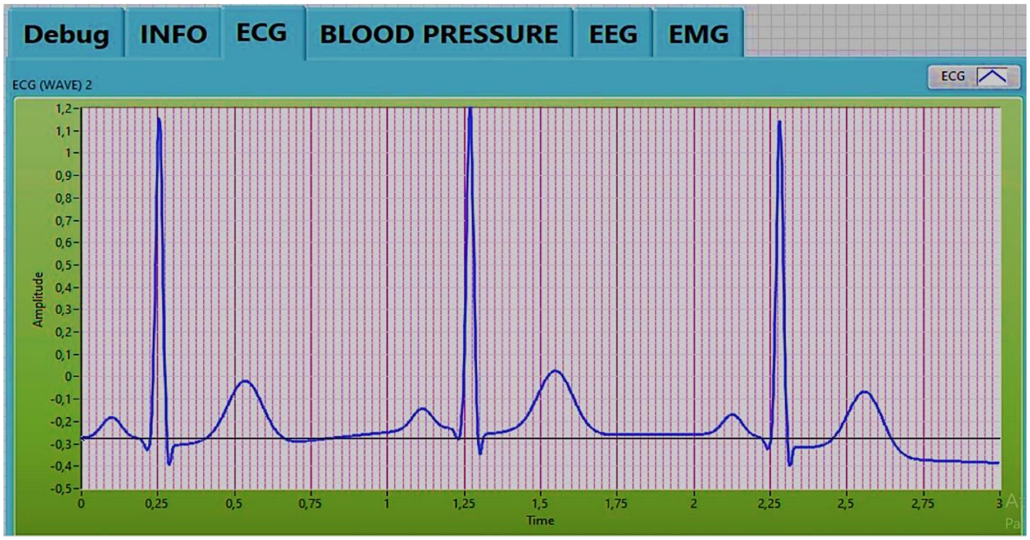

Fig. 7 Control panel (ECG module) showing normal electrocardiogram wave.

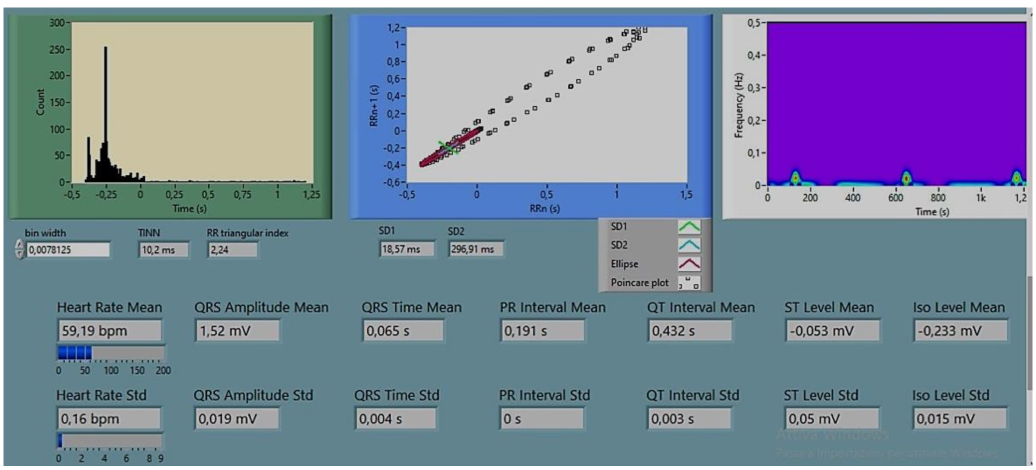

Fig. 8 Control panel for real-time ECG screening and functional parameters monitoring.

3.3.2. Features Extraction

For ECG analysis, time-domain measurements are commonly used. However, for the scientific purpose of this study, different methods were implemented to analyze ECG signals. Indeed, time-domain, frequency-time domain, and nonlinear heart rate variability analysis are performed and illustrated (Fig. 7 and Fig. 8) [57, 59].

Time-Domain Analysis

From filtered ECG signals, several time-domain measurements are extracted. Below is a detailed description of each of them. Heart rate, expressed in beats per minute (BPM), has been calculated starting from the electrocardiogram using the R waves, which are part of the QRS complex of the ECG signal. Specifically, the RR interval extraction process involves a peak detection step by thresholding. Moreover, this parameter's mean value (Heart Rate Mean) and standard deviation (Heart Rate Std) are evaluated. Features extractor involves not only the detection of R peak but also the finding of other signal features, such as P, Q, S, and T amplitudes and durations. After R peak detection, all waves were extracted by searching the local maxima in specific time intervals. The PR interval is the period, measured in seconds, from the beginning of the P wave (the onset of atrial depolarization) until the front of the QRS complex (the start of ventricular depolarization). This parameter's mean value (PR Interval Mean) and standard deviation (PR Interval Std) are indicated. The QT interval is the time, measured in seconds, from the beginning of the QRS complex, representing ventricular depolarization, to the end of the T wave, resulting from ventricular repolarization. This parameter's mean value (QT Interval Mean) and standard deviation (QT Interval Std) are indicated. The ST Level is the amplitude, measured in mV, of the ST segment, between the end of the S wave and the beginning of the T wave. This parameter's mean value (St Level Mean) and standard deviation (ST Level Std) are indicated. Another valuable analysis for physicians is the histogram plot of RR intervals. TINN (Triangular interpolation of RR histogram), measured in ms, is the baseline width of the RR interval histogram. RR triangular index is the total number of all RR intervals divided by the height of the histogram of all RR intervals.

Time-Frequency Domain Analysis

The frequency-domain analysis method works well for RR interval signals that do not vary much over time. However, for such HRV analyses, RR interval signals differ significantly over time. So, the time-frequency methods to analyze stationarity and time-frequency behavior were chosen. Short-Time Fourier Transform (STFT) was implemented to show the time-frequency plots and perform qualitative analysis.

Nonlinear Analysis

Analysis based on the Poincaré plots was also adopted, considering that the RR interval signals are nonlinear because they result from complex hemodynamics, electro-physiological, humoral variables, and autonomic and central nervous regulations [58]. Poincaré plot is the most used approach among the nonlinear methods to calculate heart rate variability [26]. The graph plots the RR intervals (the distance between each heartbeat), with the RR interval just prior, showing how well each RR interval predicts the next. More in detail, this scatter plot represents a map of points (RR_ivs RR_{i+1}) in Cartesian coordinates, and each of them is represented on the x-axis by the previous normal RR interval (RR_i) and on the y-axis by the following RR interval (RR_{i+1}) [26]. The plot is fitted with an ellipse with a semi-major axis as a bisector of plot axes. SD1 (transverse semi-axis of the ellipse) is the short-term variability and reflects beat-to-beat variation. It is expressed in ms. SD2 (longitudinal semi-axis of the ellipse) is the long-term variability and reflects the overall fluctuation. It is said in ms.

3.4. System Key Features

Compared to the current wearable device that records the heart's rhythm, the proposed system can be used for real-time ECG monitoring and to acquire EMG bio-signals. Moreover, the system does more than just record and transmits the received signals to the cloud application, such as available Holter monitors. Thanks to the Raspberry hub, it carries out a preprocessing of the movement, efficiently managing the transmission of the received data. The signal analysis can be performed in real-time, not only after the acquisitions. Thus, immediate feedback can be provided to the patient on their health condition. Considered the overall SIMpLE platform, this system allows remote monitoring acquiring; the system helps monitor vital physiological user parameters and bio-signals in real-time to ensure high-security conditions. The platform allows medical staff to monitor the patient's health conditions remotely and intervene in the setting of the electronic system. Thus, using the design provided, it is possible to carry out the first intervention screening with a remote teleconsultation method and process bio-signals, such as ECG and EMG signals.

4. Results

This proof-of-concept study aims to introduce a real-time remote monitoring system for cardiovascular diseases and to describe the proposed system modules and the ECG signal processing algorithms. The performance of the proposed monitoring system in terms of ECG signals data acquisition procedure through the commercial Shimmer sensors and for identification of fundamental heart anomalies was assessed and confirmed in the literature [52]. In addition, the ECG signal processing pipeline was tested considering data from the PhysioNet service (http://www.physionet.org) from the MIT-BIH Arrhythmia database. Fig. 7 and 8 reported illustrations of the control panel (ECG module) showing regular electrocardiogram waves and a sub-section related to real-time ECG screening and functional parameters monitoring. As preliminary results from time-domain, frequency-time domain, and nonlinear heart rate variability analysis, a quantitative analysis of operating parameters, visualized on the control panel (Fig. 8), is performed. Fig. 9 presents the bio-signals viewer developed for the SIMpLE project on which a regular ECG pattern (data from the MIT-BIH Arrhythmia database) is illustrated [30-31, 54].

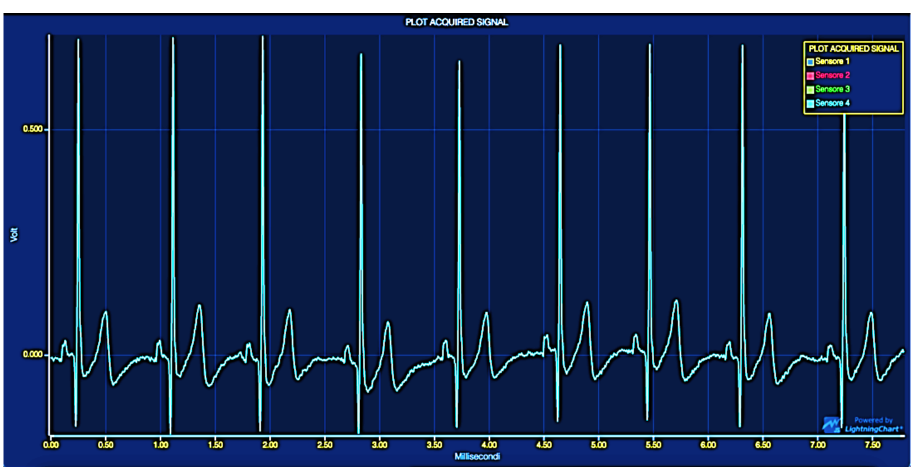

Fig. 9 ECG remote visualization.

5. Discussions

The advancement in sensor-based systems development technology enabled real-time and continuous ambulatory monitoring of vital human signs during daily life, minimizing discomfort and interference with routine human activities and supporting bio-signal-based early diagnosis. During the pandemic emergency of the coronavirus disease 2019 (COVID-19), to avoid (or at least reduce) the infection from Covid-19 and to replace (or at least support) the traditional face-to-face interaction between patients and doctors, remote consultation and monitoring systems have become indispensable to cardiovascular disease management across the world [22].

Furthermore, the exponential growth in cardiac monitoring needs has far exceeded the capabilities of healthcare facilities and many hospital telemetry units. For this reason, innovative approaches are increasingly required and essential to continuously assess cardiac activity and electrocardiographic intervals [59]. The paper aims to introduce a real-time remote monitoring system for cardiovascular diseases, describe the proposed system modules and the ECG signal processing algorithms, and hypothesize a future application scenario in a global pandemic context. Although it is a proof-of-concept study, what makes this contribution innovative is the conception of the described ECG solution as an integrative node of a more sophisticated and secure medical platform, named SIMpLE, described in detail in our previous works [30, 31]. Simple is a mobile cloud-based system to improve the monitoring of disease complications in patients affected by neurodegenerative diseases, such as ALS patients and the elderly [30, 31].

The SIMpLE platform can provide healthcare facilities and users with a complete system for small home cardiological monitoring. Another innovative feature of the integrated ECG system is the implementation of security mechanisms to protect sensing data and user privacy. Data leakage and privacy are significant issues and still represent the principal limits for adopting mobile and cloud technologies in the medical field. The SIMpLE system is hardened and secured according to cybersecurity best practices: firewall, anti-DDoS, and SELinux [30].

Despite the potential of the proposed method in terms of cardiac health monitoring, it needs further improvements in several aspects. First, to test the system and confirm its robustness, the extension of the validation procedure to real ECG acquisitions on control and pathological subjects is required. Secondly, it is necessary to integrate the current system with an automatic detection algorithm that can accurately identify cardiac abnormalities, extract specific features, perform correct predictions, and alarm the patient or the physician [54, 55]. Since the most critical applications of cardiac telemetry in current practice are arrhythmia and other abnormalities detected in hospitalized patients and a living environment, applying specific and sophisticated algorithms can be the optimal way to extend ECG monitoring systems' horizons. Indeed, machine learning and artificial intelligence techniques could transform healthcare services by improving diagnostics and predictive modeling. The preliminary experimental results confirmed that the system could offer an efficient solution for remote and real-time monitoring of multiple patients. The system's key features such as sophisticated signal processing algorithms for faster processing, low power consumption, low cost, and less complexity, as well as the integration of multiple services (patient summary management services, remote control, visualization, and the analysis of acquired signals, management of diagnostic imaging conducted on the patient, and teleconsultation), once validated, could provide significant improvements in a cardiological monitoring context.

6. Conclusion

Our scientific research group's interest has focused for years on developing innovative biomedical technological solutions, providing healthcare facilities (hospitals, clinics, rehabilitation centers, orthopedic clinics) and end users with a complete system for remote home rehabilitation and cardiological monitoring. This paper aims to introduce a real-time remote monitoring system for cardiovascular diseases, describe the proposed system modules and the ECG signal processing in detail, and illustrate the preliminary results on example data. The described system can monitor the patient's cardiac activity, allowing the specialist to control the electronic instruments remotely without leaving their office. The system is thought out for all cardiopathic patients with objective motor difficulties either because they are bedridden or geographically located in places distant from the health facility of interest. Considering the real-time monitoring approach of this system, which allows patients to enjoy real-life activities, including physical exercise and running, and energy-efficient devices and communication technologies, a future application scenario of this system in a global pandemic context can be hypothesized.

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Author Contributions

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