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GoCardio – A novel approach for mobility in cardiac monitoring

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Abstract. *Remote cardiac monitoring of patients helps to improve their quality of life, as it avoids frequent commuting to the health center. Patients are thus able to continue with their everyday life while at the same time they remain non-intrusively monitored. However, current solutions in remote cardiac monitoring are not massively found, due in part to their high price, as well as the difficulties encountered when deploying them in real world clinical environments. In this paper we present the general overview of a novel tele-monitoring system for cardiologic patients, covering both the hardware and software perspectives. Our main objective is to provide an economically feasible solution that preserves quality and efficacy. At the sensor level, we propose an innovative easy-to-wear hardware system that measures the complete 12 ECG leads and the activity patterns of patients. We also propose the architecture of a modular software solution for supporting patient monitoring. Our system offers advanced visualization capabilities mainly based on Visual Analytics techniques and also mining of the collected cardiac data. Our approach is still in its development phase and hence in this article we introduce the basic concepts that have been taken into account for the implementation of the first prototypes.*

Keywords: Cardiovascular disease, monitoring, tele-rehabilitation, electrocardiogram, activity monitoring, multi-agent system, visual analytics

1 Introduction

Cardiovascular diseases (CVDs) are the main cause of death all around the world [1]. Each year CVDs lead to over four million deaths in Europe (47% of the total amount of deaths) and over 17 million deaths worldwide (30% of the total sum) [2, 3]. Due to population ageing and increasing risk factors (i.e. unhealthy diet, physical inactivity, tobacco use and harmful use of alcohol) global annual deaths caused by CVD will increase up to 23 million by 2030, while remaining the single leading cause of death [3, 4]. The economical impact of CVD is as well high: the current estimated overall cost in Europe amounts to €196 billion a year [2]. Considering the increase of the costs in the forthcoming years and the need for maintaining sustainable health systems, the creation of medical services for effective and more efficient treatment and rehabilitation of cardiologic patients has arisen as a relevant necessity.

Cardiac monitoring systems, such as electrocardiogram (ECG) devices, or activity monitoring systems have been applied for years in cardiologic rehabilitation, but their use has been limited to the hospital domain and to small-medium sized groups of patients. Particularly, classical ECG solutions require patients to be physically at their corresponding medical centers, in order to carry out stress tests under medical supervision [5]. This approach requires huge investments both in infrastructure and medical resources, and becomes clearly unsustainable with the increase in number of patients. Although the results obtained are very promising, the analysis time is too short in order to capture infrequent anomalies.

Newer approaches include Holter external systems, which are portable devices for the continuous measurement of electrocardiographic patient signals among large time periods (e.g. 24 hours). They enable the detection of less frequent episodes of interest, and patients do not necessarily need to stay in hospital while data is been acquired. Nevertheless, these systems are too big and uncomfortable for patients, and thus disturb their daily routines. Furthermore, the quantity of acquired data per patient is too high, and tools that facilitate the analysis and the decision making of physicians are still in need.

Recently, other systems have entered to the market, based on mobile devices and portable sensors located in a belt or a T-shirt, such as Nuubo [6], Vitaljacket [7] and LOBIN [8]. They are based on 1-lead or 5-lead ECG configurations and their use is mainly oriented to the sports domain. For the medical domain, solutions covering a more precise signal analysis (i.e. 12-lead), are still needed.

In this work we propose the GoCardio system, a novel approach for cardiologic patient monitoring. It is based on an innovative application of wearable sensors and on an accompanying software platform that embeds advanced visualization and analysis tools. The objectives of the GoCardio system are (i) portability of the system and high autonomy, (ii) usability (unsupervised set up, easy also for older patients), and (iii) economical feasibility of the solution for a real clinical scenario. Our main contributions are focused at two aspects, hardware and software. At the sensor level, we propose an easy-to-wear hardware solution that measures both, the complete 12 ECG leads and the activity patterns of patients. From the software perspective, we also propose a modular solution for supporting patient monitoring. Our contributions in this area are focused on an architectural level, as well as on the classification of cardiologic events and the application of Visual Analytics techniques. Currently the system is still in development and in this article we introduce the basic concepts regarding the implementation of the first prototypes.

This paper is structured as follows: in Section 2 we present some related work relevant for our approach; in Section 3 the general architecture of our system is proposed; in Section 4 a case study of our proposed architecture is presented, and lastly in Section 5, the conclusions and future work are summarized.

2 Related Concepts

In this chapter, we introduce some concepts relevant to our work, regarding cardiac monitoring, activity monitoring, and cardiologic knowledge mining and visual analytics.

2.1 Cardiac monitoring

The most interesting technique to analyze cardiac activity is electrocardiography (ECG). It is a trans-thoracic measurement of the electrical activity of the heart (*i*) detected by electrodes attached to the surface of the skin and (*ii*) recorded by a device external to the body. The standard ECG consists of 12 leads (i.e. I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6). Each lead is determined by the placement and orientation of various electrodes on the body and views the heart at a unique angle. In this way the activity of each of the electrodes can be focused on a particular region of the heart.

Several techniques and electrode configurations have been developed for ECG signal monitoring [9]. However, most of those techniques are not suitable for a remote monitoring system. This is not only caused by the difficulty that a patient may experience during the set up of the system, but also because these systems are often expensive and unpleasant for the patient.

From the hardware perspective, performance optimization is an important issue that needs to be approached. In order to do so, four areas of interest have been identified in the literature [10]: (i) signal acquisition, (ii) signal processing, (iii) wireless communications, and (iv) power management. Fig. 1 depicts the four areas of interest where strategies can be applied to improve the performance.

Electrode impedance, static interference and motion artifact induced by various means are the main points to be analyzed from the signal acquisition point of view. Also, a good processing strategy can simplify the analysis of the signal as well as decrease the information to be sent by the sensors. Additionally, the used data transmission standard sets the main power consumption of the sensor (e.g. Zigbee 30mW, Bluetooth 2.5-100 mW, and MIC 25 mW)[11].

2.2 Activity Monitoring and Energy Expenditure

By combining ECG data with patient's activity, doctors can analyze the progression in patient's recovery. In this way, cardiac problems that only appear during physical activity can be detected. Patient activity is assessed in terms of Metabolic Equivalent of Task (MET), which is the ratio of the metabolic rate during a specific physical activity to a reference metabolic rate (3.5 $ml \cdot kg^{-1} \cdot min^{-1}$ by convention) [12]. Hence, it provides the energy expenditure required by the exercise.

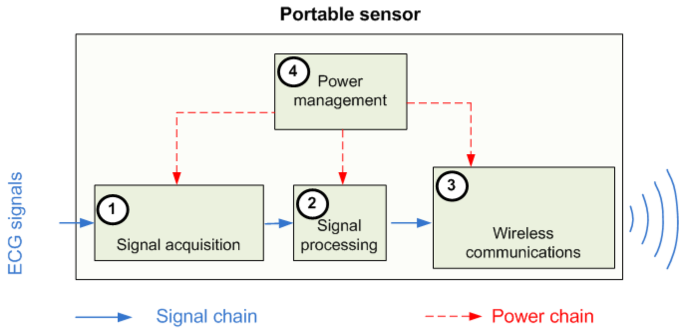

Fig. 1. Areas of interest for the improvement of ECG performance

MET is usually obtained by measuring the oxygen cost of the activity and dividing it by the resting oxygen consumption of an average person [12]. However, it is impractical and expensive to provide every patient with a portable gas analysis system. There is a compendium that gathers the energy cost of a wide variety of physical activities [12], but the level of detail is insufficient for our application.

Another option is the use of accelerometers and gyroscopes, whose output has been found to be related to the metabolic energy expenditure [13, 14]. It is an inexpensive output, but there are some related issues that need to be tackled: (i) sensor placement [15, 16], (ii) automatic classification of the physical activity [17], and (iii) the accuracy of the MET value and the techniques used for the estimation of the reference rates [18, 19].

2.3 Cardiologic Knowledge Mining and Visual Analytics

Cardiac monitoring, rehabilitation and treatment systems require doctors to analyze complex and arguably large amounts of cardiac data per patient in a very short time. Thus, support tools for data analysis, event classification and visualization could be very beneficial for the medical community.

Several ECG data analysis Open Source tools are already available, such as the ones offered by the PhysioNet initiative [20]. One of the provided tools is PhysioToolkit [20], which offers the detection of relevant physiological events, characterizes and visualizes the signals, simulates them, and provides a framework for evaluation. Other tools such as Ecgpuwave [21] are only oriented to the identification and delimitation the different parts of an ECG signal. Also, the PhysioBank ECG database is provided to allow the testing of the performance of new algorithms [20]. Traditional data mining and classification techniques have also been applied in the literature, both for ECG data classification, such as in the work of Rodriguez et Al. [22], and for activity classification [17]. In our work we will reuse available tools for signal analysis and will focus on the development of new visualization techniques and systems.

In this context, Visual Analytics is defined as the science of the analytic reasoning supported by visual interactive interfaces [23]. It integrates new computational tools for visual representation based on cognitive, perceptual and design principles, and oriented to facilitating the human-information relation. The application of Visual Analytics techniques to cardiologic data visualization is intended to improve the efficacy and the efficiency of cardiac monitoring systems. During the last years new theories and paradigms have been proposed, such as the bull's eye 17 segment visualization in [24] and 3D surface visualizations [25]. In our work, we will focus on multi-patient visualizations, as well as on combined representation of ECG and activity data.

3 Proposed Methodology

In this section we propose the general architecture of the GoCardio system. It combines both the hardware and software perspectives needed for cardiac monitoring. In particular, it is oriented for patients in phase II and III of cardiac rehabilitation (CR). Phase II of CR includes supervised exercise in a hospital, whereas it is unsupervised in phase III but maintains periodic monitoring [5]. GoCardio aims (i) the minimization of the commuting process of phase II, (ii) the improvement of the monitoring of phase III, and at the same time, (iii) the reduction of the costs of CR. For this purpose we propose a 5-layered architecture, depicted in Fig 2. The different layers are: ***Sensor***, ***Communications***, ***Data Handling***, ***Application*** and ***User***.

The **Sensor Layer** contains both the ECG and the activity sensors. 10 ECG wet sensors will be placed in a t-shirt, locating transducers, cables, the signal amplifier and the microprocessor in the configuration that offers the optimum signal-to-noise ratio. Activity sensors will be composed by accelerometers, which measure the intensity and frequency of the movement, and also gyroscopes, which sense the angular motion. With the data provided by these inertial sensors (*i*) a classification algorithm can predict the kind of activity that the user is doing, and (*ii*) a regression algorithm can estimate the energy expenditure in METs. This methodology has been proven valid in either clinical settings or free-living environments [26, 27]

The **Communications Layer** is in charge of handling communication channels and protocols between (*i*) the sensors and the patient mobile devices, and (*ii*) the latter and the cloud platform. As data transmission is the most energy-demanding task done by the Sensor Layer, the selection of the first will strongly affect the battery autonomy of the sensors. In that regard, and even if energetically it is not the most efficient one, we propose the use of a Bluetooth solution. Its power consumption rate is acceptable and most mobile devices provide this communication protocol.

The **Data Handling Layer** connects to a cloud platform that will (*i*) store data sent by patients' mobile devices, (*ii*) analyze the data for the detection of relevant cardiologic episodes, (*iii*) handle alerts and recommendations related to the detected episodes, and (*iv*) provide intuitive visualizations to support physicians. In order to provide the platform with the needed modularity and scalability a Multi Agent Based (MAS) approach is proposed (depicted in Fig 3.), following our previous work on architectures for decision support systems [28]. In particular, five different agents are proposed: (*i*) majordomo, (*ii*) information, (*iii*) classification, (*iv*) alert management, and (*v*) interaction and visualization. Our architecture follows a blackboard approach [29], where inter-agent communication is only carried out through the majordomo agent. In this way, security- and asynchronism-related issues are avoided. The majordomo agent is thus in charge of coordinating the rest of the agents. The first of them is the *information agent*, which is responsible for accessing, storing and editing cardiologic data in the patients' database. This database includes ECG and activity data from patients during rehabilitation sessions that have been monitored. The *classification agent* is responsible for classifying these data and identifying the relevant episodes of a patient data stream, as well as the activity performed at every stage. Depending on the episodes detected for each patient, the *alert management agent* will send alerts to the corresponding doctors. Finally, the *interaction and visualization agent* is responsible for visualizing patients' ECG and activity data, the generated events as well as the alerts.

The interaction between users and the system will be held by graphical user interfaces (GUI) in the **Application Layer**. Patients will switch on and off the data acquisition and transmission by a mobile application. Doctors will be provided with a web application, where they can access their patients' data, visualize them in an intuitive way, get alerts from relevant episodes, as well as recommendations to follow.

Lastly, the **User Layer** contains patients and doctors using the system. A user profiling module will characterize each user, in order to provide a personalized service. Security and confidentiality of data will be guaranteed.

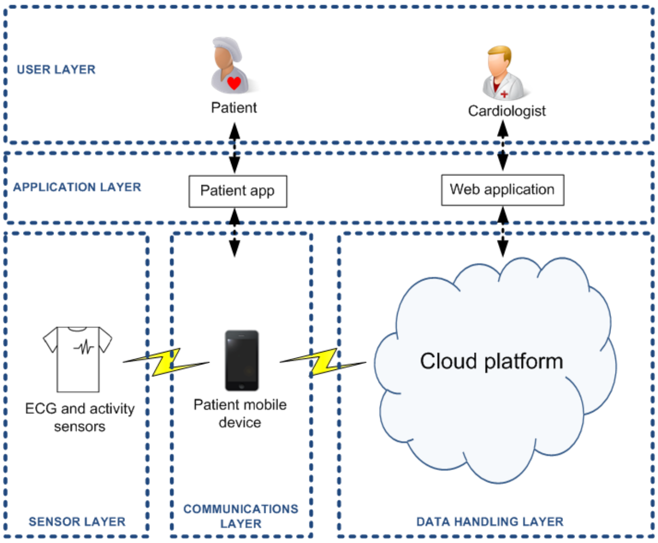

Fig. 2. General architecture of the system

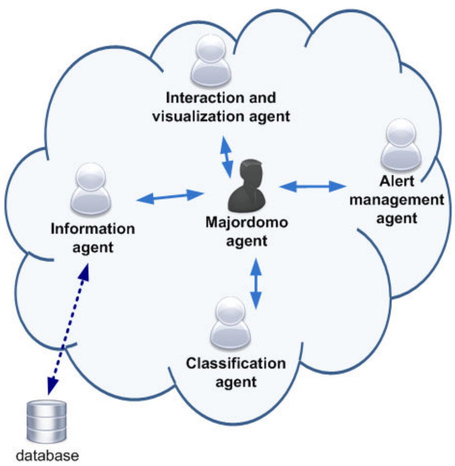

Fig. 3. General architecture of the system

4 Case Study

As mentioned early, the GoCardio system is still in its development phase. However, in this section we will describe the test scenario that we will follow during the forthcoming months, as well as some implementation details of interest.

4.1 Test Scenario

The test group will be composed by forty patients from the Donostia University Hospital in Spain. In particular they correspond to patients in CR of phase II and III, of different ages and physical conditions, 20 of them men and 20 women.

The participants will carry the GoCardio ECG and activity sensors described below, and also a portable gas analysis system to measure the oxygen consumption. During the tests, they will perform four different exercise routines, which are part of the current cardiac rehabilitation process of the hospital: (*i*) walking in a treadmill at different speeds and with different slopes; (*ii*) cycling in a stationary bike at different speeds; (*iii*) upper body workout; and (*iv*) low body workout.

The purpose of this test is twofold: (i) to provide the required data for the validation of the physical activity detection algorithms; and (ii) to evaluate GoCardio as a valid tool for physicians in terms of performance, usability and utility of the system.

4.2 System implementation

For the ECG sensors in the **Sensor Layer**, a 12-lead ECG system is being developed, based on the Texas Instruments amplifier ADS1298. Regarding sensor locations, we have performed preliminary experiments, which show that to obtain the best signal quality the ECG cables have to be placed over the shoulders. This placement reduces the artifacts that are generated in the signal due to the changes in the electrode-skin impedance when the patient is not at rest. Following this sensor placement we have proposed a design of a sports shirt, where the cables of the ECG sensors are routed as depicted in Fig 4.

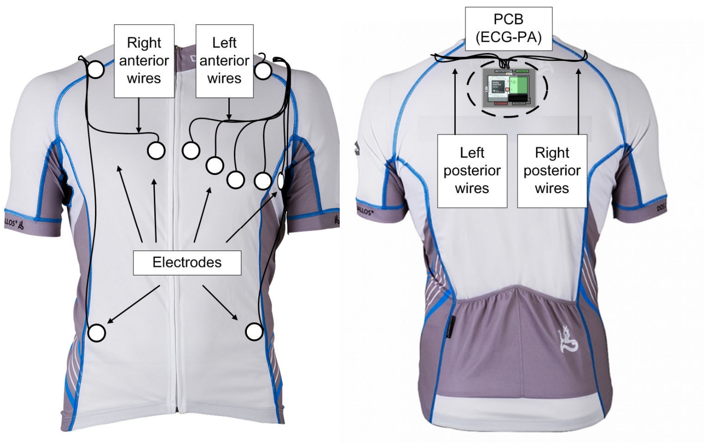

Fig. 4. Routing the cables of the ECG system

For the activity sensors the STT-IBS inertial sensors will be used. They provide 9 degrees of freedom, as a three-axial accelerometer, a gyroscope and a magnetometer are included in each unit. For the test scenario a 4-inertial-sensor-configuration will be followed for each patient, placed on the waist, ankle, low back and upper back. During this testing, a study will be made to discard the least informative locations and if possible propose a final design containing less inertial sensors.

As it was explained in section 3, GoCardio implements inertial sensors to detect the kind of exercise that the user is doing and to estimate the energy expenditure in METs based on classification and regression algorithms respectively. These algorithms will be developed by us, hence, with the data provided in the test scenario both algorithms will be validated and compared to the ones presented in the state of the art [12, 19]

The collected ECG and activity data will be sent by Bluetooth (**Communications Layer**) to the patient's Smartphone and by 3G from there to the GoCardio Cloud Platform (**Data Handling Layer**).

In the GoCardio Cloud Platform the acquired data will be classified. The proposed implementation steps for the beat classifier of the GoCardio system are shown on Fig. 5. A training dataset will be extracted from the open PhysioBank database [20] and a classifier will be build with Weka [30], comparing different algorithms and selecting the optimum. Following the results presented by Rodriguez et *Al*. [22], we will start our study with the C4.5 decision tree classifier, the IB1 Nearest Neighbor algorithm, and the Multilayer Perceptron Neural Network.

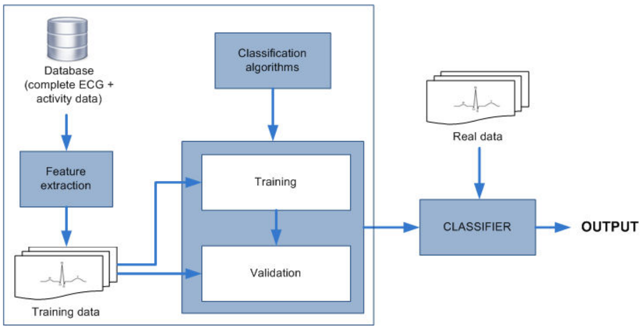

Fig. 5. Classification schema

For the visualization of the results we propose three different paradigms, which are oriented at three different levels: (i) the visualization of the data corresponding to a patient at a certain rehabilitation session; (ii) the visualization of the evolution of a patient among the rehabilitation period, and (iii) the visualization of the state of the different patients at a certain time, in order to prioritize medical efforts. The analytics will be implemented following a role based approach that will generate multi dispositive representations initially of one set of ECG and activity data, and if required, a multiple set view that will present in one output the general view of the patients being monitored.

5 Conclusions and Future Work

In this paper we have presented a cardiologic tele-monitoring system for CVD rehabilitation. The presented system allows a better unsupervised monitoring of patients, and rehabilitation tasks can be continued without collapsing hospital resources.

We have presented the general architecture of the system, covering both the hardware and the software perspectives. For the hardware solution we have proposed the combination of ECG and activity sensors. We have presented a 12-lead ECG sensor design, as well as the use of 4 inertial sensors for the measurement of the activity performed by patients in METs. All these sensors are easy-to-wear and patients can easily set up the system without professional help.

For the software solution, we have proposed the architecture of a cloud platform dealing with detection of cardiologic events of interest and visualization of data.

The proposed architecture is based on a MAS paradigm, which allows the needed modularity and scalability of the system in a real clinical environment.

The GoCardio system is currently been implemented. Details of such implementation have also been presented in this article. The system will be tested in Donostia University Hospital in a near future and results from such validation will be further published.

As future work we will study multi-patient visualization paradigms, which could improve efficiency and speed up the data analysis effort done by doctors.

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