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A smartphone-centric platform for remote health monitoring of heart failure

Igor Bisio, Fabio Lavagetto, Mario Marchese*,† and Andrea Sciarrone

Department of Electrical, Electronics, and Telecommunications Engineering and Naval Architecture, University of Genoa, Via dell'Opera Pia 13, 16145, Genoa, Italy

SUMMARY

Heart failure is a chronic disease that alternates intense and weak phases and requires repeated and frequent hospital treatments. The use of automatic instruments for a remote and ubiquitous monitoring of biological parameters relevant to heart failure pathophysiology offers new perspectives to improve the patients' quality of life and the efficacy of the treatment.

The platform described in this paper represents an implementation of an automatic remote monitoring tool where smartphones play a crucial role. They are not employed just to communicate through traditional client-server applications and they are not only the hub of information sent by sensors, but they also act as intelligent processors and autonomous sensors of the patients' motion through a high-accuracy activity recognition algorithm. The proposed platform combines the evolution of health systems and the consequent needs of modern telemedicine with the current *context-aware* capability of recent smartphones, obtained by implementing specific algorithmic solutions, and with the *anything*, *anytime*, and *anywhere* communication capability of the pervasive communications paradigm. Performance evaluation focuses on the accuracy of the activity recognition estimation, on its applicability to real life, and on the data exchange between smartphones and medical server, allowing to envisage the potential of the designed platform. Copyright © 2014 John Wiley & Sons, Ltd.

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KEY WORDS: wireless communications; remote health monitoring; activity recognition; smartphones

1. INTRODUCTION

1.1. Modern telemedicine

Telemedicine applications provide healthcare services through information and communications technologies overcoming the geographical separation of patients and providers [1] and may be structured into three categories: televisits, to conduct patient examinations from remote sites; teleconsults, to provide remote medical consults; and telemonitoring, where patient's vital clinical data are collected and transmitted from home, streets, and other locations, to remote medical centers. Telemonitoring is widely used and is beneficial for chronic diseases such as diabetes, heart failure (HF), and chronic obstructive pulmonary disease. It represents the framework in which this paper is developed.

Modern telemedicine includes the ability to provide medical services through wireless devices and is the result of the evolution of two systems [2], Health and Technology. Health needs telemedicine for economic and efficiency reasons, and technology offers the tools: sensors, telecommunications networks, mobile phones, and smartphones. Solutions have been recently developed to control obesity through mobile applications [3], to monitor the biological activity of an individual [4], and to detect possible falls of elderly and ill people [5, 6].

*Correspondence to: Mario Marchese, Department of Electrical, Electronics, and Telecommunications Engineering and Naval Architecture, University of Genoa, Via dell'Opera Pia 13, 16145, Genoa, Italy.
†E-mail: mario.marchese@unige.it

The paradigm of pervasive computing [7], also called ubiquitous computing, is a model of human-machine interaction where computing and processing power is totally integrated in everyday objects and activities and considers seamless, intuitive accesses [8]. These objects can communicate with each other and with other components, thus forming a pervasive/ubiquitous network. The idea, perfectly focused in [9], is to sense physical quantities, which present a wide set of input modalities (vibrations, heat, light, pressure, magnetic fields, and so on) through sensors, and to transmit them over suitable seamless communication networks with the goal of gathering information and supporting decision and control processes and authentication [10]. Historically, the concept of ubiquitous computing and networking was introduced by Mark Weiser and is described in [7], which presents a world where sensors and digital information are an integral part of everyday life. The resulting scenario involves the complete immersion of people in a telecommunication network that allows sending and receiving digital information from the surrounding physical world and unconsciously interacting with it. Modern telemedicine and telemonitoring is quite close to Weiser's vision and represents a real implementation of pervasive computing where anything may be connected anytime and anywhere.

1.2. Structure of a modern telemonitoring platform

A person-centered modern telemonitoring platform may be structured into four essential elements [11]: (i) people who need to be monitored (regarding, for example, vital physical quantities such as temperature, cholesterol, blood pressure and sugar level, heart rate, and weight, but also motion and activity); (ii) sensors/devices/systems actually measuring physical quantities, motion, and activity, such as thermometers, cholesterol test kits, blood pressure cuffs, glucose meters, weighting scales, and electronic vests composed of groups of sensors, as done for the ElectroCardioGrams (ECG)—shirt with dry electrodes woven into the plastic fibers, described in [12]—and for MyHeart Project summarized in [13]; (iii) hubs, which collect the measurements and send them to the final destinations through telecommunication networks; they may be personal computers, laptops, mobile phones, and smartphones; (iv) final destinations, such as physicians and other health care providers, disease management services, and family care givers. The mentioned four elements should be integrated with a telecommunication network connecting hubs to final destinations, also considering the interoperability issue, widely discussed in [11]. The communication scheme of a modern telemonitoring platform is shown in Figure 1.

1.3. A new role for smartphones

Smartphones can play an important role in future telemonitoring for health. The hub role of smartphones and mobile phones, mentioned earlier and employed in many real systems as indicated in [11], in the Phmon research project [14], led by the Institut für Technik der Informationsverarbeitung at the Universität Karlsruhe, in [15] and [16], among the others, simplifies both the acceptance of the system by the patients and, technologically, the sensor connection and the forwarding of measurements to the interworking network. In more detail, enhancing the role of personal phones in health telemonitoring

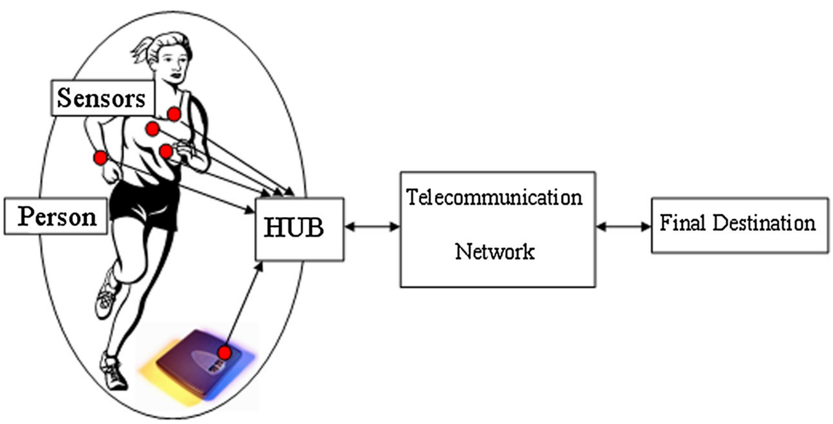

Figure 1. Example of communication system of a person-centered telemedicine platform.

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platforms should increase the role of patients driving care coordination and being part of the care planning process [11]. From the technical viewpoint, one of the open problems of real telemonitoring systems is interoperability, both between devices and hub and between hub and final destinations. Mobile phones and smartphones are already integrated within an extensively tested telecommunication network for data and voice transmission [17] and, in many cases, already provide the necessary interfaces to connect to devices. Moreover, Internet-connected smartphones are increasingly present in people's pockets and homes [1]. In consequence, the great expansion of cellular communication networks can solve many problems concerning connectivity coverage. Beyond connectivity, Pecchia *et al.* [18] outlined three other critical factors for telemonitoring platforms: usability, quality of transmitted data, and interference with other devices. Even without completely solving all such issues, smartphones represent a suitable solution. Their usability has made them extremely widespread and the technical solutions they employ to assure data and voice transmission provide both data integrity and robustness to interference.

The idea carried on in this paper is to give smartphone a new additional role: not only hub but 'hub + sensor + processor'. The idea of having a 'hub + sensor' capability is not totally new: Sarasohn-Kahn [2] stated that

> Sensor technologies combined with mobile communications can be used to track various health measurements for patients and loved ones. Among a long list of sensors that can be incorporated into smartphones and used for health monitoring are: accelerometers that register different motions and walking 'gait'; infrared photo-detectors that measure body temperature, heat flux and heart rate; glucometers to measure blood glucose.

> Boulos *et al.* [16] stresses the same concept.

This paper reasserts these ideas, adds the processing function to the smartphones, and describes a practical implementation of a technological platform, designed for remote health telemonitoring for HF, which is studied, implemented, and extensively tested by the authors of this paper, for now only from the technical, not medical, viewpoint, in which smartphones have a central 'hub + sensor + processor' role. Suh *et al.* [19] proposed an architecture, called WANDA, which implements similar functions for patients suffering from HF, although the activity recognition algorithm is different, as highlighted in the remainder of this paper.

The implemented telehealth platform is composed of a peripheral area network (PAN) that includes a pulse oximeter to measure the saturation of peripheral oxygen and a weighting scale to measure the body weight. These quantities are communicated to a smartphone through Bluetooth interfaces. The smartphone collects information from the PAN (hub function), uses its internal accelerometer (sensor function), processes data to detect the activity of the patient (processing function), and sends the information to a medical server (MS) through a wide area network (WAN), implemented through a telecommunication network accessed by the smartphone through its available radio interfaces.

The paper is organized as follows: Section 2 stresses the importance of a telemonitoring support for patients suffering from HF and presents a brief overview of the state of the art of telemedicine solutions for HF. Section 3 presents the smartphone-centric platform introduced in this paper and lists the technical details of the implemented platform. Section 4 focuses on the activity recognition algorithm. Section 5 contains the performance evaluation, and Section 6 presents the conclusions.

2. THE CASE OF HEART FAILURE

2.1. The importance of telemonitoring for heart failure

Heart failure is a chronic disease consisting in the heart's limited ability to provide a sufficient blood flow to satisfy the entire body's needs. Such condition can be diagnosed with echocardiography and blood tests. The treatment commonly consists of continuous lifestyle measurements, as well as drug therapy and, in very critical cases, surgery. Typically, the monitored lifestyle forbids smoking and includes breathing protocols, dietary changes, and light physical activity. As for patients suffering from other chronic diseases, patients affected by HF greatly benefit from a continuous monitoring

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of both vital parameters and lifestyle (see [20] and references therein). Early identification of initial instability often allows performing appropriate therapeutic actions and preventing the progression to advanced stages that require hospitalization and, in particular, cause biological damage with progressive deterioration of the patient's clinical condition.

Heart failure is an increasingly widespread disease in industrialized countries and is the leading cause of hospitalization in Italy (data from the Italian Ministry of Health). HF patients require highly frequent re-hospitalizations: over 70% of HF patients, discharged after an intense episode, will be treated at least once again in the following 12 months. Obviously, this implies high costs, which must be rationalized for budget reasons. For the mentioned medical and economic reasons, HF treatment may benefit from remote telemonitoring of vital parameters and lifestyle.

In this context, the most used parameters in medical practice are body weight, transthoracic and body impedances, blood pressure, and heart rate. In this paper, arterial oxygen saturation, body weight, and patient activity have been taken into account by following the requirements of the medical team that is participating to the research framework in which this platform has been developed.

These parameters have two characteristics that make them interesting for the purpose defined earlier: they are clear signs of clinically relevant conditions and they are easily detectable in a noninvasive way. As far as lifestyle is concerned, from the clinical viewpoint, it is very important to monitor physical activity on a daily basis. The telemonitoring platform proposed in this paper allows performing daily physical activity monitoring by using only smartphones, thus reducing the dedicated sensors worn or managed by patients.

2.2. *Brief survey of the state of the art of telemedicine for heart failure*

Concerning HF patients, a first computerized approach to store and compute clinical data has been introduced in 1995: Wijbenga [21] described a workstation where a client/server-based application was used to access an amount of stored data regarding HF symptoms and signs employed to classify the severity of the patients' condition.

More recently, the information and communications technologies community effort has focused on remote patient monitoring. Two important experiences are described in [13, 22]. Suh *et al.* [22] illustrated WANDA B. platform. It involves sensors such as a Bluetooth weighting scale and devices to monitor blood pressure and glucose, includes an activity monitoring system (an accelerometer-based activity recorder) and a modem working as a hub to send the acquired data over the phone telecommunication network toward the final destinations on the physicians' side, where data are accessed through Web interfaces. Smartphones are used only for nomadic data access through the mentioned Web interfaces. In [19], a new release of the platform WANDA B, in which the smartphone is used to detect the movements of the patients, has been presented. As previously mentioned, the main difference with respect to the proposal of this paper concerns the activity recognition algorithm and the corresponding skill to individuate precise movements of patients. A numerical comparison between the proposal of this paper and the approach in [19] is proposed in Section 5. Reference [13] proposes a system to remotely manage HFs. The proposed platform is divided into two 'sub-platforms': patient and professional platforms, respectively. The former includes *ad hoc* and commercial devices such as ECG, respiration and physical activity sensors (embedded into the underwear), and a personal digital assistant with communication capabilities. The latter is the 'hub' and includes a processing server used to analyze all data, databases, and a Web portal offering ubiquitous access to physicians. In this case, the limited communication capabilities of the personal digital assistant, usually implemented through a Wi-Fi interface, partially restrict the necessary ubiquitous characteristic of the monitoring system. Reference [23] discusses the effect of remote monitoring of patients with HF to detect early warning signs of impending acute decompensations in order to prevent hospitalization. The considered remote monitoring equipment consists of three commercially available components: a mobile phone, a weighting scale, and a sphygmomanometer for fully automated measurement of blood pressure and heart rate. From the telecommunication viewpoint, the platform is of the same type of the other referenced systems. A group of previously hospitalized patients was trained to measure blood pressure and weight and was instructed by a technician in the use of the mobile phone. Patients were asked to measure vital parameters (blood pressure, heart rate, and body weight) daily at the same time, to enter

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these values as well as their dosage of HF medication into the mobile phone's Internet browser, and to send them to the monitoring center. Mobile phone is a nonautomatic patient-managed hub. Physical activity is not taken into account. Another interesting contribution in the literature in the field is represented by Pecchia *et al*. [18] where a home monitoring system is integrated with a data mining method, based on classification and regression trees, aimed at detecting the worsening of the patients' conditions. The presented monitoring system has a common general structure where body sensors communicate with a server gathering data (acting as a hub). In this case, the work is focused on the data mining method, and communication aspects are only marginally developed.

2.3. mHealth: mobile phone telehealth systems and concepts

An important technological reference for telehealth systems is represented by the mHealth platform (also called mobile health technologies), which has been designed to acquire data such as vital parameters from the patients and to transmit them through a telecommunication network. mHealth is a subset of electronic-Health (eHealth) and refers to wireless portable devices capable of transmitting, storing, processing, and retrieving real-time and nonreal-time data among end users (e.g., patients, doctors, and pharmacists) [23]. In particular, the mHealth Alliance, hosted by the United Nations Foundation and founded by the Rockefeller Foundation, endorses the use of mobile technologies to improve the health throughout the world [24–26].

In mHealth platforms, as shown in the literature (e.g., [24, 27–29] and references therein), the role played by smartphones is of paramount importance. In particular, it is not only used as a hub capable of information aggregation and transmission but also as a measurement system itself, thanks to its internal sensors. External devices are connected to smartphones through a Bluetooth connection that uses the health device profile (HDP) [30]. In more detail, concerning the interoperability among all devices that compose the telehealth system (defined telehealth ecosystem in [30]), the reference is represented by Continua Health Alliance (CHA) guidelines that include ISO/IEEE 11073 Personal Health Data (PHD) standards [31, 32]. CHA is a nonprofit, open industry organization of healthcare and technology companies collaborating together to improve the quality of personal healthcare. The reference end-to-end architecture endorsed by CHA is reported in Figure 2.

Continua Health Alliance Design Guidelines contain references to the standards and specifications, which Continua selected to ensure interoperability of devices, and additional design guidelines to better adapt standards and specifications either by reducing options or adding features [33].

The architecture proposed in this paper, shown in the next section, is composed by taking mHealth platform as reference. In this context, referring to sensors internal to smartphones, the presented architecture relies on the use of the accelerometer that is contained in every modern smartphone, to determine the specific type of activity performed by patients, as detailed in the remainder of the paper. The other used devices, external to smartphones, are a pulse oximeter and a weighting scale, both of them capable of acquiring and transmitting measurements to the smartphone through a Bluetooth connection conformant to HDP [30]. As better remarked in the next section, referring to the terminology introduced and used by

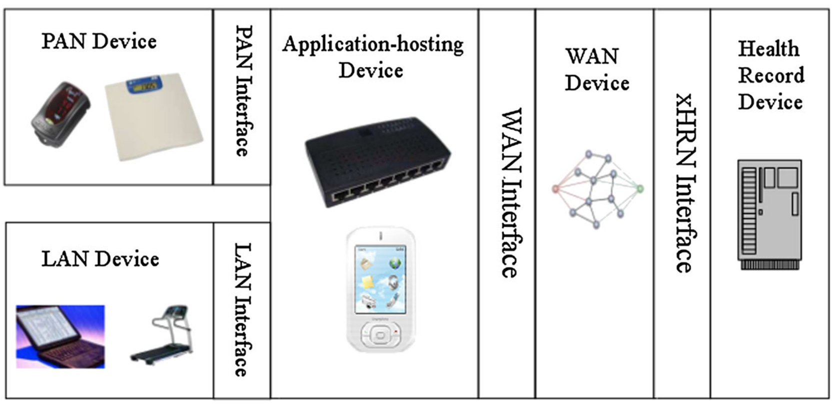

Figure 2. Continua end-to-end reference architecture [34].

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CHA in [34] and shown in Figure 2, the smartphone in the proposed architecture is an application hosting device, while pulse oximeter and weighting scale are PAN devices. The PAN Interface upper layers have been implemented in our architecture by developing an application running over an Android smartphone that interacts with PAN devices through a Bluetooth low energy socket as in [24, 29].

3. COMMUNICATION STRUCTURE OF THE IMPLEMENTED SMARTPHONE-CENTRIC PLATFORM FOR HF REMOTE MONITORING

The main feature of the architecture proposed in this paper is the smartphone-centric nature of the platform. As previously stated, the smartphone is employed not only as a hub but also as a sensing, processing, and transmitting device (applying the 'hub + sensor + processor' paradigm mentioned in Section 1.3) by using several communication interfaces such as Wi-Fi, 2G/3G, and general packet radio service. This choice allows reducing the number of required components and implementing a ubiquitous and automatic monitoring. For example, in our case, the accelerometer sensor is embedded in the smartphone. A first use of this paradigm may be found for fitness applications such as, among many others, Nike+, Endomondo, and RunKeeper but, in these cases, the smartphone: (i) contains a global positioning system receiver, (ii) is used only to track distances and times covered during workouts and fitness activities, not to recognize specific movements, and (iii) does not use any accelerometer or other sensor to detect the type of activity, which is the aim of this paper.

The block scheme composing the platform introduced in this paper is shown in Figure 3 by using the same blocks of Figure 1 to allow an immediate comparison.

In general, a PAN may be composed both by wearable sensors that define a body area network (BAN), see [35] for a tutorial about BANs, as well as by nonwearable sensors. In our case, nonwearable sensors include a pulse oximeter needed to measure the S_pO_2, which is the saturation of peripheral oxygen, and a weighting scale needed to measure the body weight. These parameters are measured once a day and sent to the smartphone through the mentioned HDP conformant Bluetooth interfaces. The smartphone, being used as an accelerometer sensor, may be considered part of the BAN and is, as said, the application hosting device, that is, the hub that conveys information through a WAN to the final destination, that is, the health record device. The WAN is a telecommunications network implemented through a solution such as, in our case, either the mobile phone network typically used by smart and mobile phones during ordinary operations or the Internet accessed through general packet radio service/Wi-Fi interface. The final destination, in the designed platform, is a server, called MS, where the parameters of all monitored patients are stored and made available to the medical staff.

Neither accelerometer nor localization wearable sensors are used because motion and localization are provided by using the smartphone. The designed platform includes a number of smartphones, one for each monitored patient. Samsung Galaxy S™ smartphones with the Android™ operating system are employed in the platform, but obviously, this choice does not limit the general applicability

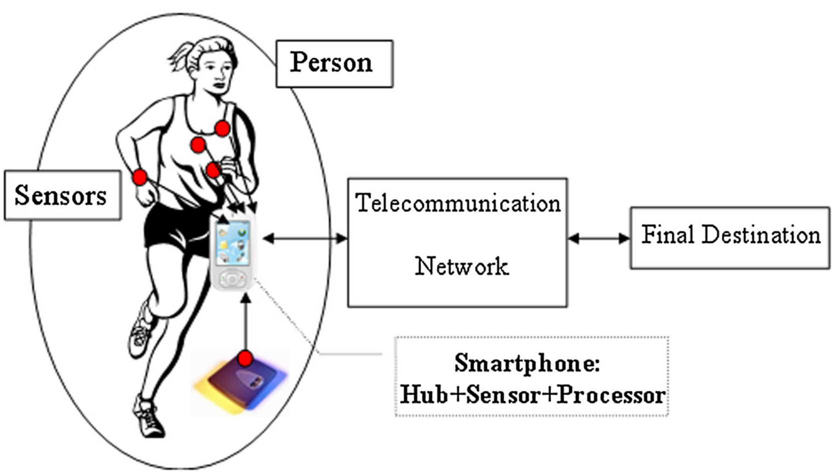

Figure 3. Communication system of smartphone-centric platform for heart failure remote health monitoring.

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of the solution. Smartphone interfaces are also ready to include in the PAN a chest strip worn by patients, capable of providing an approximation of the transthoracic impedance and the heart rate, ECG, ElectroEncephaloGram (EEG), Glucose, and blood pressure sensors, but, at the moment, these physiological data are not part of the implemented platform because they are not included in the experimental clinical protocol that the medical staff involved in the activity is going to apply.

3.1. Implementation details

The implemented communication architecture is shown in Figure 4. The smartphone platform sends data either by a JavaScript Object Notation (JSON) string [36] through an Internet connection or, if not available, by a text message through a traditional mobile network. JSON stands for JavaScript Object Notation and is a lightweight data interchange format. The text message content, before being delivered, must be parsed by a special tool called local tracker, which encapsulates the text message into a JSON string.

Data are stored in the health record database and are accessible from the MS application hosting device, a computer on which vital parameters and patients' history are available to be consulted. Specifications and implemented connection methods between used devices (pulse oximeter and weighting scale) and smartphone are presented in the following.

3.1.1. Nonin 9560 Onyx II pulse oximeter. Pulse oximeter (in Figure 5 the model we have used) allows clinicians to remotely monitor oxygen saturation levels of blood and patients pulse rates. It can detect saturation values from 0% to 100% and pulse rate values ranging from 18 to 321 beats per minute. Concerning data communication interface, the oximeter we used follows IEEE 11073-10404 Standard [31]. Referring to Bluetooth communication standard, 9560 oximeter is a slave device. In consequence, the master device (the smartphone, in our case) must initiate the connection with the 9560 slave device by implementing a pairing action. The 9560 device has a six-digit identification number printed on the battery door. To complete the pairing process, the six-digit number must be provided to the master as Bluetooth PassKey (Bluetooth PIN). Once the pairing is complete, the 9560 will automatically reconnect to the master device whenever possible. The six-digit Bluetooth PassKey must be entered only during the pairing action to a new master.

The most important part of the Java code used into the Android application developed by the authors to allow the smartphone to interact with the pulse oximeter is contained in Figure 6. Starting from Android version 4.0, the application programming interface (API) providing standard methods and classes to manage Bluetooth health devices have been released (API level 14). The code snippet in Figure 6 represents a *callback* method, which is delegated to listen the incoming Bluetooth connections and to detect if data are incoming from the pulse oximeter.

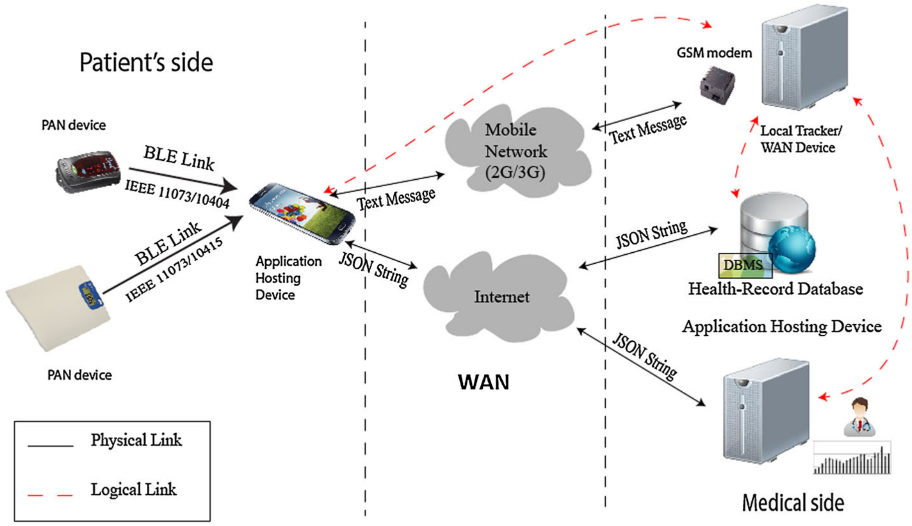

Figure 4. The implemented architecture.

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Figure 5. Nonin 9560 Onyx II pulse oximeter.

```
private BluetoothHealthAppConfiguration mHealthAppConfig;
private BluetoothHealth mBluetoothPulsiOx;
private BluetoothDevice mDevice;

public void onServiceConnected(int profile, BluetoothProfile proxy) {
mBluetoothPulsiOx = (BluetoothHealth) proxy; }

mBluetoothPulsiOx.connectChannelToSource(mDevice, mHealthAppConfig);

// Callback to handle channel connection state changes.
// When the Health BLE device is connected, the received file descriptor is passed to the ReadThread to
read the content.
public void onHealthChannelStateChange(BluetoothHealthAppConfiguration config,BluetoothDevice device,
int prevState, int newState, ParcelFileDescriptor fd,int channelId) {

if (prevState == BluetoothHealth.STATE_CHANNEL_DISCONNECTED && newState ==
BluetoothHealth.STATE_CHANNEL_CONNECTED) {
       if (config.equals(mHealthAppConfig)) {
                                   //Connected to the HDP device and read the PulsiOx data
                                   (new Read_PlsOx_Data(fd)).start();
                       }
```

Figure 6. Java code of the Android application developed to allow smartphone-pulse oximeter interaction.

3.1.2. UC-321PBT precision health scale. The used weighting scale (shown in Figure 7) can send data by using a Bluetooth connection. It can store up to 40 weight measurements, which are transmitted to the Smartphone device once the pairing process is done. Differently from the pulse oximeter, the scale behaves as a master device, so it must initiate the connection operation while the Smartphone is used as a slave device. The code snippet in Figure 8 represents the Java code of the Android application used by the smartphone to connect and receive the measurement data from the UC-321PBT Scale, which is compliant to the IEEE 11073-10415 Standard [32].

4. PHYSICAL ACTIVITY DETECTION

The algorithm for patient activity detection running on the smartphone, which should be kept by the patients in their pockets, has been preliminarily described in [37] and is summarized in the following. Similarly to the literature in the field (e.g., [38] and [39]), the activity detection algorithm is based on processing and classification of data sensed by the smartphone-embedded accelerometer. In this paper, two different versions of this algorithm have been evaluated: the first is aimed at recognizing four different classes of physical activities, which are considered of interest in the context of this paper: (*i*) *Idle,*

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Figure 7. UC-321PBT Precision Health Scale.

```java
private BluetoothHealthAppConfiguration mHealthAppConfig;
private BluetoothHealth mBluetoothWeightScale;
private BluetoothDevice mDevice;

public void onServiceConnected(int profile, BluetoothProfile proxy) {
mBluetoothWeightScale = (BluetoothHealth) proxy; }

mBluetoothWeightScale.connectChannelToSource(mDevice, mHealthAppConfig);

// Callback to handle channel connection state changes.
// When the Health BLE device is connected, the received file descriptor is passed to the ReadThread to
read the content.
public void onHealthChannelStateChange(BluetoothHealthAppConfiguration config,BluetoothDevice device,
int prevState, int newState, ParcelFileDescriptor fd,int channelId) {

if (prevState == BluetoothHealth.STATE_CHANNEL_DISCONNECTED && newState ==
BluetoothHealth.STATE_CHANNEL_CONNECTED) {
       if (config.equals(mHealthAppConfig)) {
                                        //Connected to the HDP device and read the Weight Scale data
                                        (new Read_WeightScale_Data(fd)).start();
                                }
```

Figure 8. Java code used in the Android application used by the smartphone to interact with the health scale.

(ii) Still, (iii) Walking, and (iv) Running. It is called four-classes approach in the following; the second version, which is an extension of the first one, is designed to recognize eight different classes: *(i) Idle, (ii) Sitting, (iii) Standing, (iv) Walking, (v) Going up the stairs (contracted in upstairs), (vi) Going down the stairs (contracted in downstairs), (vii) Running*, and *(viii) Cycling*. We consider these classes of particular interest for the applicative field of this paper because they allow identifying more specific movements. This activity detection version is called eight-classes solution hereafter.

Idle class recognizes if the patient has abandoned the smartphone. Sitting and Standing classes represent the case in which the patient is in a sedentary condition (in the four-classes solution, they are conveyed in the Still class). The other classes refer to the cases in which the patient is walking, going up the stairs, and down the stairs (combined in the Walking class in the four-classes case) or running. Cycling class concerns the case where a patient is cycling by using either a bike or an exercise bike, indifferently. The smartphone employed during the tests integrates a triaxial, piezoresistive accelerometer that measures the acceleration values on the three Cartesian axes in meter per second squared.

The acquisition of training data for the activity detection algorithm has been performed by keeping the smartphone in four different positions, based both on the display position: (i) facing toward the user; (ii) toward the opposite side; and on the smartphone orientation: (iii) pointing up and (iv) pointing down.

The algorithm collects raw measurements (one for each Cartesian axis: x, y, and z) from the smartphone accelerometer for a time of length F [s], called frame, after which measurements are

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interrupted to save energy for a time N [s]. N is called pause and is a multiple of F. After the pause, measurements are acquired again for F [s] and so on. The quantity $T = F + N$ [s] is defined as period. Similarly to the windowed approach proposed in [40], a group of n periods T composes the window $W = n \cdot T$ [s]. The mentioned quantities are shown in Figure 9. The described windowed approach, which differs from the previously mentioned approach in [37], allows limiting the accelerometer signal readings and, as a consequence, the related energy consumption that represents a key issue when smartphones are employed because of their limited battery change.

In order to be classified, a feature vector is associated to each frame, which is composed of M samples. As done in [41], the employed features for single-frame classification are the mean (μ_j), standard deviation (σ_j), and number of peaks of the measurements P_j of the accelerometer for each axis $j \in \{x,y,z\}$, computed as in (1).

$$P_j = \sum_{m=1}^{M} \rho_{j,m}, \quad \rho_{j,m} = \begin{cases} 1 \; if \; (s_{j,m+1} - s_{j,m})(s_{j,m} - s_{j,m-1}) < 0, |s_{j,m}| \geq \varepsilon \\ 0 \; otherwise \end{cases} \tag{1}$$

$s_{j,m}$ is the value of the $m-th$ sample of accelerometer signal along axis j; ε is a threshold employed to define a signal peak. The feature vector is $\{\mu_x,\mu_y,\mu_z,\sigma_x,\sigma_y,\sigma_z,P_x,P_y,P_z\}$.

Once a feature vector has been computed for a given frame, it is used by a classifier in order to associate the corresponding frame to one of the considered classes. The employed classifier is a decision tree proposed in [42] and employed also in [41] and [43]. Using the Weka workbench [44], decision trees are designed and compared on the basis of their recognition accuracy (RA). A decision tree is trained for every combination of two and three of the users employed in the dataset creation described in the results.

After classifying each frame, each window, composed of n frames, is assigned to one of the considered classes as specified in the following, through a windowed decision policy. The window W subsequently slides $(n-1)T$ [s] forward and the algorithm restarts.

Four different windowed decision policies are proposed, evaluated, and compared, as detailed in the following.

1. *Majority decision*. The simplest windowed decision policy is a majority-rule decision: the window is assigned to the class to which the largest number of frames in the window has been associated. Such decision mechanism is employed in some earlier works such as [45]. While it is clearly simple to implement and computationally inexpensive, the majority-rule windowed decision treats all frames within a window in the same way, without considering when the frames occurred and the single-frame classification reliability.
2. *Time-weighted decision*. It gives different weights to the frames of a window on the basis of their position in the window and assigns the window to the class with the largest total weight.

Its basic idea is that a frame has a larger weight if it is closer to the end of the window, under the assumption that more recent classifications should be more reliable to determine the current user activity. Weights are assigned through function $\Omega(t)$ designed according to the criteria that $\Omega(0) = 1$ and $\Omega(t_1) \geq \Omega(t_2)$ for any $t_1 \leq t_2$ and $t \geq 0$, and $t = 0$ represents the time the most recent frame occurred.

If T_f is the arrival instant of a frame and T_d is the instant when the windowed decision is made, then the frame is assigned a weight equal to $\Omega(T_d - T_f)$. Two different weighting functions are compared: a

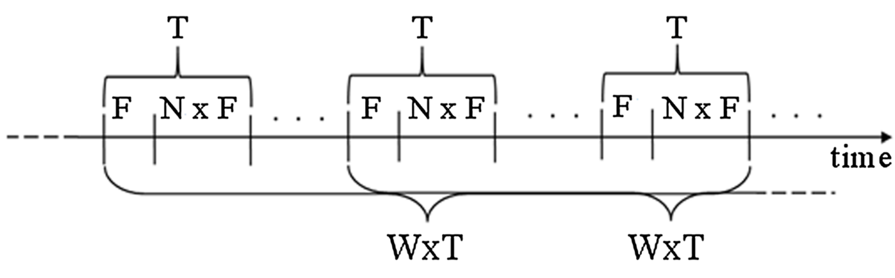

Figure 9. Diagram representing the accelerometer signal acquisition.

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Gaussian $\Omega_g(t)=e^{\frac{-t^2}{2k_g^2}}$ and a negative exponential $\Omega_e(t)=e^{-k_e t}$. For each function type, five different functions are compared by choosing k_g and k_e based on a reference instant T_r and forcing $\Omega_i(T_r)=\omega$, $i=g,e$, where ω is one of the five linearly spaced values between 0 and 1.

1. *Score-weighted decision*. A score representing the reliability of the classification is assigned to each frame [45]. The basic idea is that the closer a frame feature vector is to the decision boundary, the more unreliable the frame classification is, under the hypothesis that the majority of badly classified samples lie near the decision boundary. The distance of a feature vector from the decision boundary is given by the shortest distance between the feature vector and the leaves with different class labels. This distance is obtained by solving a constrained quadratic problem. An estimate of the correct classification probability conditional to the distance from the decision boundary is produced by using separate training data for each leaf.
2. *Joint score-weighted/time-weighted decision*. The last decision policy is given by combining the temporal weights and the classification scores into a single, joint time-and-score weight. Fusion is obtained by multiplying the corresponding time weight and classification score, because both are between 0 and 1.

5. PERFORMANCE EVALUATION

5.1. Introduction to the tests

As said in Section 1.3 (from [18]), the critical factors for telemonitoring platforms are connectivity, usability, quality of transmitted data, and interference with other devices. Under these aspects, smartphones assure full connectivity coverage and usability, as well as data integrity and robustness against interference with other devices. These aspects are deeply analyzed in the literature; smartphones currently offer commercial data and voice services, and if they did not offer guarantees in each single mentioned aspect, they would not be so widespread and used. Therefore, even if not all such issues might be completely solved and improvements are still possible, the authors prefer leaving these aspects to the literature and to the experts in electromagnetic interference and data protection and focusing on the performance evaluation of the four-classes activity recognition solution (in Section 5.2), and of the eight-classes activity recognition solution showing its comparison with the solution proposed in [19] (in Section 5.3), and on the description of the data exchange between smartphone and MS (in Section 5.4), both designed by the authors and parts of the designed platform. The impact of the technical innovations on the medical results will be verified once the platform will be currently used by the medical team part of the research project. The use of the platform for real patients is planned in the next few months.

5.2. Four-classes activity recognition accuracy

5.2.1. Dataset. The dataset employed in the experiments was acquired by four volunteers. Each volunteer acquired about 1 h of data for each class, so producing globally almost 33 h of data, as shown in Table I.

The phone was kept in the user's front or rear pants pocket. The acquisition of training data was performed by keeping the smartphone both with the display facing toward the user and away from him and keeping the smartphone pointing both up and down.

Table I. Employed dataset for the four-classes case.

	Sitting	Standing	Walking	Running
Frames	3702	3981	3822	3711
Duration [min]	246.8	265.4	254.8	247.4

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5.2.2. Parameter setting. In order to determine proper values for parameters W, O, N, and ω, an additional *ad hoc* sequence, not included in the dataset used to train and test the classifier, was acquired by a fifth volunteer. Such a sequence was made of an hour of raw accelerometer measurements and included all four considered activities, performed randomly. Their labels were used as ground truth (GT), which is defined as the activity actually carried out. At first, single-frame classification (i.e., without any windowing mechanism, obtained by setting $N = 0$ [s]) was performed on the sequence, producing recognized-class labels and classification scores. After that, the windowed decision accuracy was evaluated (as described in the following results) for all admissible combinations of W, O, and N. Δ was set to 60 s, and W, O, and N were evaluated in the following empirically determined ranges: $W \in [3 \cdot F, 9 \cdot F]$, $O \in [0, W-1]$, and $N \in [0, 14 \cdot F]$. Therefore, 411 different $\{W,O,N\}$ sets were evaluated. F was set to 4 s.

5.2.3. Numerical results. The confusion matrix (with percentages) concerning single-frame classifications is shown in Table II. The activities highlighted in gray in the first column represent the GT. The other four columns contain the estimated activities (EAs).

All decision policies described in Section 4 were compared for each parameter configuration by using five different values of ω (linearly spaced between 0 and 1, as said previously) and two different values for T_r (60 and 120 s) for each policy. The results are shown in Table III, which contains the average Recognition Accuracy - RA (%), defined as the average correct detection over all considered classes, and the reading time (%), which is the percentage of time dedicated to read accelerometer data with respect to continuous measurements. In other words, if a single-frame approach is used, reading time is 100%, while if a windowed mechanism with $N = 4 \cdot F$ is used, reading time is 20%. This has a direct impact on energy consumption. The accuracy is very high in case of the single-frame approach, as clearly shown in Tables II and III that show an average accuracy of 98%. This result is obviously paid in terms of reading time and, consequently, of energy consumption. All windowed approaches allow to save energy and assure a satisfying RA. Score weighted, and joint score-weighted/time-weighted solutions applying $W = 5 \cdot F$, $O = 1 \cdot F$, $N = 7 \cdot F$, and $T_r = 120$ s are particularly efficient leading to a reading time of about 9% and to a RA above 88%. This result is very satisfying because the energy efficiency is really high and the obtained result leads to an improvement in decision accuracy of more than 8% if compared with the classical majority-rule decision. The result is good also compared with other approaches in the literature such as [41], [43], and [46].

Table II. Confusion matrix in case of single-frame classification for the four-classes case (%).

	Sitting	Standing	Walking	Running
Sitting	**99**	0	1	0
Standing	0.27	**98.68**	0.82	0.23
Walking	0	0.05	**98.85**	1.1
Running	0.28	0.1	4.4	**95.22**
Average	**97.93**			

The bold values represent the percentage of correct decision for each class and the average recognition accuracy.

Table III. Performance of the proposed windowed decision policies.

	Decision policy	RA (%)	Reading time (%)
Frame-based	Single-frame classification	98	100
Window-based	Majority	80	12.5
	Time weighted (Gaussian/exponential)	80/84.62	12.5/20
	Score weighted	88.24	9.09
	Joint score weighted/time weighted (Gaussian/exponential)	88.24/88.24	9.09/9.09

RA, recognition accuracy.

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5.2.4. Activity recognition: behavior over time. In order to complete the evaluation of the activity recognition algorithm, the behavior over time of the algorithm was analyzed by focusing on a single example user. A 45-min test was carried out. For the sake of completeness and in order to make the test realistic, we tried to reproduce the normal human daily activity compressed in about 45 min. For this purpose, we divided the testing period as shown in Table IV, which reports the set of activities actually carried out, that is, the GT. The joint score-weighted/time-weighted—Gaussian policy—is used with the parameters specified in the previous section as getting the best results.

Figure 10 shows the temporal behavior of the EA compared with the GT. Figure 10 shows that motion (walking and running) is very well recognized and also that the Still case is often confused with the Idle case. Practically, idle means that the smartphone lies upon a table or a desk, with zero acceleration. On the other hand, in the Still class, the user is motionless (sitting or standing) and the sensor measures a very low acceleration, often very close to zero when the user is sitting still. Hence, if the smartphone is put on a desk, its acceleration is constantly zero and the corresponding state is immediately classified as idle; but if the user is sitting, completely motionless, the Still class may be mistaken with the idle one because the acceleration is zero also in this case. This may be seen globally in Table V, which shows the overall time in minutes spent in each case and the corresponding percentage both for the GT and for the estimation and, for each instant, in Figure 10, where it is clear that the Still class is perfectly recognized in the period between minute 37 and 42 but is confused with the Idle class from minute 8 to 17. Actually, the user is standing in the period [38–43] and has natural, often involuntary, slight movements leading to nonzero acceleration, while he or she is sitting motionless from minute 8 to 17.

It is clear from Table V that the Walking class is well recognized: EA (11 25″, 25.3%), and GT (11 58″, 27.16%) are almost overlapped. A similar analysis can be applied to the Running class: 4 54″ (11.11%) of GT are estimated as 5 10″ (11.45%) by the proposed algorithm. On the contrary, as

Table IV. Type and timing of the activities actually carried out: ground truth.

Period (min)	Activity	Description	Notes
2	Walking		I walk down the stairs
3	Running		
3	Walking	Return to the office	I walk up the stairs
9	Still	Sitting at my desk	Sitting
5	Walking	I walk to get a coffee	I walk down and up the stairs
7	Still	Back to my desk	Sitting
1	Walking		
3	Still		Sitting
2	Running	I run	
5	Still		Standing
5	Idle	Put the mobile on the desk	Take mobile out of the pocket
45			Total

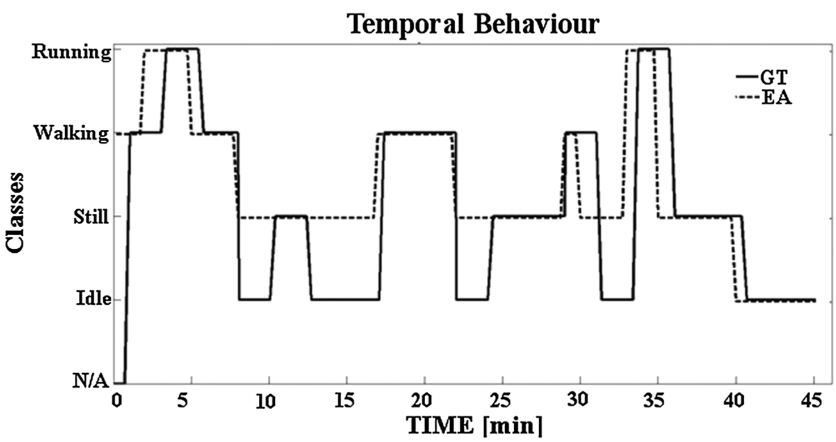

Figure 10. Temporal behavior of the activity recognition algorithm.

Table V. Overall time and time percentage spent in each case.

		Estimated activity				Ground truth			
		Time	%	Time	%	Time	%	Time	%
Nonmotion	Idle	5 10″	11.45	28 33″	64.34	15 46″	35.80	27 11″	61.73
	Still	23 23″	51.81			11 25″	25.93		
Motion	Walking	11 25″	25.30	16 35″	35.66	11 58″	27.16	16 35″	38.27
	Running	5 10″	11.45			4 54″	11.11		

previously evidenced, the Still case is easily mistaken with the Idle class. However, it is worth noticing that if we consider the more general case of Nonmotion class composed of Idle and Still cases grouped together, the performance is very satisfactory: 28 33″ (64.34%) of EA nonmotion estimates 27 11″ (61.73%) of GT. The Motion class, defined as the sum of Walking and Running classes, is also accurately estimated: 16 35″ (38.27%) of Motion is exactly estimated as 16 35″ (35.66%). Assuming the user in good faith (i.e., when the smartphone is in the Idle state, the user, future patient, is actually not walking or running without the smartphone) because an accurate monitoring is beneficial for his or her health, a confident estimation of nonmotion is very important from a medical viewpoint because it allows to reliably discriminate sedentariness from movement. A physician monitoring the patient's daily physical activity needs to know if a patient has performed a sufficient amount of activity (i.e., walking and running), while it is not so crucial to understand the type of sedentary activity. From this point of view, also the lack of good faith (e.g., the patient leaves the smartphone at home to walk and run) may not have a strong impact on health monitoring, although these aspects must be further investigated together with the medical staff and with the help of real patients.

5.3. Eight-classes activity recognition accuracy and comparison

5.3.1. Dataset. The dataset employed in the eight-classes experiments was acquired by eight different volunteers, both male and female. Each of them acquired around 30 min of data for each class, so producing an overall amount of data of almost 30 h, as shown in Table VI. The smartphone was kept in the user's front or rear pants pocket except for Sitting and Cycling classes in which the smartphone was held in the front pocket only to avoid possible damages to the device. Again, the acquisition of training data was performed by keeping the smartphone both with the display facing toward the user and away from him and keeping the smartphone pointing both up and down.

5.3.2. Parameter setting. In order to fairly compare the proposed decision-tree classifier with the approach proposed in [19], we applied the single-frame classification without the windowed approach (i.e., $N = 0$). Since in [19] the accelerometer signal is sampled with a rate of about 20 Hz with frames of 1 min, we read the accelerometer values every 60 ms, so obtaining a sample rate close to 20 Hz. A more precise sample rate selection is not possible because the Android operating system allows choosing the sample rate only within a set of predefined values. Finally, we also fixed the frame length to $F = 60$ [s], so obtaining around 1200 samples per frame.

5.3.3. Results. The first set of results of this session is aimed at evidencing the values of the parameter K_m for each activity class considered in this paper. The activity recognition carried out in [19] is based on the values of K_m that has a high correlation with the total energy expenditure and is defined as

Table VI. Employed dataset for the eight-classes case.

	Cycling	Downstairs	Idle	Running	Sitting	Standing	Upstairs	Walking
Frames	3187.5	3063	2055	3711	3702	3981	2959.5	3822
Duration [min]	212.5	204.2	137	247.4	246.8	265.4	197.3	254.8

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$$K_m = \sqrt{\frac{1}{M-1}\left(\sum_{j\in[x,y,z]}\sum_{m=0}^{M} s_{j,m}^2 - \frac{1}{M}\left(\sum_{j\in[x,y,z]}\sum_{m=0}^{M} s_{j,m}\right)^2\right)} \quad (2)$$

where M is the number of samples in a frame and $s_{j,m}$ is the value of the $m-th$ sample of the accelerometer signal along the axis $j \in \{x,y,z\}$. The parameter is, in practice, a measure of the energy of the accelerometer signal. Figure 11 shows the numerical values of K_m for each considered class. The box-plots show that classes Cycling, Downstairs, Upstairs, and Walking have almost the same average value of K_m, as well as, less importantly in medical applications, Nonmotion classes Idle, Sitting, and Standing. Being the decision about the activity taken in [19] exclusively based on the value of K_m, classes with very similar K_m values shall not be distinguished. Differently, because it requires more energy, Running class is well distinguished with respect to the others. Summarizing, the approach in [19] allows a macroscopic classification of movements in three categories: light, moderate, and vigorous. A more discriminating classification is hardly reachable, as should be clearer from the results reported in the following.

The second set of results concerns the evaluation of the eight-classes version of the approach proposed in this paper and its comparison with a K_m-based approach. The employed features of the accelerometer signal are again the means, standard deviations, and number of peaks. The confusion matrix obtained by using our approach is shown in Table VII. The proposed solution allows reaching an average recognition accuracy (RA) of about 80%.

Similarly to the results proposed for the four-classes version, we have reported in Figure 12 a single-user example of the temporal behavior where EA is compared with GT. Figure 12 is based on the mentioned eight actions the exclusion of Cycling that is not part of this test. It is clear that EA is very similar to GT except for the case of Walking class that is sometimes confused with the Downstairs one.

To allow a direct comparison between our approach and a K_m-based solution, we have tested an eight-classes classifier, always based on a decision-tree algorithm, where only the parameter K_m is

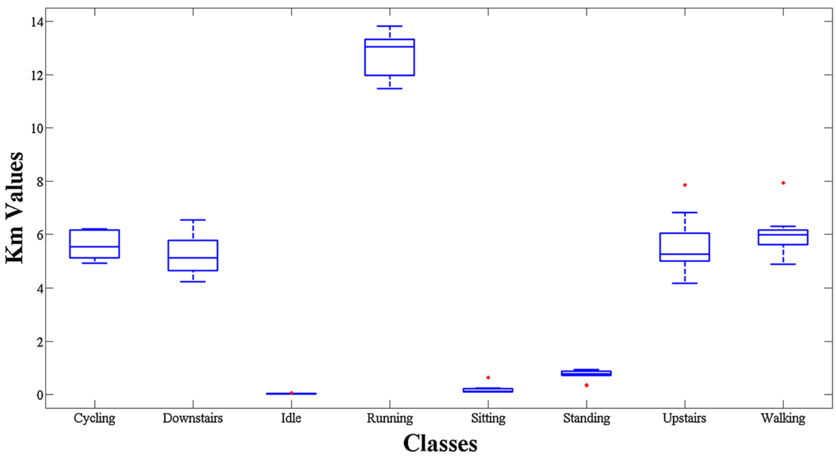

Figure 11. K_m values versus classes.

Table VII. Confusion matrix for the all the features for the eight-classes single-frame classification (%).

	Cycling	Downstairs	Idle	Running	Sitting	Standing	Upstairs	Walking
Cycling	**84.9**	0	0	0.1	0	0	0.1	14.9
Downstairs	6.15	**69.5**	0	0	0	0	9.68	14.7
Idle	0	0	**79.2**	0	20.8	0	0	0
Running	0.2	0.6	0	**99.2**	0	0	0	0
Sitting	0	0	0	0	**98.4**	1.6	0	0
Standing	0	0	0	0	8.8	**91.2**	0	0
Upstairs	6.70	19.9	0	0	0	0	**63.1**	10.3
Walking	21.4	6.04	0	4.90	0.26	0	16.3	**51.1**
Average	**79.6**							

The bold values represent the percentage of correct decision for each class and the average recognition accuracy.

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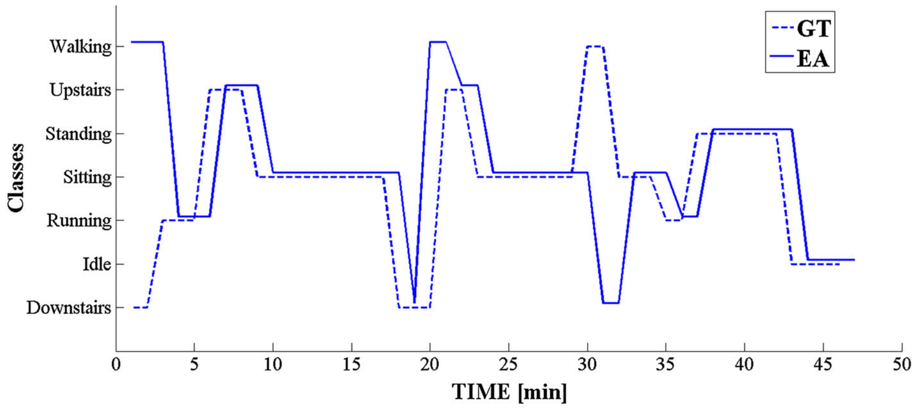

Figure 12. Temporal behavior of the activity recognition algorithm, eight-classes version.

used as a feature. The obtained performance is shown in Table VIII. The average percentage of accuracy is about 58%. As expected, an activity detection method based only on the values of K_m cannot distinguish among the considered eight different classes.

5.4. *Activity data exchange between smartphone and medical server*

The results of the physical activity detection must be transmitted to the MS. The issue has been discussed in Section 3 from the communication viewpoint. In the following, a short description is presented regarding the data exchange communication protocol operating on the smartphone at the application layer, designed, and implemented by the authors to transfer data between smartphone and MS. The communication protocol is based on JSON. JSON is a lightweight text-based open standard designed for human-readable data interchange, derived from the JavaScript scripting language

Table VIII. Confusion matrix for the sole K_m feature for the eight-classes single-frame classification (%).

	Cycling	Downstairs	Idle	Running	Sitting	Standing	Upstairs	Walking
Cycling	**60.3**	0	0	0.2	0	0	35.6	3.90
Downstairs	1.80	**0**	0	0	0	0	51.9	46.3
Idle	0	0	**0**	0	99.4	0.6	0	0
Running	0	0	0	**96.1**	0	0.15	0	3.75
Sitting	0.80	0	0	0	**85.5**	13.7	0	0
Standing	0.70	0	0	0	52.0	**47.3**	0	0
Upstairs	14.2	0	0	0	0	0	**70.7**	15.1
Walking	15.1	0	0	5.00	0	0	25.2	**54.7**
Average	**58.2**							

The bold values represent the percentage of correct decision for each class and the average recognition accuracy.


```
{
"ts_upload": "2011-06-16T10:20:19+02:00",
"username": "Alessandro"
"imei:" "359440022467713",
"activity": "WALKING"
}
```


Figure 13. Example of JavaScript Object Notation message sent from the smartphone to the medical server concerning activity detection.

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and applied to simple data structures and associative arrays. JSON format is described in [36]. This standard is used in this paper as an alternative to XML to serialize and transmit structured data over the telecommunications network shown in Figures 3 and 4. The JSON message sent to the MS by the smartphone contains a time stamp (the *ts_upload* field), the name of the user/patient (the *username* field), the smartphone International Mobile Equipment Identity (which is a unique number to identify mobile phones) to recognize the specific employed terminal (the *imei* field), and the physical activity performed by the patient (the *activity* field). An example of JSON message is shown in Figure 13. Similar messages are sent by the smartphone to transmit the other monitored parameters. On the MS side, the mentioned fields are used to display information about users/patients. Physicians will obtain information about a specific patient by using the implemented Web interface in the MS.

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

A remote health monitoring architecture thought for patients suffering from HF is described in this paper. The technological core of the architecture is the smartphone, which simultaneously plays the role of hub, to convey data received by other sensors; sensor, to measure physical quantities; and processor, to process the measurements. After describing the telemonitoring platform, the paper mainly focuses on one processing task, essential for HF monitoring: patient activity detection. Such a task is based on processing and classification of data sensed by the smartphone-embedded accelerometer and is designed to recognize eight different classes of physical activities: Idle, Sitting, Standing, Walking, Upstairs, Downstairs, Running, and Cycling.

The performed tests show that the applied activity detection algorithm leads to very satisfying results, assuring an RA of about 88% in the case of a four-classes based classifier and about 80% if a eight-classes classifier is used, as well as to outstanding energy saving (reading time of about 9% in the four-class case).

From a technological perspective, future developments will include additional processing functions in the smartphone such as the precise computation of the pedestrian speed of the patients (by using the accelerometer), and the integration between smartphones and other sensor nodes applied to other physical activities. From the medical viewpoint, the monitoring platform is entering the experimental phase involving real patients and will provide the first medical results in the next few months.

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REFERENCES

1. Lykke F, Holzworth M, Rosager M, Rhoads J, Turisco F. CSC Report, April 2013, http://assets1.csc.com/health_services/downloads/CSC_Telemedicine_An_Essential_Technology_for_Reformed_Healthcare.pdf
2. Sarasohn-Kahn J. California Healthcare Foundation, "How Smartphones Are Changing Health Care for Consumers and Providers", April 2010, http://www.chcf.org/~/media/MEDIA%20LIBRARY%20Files/PDF/H/PDF%20HowSmartphonesChangingHealthCare.pdf.
3. Rodrigues JJ, Lopes IM, Silva BM, de la Torre I. A new mobile ubiquitous computing application to control obesity: Sapofit. *Informatics for Health and Social Care*, 2013; **38**(1):37–53.
4. Pereira ORE, Caldeira JMPL, Rodrigues JJPC. Body sensor network mobile solutions for biofeedback monitoring. *Mobile Networks and Applications (MONET)*, Springer, December 2011; **16**(16):713–732.
5. Abbate S, Avvenuti M, Bonatesta F, Cola G, Corsini P, Vecchio A. A smartphone-based fall detection system. *Pervasive and Mobile Computing* 2012; **8**(6):883–899.
6. Lan M, Nahapetian A, Vahdatpour A, Au L, Kaiser W, Sarrafzadehm M. SmartFall: an automatic fall detection system based on subsequence matching for the smartcane. Bodynets, April 2009.

7. Weiser M. The computer for the 21st century. ACM SIGMOBILE Mobile Computing and Communications Review archive, Special issue dedicated to Mark Weiser, July 1999; **3**(3):3–11 reprinted, article first appeared in Scientific American, 1991; **265**(3):94–104.
8. Park JH, Woungang I, Ma J, Kawsar F. Ubiquitous computing for communications and broadcasting. *International Journal of Communication Systems* 2012; **25**(6):689–690.
9. Estrin D, Culler D, Pister K, Sukhatme G. Connecting the physical world with pervasive networks. *Pervasive Computing* 2002; **1**(1):59–69.
10. Chen C-L, Lee C-C, Hsu C-Y. Mobile device integration of a fingerprint biometric remote authentication scheme. *International Journal of Communication Systems* 2012; **25**(5):585–597.
11. Smart Personal Health, European Commissions Information Society. Enabling smart integrated care: recommendations for fostering greater interoprability of personal health systems. 2011, http://sph.continuaalliance.org/docs/SmartPersonalHealth_publication_web.pdf.
12. Weigand C, Schmidt J. Mobile health assistant. ERCIM News 2007, at http://ercim-news.ercim.eu/mobile-health-assistant.
13. Villalba E, Salvi D, Ottaviano M, Peinado I, Arredondo MT, Akay A. Wearable and mobile system to manage remotely heart failure. *IEEE Transactions on Information Technology in Biomedicine* 2009; **13**(6):990–996.
14. University of Karlsruhe, Instituts für Technik der Informationsverarbeitung (ITIV), Personal health monitoring system, Technical Report, Available at http://www.phmon.de/englisch/kommunikation.html
15. Massé F, Penders J, Serteyn A, van Bussel M, Arends J. Miniaturized wireless ECG-monitor for real-time detection of epileptic seizures. *Wireless Health 2010 (WH'10)*, San Diego, USA, October 5–7, 2010;111–117.
16. Boulos MNK, Wheeler S, Tavares C, Jones R. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX. *BioMedical Engineering OnLine* 2011; **10**(24), doi:10.1186/1475-925X-10-24, April 2011, http://www.biomedical-engineering-online.com/content/10/1/24.
17. Chen M, Zhou L, Hara T, Xiao Y, Leung VCM. Advances in multimedia communications. *International Journal of Communication Systems* 2011. DOI: 10.1002/dac.1349.
18. Pecchia L, Melillo P, Bracale M. Remote health monitoring of heart failure with data mining via CART method on HRV features. *IEEE Transactions on Biomedical Engineering* 2011; **58**(3):800–804.
19. Suh MK, Chen C-A, Woodbridge J, Kai Tu M, Kim JI, Evangelista LS, Sarrafzadeh M. A remote patient monitoring system for congestive heart failure. *Journal of Medical Systems (JOMS)* 2011; **35**(5):1165–1179.
20. Müller A, Schweizer J, Helms TM, Oeff M, Sprenger C, Zugck C. Telemedical support in patients with chronic heart failure: experience from different projects in Germany. *International Journal of Telemedicine and Applications* 2010, Article ID 181806, 1–11, Available at http://dx.doi.org/10.1155/2010/181806.
21. Wijbenga JAM, van Ginneken AM, Stam H, Cornet R, Deckers JW. Supporting patient care and medical research at a heart failure outpatient clinic using a medical workstation with a computerized patient record, Computers in Cardiology, Wien, Austria, September 10–13, 1995; 129–131.
22. Suh M-k, Evangelista LS, Chen V, Hong W-S, Macbeth J, Nahapetian A, Figueras F-J, Sarrafzadeh M. WANDA B.: weight and activity with blood pressure monitoring system for heart failure patients. *IEEE International Symposium on a World of Wireless Mobile and Multimedia Networks (WoWMoM)*, Montreal Canada, June 14–17, 2010; 1–6.
23. Scherr D, Kastner P, Kollmann A, Hallas A, Auer J, Krappinger H, Schuchlenz H, Stark G, Grander W, Jakl G, Schreier G, Fruhwald FM. Effect of home-based telemonitoring using mobile phone technology on the outcome of heart failure patients after an episode of acute decompensation: randomized controlled trial. *Journal of Medical Internet Research* 2009; 11(3):1–11. Available at http://www.jmir.org/2009/3/e34/.
24. Adibi S. Link technologies and BlackBerry mobile health (mHealth) solutions: a review. *IEEE Transactions on Information Technology in Biomedicine* 2012; **16**(4):586–597.
25. mHealth Alliance. http://www.mhealthalliance.org/
26. 1750 Pennsylvania Avenue, NW, Suite 300, Washington, DC 20006. http://www.who.int/goe/publications/goe_mhealth_web.pdf
27. Poon CCY, Zhang Y-T, Bao S-D. A novel biometrics method to secure wireless body area sensor networks for telemedicine and m-health. IEEE Communications Magazine, April 2006.
28. Chiarini G, Ray P, Akter S, Masella C, Ganzm A. Health technologies for chronic diseases and elders: a systematic review. *IEEE Journal on Selected Areas in Communications/Supplement* 2013; **31**(9):6–18.
29. Jara AJ, Zamora-Izquierdo MA, Skarmeta AF. Interconnection framework for mHealth and remote monitoring based on the Internet of things. *IEEE Journal on Selected Areas in Communications/Supplement* 2013; **31**(9).
30. Bluetooth Special Interest Group, Health Device Profile, The Bluetooth SIG Health Device Profile (HDP), Available at https://www.bluetooth.org/en-us/specification/assigned-numbers/health-device-profile
31. INTERNATIONAL STANDARD, ISO/IEEE 11073-10404: 2010 (E), Health informatics, Personal health device communication, Part 10404: Device specialization — Pulse oximeter.
32. IEEE Standard 11073-10415™-2008, Health informatics—personal health device communication, Part 10415: Device specialization—weight scale.
33. Continua Health Alliance, The Continua Version 2012 Design Guidelines, Available at http://www.continuaalliance.org/products/design-guidelines.
34. Carroll R, Cnossen R, Schnell M, Simons D. Continua: an interoperable personal healthcare ecosystem. *IEEE Pervasive Computing* 2007; **6**(4):90–94.
35. Chen M, González S, Vasilakos A, Cao H, Leung VCM. Body area networks: a survey. *ACM/Springer Mobile Networks and Applications (MONET)*, February 2011, DOI: 10.1007/s11036-010-0260-8.

36. Crockford D. The application/JSON media type for JavaScript Object Notation (JSON). RFC 4627, July 2006.
37. Bisio I, Lavagetto F, Marchese M. Context-aware smartphone services. Chapter of the book. *Pervasive Computing and Communications Design and Deployment: Technologies, Trends, and Applications*, Malatras A (ed.). IGI Global, Hershey: PA, USA, 2011; 24–47.
38. Kwapisz JR, Weiss GM, Moore SA. Activity recognition using cell phone accelerometers. SIGKDD Explor. Newsl. 12, 2 (March 2011), 74–82, 2011.
39. Lockhart JW, Pulickal T, Weiss GM. Applications of mobile activity recognition. *Proceedings of the* 2012 *ACM Conference on Ubiquitous Computing*, Pittsburgh, Pennsylvania, September 5–8, 2012.
40. Kim Y, Park D-S, Kim H, Kim U. 2011. A sliding window-based false-negative approach for ubiquitous data stream analysis. *International Journal of Communication Systems*. DOI: 10.1002/dac.1211.
41. Miluzzo E, Lane N, Fodor K, Peterson R, Lu H, Musolesi M, Eisenman SB, Zheng X, Campbell AT. Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application, in SenSys '08, *Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems*. November 5–7, 2008; 337–350.
42. Ross Quinlan J. *C4.5: Programs for Machine Learning*. Morgan Kaufmann Publishers Inc.: San Mateo, CA, USA, 1993.
43. Ryder J, Longstaff B, Reddy S, Estrin D. Ambulation: a tool for monitoring mobility patterns over time using mobile phones". *Proceedings of International Conference on Computational Science and Engineering (CSE'09)*, Vancouver, Canada, August 2009; 927–931.
44. Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter* 2009; **11**(1):10–18.
45. Toth N, Pataki B. Classification confidence weighted majority voting using decision tree classifiers. *International Journal of Intelligent Computing and Cybernetics* 2008; **1**(2):169–192.
46. Wang Y, Lin J, Annavaram M, Jacobson QA, Hong J, Krishnamachari B, Sadeh N. A framework of energy efficient mobile sensing for automatic user state recognition. *Proceedings of the 7th International Conference on mobile Systems, Applications, and Services (Mobisys'09)*, Krakòw, Poland, June 22–25 2009; 179–192.