A non invasive, wearable sensor platform for multi-parametric remote monitoring in CHF patients

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Abstract. The ageing of European population is now requiring novel solutions that help the healthcare systems face the new challenges. Novel monitoring solutions, combining state-of-the-art technologies will take a main role in the new healthcare models. In the present paper a prototype of an implemented non-invasive, wearable sensor platform for Congestive Heart Failure (CHF) patients is shown and described. The platform monitors all the required parameters from sensors, collects and processes the data in a mobile platform and sends the data to a server.

Keywords: Wearable sensor platform; Congestive Heart Failure (CHF); Multi-parametric monitoring; Electrocardiogram (ECG); Skin temperature; Sweat index; Activity recognition; Energy Expenditure.

1 Introduction

European healthcare models are facing important challenges due to the ageing of population and the increment of the number of patients with cardiovascular diseases, specifically, patients with congestive heart failure (CHF) [1]. These models, in which limited resources face an increasing need, should not only focus on disease treatment but also on disease prevention in order to reduce the number of hospitalizations and professionals devoted to patients, while improving the quality of the healthcare by means of a continuum of care in home, nomadic or hospital environments.

This ambitious goal requires the use of state-of-the-art technologies that provide accurate and long-term health monitoring in a transparent way, i.e. avoiding invasive devices. Along with this, all the data obtained from patient monitoring need to be also

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combined and interpreted in order to build a physiological model for proper clinical diagnoses and by means of a seamless integration with the hospital workflow.

There have been previous efforts in CHF patient monitoring solutions. A recent meta-analysis presents several studies related to remote monitoring for CHF disease [2]. However, all of them present several limitations. Either they offer only at home devices or do not take into account parameters that can be relevant to CHF crisis detection, as skin humidity or ST segment shift with heart range changes. Therefore, a necessary previous step is to carefully choose the relevant parameters for CHF patients' care. A literature research was performed resulting in a long list of parameters, which were classified in short-term and long-term together with its relevance as potential risk factors. The present solution focuses on the short-term parameters: electrocardiogram (ECG), potassium blood content (obtained from ECG), average energy expenditure evaluation through activity recognition, skin and ambient temperature, sweating and ambient humidity. This solution differs from other remote monitoring systems for healthcare as it is specifically designed for CHF patients [3].

The objective of this work is then the design and implementation of a non invasive, wearable solution for continuously monitoring of the relevant parameters of CHF patients. This solution comprises the components that are in charge of concentrating the data, extracting the proper features and sending them to the hospital servers.

2 A system description

The wearable platform comprises two different straps: one placed at the chest, which collect ECG, skin temperature, sweat index and acceleration data and a second one at the thigh collecting extra acceleration data for accurate activity recognition.

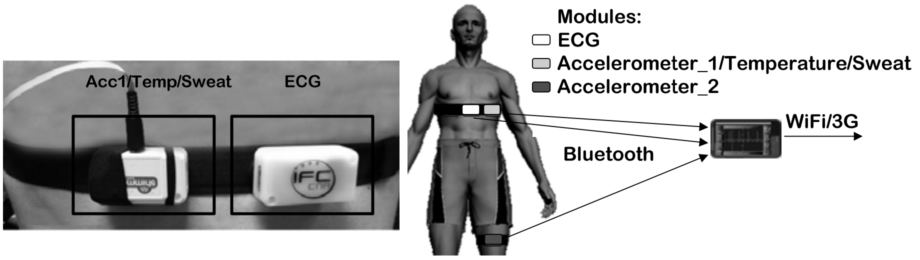

Fig. 1. Diagram and prototype implementation of the wearable sensor platform.

Fig. 1 shows a scheme of the system. The modules collect the parameters from sensors and send the data to a mobile platform by means of Bluetooth connections. Bluetooth is a proper solution for sensor communication as most mobiles integrate it and it offers higher data rate than Zigbee. Bluetooth capabilities for sensors are provided by Shimmer modules, which are an adequate choice as they provide internal accelerometers together with standard digital (I2C, SPI) communication buses for new potential sensors [4]. They also offer high storage capacity by means of a 2GB SD card, small size and good autonomy because Bluetooth connections in this solution perform under the store-and-forward principle. Data is saved for a certain amount of time in a flexible way (ranging from real time communication to 60 minutes storage) and sent when the mobile platform asks for the information.

2.1 Electrocardiogram Sensor Platform

The wearable chest strap incorporates a compact device designed for continuous monitoring of ECG as shown in Fig. 1. The Shimmer based-platform includes ECG sensing device, signal conditioning, SD card and low-power Bluetooth module.

The light weight (~100 g) and compact form factor of the sensor makes it very suitable for physiological sensing applications. The electronic board and his enclosure was redesigned to be easily plugged on the common cardio-fitness chest straps (i.e. Polar®, Adidas®), which are fully washable and guarantee an optimal and comfortable contact with the thorax for a long time, adapting itself to the body shape. The belt includes two biocompatible, dry electrodes applied directly to the patient's skin for single-lead acquisitions without skin preparation, gels, or adhesives. The signals are analogue-to-digital converted with 10-bit accuracy and the output signal range is adjustable from differential (−3 V to 3 V) to single-ended (0 V to 3 V). Actually the firmware of the microcontroller tested adopts a sampling rate of 100 Hz, but it can be easily changed acquiring the signal until more than 1000 Hz. It uses an appropriate interrupt management of data for real-time streaming or storage on SD card. Moreover it is able to download the data from SD card to smart-phone.

2.2 Skin temperature and Sweat Index Sensor Platform

Skin temperature and sweat index parameters are extracted by means of the Sensirion SHT21 digital sensor [5]. This sensor is suitable choice for temperature and sweat measurements, as it integrates both a temperature and a humidity sensor. In addition to that, the size of the sensor, its accuracy and its low power consumption makes it an adequate solution for wearable, battery-powered platforms. The temperature and humidity are measured with 0.3ºC and ±5%RH accuracy, respectively. The sensor power consumption is 1mW and 1.2µW in active mode and sleep mode, respectively.

In this solution, the sensor is placed in contact to the skin, in a stable position at the patient's armpit so that accurate measurements of temperature and sweat index can be obtained. On the other hand, the sensor is controlled by means an I2C communication protocol. A 4-wire bus connects the sensor to the Shimmer device. The firmware of the Shimmer takes temperature and humidity samples every 5 minutes as specified by doctors. Later on, samples are combined with the first accelerometer data in a single data packet and sent to the mobile platform when required.

2.3 Activity Monitoring Sensor Platform

The activity monitoring module utilizes data received from the sensor platform to identify the patient's current posture/activity and calculate the average energy expenditure expressed in the standard metabolic equivalent (MET). The method utilizes two accelerometers, one attached to the patient's chest and the other to the thigh, as well as skin temperature and heart rate information.

Activity recognition is performed with an overlapping sliding window method. We configured the Shimmer accelerometers to measure the acceleration with 50 Hz frequency. This means that we receive around 50 acceleration measurements along three perpendicular axes x, y and z every second for every accelerometer. We split this stream into 2 second windows, each of which contains around 100 measurements. The activity is recognized for each window.

The activities are recognized by a classifier trained by a machine learning algorithm. We limited our activity recognition model to recognizing the following activities: standing, walking, running, sitting, lying, on all fours, kneeling, cycling and transitions between these activities.

The raw acceleration values in each window are first transformed into attributes forming an attribute vector, which is then fed into the machine learning algorithm to train a classifier. New data are also transformed into attribute vectors and fed into the classifier, which recognizes the activities. Attributes which are used for classification, are divided into two groups: statistical attributes (average, minimum, maximum, variance, difference between minimum and maximum, correlation, orientation) and frequency domain attributes (frequency, energy) [6].

The energy expenditure estimation approach is methodologically similar to the activity recognition. The raw acceleration data are processed into an attribute vector for each time window of 10 seconds. The attribute vector is used to train a regression model for the task of human energy expenditure estimation in MET.

The attributes for the human energy expenditure regression model consist of (i) attributes derived from the acceleration, (ii) heart rate and (iii) skin temperature. The attributes derived from the acceleration were partially adopted from [7] and partially developed by us. Our original attributes are (i) the adopted attributes, but with the gravity subtracted; (ii) acceleration peak counter and summation of the peak values; and (iii) the recognized activity. The recognized activity is either the most prevalent activity in the window or transition if less than two thirds of the window contains a single continuous activity. This helps capture the movement dynamics.

2.4 Data gathering Mobile Platform

The sensors are wirelessly connected to a smartphone by means of a low profile communication protocol at this stage. The use of a smartphone has several advantages. It can be carried by patients and so it permits their mobility. It is also a familiar device and guarantees that the patient will indeed have the device with him. In addition, the processing power of the smartphone and autonomy represents a nice compromise. Therefore, the smartphone is a satisfactory and simple solution with a small learning curve for patients and their families.

The smartphone can be simultaneously connected to all the sensors or in parallel communication alternating. It could also use its own internal sensors for acquiring further data (for example GPS for locating the patient in need of intervention).

On the other hand, sensors send readings with a wide range of sampling rate, from less than 1Hz (temperature) to 500Hz (ECG). High sampling rates drains the smartphone processing capacity and reduces its autonomy, so feature extraction algorithms to process and reduce the amount of data will be included. The smartphone can also check the integrity of collected data. Artifact and noise removal algorithms can be applied because they are fairly undemanding of smartphone processor power.

Finally, the mobile platform is a fully standalone solution which synchronizes data with a central server in user defined parameters. The timestamp, triggers and content of the synch are defined in a "rule engine", which allow for dynamic change, depending on the user's needs.

3 Results

This section shows the results of the CHF patient monitoring sensor platform.

3.1 ECG Monitoring Sensor Platform Results

To test the performance of the proposed system 4 healthy volunteers were enrolled age 30 ± 3 in the study. ECG was acquired from 2 freely moving nurses at work and 2 subjects at bedside for 3 hours. All the subjects wore both the developed chest strap with the smartphone and the clinical holter ELA. In Table 1 are reported the technical features of both devices.

Table 1. Features of the chest strap and the holter ELA.

Technical features	ECG Chest strap	Holter ELA
Acquisition sampling rate:	100 Hz	1000 Hz
Resolution A/D:	10 bit	15 bit
Dimensions:	50 x 25 x 23 mm	97 x 54 x 23 mm
Weight:	~100 Grams	~300Grams
Power supply:	3V Li-ion battery 450mAh	1.5V alkaline battery
Data Transmission:	Bluetooth/802.15.4/SD Card	SD Card
Leads:	One	Three

As reported in Table 1, the main changes are due to the sampling rate i.e. ECG chest strap were sampled at 100 Hz, while ELA data were sampled at 1000 Hz. Moreover also the data transmission, the number of leads and dimensions are different. Applicability of the ECG chest strap in a clinical setting is now under investigation. Indeed, a specific study is in progress to validate the use of the system on cardiac inpatients within the Institute of Clinical Physiology of Pisa. In the first part of the study the data were collected from simultaneous ECG recordings obtained by our system and the ELA holter. The resulting waveform confirmed the signal quality was comparable to that captured using the ELA holter.

Moreover ECG chest strap provided readable signal for more than 95% and 99% of the time of acquisition while the subjects where on working and lying supine at bedside respectively. In the second part of the study we focused on the capability of the system to extract the features of cardiac rhythm. The high correlation between the two trends indicates a correct estimation of RR interval and of the average beat-by-beat heart rate from the ECG chest strap as shown in Fig. 2.

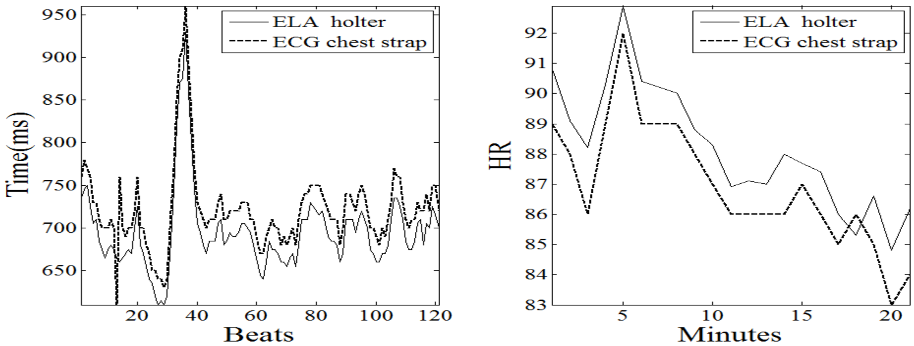

Fig. 2. Comparison between ECG chest strap and ELA holter of tachogram and heart rate, respectively.

In order to process and identify further ECG parameters as P wave, T wave, and ST segment, a template matching algorithm technique was applied. The technique relies on the use of a basis template to identify relevant features. Mean ECG cardiac cycle is extracted as matching templates from the ECG chest strap and holter ELA raw data. Their comparison allowed high correlation to be gained, although further analysis is in progress to identify and analyze P, T and ST segments.

3.2 Activity Monitoring Sensor Platform Results

The activity monitoring consists of the activity recognition and the estimation of human energy expenditure. Machine-learning algorithms used to train models for both modules are implemented in the Weka machine learning suite [8].

For the activity recognition we have evaluated multiple classifiers trained using different machine-learning algorithms: Naïve Bayes, C4.5 decision tree learner, Random Forest and Support Vector Machine (SVM). The upper two rows of Table 2 show the classification accuracy (CA) for the selected machine learning.

The results show that Random Forest, which trains an ensemble of decision trees, is the best algorithm for activity recognition. A detailed inspection of the recognition with Random Forest shows that sitting was often confused for standing, and cycling for walking. Both problems are not surprising given the nature of the activities and accelerometer placement, but they are fortunately not overly problematic from the perspective of energy expenditure estimation.

The estimation of human energy expenditure was tackled by training a regression model. For the evaluation and selection of the most accurate model, four regression models were trained. These are Linear Regression (LR), Support Vector Regression (SVR) with linear kernel, Fast Decision Tree Learner (REPTree) and M5 Rules, which induce rules with linear functions in the consequent. The lower two rows of the Table 2 show the results of the trained models expressed in relative absolute error (RAE). The models are able to estimate energy expenditure for all the activities.

Table 2. The upper rows present the classification accuracy for the activity recognition task according to the algorithm. The lower rows present the relative absolute error of the regression task in energy expenditure according to the algorithm.

Algorithm	**Naïve Bayes**	**C4.5**	**Random Forest**	**SVM**
Activity Recognition (CA)	69.5	70.1	**80.3**	75.8
Algorithm	**LR**	**SVR**	**REPTree**	**M5Rules**
Energy Estimation (RAE)	28.3	23.43	**21.68**	27.7

We can conclude from the results that the REPTree is the best machine-learning algorithm. However, the disadvantage of this algorithm is poor interpolation and extrapolation, since the regression tree it trains contains a number of fixed MET values in the leaves, and the tree can only estimate the energy expenditure to be one of those values. The second best algorithm was selected for the final regression model. The advantage of the SVR algorithm is that the model it trains is simpler (a linear function) and thus less likely to overfit to the training data.

An analysis of the results of the trained regression model showed a decrease in overall accuracy is caused by energy estimation of activities running and cycling. This problem was tackled by adding additional classifiers used only to estimate energy expenditure for the problematic activities. We then combined the complete classifier with the per-activity classifier. The complete classifier was used whenever possible and the per-activity classifier in the case of cycling and running. The composite classifier returned mean absolute error of 1.4 MET and relative absolute error 20.5%.

3.3 Temperature and sweating Monitoring Sensor Platform Results

Both temperature and sweating index parameters are required to be monitored every 5 minutes for a long period of time. However, the platform was tested at a higher rate, every 20 seconds, in order to check not only the sensor performance but also the autonomy of the temperature/humidity sensor+Bluetooth Shimmer module.

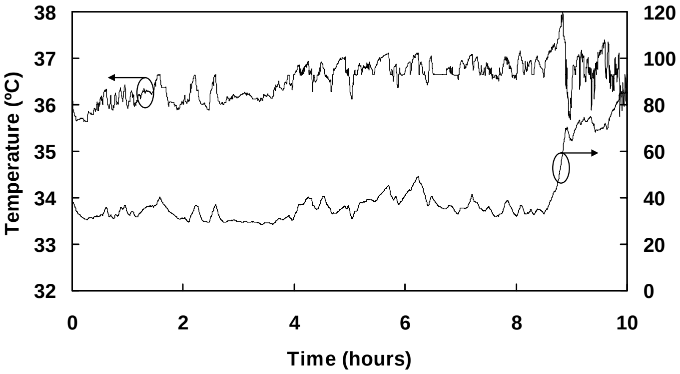

Fig. 3. Skin temperature and humidity test for ten hours of continuous monitoring and two scenarios: normal activity from 0-9h and moderate activity from 9-10h.

Fig. 3 shows the results of a 10 hour test in two different scenarios. From 0 to 9 hours, the volunteer performed normal activity: sit down, walking, etc., from 9 to 10 hours the volunteer performed moderate activity that resulted in sweating. It can be observed in Fig. 3 that the results show a rapid change in temperature together with a noticeable increment on humidity. It should be also noted that although only ten hours of parameter sampling are showed, the autonomy of the platform exceeds 16 hours at 20 second sample rate for both parameters. This autonomy would be further extended if we stick to 5 minute sampling rate.

4 Conclusions

A non invasive, wearable sensor platform implementation for CHF patient monitoring has been presented. The platform monitors accurately the ECG signal, data from two accelerometers for activity recognition and energy expenditure evaluation, skin temperature and sweating index. The platform communicates sensor parameters to a mobile platform by means of Bluetooth communications using the store-and-forward principle that preserves the platform autonomy. Results show that the combination of state-of-the-art technologies can address the challenges of the new healthcare models.

Future steps comprise the integration of collected data with those available in the Hospital Information System in order to build a physiological model of the patient (defined as Alter Ego).

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