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(Article begins on next page)

Input Clinical Parameters for Cardiac Heart Failure Characterization Using Machine Learning

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Abstract — Congestive Heart Failure (CHF) is a serious chronic cardiac condition that brings high risk of urgent hospitalization and could lead to death. In this work we show how all the input clinical parameters for classifying CHF using Machine Learning can be acquired. The requested input are Blood Pressure, Heart Rate, Brain Natriuretic Peptide, Electrocardiogram, Blood Oxygen Saturation, Height, Weight and Ejection Fraction. The next step will be designing a novel device and connecting it to our Machine Learning classifier. A particular attention will be put to the assessment of electromagnetic compatibility (EMC) with other devices, taking into account that this new device will be used in many different settings (home, outdoor, etc.).

Keywords — Congestive Heart failure, Machine Learning, Clinical input, Device, Home monitoring, ECG, Blood Pressure, Heart Rate, SpO₂, BNP, Ejection Fraction, Weight, Height.

I. INTRODUCTION

In this work it is described how to acquire input features to feed a Machine Learning (ML) Decision Support System (DSS) for Congestive Heart Failure (CHF) aiming at offering an efficient and cost-effective solution to enforce patients' home monitoring, in order to prevent inappropriate hospitalizations while improving the ability of self-diagnosing exacerbations.

This solution is based on the improvement of the multi-sensing device proposed by *Pollonini et al.* [1], together with the machine learning DSS described by *Guidi et al.* [2][3][4].

The clinical parameters that are needed as input to the selected machine learning classifier, described in [2] are the following:

- 12-Lead ECG
- Systolic Blood Pressure
- Diastolic Blood Pressure
- Ejection Fraction
- Height
- Weight
- Oxygen Saturation
- Heart Rate
- BNP (Brain Natriuretic Peptide) or NT-proBNP

Our study started by examining the most recent scientific developments in literature, focused on different wearable health devices and home telemonitoring systems. [5] The purpose of all devices is to be comfortable, small in dimensions, easy-to-use, unobtrusive and interoperable among various computing platforms, in order to provide better health care service and affordable price for aging people.

Flexibility is also a crucial point for wearable devices. *Majumder et al.* presented a review of the development in wearable systems by comparing the most significant contributions in each field. [6] Wearable sensors attracted the attention of many researchers in recent years according to the development in low-power and compact wearables (sensors, actuators, smart textiles). However, the necessity of monitoring a set of physiological parameters with a minimum number of electrodes and sensors that also ensure information privacy and data security needs more research and technology developments. Hence, we will treat each parameter aiming at obtaining an improved multi parameter system that can be adequate for the scope of the ML algorithms.

All the adopted sensors will be based on contactless measurement techniques, thus avoiding the use of gel for the conduction of the signal and possible skin irritation due to contact. Wearable and textile-based sensors are still a new field with opportunities to build innovative products and has become one of the main research avenues in the textile field. [7]

II. METHODS

A. 12-Lead ECG

To obtain a full 12-leads Electrocardiogram (ECG), instead of using the typical approach of using 10 electrodes, we consider adopting the EASI model, proposed by *Dower* [8] and further improved by using ML and regression techniques [9]. The EASI-lead monitoring system requires only five, optimally placed, electrodes and it can adequately reconstruct the waveforms of the 12 leads. The signals are derived from four thorax electrodes plus one reference electrode: this reduced number of electrodes improves the comfort and mobility for the patients while reducing the sensitivity to noise. The EASI lead system uses the *Frank* [10] E, A, and I electrode locations, plus an electrode S. The electrode S is positioned at the

upper sternum, E at the lower sternum, A and I at the left and right mid-axillary, respectively, while the final electrode can be placed at any positions for ground. In Dower's method paired signals A-I, E-S and A-S are used, derived as a weighted linear sum. [8] This could be a good basis for deriving a 12-leads ECG.

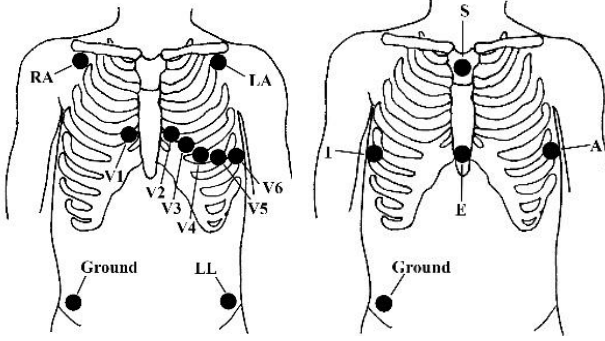


Figure 1: Standard 12-lead ECG System (left) vs. EASI-lead System (right) [9]

In a recent research *Kaewfoongrungsi et al.* [9] compared five different ML and regression techniques to find which model was more effective in deriving 12-leads ECG signals. From their experiments they concluded that the best performance was obtained using *Support Vector Regression* (SVR) and *Artificial Neural Network* (ANN). Based on the existing literature, we assume that the accuracy of this solution could be sufficient for the scope of the ML algorithms. Different considerations might be done, should the EASI model be used by a cardiologist for performing his diagnosis, which is not our case [11].

B. Systolic Blood Pressure and Diastolic Blood Pressure

Cuffless blood pressure monitoring has been presented in previous researches in which recent efforts in developing next-generation blood pressure monitoring devices with innovative wearable sensors were highlighted. [12] Pulse Wave Velocity (PWV) could be one possible method to estimate noninvasive cuffless blood pressure (BP). It can be obtained using the distance and the Pulse Transit Time (PTT) of the blood between two arterial sites. A common way to measure PWV and PTT is by combining the ECG signal and the photoplethysmography (PPG) acquired at the level of the finger or the toe. Moreover, there are several main measurements that can be applied, such as accelerometers, pressure sensors, and bioimpedance (BI). In case of the PPG sensor, the need for a light-emitting source for the reflection method and the

necessity of a direct and tight contact with the skin are drawbacks. It can require higher levels of power and users might feel uncomfortable. [13]

Calculation: $PWV = D/PTT$

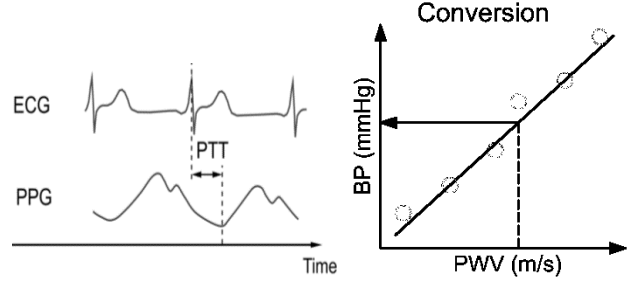


Figure 2. Methodology of pulse wave velocity (PWV)-based blood pressure (BP) estimation. D is the distance from the arterial sites. [13]

In order to cope with the limitations of the above described methods, *Liu et al.* [14] replaced the PPG signal with the impedance-plethysmography (IPG), used to detect the PTT. Then, they designed an IPG arm ring that could measure an accurate IPG signal. They compared the change of PTT_{PPG} (the PTT from the ECG and the PPG signals) with that of PTT_{IPG} (from the ECG and the IPG signals). Their results showed that the change of the systolic pressure had a better relationship with the change of the PTT_{IPG} compared to the PTT_{PPG} ($r = 0.700$ vs. $r = 0.450$). Moreover, the IPG ring with spot electrodes would be more suitable to develop with the wearable cuffless blood pressure monitors. This happens because the electrodes are placed symmetrically and the IPG ring could be rotated around, so they only need to make slight contact with the skin. Soft material would not feel uncomfortable to patients.

Although these approaches are interesting, *Simjanoska et al.* [15] have developed a method for the BP estimation by using only ECG signals. They acquired BP by introducing complexity analysis in the feature extraction process as well as a stack of ML models for more robust predictive models. In the experimental results they obtained that with the use of a calibration, the method can achieve results close to those of a common medical device for BP estimation. This research represents a contribution on the use of ECG sensor without additional devices for detecting BP. It provides with a demonstrable relationship between BP and ML that could be an innovative development in this field.

However, there is still a need for a more in-depth analysis about the most accurate cuffless method.

C. Ejection Fraction

Ejection Fraction (EF) refers to the measurement, expressed in percentage, of blood amount pumped out of the ventricles with each contraction. EF measurement requires Echocardiography or Magnetic Resonance Imaging. Hence, this clinical parameter could not be simply acquired in the proposed device, without requiring external input from these pieces of equipment.

D. Weight and Height

This parameter is crucial for diagnosis CHF worsening. There are some methods for estimating both weight and height using computer vision. Weight measurement using these techniques is currently not accurate enough, therefore it will be acquired using a Bluetooth scale, according to *Pol-lonini et al.* [1]. Instead Height will be detected with a webcam, using computer vision systems.

E. Oxygen Saturation

The blood oxygen saturation level (SpO_2) indicates the percentage of oxygenated hemoglobin molecules in arterial blood. For its detection, a textile-based sensing principle for long term PPG monitoring could be adopted [16]. This photonic textile, using embroidered optical fibers and working in reflection mode, bestows a highly flexibility. It is very versatile for wearable long-term monitoring, allowing the measurements in different parts of the body and enhancing the acceptance of the wearer. SpO_2 was determined by using a modified Beer-Lambert law for measuring the light attenuation at two different wavelengths (632 nm and 894 nm). All the recorded data were imported into MATLAB R2012b for further signal processing.

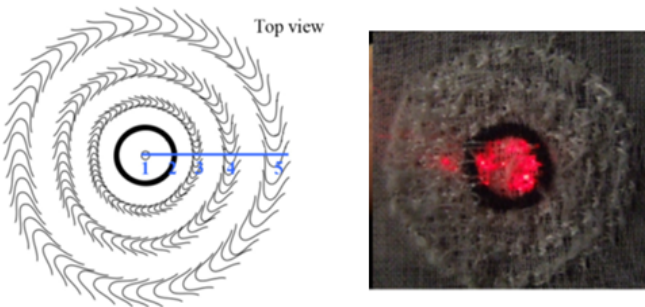


Figure 3. Sketch presenting embroidered optical fibers. Where (1) optical fibers stitched to couple the light out; (2) three-dimensional embroidered black ring to prevent light short circuit. (3),(4) and (5) represent rings of optical fibers stitched to couple the light in. Each “V”-shaped line in the rings represents a portion of a single optical fiber (left). Top view of the photonic textile: light is delivered by the central fiber, while the black ring prevents “short circuit”. A woven textile is used (right). [16]

F. Heart Rate

Heart Rate (HR) can be easily extracted from ECG (R-peak) or PPG signals [16][17]. Although these measurements have two different physiological origins, they contain a similar heart rate information. The PPG monitor is the same used for detecting SpO_2 , therefore we could monitor both these parameters using a single device.

Instead, for heart rate detection from ECG the most used algorithm was developed by *Pan and Tompkins* [17] and later improved by many authors. In 2006 *Paoletti et al.* [18] compare it with a new algorithm. They demonstrated that both algorithms showed similar performances in order to detect QRS complexes, but the new one had the advantage of being faster.

G. BNP (Brain Natriuretic Peptide) or NT-proBNP

BNP or NT-proBNP are identified as the standard biomarkers for CHF diagnosis and prognosis. *Sarangadharan et al.* [19] developed a hand-held field effect transistor (FET) based biosensor aiming at detecting Brain Natriuretic Peptide (BNP) from a single drop of whole blood, without sample pre-treatments. They created an integrated portable biosensor system that could allow whole blood diagnostics in five minutes. It works by separating the cells from plasma using gravity. The authors also show their device can be used both in a face down or a face up configuration, with no significant differences in performance. Hence its portability and its rapid diagnosis could be a plus for home caring and clinical application.

IV. CONCLUSION

In this paper we showed how all the required parameters for feeding a ML decision support system for CHF can be acquired using simple techniques and sensors that might be engineered in a single hardware device. The next step will be designing this novel device and connecting it to our ML classifier [20]. In previous researches *Guidi et al.* investigated some techniques for classifying CHF, such as Classification

And Regression Tree (CART), Random Forest and other algorithms, obtaining good results in severity assessment and in reducing clinical errors. [3] [21]

A particular attention should be put in assessing the electromagnetic compatibility (EMC) with other devices (electro medical equipment, personal devices, home devices), taking into account that this new device will be used in many different settings (home, outdoor, etc.). [22]

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