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Pulse: An unobtrusive vitals monitoring system based on innovative high sensitivity sensors

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Abstract—Disorders with a transient signature (e.g., obstructive sleep apnea, drowsy driving, sudden infant death syndrome, or atrial fibrillation) are difficult to predict. The Pulse system, including a matrix of unobtrusive strain sensors, was designed to extract four different vital parameters: actigraphy, Breath Frequency (BF), Heart Rate (HR), and Heart Rate Variability (HRV). Thanks to the high sensitivity of the innovative Nanomade strain sensors, it shows good performances (accuracy around 98.5% for HR/HRV and up to 96% for BF) in regard with the state of the art. Moreover, these sensors can easily be integrated into different equipment, are adaptive and low-cost.

Index Terms—Ballistocardiography, Heart Rate, Heart Rate Variability, Breath Frequency, Actigraphy, low-cost, strain sensor

I. INTRODUCTION

The last decades have seen a significant evolution in medical diagnosis. Yet, some disorders remain difficult to predict due to their transient nature. Among the most critical ones, there are Obstructive Sleep Apnea (OSA) [1], drowsy driving [2], sudden infant death syndrome [3] and atrial fibrillation (the leading cause of embolic stroke worldwide) [4]. These disorders are highly difficult to detect because affected persons show very few symptoms.

Yet, monitoring the following four vital parameters can substantially help diagnose these aforementioned conditions [5]–[8] :

- the actigraphy that quantifies the subject movements;
- the respiratory rate or Breath Frequency (BF) that represents the number of breaths per minute;
- the Heart Rate (HR) that is the average of time intervals between two heartbeats;
- the Heart Rate Variability (HRV) that represents the variation of these intervals.

HR and HRV can be contactless measured via BallistoCardioGraphy (BCG), a technique which evaluates the strains generated by the ejection of blood from the heart into the descending aorta [9]. This technique also helps retrieving respiratory and body movement information. Since the early 2000's, several BCG sensor technologies (e.g. accelerometers, piezoelectric sensors, strain gauges) and signal processing techniques (e.g. peak detection, machine learning, autocorrelation) have been implemented. Among the sensor solutions found in the literature, some of these use low-cost but bulky and/or heterogeneous technologies that remain difficult to be

incorporated into devices [10]–[13]. On the opposite, others are based on easy to use yet costly sensors [14]–[16].

This paper introduces an innovative, generic and unobtrusive vitals monitoring system, called Pulse. It relies on an adaptive, low-cost and high sensitivity strain gauges matrix that can easily be integrated into various types of equipment (e.g. bed, vehicle seat, wheel chair,...). An Analog Front-End (AFE) circuit and an embedded digital processing were developed according to the sensors physical characteristics, to determine HRV, actigraphy, BF and HR despite body motion artifact. The proposed system and the sensor technology are described in Section II. Then, the experimental setup is detailed in Section III. Next, the results are presented in Section IV while conclusion and perspectives are drawn in Section V.

II. SYSTEM SUMMARY

The system includes a strain sensors matrix and a dedicated circuit, as illustrated in Fig. 1. The strain sensors and the electronic front-end ensuring the signals conditioning until the analog-to-digital conversion, are detailed below. The digital signal processing, ensuring the vitals parameters extraction, were embedded in a dual-core micro-processor.

A. The Pulse sensor

The Pulse sensor used in the present study consists in 12 Nanomade strain sensors spread over an ultrathin flexible 14 cm x 19 cm surface, glued on a polycarbonate sheet, used as a strain-propagating medium (Fig. 2a).

Nanomade strain sensors were chosen for their sensitivity, flexibility, thinness and low cost:

- Nanomade-based strain sensors are usually far more sensitive than commercial strain gauges [17]–[19], thus

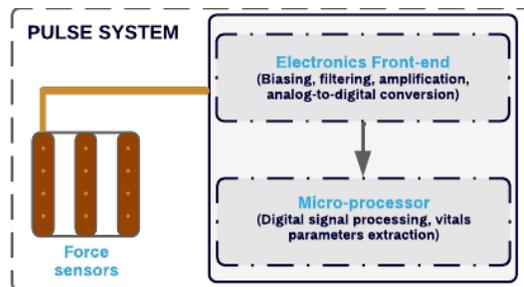


Fig. 1: Architecture of the Pulse system.

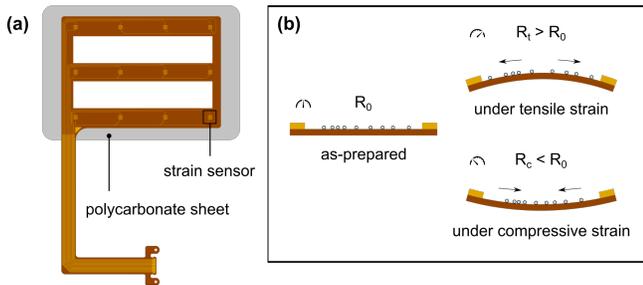


Fig. 2: PULSE sensor stack-up and working principle. (a) Sensor stack-up. (b) Strain sensor working principle.

allowing the detection of very faint signals. In the present case, they present a gauge factor of 30, while commercial strain gauges typically present a strain factor of 2.

- The thinness and flexibility of Nanomade strain sensors (250 μm thick) provide seamless integration capability into beds and seats for BCG applications.
- Nanomade strain sensors are low cost: for comparable dimensions, Nanomade strain sensors cost approximately 10 times less than commercial strain gauges.

Nanomade strain sensors rely on the tunnel effect in Conductive Nanoparticle Assemblies (CNAs) [17]–[19]. A Nanomade strain sensor consists of proprietary CNAs containing ink deposited between interdigitated conductive (copper) electrodes on an insulating (polyimide) flexible substrate.

The strain sensors are squares of $5 \times 5 \text{ mm}^2$ and are positioned to efficiently capture respiratory and cardiac signals via BCG: the sensor design consists in a 3×4 matrix with 5.5 cm spacing. This geometry allows to cover a broad spectrum of morphologies and offers versatility regarding integration (seamless and unobtrusive integration in beds, seats, etc).

The static sensor resistance R varies from 3 $k\Omega$ to 30 $k\Omega$ due to process variations. Upon compressive (resp. tensile) strain, the CNAs move closer to (resp. away from) each other, resulting in a decreased (resp. increased) sensor resistance (Fig. 2b). The resistance variations ΔR of all the strain sensors are monitored as they translate the deformations induced by respiratory and cardiac movements. The variation range for each parameter is detailed in Table I.

B. Analog Front-end circuit

The output sensors' signals are processed in the Analog Front End (AFE) circuit presented in Fig. 3. The 12 sensors are biased independently by a variable current source, to overcome the static resistance dispersion. Then, the signals are filtered by a first-order high-pass filter with a cut-off frequency of

Vital signals	$\Delta R/R$	Frequency range
Actigraphy	$\geq 1000 \text{ ppm}$	$\leq 0.5 \text{ Hz}$
Respiratory	$700 \pm 490 \text{ ppm}$	[0.08 ; 0.7] Hz
Cardiac	$75 \pm 34 \text{ ppm}$	[2 ; 14] Hz

TABLE I: Resistance variation and frequency range for each vital parameter extracted.

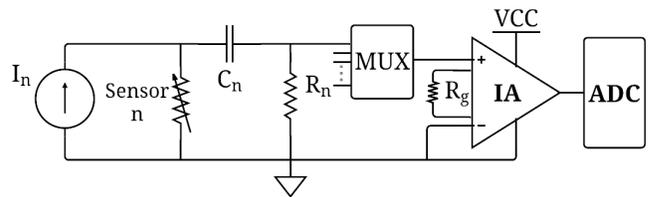


Fig. 3: AFE circuit duplicated for each sensor and then combined through the multiplexer.

0.16 Hz. The 12 signals are then routed to an instrumental amplifier (IA) through a multiplexer. The gain is defined by the application. Indeed, depending on how deep the sensor is positioned in the equipment's foam, it will be more or less sensitive. Finally, the signals are converted with a 16 bits Analog-to-Digital Converter (ADC).

III. EXPERIMENTAL SETUP

The Pulse system was seamlessly integrated in two different types of equipment.

First, the sensor is put in a economic plane seat between the stuffed tissue and the seat foam. the Pulse sensor is positioned in the seating area. It is the optimal sensor position in a seat, for two reasons:

- the BCG craniocaudal momentum (head-to-foot axis) is larger than the other translations [20],
- body motions are less important in the seating area.

Then, the sensor is inserted in a standard medical bed between the memory foam and the elastic one. This position is the most straightforward technique to integrate the sensor even though signals are significantly attenuated due to the memory foam thickness (7cm). In a bed, contrary to a seat, the craniocaudal translation is more difficult to capture. Instead, the best bed-based BCG signal is a combination of dorsoventral (back-to-chest) and transversal (side-to-side) components. To maximize the BCG amplitude, the Pulse sensor is therefore positioned around the chest area [21].

Eight healthy subjects were involved in this study, installed and asked to remain still for 10 min in three different conditions for HRV/HR results: sitting on a plane seat, lying on their back and on their side on a standard medical bed. A POLAR H10 ECG belt, attached to the subject by a chest strap, is used as reference.

To validate the BF measurement, the subjects had to breath following several rhythms given by a metronome: from very low rate (5 bpm) to hyperventilation (40 bpm). Thanks to the sensors sensitivity, the recorded signals' amplitude was high enough and reliable results were obtained.

IV. RESULTS AND DISCUSSION

The embedded software was developed to dynamically select, among the 12 sensors of the matrix, the one delivering the signal with the most useful information. Thanks to this feature, combined with the high sensitivity of the CNA-based sensors, the Pulse system is able to extract signals such as the

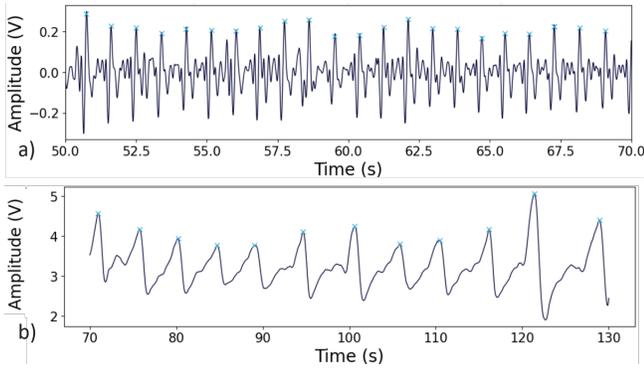


Fig. 4: Cardiac (a) and Respiratory (b) amplitude versus time.

Paper	Correct cardiac peak detection accuracy
Cathelain et al. [12]	95.6 %
Albukhari et al. [13]	83.9 %
Lee et al. [22]	73.8 %
Bruser et al. [23]	95.9 %
Pulse: medical Bed	97.8 %
Pulse: plane seat	99.9 %

TABLE II: Pulse system cardiac accuracy, in regard with state of the art solutions.

ones presented in Fig. 4, from which vital parameters can be determined with accuracy.

The Pulse system cardiac accuracy is given in Table II regarding with the state of the art. It outperforms the others solutions found in the literature, with an accuracy up to 99.9%. The performances obtained on the airplane seat are slightly better than those achieved on the medical bed because the thick memory foam of the bed significantly attenuates the signals.

The Pulse system breathing average accuracy is 96.3% and can even reaches 99% for BF around 20 bpm. This is suitable for the targeted applications and similar to [11]; others references do not quantify their accuracy.

V. CONCLUSION

The Pulse system, including a matrix of unobtrusive strain sensors, was designed to determine vitals. Thanks to the high sensitivity of the innovative Nanomade strain sensors, it shows good performances in regard with the state of the art. Moreover, these sensors can easily be integrated into different equipment (medical bed, plane seat), are adaptive and low-cost.

Yet, signals remain difficult to process in highly noisy environment (e.g. in a car). Furthermore, the relative pressure exerted by the person on each sensor could be computed to provide new features (e.g., person's position, fainting, pressure ulcer risk). As a perspective, a new AFE enhancing the SNR, allowing to combine information from separate sensor' matrices, a 32bits ADC improving the resolution and a dedicated algorithm, involving machine learning techniques should be considered to broaden application fields.

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