A Wearable, Wireless, and Long Lifetime Device to Detect Sleep Disorder Diseases

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***Abstract*—Sleep disorder disease (SDA) and sleep apnoeas are, at this moment, very common pathologies that affect at least 25% of the worldwide population. The method to investigate this disease is expensive, complicated, and needs hospitalization of patients. For these reasons, most cases remain undiagnosed. A comfortable wireless device has been designed to detect the main parameters of SDA as respiration rate (RR), time of apnea (TA), and activation of the autonomous central nervous system (SNA). The device consists of two simple sensors; a thermistor placed close to the nose, which detects the changing in airflow during breathing, and a galvanic skin response (GSR) sensor, which measures the conductivity of the skin. The information is extracted by a low power microcontroller, which calculates RR, TA and the activation of the SNA. The information is collected by a smartphone using the low energy Bluetooth feature to guarantee a long lifetime to the device that uses a small coin battery. Different algorithms are described to minimize the payload on the connection, and therefore power consumption too. The amount memory used to store data on the smartphone is approximately 0.01% compared to a continuous recording.**

***Keywords*—Biomedical applications; Breathing sensor; GSR; Sleep disorders; Wearable device; Wireless body area networks.**

I. Introduction

Sleep apnoea is a common medical disorder that occurs when breathing is interrupted during sleep, also known as sleep-disorder breathing (SDB). Apnoea events can occur up to thirty times an hour, and has direct correlation with major diverse pathologies such as; hyperactivity disorder, diabetes, cardiovascular disease (including strokes), and arterial hypertension. The diagnosis of SBD in the clinic requires the polysomnography test, which is an expensive, time-consuming and labour-intensive procedure. Consequently, many people with SDB, perhaps up to 93% of the population, remain undiagnosed [1]. Monitoring the respiration conditions and the SNA activation during sleep could be an effective screening solution in the primary core setting, thus increasing the number of patients identified. Many wearable systems propose they monitor the respiration parameters during sleep but can't assess sleep quality. Galvanic skin response (GSR) and basal skin resistance (R) are often used as indicators of autonomic activity which has led to their widespread application in physiological and pharmacological investigations [2]–[4]. GSR is also an indicator of many other sleep factors [5] and is directly related to sleep quality due to the connection with the sympathetic nerve [2]. An integrated low power, and wearable device that takes into account both the effect of respiration and the activation of SNA can be an efficient solution to detecting sleep disorders.

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II. Architecture

A. System Overview

The device is a small low energy Bluetooth module, capable to compute data and send pre-processed information to a client. In this section, we will present the main hardware components of the prototype's current implementation.

B. Breathing sensor

The breathing sensor is based on a negative coefficient thermistor (NTC) placed close to the nose. The resistance of this sensor is a function of the temperature. During respiration, the temperature of the airflow changes due to the temperature and humidity of the lungs. The air in the lungs becomes warmer and more humid. The changing of temperature allows for a variation of around four degrees Celsius during breathing. Figure 1.a. shows the signal conditioning circuit used for the temperature measurement. Figure 2a shows the measured with a 10-bit A/D converter of the microcontroller connected at the output of a simple voltage divider. In order to reduce the effect of quantification noise due to the limited number of bits of the A/D, the detected signal is amplified using the circuit of Figure 1a. Fig.2b shows the output of the amplified signal after connecting the sensor close to the nose. The effect of the warm body can be observed and the signal is clearer compared with the output of simple voltage divider circuit. To correctly measure the temperature variation and the respiration rate, we perform various tests. Since the temperature sensor is directly placed below the nose, the amplitude depends on the distance of the sensor by the nose. Then, to guarantee the effectiveness of the algorithms, the sensor is fixed at a certain distance to the nose. Figure 3 shows the temperature variation when the sensor is placed at different distances. For the first minute of the readings, a calibration is performed to identify the input parameters for the algorithm. The algorithm that detects the respiration rate and apnoea time will be described in section 4.

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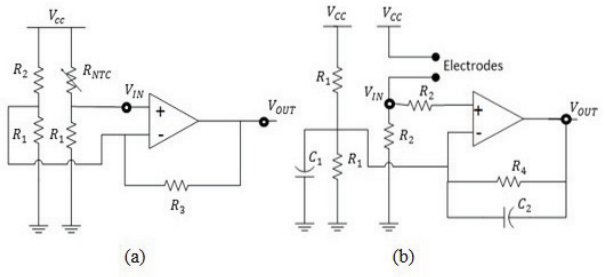

Fig. 1. (a) Schematic of the amplifier for breathing measurement. (b) Schematic of the amplifier for GSR measurement.

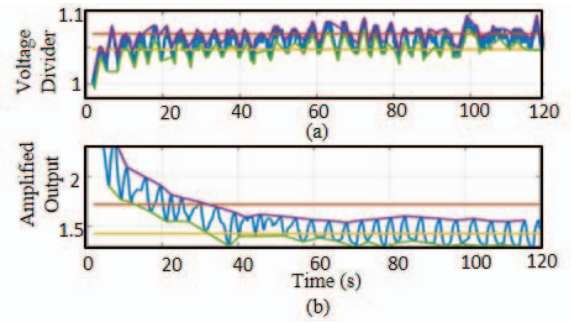

Fig. 2. Filtered and Unfiltered signal. (a) Measurement at the output of a voltage divider, (b) amplified signal just after sensor connection close to the nose.

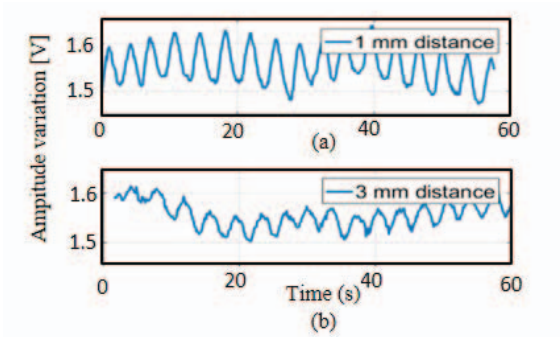

Fig. 3. Signal at different distances: (a) Signal captured at 1 mm distance from the nose (b) signal captured at 3 mm distance from the nose.

C. Galvanic skin response sensor

Galvanic skin response (GSR) can be obtained using a simple sensor that measures the resistance between two positions on the skin. The sensor consists of two electrodes, which are placed on two closed fingers and it measures the activation of the gland cells during sympathetic stimuli [2]. The signal is pre-filtered and amplified using the circuit shown in figure 1b. In comparison with the breathing sensor, the connection is not so critical and is much more conformable because it can be easily integrated in a glove [6-7]. In addition, this application can be used as an alternative method for the detection of SDA's activation. The algorithm described in section 3 manipulates the data to reduce the time in communication, therefore saving battery lifetime.

D. Communication

Data are processed on the device. The same microcontroller integrated in the Bluetooth module computes the respiration rate and captures the peaks in the GSR measurements. A Bluetooth low energy (BLE) collects the information produced by the algorithm and sends intermittent data to save battery. For this communication, an RFDUINO RF22102 is used, which is a BLE module that includes an ARM cortex M0 microprocessor.

III. Signal Processing

As the variation in time of the signals is slow (10-30 beat per minute), and the time of the measurement is very long (one night), the amount of data can use quiet a lot of internal memory storage, so the signal should therefore be processed to save storage space on the smartphone as well as its battery life.

A. Algorithm for breathing signals

Fig. 2b shows an example of normal breathing just after installing the sensor close to the nose. After this period, the temperature variation is less than four Kelvin during the respiration cycle (Fig. 4b); The temperature detected by the sensor gradually increases due to its vicinity to the body, whereas the oscillation depends on the breathing. An increase and decrease in temperature is observed during the exhalation and inhalation time. The positioning of the sensor is a critical aspect because the amplitude of the temperature depends on the relative distance between the sensor and the nasal cavity (Fig. 3). A real-time peak detection algorithm has been developed to obtain peaks and troughs of the breathing signal. The breathing rate, expressed as breaths per minute (bpm) is estimated from the inverse of the interval between two consecutive peaks, $1/\Delta t$ (Fig. 4c).

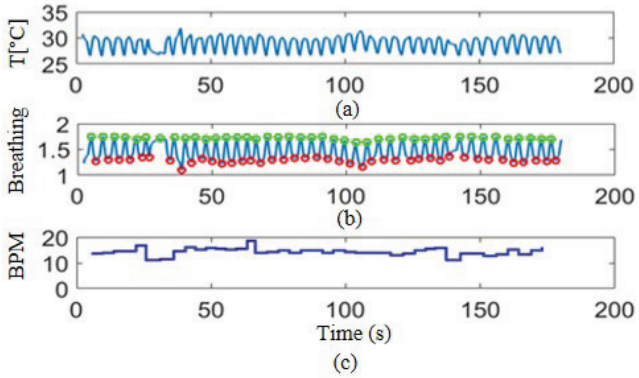

Fig. 4. Example of measurement for a user with normal breathing: (a) temperature change, (b) Voltage measurement at output of the amplifier, and (c) breathing rate in bpm as function of time.

The algorithms to detect the local maximum and minimum usually present some problems in case of noisy data such as breathing data, ECG, or GSR data. Because of consistent noise, the well-known zero-derivative method often fails when the zero crossing of the first derivative occurs. A typical solution consists of smoothing the signal by using low-pass filters. In this method, a robust peak detection algorithm is presented. The algorithm assumes that a peak occurs at its highest point between the troughs and that there are lower points around it. The algorithm explained in [8] uses a delta parameter to filter the next peaks close to the highest,

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minimising the detection of noise (see Fig. 5). The algorithm only needs the current sample and the last detected maximum (or minimum). Therefore, it can be efficiently implemented on real-time for continuous breathing monitoring.

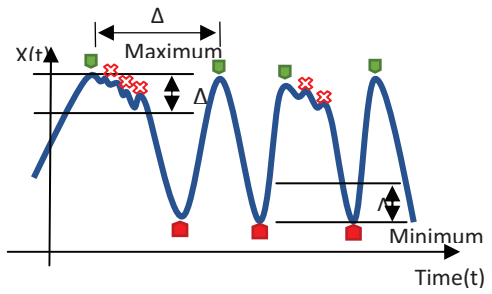

Fig. 5. Strategy to find the local maximum and minimum of the data.

B. *Algorithm for GSR signals*

GSR is a relatively slow signal because it measures the activation of gland cells located on the tip of the fingers. This activation is relatively slow due to the persistence of ions on the skin. When the SNA is active, the gland cells on the fingertips open the ion channels and the GSR sensor detects an increase in conductivity of the skin. For this reason, we are interested in the derivative of the signal. In this work, a robust algorithm for detecting the activation of the SNA is presented. At first, the algorithm filters the high frequencies, allowing that the gland cells need time to open and close the ion channels. Then, the derivative is calculated. The derivative of the signal gives useful information on the state of the SNA. Once the real-time derivative is obtained, a peak detector algorithm, described in the previous section, is applied to detect the highest relative variation in conductivity.

Figure 6a shows GSR signal captured using two simple electrodes placed onto the skin. Because the signal is very noisy, a low-pass FIR filter is applied as follows;

$$Y(t_i) = \alpha X(t_i) + (1-\alpha) Y(t_{i-1}) \tag{1}$$

$$Y_{av}(t_i) = \alpha_2 X(t_i) + (1-\alpha_2) Y_{av}(t_{i-1}) \tag{2}$$

$$GSR(t_i) = Y(t_i) - Y_{av}(t_i) \tag{3}$$

Where $X(t_i)$ is the GSR samples, $Y(t_i)$ is the low-pass FIR filter output and $Y_{av}(t_i)$ is the moving average baseline of the GSR signal. Then the filtered GSR signal is obtained as the filtered samples less the baseline. The smoothing factors α and α_2 are between 0 and 1. In this work α and α_2 are set to 0.04 and 0.08 respectively. The filter cut-off frequency is given by:

$$f_c \approx \alpha / (2\pi T) \tag{4}$$

Where T is the sampling period. Figure 6b shows the filtered signal. This kind of filtering (filter FIR) avoids the usage of vectors to store many samples that is not possible in low power microcontrollers. The GSR signal carries information about the activation of the gland cells, so we are interested in the variation. Strong variations in terms of conductivity identify an activation of the SNA. Then, a numerical derivative is applied as follows:

$$\frac{dGSR(t_i)}{dt} \approx \frac{GSR(t_i) - GSR(t_{i-1})}{t_i - t_{i-1}} \tag{4}$$

The peak detector is then applied on the derivative function. Regarding the previous section, to find the peaks a calculation of a delta parameter is required. A delta parameter is a noise filter in the derivative, which is calculated during a previous calibration.

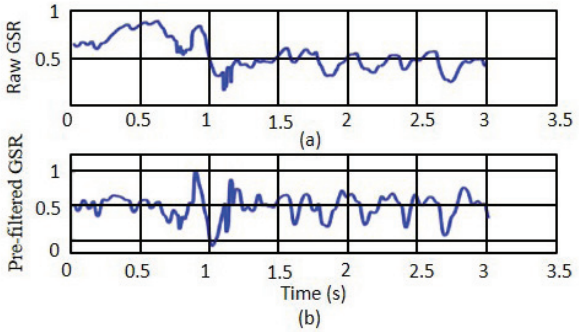

Fig. 6. Signal conditioning, (a) GSR raw data *X(t)*, (b) GSR filtered and normalized data by the algorithm *GSR(t)*.

C. *Calibration*

The first minute of acquiring the data is the calibration time. The low-pass band filter needs a few minutes to become operative. In the first minute, the user is awake and performs normal breathing. During this period the algorithm collects data. The filter expressed in (1) begins to work correctly once at least forty seconds has passed. Then, the device calculates the delta parameter as the percentage of the variation in the last twenty seconds as follows:

$$\Delta = \frac{1}{10}\left(\left(\frac{1}{n}\sum_{i=1}^{n}\max(Y(t_i))\right) - \left(\frac{1}{n}\sum_{i=1}^{n}\min(Y(t_i))\right)\right) \tag{5}$$

Where n is the number of the sample in the last twenty seconds of the measurement, and $Y(t_i)$ is the filtered signal. So, the delta parameter is approximately 10% of the entire variation of the signal.

IV. Experimental Results

To study the robustness of the algorithms, a prototype has been built. An RFDUINO RFD22102 board is used to broadcast the signal and send the data to a smartphone. An application for the mobile phone has been built to show the results using the MIT app inventor. In this section, different measurements are presented to validate the algorithms. The measurements involve: Normal breathing; Alternate breathing (deeper and slower); Alternate breathing with apnoeas. Figure 7 shows three minutes of normal breathing. The GSR is quite regular and there is not much variation in the derivative. Stimuli are not high enough to activate the sympathetic system. Then, the algorithm doesn't send information to the smartphone.

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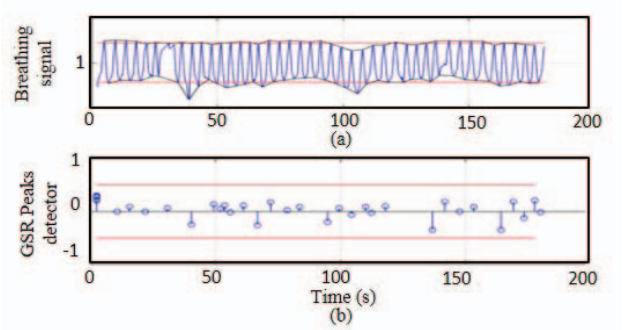

Fig. 7. Output of the GSR algorithm for the normal breathing case. (a) Measured breathing signal. Red lines show an average of the maximum and minimum of the signal in the respiration. (b) Peaks of the GSR derivative. Red lines define the threshold GSR derivative signal. The algorithm detects every variation that is stronger.

Figure 8 shows variable respiration. When the breathing is deeper it is possible recognize peaks in the GSR measurement. In this case, the device send information to the smartphone.

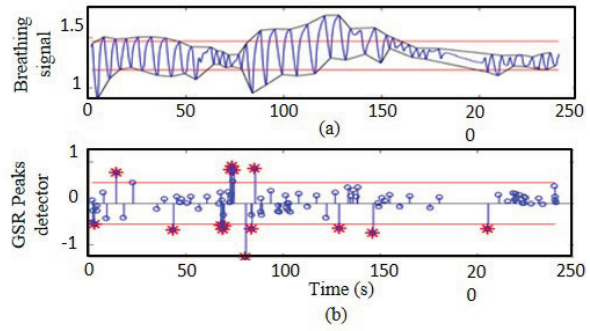

Fig. 8. Output of the GSR algorithm for the case where there is changing in respiration. After 40 seconds, deeper breathing is performed. (a) Measured breathing signal, (b) Peaks of the GSR derivative (*) where a variation in SNA is detected by the algorithm.

Figure 9 shows that apnoeas alternate with normal breathing. Just after an apnoeas, it is possible to recognize peaks in GSR measurement. The algorithm detects those peaks. Everyone gives different results since their cells behave differently, therefore the threshold cannot be defined before the test. So, during a calibration time, it is possible to define a threshold on the amplitude. It is calculated as a percentage in the deviation of the peaks detected:

$$S_{GSR} = (1+\gamma)\frac{1}{n}\sum_{i=1}^{n}\left|X_{p,i}\right| \qquad (6)$$

Where γ is a percentage of the average values of the positive and negative peaks, $X_{p,i}$. Many peaks, during the first measurement, were not strongly connected to the SNA activation, as you can see in Fig. 9, because it depends on normal ventilation. When an apnoea occurs, the recorded value is much higher than the average of the other peaks, therefore an activation of the SNA can be detected.

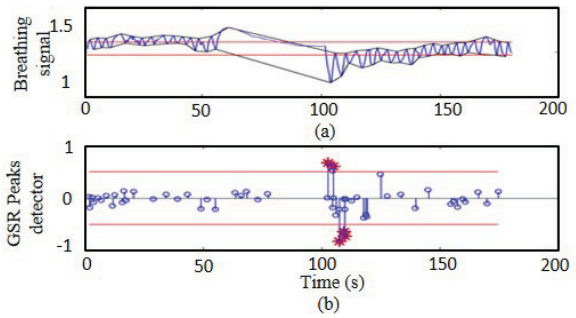

Fig. 9. Output of the GSR algorithm for the case with breathing and apnoeas. (a) Measured breathing signal, (b) Peaks of the GSR derivative (*). Red line is a derivative threshold. GSR signal variations are well detected by the algorithm.

V. Conclusion

A simple device to detect correlation between respiration and activation of SNA has been proposed. While sleeping, the measurement of an activation of the SNA is easy because the body doesn't receive any external stimulus and a risk of false negative detection is minimized. A strong correlation between apnoeas and the activation of the SNA can be noticed. A wearable GSR sensor can be used instead of the respiration sensor to detect apnoeas and SBD. The GSR device is more robust and comfortable and doesn't need to be well fixed on to the skin. Efficient algorithms have been proposed to save energy and data storage. For three minute of recording approximately 30 samples are transmitted by BLE after the calculation compared to the 3000 samples recorded. In addition to this data fusion improvement, at least 50% of battery is saved by calculating the peaks in GSR before transmitting the data.

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