New Approaches to Monitoring Respiratory Activity as Part of an Intelligent Model for Stress Assessment

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Abstract. Abnormal breathing patterns have been linked to many diseases and stress-related effect. Visually counting breaths per minute is the gold standard for measuring respiratory rate. In hospital research, most nurses recognize the physiological importance of respiratory rate however its measurement it is not considered mandatory. Current research studies offer viable options for continuous monitoring of respiratory activity, although with degraded performance due to artefact. This paper proposes five new respiratory rate estimation methods considering their strengths and drawbacks to determine the most suitable one for various activities. Photoplethysmography, accelerometry, infrared temperature and pressure sensors are therefore used to monitor respiratory activity. In addition, we present a method for estimating respiratory rate via thermographic video image processing. In terms of novelty and innovation, we highlight the intelligent algorithms developed for real-time respiratory rate extraction from Photoplethysmography signals, the mechanical sensor prototype based on pressure sensors, and the facial recognition, focus zone identification, and image pixel analysis algorithms for thermographic image processing. In addition, a multichannel sensing system characterized by distributed platform computation is utilized to extract physiological parameters forming the basis for the proposed Fuzzy Logic-based model to detect and classify stress levels. To validate the suggested approaches, an experimental protocol was established to monitor the volunteers' respiratory activity in a controlled setting, as well as health monitoring throughout the induction of thermal stress and its classification, yielding excellent indications of efficiency and accuracy.

Keywords: Contactless Health status Monitoring, Wearable Sensors, Infrared Temperature, Thermography, Digital Signal Processing, Fuzzy Logic, Photoplethysmography, Respiratory Rate, Stress Classification.

1 Introduction

Respiratory Rate (RR) is a crucial physiological parameter that provides vital information about a patient's health [1], serving not only as a basis for the diagnosis of several respiratory diseases, but also as an evaluation parameter in other clinical settings, such as cardiac failure or metabolic emergencies [2,3]. Despite its clinical significance, research indicates that respiratory rate is the most neglected vital sign in healthcare due to a lack of understanding regarding respiratory rate evaluation, nurses' perceptions of patient acuity, and a lack of time, even though the gold standard for measuring RR is manual counting the number of breaths for one minute [4].

Recent research on the sensory experience of breathing has also focused on breathing conditioning. It is crucial to understand daily conditioning and respiratory dysfunctions such as apnea and asthma. Such dysfunctions are brought on by emotional challenges. Because emotions affect respiration, diverse emotions are accompanied by distinct breathing patterns. Mental stress increases tidal volume and RR [5], therefore, monitoring stress is essential.

Concerning RR assessment, the challenge lies in the development of more efficient and user-friendly solutions. As a result, we propose five new methods for RR assessment based on Photoplethysmography (PPG) sensors, thermography, infrared-temperature sensors, pressure sensors, and accelerometers. A comparison between the proposed methods, based on their accuracy, sensitivity and specificity is also considered. In terms of novelty, a small, mechanical, pressure-sensor-based wearable device prototype is proposed for RR assessment. In terms of innovation, we propose a new method for RR assessment based on thermographic video acquisition and processing, the identification of highlighted areas, and the monitoring of the skin temperature oscillations in the face region using FLIR Tools and MATLAB.

Regarding stress assessment, most studies only detect the presence of stress, with few classifying it. As such, in this work we also propose a new Machine Learning (ML) model based on Fuzzy Logic to assess stress. Thus, we propose a Fuzzy Logic-based Machine Learning (ML) model to assess stress. We used a multichannel sensory system from the authors' previous work [6] to implement PPG signal processing and develop real-time algorithms for physiological parameter extraction, such as Heart Rate (HR), Heart Rate Variability (HRV), Blood Oxygen Saturation (SpO2), and RR. This multichannel sensor system also collects Galvanic Skin Response (GSR) data, a stress-related physio-logical parameter. The intelligent Fuzzy Logic model classifies each of the five physiological parameters and stress into five levels. This algorithm was also evaluated using data from the 5 proposed RR monitoring methods to determine the most suitable for RR monitoring and stress assessment.

This paper is organized as follows. Section 2 presented a brief literature review, for a better theoretical framework. Section 3 discusses the methodology adopted. Section 4 presents the results obtained, as well as some considerations and comparisons. Conclusion and future work follow in Section 5.

2 Related Work

In order to understand the aforementioned concerns and the proposed objectives of this study, this section addresses key concepts linked to the assessment of respiratory activity, as well as its relationship to stress, and stress levels assessment.

2.1 Respiratory Activity and Healthcare

RR has many clinical uses, such as, defining baselines for postoperative or comparative monitoring, identifying blood transfusion or drug reactions, and acid-base imbalance detection and compensation. Big RR variations may indicate health deterioration. An irregular RR can also predict other conditions such as organ failure. Yet, it's concerning because RR is the least measured vital sign in clinical settings [4].

RR values are expressed in Breaths Per Minute (BPM), and in the case of healthy resting adults, a normal RR can range between 12 and 20 BPM [7]. Manually counting chest wall movements and auscultation with a stethoscope is the gold standard for measuring RR [8], however, it's not very practical. Most hospital nurses understand the physiological necessity of RR, yet many believe they are enhancing patient outcomes by focusing on other tasks.

In Intensive Care Units (ICU), other more complex automated methods are used, such as Capnography, Impedance Plethysmography and Thermography [9]. Capnography ensures that anaesthetized patients obtain enough oxygen during surgery. The RR is estimated from the patient's gas (anesthesia) intake [9]. Regarding Impedance Plethysmography, this non-invasive method measures small relative changes in electrical resistance in different areas of the human body to determine blood vessel size or lung gas volume, which is used to estimate RR [9].

2.2 Solutions for Respiratory Assessment

There is a wide variety of proposed methods for RR assessment, as shown in Fig.1.

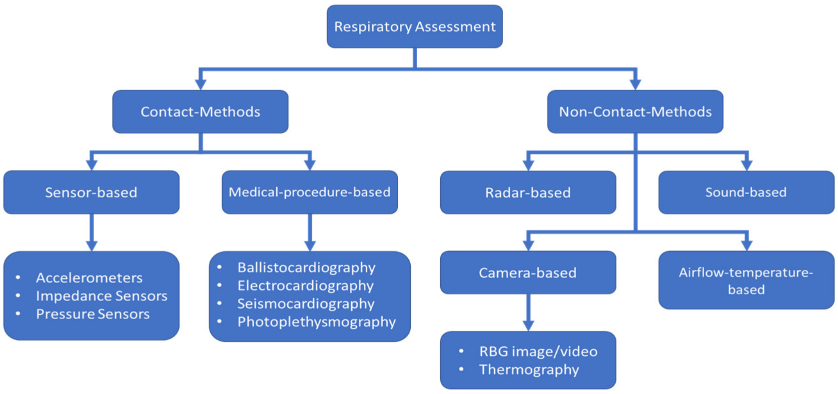

Fig. 1. Classification of Respiratory Assessment Methods

Breathing consists of two distinct movements, inspiration (thorax expands and abdomen rises) and expiration (thorax contracts and abdomen lowers) . Using accelerometer and/or gyroscope sensors, the motions of the thoracic and/or abdominal cavities can be monitored to extract the RR [10]. Although several advantages, such as reduced size and low weight, these methods are susceptible to motion artefacts.

Through the monitoring of body posture based on impedance sensors, it is also possible to extract RR, considering different postures [11]. The problem lies in the fact that it is necessary to map all postures. With the introduction of intelligent algorithms and classifiers such as Support Vector Machine (SVM) the problem can be attenuated, however, this adds more complexity to the systems. In addition, accuracy can be affected by variations in body composition and clothing.

Regarding Ballistocardiography (BCG), it is a non-invasive technique based on the monitoring of body movement caused by blood ejection during cardiac cycle. BCG signals associated with cardiac activity are modulated by respiration, and as such, the RR can be extracted through BCG signal processing [12]. However, it's limited by noise artefacts, motion inhibition, and cannot be integrated into wearable devices.

Electrocardiography (ECG) measures heart electrical activity through repeated cardiac cycles, while PPG detects tissue blood volume changes in the microvascular bed. Both methods are used to monitor heart activity, such as HR, HRV, and SpO2 [6,13]. Further investigation showed that respiratory activities modulate PPG signals in amplitude, frequency, and baseline shift [14,15], which are used in RR estimation.

RGB cameras can capture chest and abdominal movements for RR estimation [16]. Nonetheless, body motion artefacts and even the subject's clothing can affect this method. Convolutional Neural Networks (CNNs) help training models to predict RR and reduce artefacts [17]. In the case of thermographic cameras, they estimate RR by measuring the airway's ambient temperature, which is usually lower than body temperature. When a person inhales, this air cools the airways. When a person exhales, body-temperature air leaves the airways, warming the airways [18]. These fluctuations in temperature observed by thermographic cameras correspond to the respiratory cycle, enabling the estimation of RR [19].

2.3 Stress and Respiration

Stress is a major health issue that affects many people regardless of age, environment, social standing, or other factors. It caused 51% of work-related illnesses in 2019/2020, according to the Labor Force Survey (LFS) [20]. These effects may cause fatigue or even worsen chronic conditions. Hence, early stress monitoring is crucial.

When confronted with a stressor, the autonomic nervous system releases hormones into the bloodstream, which affects various physiological parameters, including HR, RR, SpO2, Muscle Tension, among others. This autonomous response depends on the stressor's duration. Stress can lead to major health disorders such cardiovascular disease, respiratory disease, mental illness, diabetes, sleep disturbances, immune system degeneration, cancer, anxiety, and depression [21].

2.4 Stress Assessment

Currently, the monitoring of stress levels is not objective because it is primarily based on self-assessment questionnaires, such as the Perceived Stress Scale (PSS) [22], or even through the monitoring of brain activity via Electroencephalogram (EEG) [23], which is performed in controlled environments, such as laboratories, thereby limiting the applicability of these techniques in everyday life.

New promising studies address physiological stress employing vital signs monitoring from various methodologies. These works always include the GSR, which is strongly correlated with stress, although it cannot accurately measure stress alone. There are studies that propose the correlation of GSR with several physiological parameters like HRV [24], Blood Pressure (BP) [21] and Respiration [21], or even combining GSR with techniques like PPG [13], ECG [21], EEG [25], or Electromyography (EMG) [26], but most of them only detect stress and do not classify or quantify it. Because ECG and PPG can extract relevant physiological parameters from signal processing, they are one of the best solutions for stress assessment systems [21].

3 Materials and Methods

The proposed work aims at implementing an intelligent algorithm for assessing stress levels using the previously built multichannel system [6]. In this system, methods for estimating HR, HRV, RR, and SpO2 based on the capture and processing of PPG data are proposed. Since the RR method based on PPG signal presented an accuracy of 90.91%, to maximize the potential of the algorithm based on Fuzzy Logic presented for stress assessment, we first proceeded to study new and more accurate methods for estimating RR. As such, in this section, we will address the different new approaches proposed for RR estimation, the implementation of the novel Fuzzy Logic-based algorithm for stress assessment, and the experimental procedures.

3.1 Respiratory Rate Estimation

Five methods are proposed for RR estimation, using a PPG sensor, a 3D accelerometer, a pressure sensor, an infrared temperature sensor, and thermography.

Regarding the accelerometer-based RR estimation, it's a non-invasive and mechanical contact method, consisting of an ESP32 microcontroller, a BMA400 digital accelerometer, and an OLED LCD display. The used ESP32 microcontroller is characterized by Dual-Core 32-bit CPU, maximum Clock of 240 MHz, ROM memory of 448 Kbytes, RAM memory of 520 Kbytes, Flash memory of 4 MB, and is responsible for processing the data acquired by the accelerometer and applying the implemented algorithm for RR estimation. This estimation is then available through an OLED LCD display. The BMA400 accelerometer is a 3-axis, 12-bit digital accelerometer with intelligent chip and position-driven interrupt functions.

In this method, the accelerometer is attached to an elastic band, as can be seen in Fig.2 (a) below, which should be positioned on the person chest. This way, whenever the individual inhales, there is an increase in the volume of the rib cage, causing the three axes of the accelerometer to vary, which increases an implemented counter (bCounter). Knowing the time that has elapsed since the start of data acquisition (bTime) and bCounter, RR is then estimated based on Equation (1), as shown in [6].

$$RR = (bCounter * 60) / \mathrm{bTime} \quad (1)$$

Regarding the pressure sensor-based RR estimation, the mechanism of which the pressure sensor is part is contained inside a small module, as can be seen in Fig.2 (b) below, which must be positioned on the person chest. In this way, whenever the individual inhales, there is an increase in the volume of the rib cage, exerting pressure on the sensor through the mechanism. These pressure variations result also in the implemented counter (bCounter) increase, providing the RR estimation also through Equation (1). This method is also classified as non-invasive and mechanical contact.

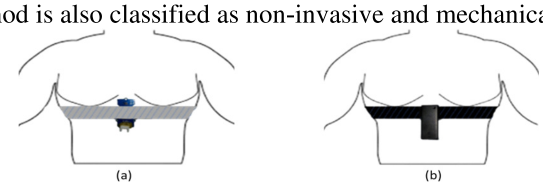

Fig. 2. Prototypes for RR Estimation. (a) BMA400 Accelerometer attached to an Elastic Band. (b) Proposed Prototype based on Pressure Sensor Mechanism.

The method based on PPG signal uses a MAX30102 PPG sensor, classified as a reflective sensor, i.e., it has two emitting LEDs, one of infrared light and the other of red light, which penetrate to a certain depth in the human tissue and are then reflected. This sensor has a photodetector LED, capable of acquiring both emitted lights, from which it is possible to monitor blood flow variations. After acquisition the signal is filtered and processed. Thus, a first-order low-pass filter is applied to reduce noise artifacts. With the filtered PPG signal, it is then possible to determine the signal maximum values, and through this, the developed algorithm estimates in real time the RR [6]. Note that this method is also classified as non-invasive and mechanical contact.

Infrared temperature-based RR estimation is a non-invasive and contactless method that consists of an ESP32 microcontroller, an MLX90614 infrared temperature sensor, and an OLED LCD display. The MLX90614 is a sensor designed for contactless temperature detection, which features a 17-bit internal Analogic Digital Converter (ADC) and high accuracy of 0,5ºC and measurement resolution of 0,02ºC. This sensor is factory calibrated in wide temperature ranges from -40°C to 85°C for ambient temperature, and from -70°C to 382.2°C for object temperature. In this method, the temperature of the nostrils is measured. When a person inhales, air at ambient temperature is inhaled, causing the nostril orifices to cool. In turn, when a person exhales, the exhaled air has the same temperature as the human body, and as such, an increase in temperature is visible in the nostril orifices. Our method can distinguish these temperature variations and account for them (bCounter), which in turn allows us to estimate the RR also using Equation (1).

Regarding the estimation of RR based on thermography, this is a non-invasive and contactless method. For this estimation the FLIR E64501 thermographic camera was used (Fig.3 below), capable of acquiring both thermographic images and videos, presenting a sample rate of 60HZ. This camera is capable of measuring temperatures up to a maximum of 650ºC, with an accuracy of +/-2% and a sensitivity of 0.05ºC.

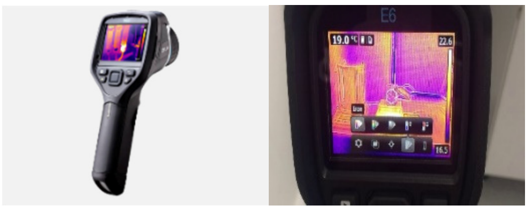

Fig. 3. FLIR E64501 Thermographic Camera

During the conducted experiment, the FLIR E64501 was used to acquire video, which was analyzed using the FLIR Tools platform provided by the manufacturer. As with the infrared temperature sensor method, each time a person inhales, a decrease in temperature is visible at the nostrils, while when a person exhales, an increase in temperature is visible, as can be seen in Fig.4 below. In the specific case of the experiment conducted, the temperature focus was the nostril orifices, and as such, in the graph of Fig.5 below is an example of the wave corresponding to the temperature variation at that location and analyzed by FLIR Tools for a randomly chosen participant. Note that the data presented relate to the period of the experiment, that is, for 60 seconds, the period needed to estimate the RR.

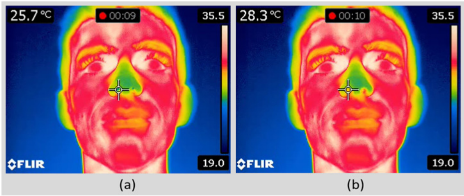

Fig. 4. Thermographic Image associated with Respiratory Cycle. In (a) it is possible to observe the component of the respiratory cycle regarding inspiration phase (nostril orifices cooling to a temperature of 25.7ºC). In (b) it is possible to observe the component of the respiratory cycle regarding expiration phase (nostril orifices heating to a temperature of 28,3ºC).

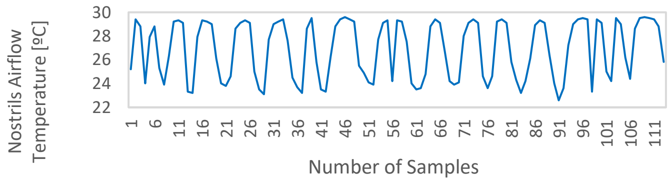

Fig. 5. Thermographic Image associated with Respiratory Cycle. In (a) it is possible to observe the component of the respiratory cycle regarding inspiration phase (nostril orifices cooling to a temperature of 25.7ºC). In (b) it is possible to observe the component of the respiratory cycle regarding expiration phase (nostril orifices heating to a temperature of 28,3ºC).

As can be seen in the graph of Fig.5, each minimum of the wave allows us to identify one breath. In this case, it is possible to identify that the participant presented a RR of 19 BPM. To automate the estimation process, the MATLAB platform is a great solution for working on video image processing, thus allowing not only facial recognition, but also to automatically recognize the region of interest for detecting temperature variations, such as the nostrils or the mouth region.

3.2 Intelligent approach to stress assessment

The proposed algorithm for stress assessment is based on the acquisition of stress related physiological parameters, such as HR, PRV, RR, SpO2 and GSR. The classification of stress levels was performed through the implementation of Fuzzy Logic, where we defined for each physiological parameter its reference values (HR [18], PRV [19], RR [20], SpO_2 [21], GSR [22] and BT [23]), the classification and the type of Membership Function, according to Table 1.

It is important to point out that in the case of HRV, the values tabulated for the approach employed Root Mean Square of Successive Differences (RMSSD) were considered, and as a result, Table 1 presents the range of potential values for all healthy age groups excluding children.

A Membership function for a Fuzzy set A on the universe of discourse X is defined as $\mu A:X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A.

Table 1. Physiological Parameters Treatment.

Parameter	Classification based on Parameter Reference Values				
	Very Low	Low	Normal	High	Very High
HR [beat-per-minute]	0-50	50-60	60-90	90-100	100-200
HRV [ms]	0-19	19-32	32-77	77-107	107-160
RR [breaths-per-minute]	0-10	10-12	12-18	18-22	22-30
SpO2 [%]	85-90	90-95	95-97	97-99	100
GSR [kOhm]	10-20	20-30	30-50	50-70	70-100

Based on previous Table 1, the Membership Functions used in the proposed model are categorised as Trapezoidal Function Type R for "Very Low", defined in Equation (2), Trapezoidal Function Type L for "Very High", defined in Equation (3), and Triangular Function for "Low", "Normal" and "High", defined in Equation (4). According to physiological parameter classification based on the reference value ranges, the minimum value is "a", the maximum value is "b", and the average value is defined as "c".

$$\text{Trapezoidal\_Type\_R} = \begin{cases} 0 & , x > b \\ \frac{b-x}{b-a} & , a \leq x \leq b \\ 1 & , x < a \end{cases} \tag{2}$$

$$\text{Trapezoidal\_Type\_L} = \begin{cases} 0 & , x < a \\ \frac{x-a}{b-a} & , a \leq x \leq b \\ 1 & , x > b \end{cases} \tag{3}$$

$$\text{Triangular\_Function} = \begin{cases} 0 & , x \leq a \\ \frac{x-a}{c-a} & , a < x \leq c \\ \frac{b-x}{b-c} & , c < x < b \\ 0 & , x \geq b \end{cases} \tag{4}$$

To assess the stress levels, five rules based on the investigated relationship between physiological parameters and stress [6] were established. These rules are presented below in Table 2. The quantification of stress is then given by Equation (5).

Table 2. Classification of Stress Levels According to the Fuzzy Logic Algorithm.

Stress	Rules (R)	Stress Level (S)
Very Calm	R1 = VeryLow(HR) Λ VeryLow(HRV) Λ VeryLow(RR) Λ VeryHigh(SpO2) Λ VeryHigh(GSR)	S1 = R1 * 1
Calm	R2 = Low(HR) Λ Low(HRV) Λ Low(RR) Λ High(SpO2) Λ High(GSR)	S2 = R2 * 2
Normal	R3 = Normal(HR) Λ Normal(HRV) Λ Normal(RR) Λ Normal(SpO2) Λ Normal(GSR)	S3 = R3 * 3
Stressed	R4 = High(HR) Λ High(HRV) Λ High(RR) Λ Low(SpO2) Λ Low(GSR)	S4 = R4 * 4
Very Stressed	R5 = VeryHigh(HR) Λ VeryHigh(HRV) Λ VeryHigh(RR) Λ VeryLow(SpO2) Λ VeryLow(GSR)	S5 = R5 * 5

$$Stress = \frac{S1+S2+S3+S4+S5}{R1+R2+R3+R4+R5} \quad (5)$$

3.3 Experimental Procedure

In the scope of this work, two experiments were carried out, with 26 volunteers aged between 16 and 91 (mean age approximately 38, and age standard deviation approximately 20). All participants were informed about the experiments and gave their verbal consent. None of the participants reported any mental, cardiac, respiratory, or other disturbances.

In the experimental procedure implemented in this work two experiments were conducted. The first experiment was aimed at determining the feasibility of each proposed method for estimating RR. The second experiment was aimed at monitoring HR, HRV, RR, SpO2, and GSR during the thermal stress induction, to serve as a basis for the proposed model for stress levels assessment.

The first experiment was performed in a controlled environment. The duration of the experiment was 1 minute, in which each participant was asked to remain seated and to avoid motions, thus facilitating data acquisition. Before the beginning of the experiment, each system relative to the 5 methods proposed in this paper was positioned, i.e., a PPG sensor was placed on the index finger of the participants, the device with the built-in pressure sensor and accelerometer was positioned on the chest of the participants, the participants were also asked to bring the infrared temperature sensor near the nasal orifice with their vacant hand, and the thermographic camera was also positioned in front of the participants, thus enabling facial capture. The considered acquisition rate was 2 samples per second, and each method generates about 120 samples per minute.

The second experiment was conducted at room temperature in a controlled environment. The participants remained seated and at rest during the entirety of the experiments. Participants were instructed to use their right to collect physiological parameters, and their left hand as the target of thermal stress induction (hot and cold). Limits were established to guarantee the participants physical integrity, being defined as low temperature 20ºC and high temperature 40ºC. This experiment has divided in 5 phases. Phase 1 lasted 5 minutes, in which only the physiological parameters were acquired, thus intended to establish a baseline for each participant. Phase 2 lasted 1 minute, in which the participants physiological parameters were monitored when in contact with cold. Phase 3 lasted 10 minutes, the period necessary for the human body to recover from contact with cold. Phase 4 lasted 1 minute, with the participants' physiological parameters being monitored when in contact with heat. Finally, phase 5 lasted 10 minutes, the period necessary for the human body to recover from the contact with the heat. At the end of each phase, each participant was asked to self-assess stress on a scale from 1 to 5, serving as reference values for model validation.

4 Results and Discussion

This section discusses the results and accuracy of the five proposed methods for RR estimation, also determining their sensitivity and specificity. In this section is also discussed the thermal stress induction study, and the validation of the algorithm for stress levels classification.

4.1 Assessment of the Proposed Methods for Estimating Respiratory Rate

A statistical analysis was performed according to the type A measurement of uncertainties, i.e., data collected from a series of observations and evaluated using statistical methods. To calculate the accuracy of the proposed methods each volunteer was asked to use a small counter during the experiments, that is, every time they took a breath, they had to press a small button that incremented the number of breaths, thus giving us a real breathing counter (reference values). Methods base on thermography, pressure sensor and infra-red temperature presented a mean relative error of 0,01%. Regarding accelerometer-based method, it presented a mean relative error of 10,79%. PPG-based method presented a mean relative error of 2,49%.

In addition, linear regression was also determined for each proposed method. Since methods based on thermography, infrared temperature and pressure sensor presented an accuracy of 99.99%, the linear regression is defined by y=x. For PPG and Accelerometer based methods, the respective linear regressions are presented below in Fig.6.

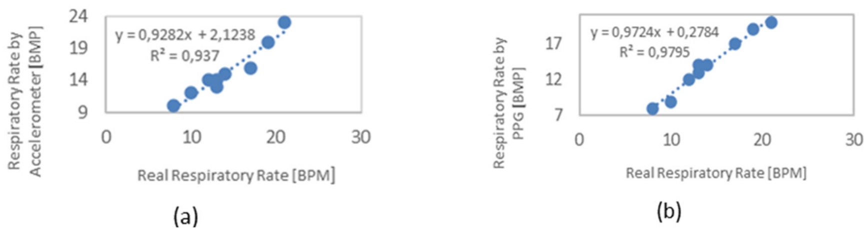

Fig. 6. PPG and Accelerometer based Methods Evaluation. (a) Linear Regression for Accelerometer-based Method. (b) Linear Regression for the Photoplethysmography-based Method.

The performance of the 5 proposed methods was evaluated using a multi-class confusion matrix and metrics such as sensibility and specificity were applied. Regarding the methods based on thermography, pressure sensor and infra-red temperature, the mean sensibility was 1 and the mean specificity was also 1. For accelerometer-based method, the mean sensibility was 0,99 and the mean specificity was 0,98. Regarding PPG-based method, the mean sensibility was 0,98 and the mean specificity was 0,99. In general, we can say that the proposed methods present satisfactory results, in that there are few false negatives and few false positives.

4.2 Thermal Stress Induction and Validation of Stress Level Classification

This experiment's main objective was to investigate the effects of temperature stressors on physiological parameters. In this instance, HR, HRV, RR, SpO2 and GSR are examined. The behavior of the acquired physiological parameters follows a pattern, in that the induction of thermal stress results in significant changes in the physiological parameters. During the recovery periods, however, physiological parameter values tend to stabilize at normal levels. To facilitate the data analysis, the average values of each physiological parameter obtained throughout the experiment were calculated. Fig.7 illustrates the RR and GSR averages of each participant, based on the PPG-based method. For better data comprehension, not all participants were considered.

In Fig. 7 (a) bellow, the induction of thermal stress, mainly with cold, generates direct changes in respiration, i.e., when stress is induced, RR typically increases. During recovery periods, the body attempts to normalize the levels, leading to a decrease in

RR. In contrast to other physiological parameters such as HR, HRV, SpO2, and GSR, RR is the only parameter that can be controlled by the patient, such as by breathing exercises, decreasing the RR and consequently decreasing stress levels.

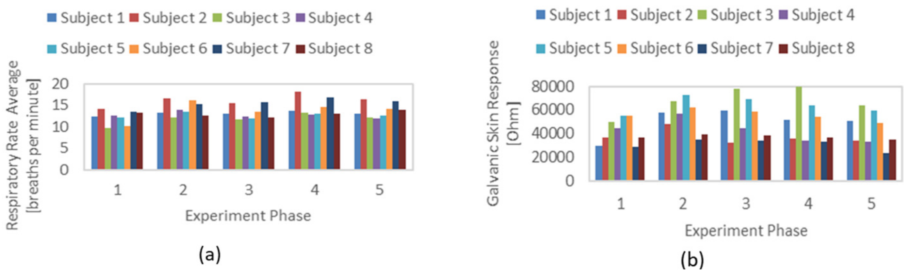

Fig. 7. Averages Values for each Participant. (a) RR Averages during each Testing Phase. (b) GSR Averages during each Testing Phase.

In the specific case of the GSR, after the first cold perturbation, there is a noticeable increase in the values, but in the recovery period, a large decrease in the values is not observed, as is the case with the other physiological parameters, leading us to believe that due to the strong relationship between the GSR and stress, it is affected for a longer period of time by the stressor. As seen in Fig.7 (b), another interesting aspect of the GSR is that the heat disturbance works as a technique to assist relax the participants rather than as a stressor.

Age also affects how the body responds to the stressor. The time it takes the bodies of persons over 65 to recover is longer than that of persons younger than 65. Moreover, the response time to the stressor itself is lengthened. This is demonstrated in Fig.8 by contrasting one of the randomly selected young participants (age criteria ranged from 16 to 30 years) with a randomly selected senior participant (age criteria ranged from 60 to 91 years). In addition, the male gender was a factor in the selection process (larger number of participants).

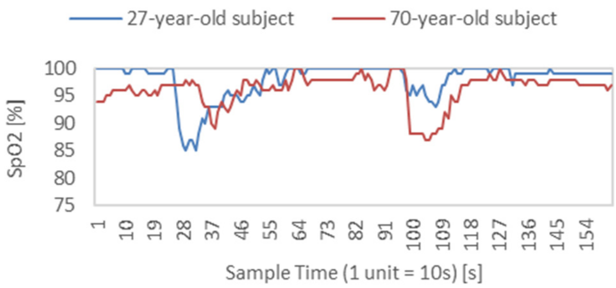

Fig. 8. Comparison between the SpO2 Values obtained by a 27-year-old Participant (highlighted in blue) and a 70-year-old Participant (highlighted in orange) throughout the duration of experiment 2 (Thermal Stress Induction).

To validate the Fuzzy Logic model for estimating stress levels, participants were given a slider button and asked to estimate their stress level on a scale from 0 to 5. After the experiments, the data were thoroughly analyzed using the Fuzzy Logic approach. This resulted in a rating of stress levels from 0 to 5 that was compared to the participants' self-assessment.

The suggested Fuzzy Logic methodology yields satisfactory results, evaluating the stress levels with precision. The self-classification done by the participants and the classification generated by Fuzzy Logic yielded identical findings.

5 Conclusion

This work proposes five new approaches for respiration rate estimation and integrates them into a multichannel system that extracts physiological data for health monitoring and stress classification using a Fuzzy Logic algorithm. The five methods for estimating RR performed well, except for the accelerometer-based method, which was expected due to noise artefacts. The proposed algorithm for stress classification also rejected the thermography-based RR estimation technique due to thermal stress induction. The RR estimation failed because the heat water container's vapor made thermographic detection impossible during thermal stress induction. Only pressure, infrared-temperature, and PPG sensor approaches were considered for RR estimation and stress classification. The infrared-temperature method was one of the most accurate for RR estimation, but it conditions breathing because it must be placed near a nasal orifice. In the case of the pressure sensor solution, this proves to be the most viable option. The fact that it is a wearable device with tiny dimensions makes it simple to operate, since it is quite accurate even during moderate motion. For stress classification, the physiological parameters extraction accuracy is essential; nevertheless, the tiny variation regarding accuracy between solutions based on PPG and pressure sensors does not translate into any difference in stress classification. In addition, the fact that the multichannel system already utilizes PPG to extract other physiological parameters makes RR estimation based on PPG more accessible. Thus, taking into consideration the methodology for stress classification, the most acceptable method for RR estimation is the one based on PPG.

As future work can be mentioned the improvement to the integration of the method based on thermographic cameras, for example, regarding facial recognition algorithms and multi-zone target region monitoring. In the case of stress assessment system, one of the challenges is to make the system more robust, with the possible addition of new mechanisms and improvements. The replacement of the Fuzzy Logic technique by other more robust machine learning techniques is also part of the goals. In addition to what has already been mentioned, a first wearable prototype for real time monitoring during daily life is under development.

References

1. A. Fusco, D. Locatelli, F. Onorati, G. C. Durelli, and M. D. Santambrogio, “On how to extract breathing rate from PPG signal using wearable devices,” IEEE Biomed. Circuits Syst. Conf. Eng. Heal. Minds Able Bodies, BioCAS 2015 - Proc., pp. 3–6, 2015, doi: 10.1109/BioCAS.2015.7348369.
2. J. F. Fie, M. Hendryx, and C. M. Helms, “Respiratory Rate Predicts Cardiopulmonary Arrest for Internal Medicine lnpatients,” J. Gen. Intern. Med., vol. 8, no. 7, pp. 354–360, 1990.
3. G. M. Yuill, D. Saroya, and S. L. Yuill, “A national survey of the provision for patients with latex allergy,” Anaesthesia, vol. 58, no. 8, pp. 775–777, 2003, doi: 10.1046/j.1365-2044.2003.03256.x.

4. M. Elliott, “Why is Respiratory Rate the Neglected Vital Sign? A Narrative Review,” Int. Arch. Nurs. Heal. Care, vol. 2, no. 3, pp. 2–5, 2016, doi: 10.23937/2469-5823/1510050.
5. Y. Masaoka and I. Homma, “Anxiety and respiratory patterns: Their relationship during mental stress and physical load,” Int. J. Psychophysiol., vol. 27, no. 2, pp. 153–159, 1997, doi: 10.1016/S0167-8760(97)00052-4.
6. G. Ribeiro, O. Postolache and F. F. Martín, "A Practical Approach to Health Status Monitoring Based on Heart Rate and Respiratory Rate Assessment," 2022 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Messina, Italy, 2022, pp. 1-6, doi: 10.1109/MeMeA54994.2022.9856576.
7. T. Flenady, T. Dwyer, and J. Applegarth, “Accurate respiratory rates count: So should you!,” Australas. Emerg. Nurs. J., vol. 20, no. 1, pp. 45–47, 2017, doi: 10.1016/j.aenj.2016.12.003.
8. Y. Nam, B. A. Reyes, and K. H. Chon, “Estimation of Respiratory Rates Using the Built-in Microphone of a Smartphone or Headset,” IEEE J. Biomed. Heal. Informatics, vol. 20, no. 6, pp. 1493–1501, 2016, doi: 10.1109/JBHI.2015.2480838.
9. D. A. Birrenkott, M. A. F. Pimentel, P. J. Watkinson, and D. A. Clifton, “A robust fusion model for estimating respiratory rate from photoplethysmography and electrocardiography,” IEEE Trans. Biomed. Eng., vol. 65, no. 9, pp. 2033–2041, 2018, doi: 10.1109/TBME.2017.2778265.
10. A. Siqueira, A. F. Spirandeli, R. Moraes, and V. Zarzoso, “Respiratory Waveform Estimation from Multiple Accelerometers: An Optimal Sensor Number and Placement Analysis,” IEEE J. Biomed. Heal. Informatics, vol. 23, no. 4, pp. 1507–1515, 2019, doi: 10.1109/JBHI.2018.2867727.
11. G. Liu, K. Li, L. Zheng, W. H. Chen, G. Zhou, and Q. Jiang, “A Respiration-Derived Posture Method Based on Dual-Channel Respiration Impedance Signals,” IEEE Access, vol. 5, pp. 17514–17524, 2017, doi: 10.1109/ACCESS.2017.2737461.
12. T. Reinvuo, M. Hannula, H. Sorvoja, E. Alasaarela, and R. Myllylä, “Measurement of respiratory rate with high-resolution accelerometer and EMFit pressure sensor,” Proc. 2006 IEEE Sensors Appl. Symp., no. February, pp. 192–195, 2006, doi: 10.1109/sas.2006.1634270.
13. G. Ribeiro and O. Postolache, “Sensors and Mobile Interfaces for Stress level Monitoring in People with Diabetes,” 12th Int. Symp. Adv. Top. Electr. Eng. ATEE 2021, 2021, doi: 10.1109/ATEE52255.2021.9425134.
14. W. Karlen, S. Raman, J. M. Ansermino, and G. A. Dumont, “Multiparameter respiratory rate estimation from the photoplethysmogram,” IEEE Trans. Biomed. Eng., vol. 60, no. 7, pp. 1946–1953, 2013, doi: 10.1109/TBME.2013.2246160.
15. P. H. Charlton, T. Bonnici, L. Tarassenko, D. A. Clifton, R. Beale, and P. J. Watkinson, “An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram,” Physiol. Meas., vol. 37, no. 4, pp. 610–626, 2016, doi: 10.1088/0967-3334/37/4/610.
16. K. Y. Lin, D. Y. Chen, and W. J. Tsai, “Image-Based Motion-Tolerant Remote Respiratory Rate Evaluation,” IEEE Sens. J., vol. 16, no. 9, pp. 3263–3271, 2016, doi: 10.1109/JSEN.2016.2526627.
17. J. Brieva, H. Ponce, and E. Moya-Albor, “A contactless respiratory rate estimation method using a hermite magnification technique and convolutional neural networks,” Appl. Sci., vol. 10, no. 2, 2020, doi: 10.3390/app10020607.
18. H. M. Kwon, K. Ikeda, S. H. Kim, and R. H. Thiele, “Non-contact thermography-based respiratory rate monitoring in a post-anesthetic care unit,” J. Clin. Monit. Comput., vol. 35, no. 6, pp. 1291–1297, 2021, doi: 10.1007/s10877-020-00595-8.

19. Y. Takahashi, Y. Gu, T. Nakada, R. Abe, and T. Nakaguchi, “Estimation of respiratory rate from thermography using respiratory likelihood index,” Sensors, vol. 21, no. 13, pp. 1–12, 2021, doi: 10.3390/s21134406.
20. Health and Safety Executive. Work-Related Ill Health and Occupational Disease in Great Britain. Accessed: Sept. 19, 2022. [Online]. Available: https: //www.hse.gov.uk/statistics/causdis/
21. A. O. Akmandor and N. K. Jha, “Keep the Stress Away with SoDA: Stress Detection and Alleviation System,” IEEE Trans. Multi-Scale Comput. Syst., vol. 3, no. 4, pp. 269–282, 2017, doi: 10.1109/TMSCS.2017.2703613.
22. P. Schmidt, A. Reiss, R. Duerichen, and K. Van Laerhoven, “Introducing WeSAD, a multimodal dataset for wearable stress and affect detection,” ICMI 2018 - Proc. 2018 Int. Conf. Multimodal Interact., pp. 400–408, 2018, doi: 10.1145/3242969.3242985.
23. V. Vanitha and P. Krishnan, “Real time stress detection system based on EEG signals,” Biomed. Res., vol. 2016, no. Special Issue 2, pp. S271–S275, 2016.
24. G. Giannakakis et al., “Stress and anxiety detection using facial cues from videos,” Biomed. Signal Process. Control, vol. 31, pp. 89–101, 2017, doi: 10.1016/j.bspc.2016.06.020.
25. A. Arsalan, M. Majid, S. M. Anwar, and U. Bagci, “Classification of Perceived Human Stress using Physiological Signals,” Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, pp. 1247–1250, 2019, doi: 10.1109/EMBC.2019.8856377.
26. J. Aigrain, M. Spodenkiewicz, S. Dubuiss, M. Detyniecki, D. Cohen, and M. Chetouani, “Multimodal Stress Detection from Multiple Assessments,” IEEE Trans. Affect. Comput., vol. 9, no. 4, pp. 491–506, 2018, doi: 10.1109/TAFFC.2016.2631594.
27. Healthy Lifestyle Fitness. What's a normal resting heart rate?. Accessed: Sept. 19, 2022. [Online]. Available: https://www.mayoclinic.org/healthy-lifestyle/fitness/expert-answers/heart-rate/faq-20057979.
28. EHRV. Normative HRV Scores by Age and Gender [Heart Rate Variability Chart]. Accessed: Sept.19, 2022. [Online]. Available: https://elitehrv.com/normal-heart-rate-variability-age-gender.
29. healthline. What Is a Normal Respiratory Rate for Adults and Children?. Accessed: Sept. 19, 2022. [Online]. Available: https://www.healthline.com/health/normal-respiratory-rate.
30. OnHealth. Safe, Normal, Low Blood Oxygen Levels: Pulse Oximeter Chart. Accessed: Sept.19, 2022. [Online]. Available: https://www.onhealth.com/content/1/normal_low_blood_oxygen_pulse_oximeter_levels.
31. M. V. Villarejo, B. G. Zapirain, and A. M. Zorrilla, “A stress sensor based on galvanic skin response (GSR) controlled by ZigBee,” Sensors (Switzerland), vol. 12, no. 5, pp. 6075–6101, 2012, doi: 10.3390/s120506075.