Development of an IoT Device for Measurement of Respiratory Rate in COVID-19 Patients

Jean Pierre Tincopa[1], Paulo Vela-Anton[2], Cender U. Quispe-Juli[3], Anthony Arostegui[4]
Departamento de Ingeniería, Laboratorios de Investigación y Desarrollo, Facultad de Ciencias y Filosofía
Universidad Peruana Cayetano Heredia, Lima, Perú[1, 2, 3]
Centro de Investigación en Transformación Digital, Universidad Privada Norbert Wiener, Lima, Perú[1]
Dirección de Investigación en Salud, Instituto de Evaluación y Tecnologías en Salud e Investigación, Lima, Perú[2]
Departamento de Ingeniería Industrial, Universidad de Ingeniería y Tecnología, Lima, Perú[4]

***Abstract*—During the COVID-19 pandemic, patients who required face-to-face attention and tested positive, even showing signs of high risk, were forced to isolate themselves in their own homes immediately without adequate medical monitoring. Continuous remote monitoring of their vital signs would have helped to avoid subsequent hospitalization caused by the progression of the virus. Using deterministic design methods, a system to measure respiratory rate through impedance pneumography was proposed, amplifying microvolt signals to read and process data with a microcontroller. An embedded algorithm was designed to measure inspiration and expiration time. The values captured were sent via WiFi to a server, for posterior evaluation by the clinician. The key findings of this study are as follows (1) a respiratory-rate remote monitoring system was developed, displaying values calculated from impedance pneumography signals, (2) the correlation of the respiratory rate values from a patient during exercising and resting time, measured by a physician and by the device, was 0.96. (3) when analyzing separately the data obtained by the resting test and the exercise test, the performance of the device presented an average error percentage of -5.36% and +1.97%, respectively. As a conclusion, this device has practical applications for acute and chronic respiratory diseases, where respiratory rate is an indicator of the progression of these conditions.**

***Keywords*—Covid-19; respiration rate; internet of things; vital signs; hardware**

I. Introduction

At the beginning of the COVID-19 pandemic, 80% of patients were mild cases, meaning they required outpatient care [1]. However, unmonitored patients quickly developed acute respiratory reactions often overlooked by physicians [2]. Constant follow-up on a high number of patients is a challenging task for public healthcare due to the shortage of human resources, as well as the lack of equipment or technology intended for this purpose, especially in low- and middle-income countries.

The traditional way of measuring vital signs requires face-to-face evaluation at a distance of less than one meter, contrary to the preventive measures established to reduce the spread of COVID-19. Due to this, healthcare professionals on the frontline were forced to use personal protective equipment (PPE), while still being exposed to a high rate of contagion, which according to initial estimates represented 10-20% of all diagnoses from each nation [3]. Moreover, the direct consequences of the frequent use of PPE -such as eczema and blisters-, as well as the social stigma of healthcare professionals, considered "agents of contagion", should not be ignored. This scenario was seen in cities like Italy, Brazil, and Peru, where healthcare systems collapsed due to the high demand for outpatient care for cases of COVID-19 [4,5].

To address some of these challenges, the utilization of the Internet of Things (IoT) remains a promising solution. The Internet of Things (IoT) is based on establishing a connection between the Internet and electronic devices to achieve certain goals. IoT applications are increasingly implemented in different areas such as medical care settings as are the case with wearables, agricultural monitoring, or even transportation to control traffic [6].

Following on these applications, the Internet of Medical Things (IoMT) has gained wide adoption lately due to its multiple advantageous features, such as facilitating disease and drug management, improving treatment methods and patient experience, and reducing clinical expenses of various kinds. These systems require adequate attributes for effective performance: security, adaptability, real-time measurement, intelligent decision-making technologies, and compliance with information management regulations [7].

Respiratory rate is a prognostic factor that could be crucial for early respiratory risk detection [2]. Its consistent and reliable monitoring would allow for a more effective control of the patient's progress for timely care. The proposed solution is a hardware-based system using Internet of Medical Things (IoMT) technology, capable of capturing respiratory rate measurements through impedance pneumography, which is a technique based on the direct relation between the volume variations in the lungs and the electrical impedance from the electrodes located in separated areas of the chest.

II. Literature Review

In 2018, thirteen medical subfields have benefited from the development of IoMT applications, with neurological, cardiovascular and mental diseases having the greatest presence of this type of solution. Chronic diseases impose enormous costs on the healthcare system. In that manner, IoMT applications for patients suffering these conditions are expected to increase, particularly for those in need of

rehabilitation. 22% of IoMT applications are commonly used to monitor, manage, and treat cardiovascular disease [8]. The findings indicates that IoMT applications have hardly been developed and implemented for diseases with a high mortality rate, such as chronic respiratory infections [8]. One example of this is Whoop [9], a wrist fitness tracker that collects patient data for an analysis of the change in the patient's respiratory system to prevent respiratory episodes.

However, some devices have been utilized in other medical fields. For instance, Sarmah et. al. [10] developed a system which consists of monitoring patients with IoT hardware in conjunction with a deep neural network to aid in the diagnosis of heart disease. Additionally, Dese et al. [11] developed LVital, a device for monitoring vital signs of pregnant women including blood pressure, heart rate, and body temperature. The device has the notable benefit of monitoring maternal vital signs and is appropriate for those located in low-resource environments.

In the context of the pandemic, IoMT initiatives emerged to combat COVID-19. Ashraf et. al. [12] reported the monitoring of a set of physiological parameters (temperature, heart rate and respiratory rate) embedded in a wearable to map people with this infection. Similarly, Amachi-Choqque et. al. [13] developed an IoT system that measures heart rate, blood oxygen saturation and body temperature of patients with preliminary diagnosis of coronavirus, and then transmits data via WiFi to an IoT platform. The technology establishes the different levels of severity of the signs using a web-based system, in which the physician visualizes statistics and graphs of the different signals, sending alerts to an email or a smartphone.

The background above indicates the extensive interest in monitoring physiological parameters remotely, even more so with the endemization of COVID-19 in the following years. In this study, a device focused on respiratory rate, a vital sign of great relevance to the progression of the coronavirus infection, is proposed. This parameter is paramount to provide early warning of any respiratory episode arising, in the course from moderate to severe phase, which can result in dire consequences for the patient when not treated at an initial stage. This solution helps to ease the workflow in healthcare systems, aiming to reduce the rate of hospitalization in the Intensive Care Units (ICU) due to acute respiratory complications.

III. Design and Development

For the development of this electronic device, the project was divided into the following stages using the deterministic design method:

A. Establishment of Functional and Non-Functional Requirements

Functional requirements are understood as those operational aspects that the solution must perform throughout its execution. Meanwhile, Non-functional requirements are those qualities of the device that are observable at the time of its execution. The established requirements are:

Functional requirements (FR):

- The device must be able to read the electric potential difference through electrodes placed on the chest.
- The device must amplify analog signals to the microvolt level.
- The device must have the capacity to convert analog values read into digital ones.
- The device must transmit the processed data to a server.

Non-Functional requirements (NFR):

- The device must have a shape that allows its placement in the patient's body.
- The device must have an on and off switch.
- The device must have indicators of operating modes.

B. Selection of Electronic Components

Once the functionalities that the device will have been established, the electronic components were determined, being the main ones those mentioned below:

1) ADS1292R: It is a 24-bit multi-channel analog-to-digital converter (ADC) with a built-in programmable gain amplifier (PGA) that incorporates all the features commonly required in low power [14] portable medical devices. For this work, the ProtoCentral module that contains this integrated circuit was used (Fig. 1).

Fig. 1. Protocentral ADS1292R Module.

2) ESP32-WROOM-32: It is a powerful module containing a microcontroller with Wi-Fi and Bluetooth communication capabilities that are used in a wide variety of applications, ranging from low-power sensor networks to speech encoding. [15].

3) XC6203: A highly accurate, low-power, 3-terminal positive voltage regulator, providing up to 400 mA current with a significantly small dropout voltage [16]. In this design, the 3.3 V output version was used.

4) Li-Po 522040: A rechargeable lithium polymer battery with a capacity of 360 mAh (Fig. 2).

Fig. 2. 3.7 V LiPo Battery.

5) RGB Led: A LED with the ability to change color based on the 3 channels (red, blue and green) that will allow us to indicate the different phases of operation of the device.

C. Circuit Schematic Design

For the power stage of the circuit, the XC6203 voltage regulator was used, which converts the LiPo battery voltage from 3.7 volts (Vin) to 3.3 volts (V33) (Fig. 3). The datasheet of the regulator also indicates that both the input and the output must have 1 uF ceramic coupling capacitors. In addition, the output must have a 10 uF electrolytic capacitor. In this case, a tantalum capacitor is being used.

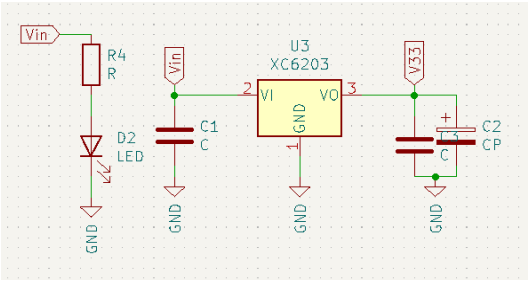

Fig. 3. Circuit Power Stage with Voltage Regulator XC6203.

Once a voltage of 3.3 V is obtained, this will be the stable level for all other active components. The communication between the ESP32 and the ADS1292R module is through the SPI protocol that uses the following pins: MISO, MOSI, SCK, CS, VCC and GND. Additionally, they have control pins (DRDY, START and PWDRST). 3 GPIOS were used to control the colors displayed by the RGB LED (Fig. 4).

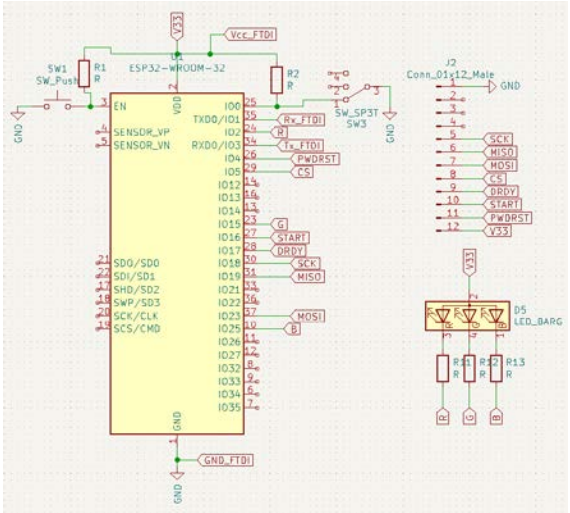

Fig. 4. Connection between ESP32 and ADS1292R Module.

Seeking to optimize the physical size of the device, a custom printed circuit board (PCB) was designed with the previously described circuits including a port to program the microcontroller with an FTDI module. On and off buttons were added as well (Fig. 5).

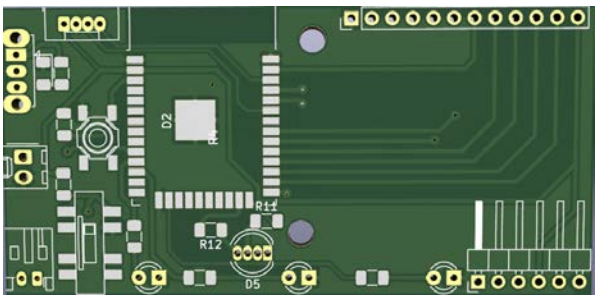

Fig. 5. Custom Printed Circuit Board (PCB).

To give the device wearable characteristics that make it comfortable on the body, an enclosure was designed to be 3D-printed using PLA-type filament. The bracelet-shaped device can be worn on the arm with an elastic band with Velcro patches (Fig. 6).

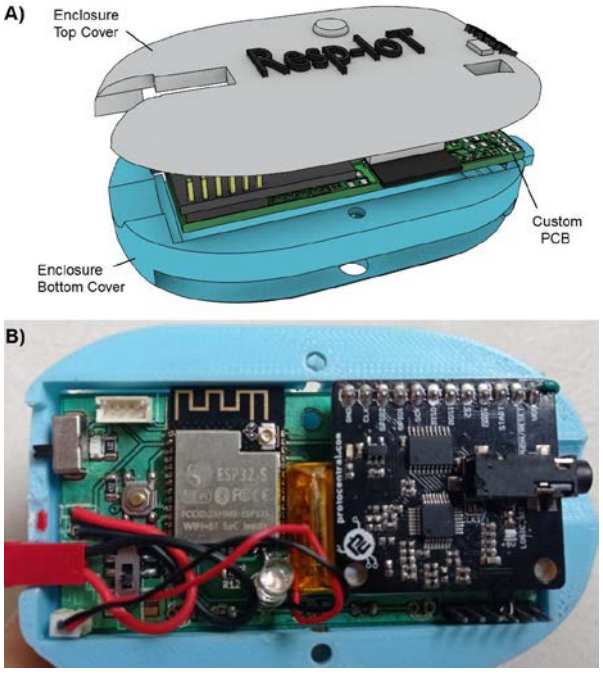

Fig. 6. Enclosure to Protect the Circuit. (A) 3D Design Rendering of the Enclosure. (B) PCB Placed Inside the 3D Printed Enclosure.

D. Respiratory Rate Measurement Algorithm

The first step in the script is to initialize the data acquisition and communication modules when the value obtained from the electric potential difference of the electrodes (previously amplified by the ADS1292R) is obtained. This signal presented high levels of noise; therefore, it was essential to use a filter to stabilize it and prepare it to be processed. The value obtained is stored in a memory space and an average of the last 10 values is made with a separation of 10 ms. This amount of time between each reading was chosen because 100 ms is less than the duration that an

inspiration or expiration phase could have, so it does not affect the real-time reading of the sensor. This average value will allow the detection of increasing or decreasing values. The range of values indicates whether it is in the patient's inspiration or expiration phase (Fig. 7).

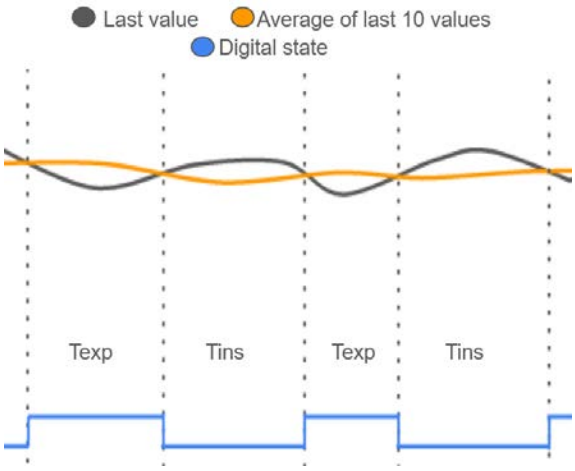

Fig. 7. Inspiratory and Expiratory Phases of the Patient.

The human respiratory cycle is defined as the time interval between the start of inspiration (Tins) and the end of expiration time (Texp). To calculate the duration of the breathing cycle (Tc), the inspiration and expiration phases are timed. The duration time of both phases are added to obtain the cycle time as follows:

Tc = Tins + Texp (seconds)

Once the Tc is calculated, in order to know how many breaths per minute (BpM) the patient performs, the conversion is calculated with the following formula:

BpM =60/Tc (breaths/min)

When the breaths per minute is obtained, the data is verified, as it has limit values that establish that it cannot be greater than 30 cycles/min and not less than 5 cycles/min. When the value obtained is not within that range, the algorithm redirects to the reading of the electrical potential obtained by the electrodes to start the whole process once again. If the value is valid, it is stored and sent via WiFi to the server. The flow of the algorithm can be seen in Fig. 8.

For each of the stages of the algorithm (Fig. 9), the RGB LED lights up a different color indicating the user if the reading is being captured correctly. The color legend is as follows.

E. Experimental Setup

To evaluate the performance of the device, multiple tests were carried out on real patients, comparing the value obtained by the device with values measured by a doctor using a stethoscope. For this purpose, the diaphragm of the device was placed on the chest wall, so that it does not rest on any structure. Then, the number of breaths in 60 seconds was quantified. For this pilot, five healthy patients were recruited, taking measurements in two different scenarios: total rest and after physical effort.

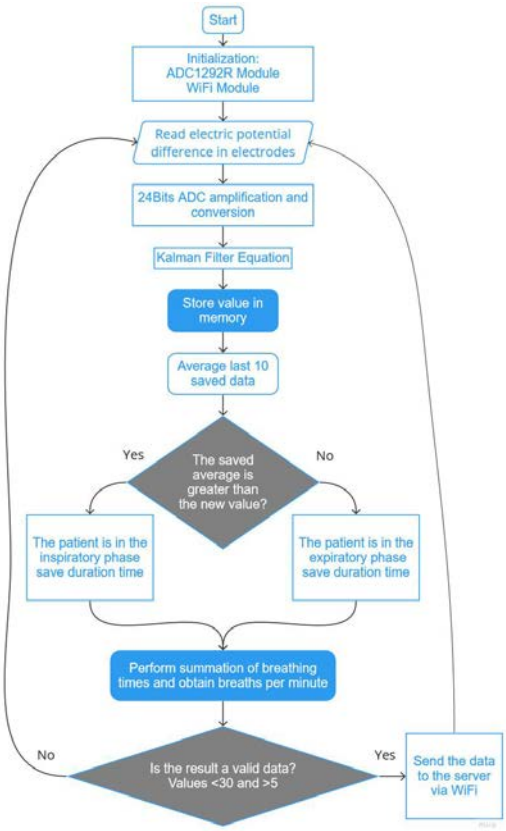

Fig. 8. Flowchart of the Algorithm for the Calculation of Breaths per Minute.

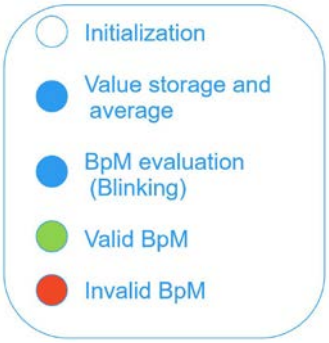

Fig. 9. Color Legend According to Script Execution Stage.

The device is placed on each patient's arm, secured with Velcro to reduce the risk of falls or impacts due to detachment (Fig. 10).

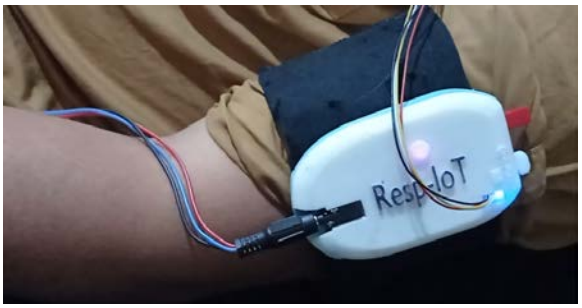

Fig. 10. Device Placed on the Patient.

Fig. 11. Electrodes Placed on the Patient.

Once the device was fixed, the electrodes were placed on the upper part of the patient's chest (Fig. 11). For the tests at rest, measurements were made for a total of two minutes, both by the doctor and the device. For the next test, the patient was instructed to do exercises such as planks or jogging for a total of five minutes with the device on, immediately after which the device was turned on and the doctor began with the quantification of breaths.

IV. Results and Discussion

The results of the tests can be seen in Table I. When separately analyzing the data obtained by the resting test and the exercise test, the performance of the device presents an average error percentage of -5.36% and +1.97%, respectively. For small values, it shows a tendency to overestimate the number of breaths per minute. Meanwhile for high respiratory rate, the measurement tends to be slightly below the real one. When considering both tests, it has an average error value of -1.70%, meaning that the accuracy of the device is approximately 98.3%.

A comparison was performed using the values obtained by the device and by the doctor from both contexts (resting and exercising) as shown in Fig. 12. A correlation coefficient of 0.96 was obtained.

Numerous initiatives have sought to measure the respiratory rate through electronic devices. Adapting sensors to masks could be one strategy, as was demonstrated by Huang et. al. [17]. By using a temperature sensor, the device presented an insignificant error according to its results. However, its precision was evaluated by contrasting its performance with an uncalibrated belt-shaped device that measures thoracic diameter variation.

A similar design is presented by Güder et. al. [18], who introduced a carbon-electrode based paper sensor that varies its conductivity along with the different respiratory phases. To validate its performance, an analysis of the breathing cycles per minute between a light and vigorous exercise session was conducted without selecting a gold standard. Moreover, the sensor electrodes were prone to breaking if the paper was folded, which complicated the process of putting on and taking off the mask.

Different projects have tried to measure respiration rate through chemical sensors that can be mounted on the skin [19] and flexible electronic skins [20], showing promising results. However, it presented an uncomfortable user experience, as the sensors should be placed on the space near the mouth and under the nose. Min et. al. [21] reported a device for respiratory rate measurement analogous to the proposed design. Despite calculating the lung's volume variation, it used a textile-based capacitive respiration sensor, comparing its performance to a nasal thermocouple. The strap surrounding the entire torso demonstrated a precision comparable to the proposed device ($R^2 = 0.98$).

Finally, Pegan et. al. [22] used a wrinkled platinum strain sensor, placed on a part of the chest with a flexible PCB, obtaining a similarity of 95% when compared to a spirometer, which is reliable up to 1000 cycles. Among the advantages of this device is the ability to measure respiratory rate based on the volume of the rib cage, without wrapping the entire torso or causing discomfort near the mouth or nose. One of the disadvantages is the short electrode life cycle, needing to change the electrode each five measurements, and adding conductive gel to improve the quality of the signal.

TABLE I. Comparison of Values Obtained by the Device and by Physician during the Respiratory Rate Test

Test	Patient ID	Device	Physician	%Error
Rest	1	9.49	10	5,10
	2	11,43	11,5	0,61
	3	9,4	9	-4,44
	4	8,7	8	-8,75
	5	12,53	10,5	-19,33
Exercise	1	17,4	20	13,00
	2	23,59	24	1,71
	3	19,72	20,5	3,80
	4	26,1	25	-4,40
	5	21,9	21	-4,29
			Average % Error	**-1,70**

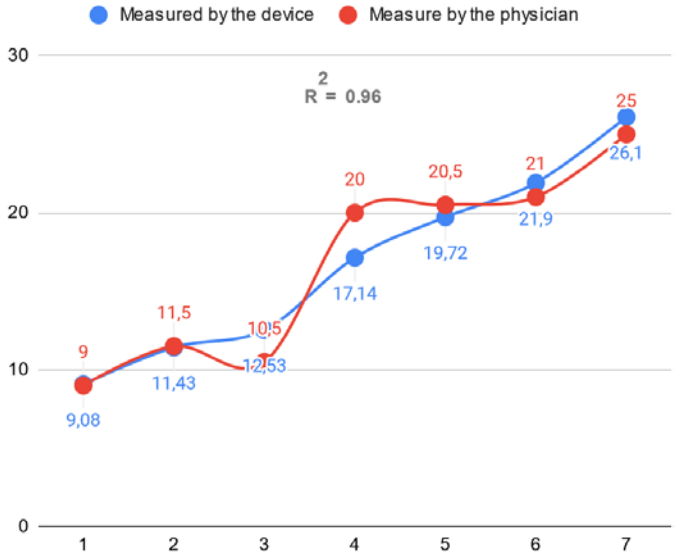

Fig. 12. Relationship between BpM Measured by the Device and by the Physician.

Among the factors that can generate an error in the reading of the proposed device, if the person using it constantly moves or continues to speak, it can generate misreading. It is recommended that patients remain in a state of rest for at least three minutes.

V. Conclusion and Future Work

In this work, an IoT device was developed and tested for remote and continuous monitoring of vital signs related to COVID-19, able to display respiratory rate measurements by calculating the electric potential difference from ECG electrodes located on the chest. The device was calibrated against a visual count performed by a trained healthcare professional in a patient while resting and exercising, demonstrating an accuracy of 96%.

As future work, this device will be tested on a wider population, and at extreme values, through randomized clinical trials with ICU patients and distinct respiratory conditions. It also needs to be calibrated by a metrology laboratory, following ISO standards for measurement management, before being tested in healthcare facilities. As COVID-19 becomes an endemic disease, this device will fill the need for monitoring from conditions like COPD or asthma.

The creation of an open database of respiratory rate values related to mild and severe COVID-19 patients would be of great impact for further research about this disease. Additionally, it will allow the development of machine learning models that anticipate the appearance of a chronic respiratory episode that may aggravate the patient's condition.

Acknowledgment

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