A Prototype of IoT-based Real-time Respiratory Rate Monitoring Using an Accelerometer Sensor

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***Abstract*—The emergence of the internet of things (IoT) has provided a dynamic change of healthcare system that enables interoperability and secure data transmission for a more effective healthcare delivery. This paper extends the implementation of IoT in combining medical devices and sensors with an IoT platform. Among various fundamental vital signs, respiratory rate is one of the most sensitive indicators of physiological conditions. Although it is deemed as a prognostic parameter that can predict miscellaneous diseases, respiratory rate monitoring remains frequently omitted and considered as time-consuming using manual counting methods. To address this problem, this paper presents a prototype of a respiratory rate monitoring device based on IoT and real-time systems. The device is equipped with an accelerometer sensor to measure abdominal movement generated by the inhale-exhale process. Butterworth filter and peak detection algorithm are applied to the signal to detect respiratory cycles. The proposed system uses the message queuing telemetry transport (MQTT) protocol that implements publish-subscribe systems. Respiratory rate results are featured on the Node-RED dashboard with motion and peak signals plotted during the test. Monitoring was carried out on five participants and the results were analyzed using paired t-test. Good performance was demonstrated by having no significant difference in respiratory rate using the proposed method compared to the actual values (p>0.05). Hence, this work provides a convenient technique for respiratory rate estimation and may further allow for the improvement of the effectiveness of remote patient monitoring.**

***Index Terms*—Accelerometer, Internet of Things, Monitoring, MQTT, Real-time systems**

I. Introduction

Respiration is a vital rhythmic behavior in maintaining the sustainability of human life, that is by supplying the basic element of oxygen for metabolism. During inhalation, oxygen travels to the alveoli for gas exchange, diffuses through the capillary endothelium, and subsequently binds to hemoglobin solution in red blood cells for local circulation [1]. As a result of metabolic processes, carbon dioxide byproducts are released in the complementary direction of oxygen and composed in the exhaled air. The number of cycles per minute involving an inhalation, an expiration, and the gap in between denotes the respiratory rate. Central respiratory chemoreceptors have been identified to be responsible for regulating breathing frequency based on the brain PCO2 [2].

Respiratory rate is a sensitive marker that can be evaluated to recognize the patient's current physiological state applicable as a clinical assessment tool. Normally, the adult's respiratory rate ranges from 12 to 20 breaths per minute (bpm), with greater specifying tachypnea [3]. Studies have shown that abnormal respiratory rate is associated with various pathological conditions, predicting pneumonia and adverse cardiac events [4], [5]. Elevated respiratory rate may also be impacted upon stressors, such as hypoxia, panic, mental stress, hypothermia, and hyperthermia [6]–[8]. Respiratory rate serves as an accurate predictor of acute deteriorations and perceives the needs of treatment [9], [10]. Despite the importance of such monitoring, respiratory rate remains one of the frequently neglected vital signs due to the high workload of healthcare workers to complete a 60-second manual counting [11], [12].

A technological approach capable of automating respiratory rate measurement can be devised to alleviate such problems. Recent studies have shifted towards the development of noninvasive respiratory rate devices based on electrical sensors to detect the inhale-exhale movements. Previously reported respiratory inductive plethysmography device combined thoracic and abdominal belts with nasal pressure, in which the sensor is based on measuring the current as a result of an alternating magnetic field in coils [13]. Other studies proposed bioimpedance-based sensors and showed a linear relation between bioimpedance and respiratory volumes [14], [15]. Furthermore, a multi-channel recording device has been proposed to record the lung sound to estimate respiratory airflow [16]. However, most of these devices are expensive, require trained operation, and can coincidentally capture environmental noises.

Further respiratory rate measurement can be derived from a single accelerometer-based sensor [17]–[19]. Respiration initiates the movements of thoracic and abdominal walls [20]. Such movements are an important aspect in measuring respiratory rate using acceleration. An accelerometer sensor is attached to the respiratory belt, suppressing the chest to enable rotation estimate during inhalation and expiration. However, the data were influenced by heart sound and external noises that resulted in poor signal. Further configuration that required importing data to softwares after each test may also decelerate the monitoring process.

In recent years, the adoption of IoT in medical technologies has increased significantly. This offers opportunities for smart healthcare services to provide a more convenient, efficient, and improved ecosystem of healthcare delivery. Health IoT makes use of a network level which consists of wired and wireless connections, in which the data storage is either local or cloud-based [21]. The IoT may provide flexibility and scalability as well as to facilitate the workflow of sensor and wearable devices in transmitting and processing data through cloud computing, allowing such data to be fast-tracked by healthcare professionals [22]. Low-cost and real-time monitoring systems are prominent, particularly in the distribution of healthcare services in various regions. More recently, a transformation towards digital health provides a room of innovation in presenting IoT-based medical technologies.

This study underlines a design of a noninvasive low-cost respiratory rate measuring system for the detection of the patient's respiratory rate using an accelerometer sensor. A solution to the aforementioned clinical efficiency issues is made by introducing the IoT into the design framework. The integration of the IoT system may contribute to the improvement of healthcare operation in the respiratory rate monitoring system and delivery system. Results are featured in a secured cloud connection that can be remotely accessible for real-time monitoring.

II. Method

A. Prototype Set-up

The prototype monitoring system was based on the combination of the MPU-6050 (InvenSense Inc., CA, USA) accelerometer sensor with the ESP32-DevKitC V4 (Espressif Systems, China) microcontroller to collect respiratory rate data and Node-RED platform which provided user interface to present the results (Fig.1).

The system implemented the message queuing telemetry transport (MQTT) protocol with the principle of publishing and subscribing to topics. MQTT offers real-time communication and provides scalability and reliability of data transmission by implementing security measures to specifically allow devices to link to the MQTT server. In transmitting respiratory signals, ESP32 was assigned as a publisher that published data to the MQTT broker of Eclipse Mosquitto (Eclipse Foundation, Canada) which implemented MQTT protocol (version 3.1). The communication was handled under a managed cloud server Amazon Web Service (AWS) IoT Core that enabled data transmission to Node-RED.

MPU-6050 accelerometer was selected to measure acceleration on account of respiratory motion. The sensor features a three-axis accelerometer sampled simultaneously by a 16-bit ADC with a full-scale range of ±2g, providing 16384 LSB/g sensitivity that is preferable in this study. The accelerometer was accessed through an auxiliary master I^{2}C bus interfaced with ESP32 through dedicated SCL (serial clock) and SDA (serial data) digital pins. Serial port was selected with a speed of 115200 bauds. For a proper measurement of respiratory rate, the sensor was associated with an abdominal belt placed underneath the sternum (Fig.2). In such a manner, the tilt angle established by abdominal movement during respiration could be measured by the sensor. Increased sensitivity of the sensor reading was achieved by adjusting the patient's body in supine position throughout the measurement.

B. Respiratory Rate Estimation

Owing to the placement of the sensor, tilt angle measurement was performed in the x-axis. Raw acceleration was first obtained in the MPU-6050 accelerometer registers through I^{2}C protocol. Rotational matrix of the three-axis acceleration reading was derived such that the roll angle equation could be obtained in equation (1). It was further expressed in the atan2 function for the computation in the microcontroller.

$$\phi = \arctan \frac{A_y}{A_z} \tag{1}$$

Here A_y and A_z denote the acceleration in y- and z-axis respectively. The roll angle signal was then converted from radians to degrees. Oscillatory motion of the respiratory signal was filtered using a second order Butterworth low-pass filter (LPF) with cutoff frequency of 0.6 Hz, allowing breathing frequency to pass and isolated from any external noise. This cutoff frequency must be lower than that of Nyquist frequency (F_{max}) to prevent corrupting signals. Adjusting to F_{max}, the sampling frequency was set to 100 Hz. In designing the filter, coefficients of the difference equation were derived from the discrete transfer function and embedded to the program in order to filter the raw roll angle signal.

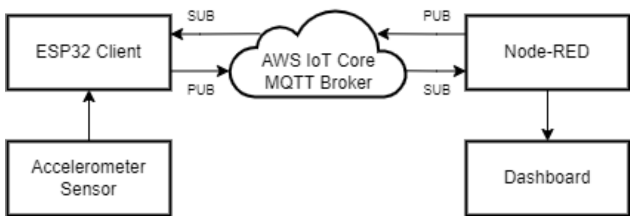

Fig. 1. Block diagram of the proposed monitoring system.

Fig. 2. Sensor placement in the middle front of the abdominal belt.

A peak detection algorithm was then applied to the filtered roll angle signal to identify peaks whenever the patient inhaled [23]. The algorithm computed the moving mean and deviation and returned peak values once the new datapoint was at a certain standard deviation away from the mean value, evaluated by the Z-score. Three parameters were introduced in this algorithm, including lag to adjust the adaptedness of the algorithm, threshold to set the standard deviation, and influence to determine the sensitivity of the threshold towards the signal. The total amount of peaks generated throughout the measurement specified the respiratory rate in bpm.

C. IoT-based Real-time Monitoring System

Inside Node-RED, flows were developed by concatenating inject, function, sequence, network, and dashboard nodes. Respiratory rate results were sent in the form of message payloads which were read by the MQTT input node. This node was assigned a topic that was a specific destination whenever the ESP32 client published. The message payload was set to string with quality of service (QoS=1). Transport layer security (TLS) was enabled and configured with AWS IoT to ensure a secure connection between the device and the server. Multiple MQTT input nodes were employed for results such as filtered roll angle signal, peak detection, and bpm which were displayed on line charts and texts.

The design framework of respiratory rate measurement is shown in Fig.3. In order to initialize data transmission through MQTT broker, WiFi and AWS connections must be established, that is by declaring WiFi SSID, password, and AWS IoT endpoint. Further callback functions were deployed since several MQTT output nodes were used for measurement results. That is, the user must input the age information prior to the measurement such that the obtained respiratory rate could be synchronized to the standard value with respect to the age range. A run toggle was included on the Node-RED dashboard to dictate the program status through an MQTT output node to terminate or enable a loop function responsible for the respiratory rate measurement. Once the program was completed, the loop was automatically terminated through an MQTT input node and the respiratory rate was generated.

D. Statistical Analysis

Five subjects were tested for respiratory rate monitoring using proposed work and gold standard measurement technique. Gold standard values were obtained by visually observing chest movements due to respiration at periodic intervals. Controlled respiration was performed by the subjects to achieve the respiratory rate of 12-16 bpm. Paired t-test was performed to address the statistical difference between the two methods and $p<0.05$ was considered statistically significant.

III. Results and Discussion

Respiratory rate monitoring was carried out on healthy subjects with a complete duration of 60 seconds. They were asked to use a belt that had been associated with the accelerometer sensor around the abdomen and to maintain a supine position during the measurement. Accelerometer readings on 3 axes were performed to measure the roll angle caused by inspiratory and expiratory contractions of abdominal muscles. The reading results were sent by the ESP32 client to the Node-RED platform via the MQTT broker, in which the messaging protocol was accommodated by AWS IoT Core. Users could access the Node-RED dashboard during the monitoring process. To initialize the device, they must provide age information followed by switching on the run toggle.

From the test, measurement data was exported to visualize the response of the filter and peak algorithm to the roll angle reading (Fig.4). It appeared that the second order Butterworth LPF sufficiently provided a better estimation of the roll angle before being analyzed by the peak detection algorithm. The algorithm calculated the moving mean of the filtered signal and evaluated the standard deviation of each datapoint against a predetermined adaptive threshold. Expiration was shown

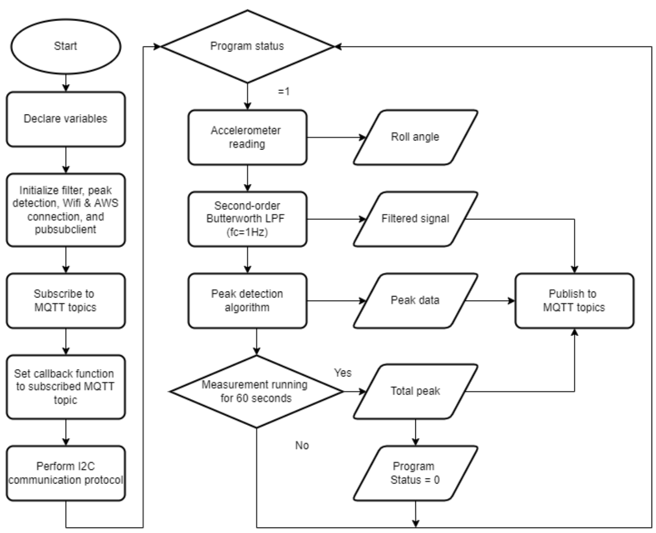

Fig. 3. Respiratory rate monitoring flowchart.

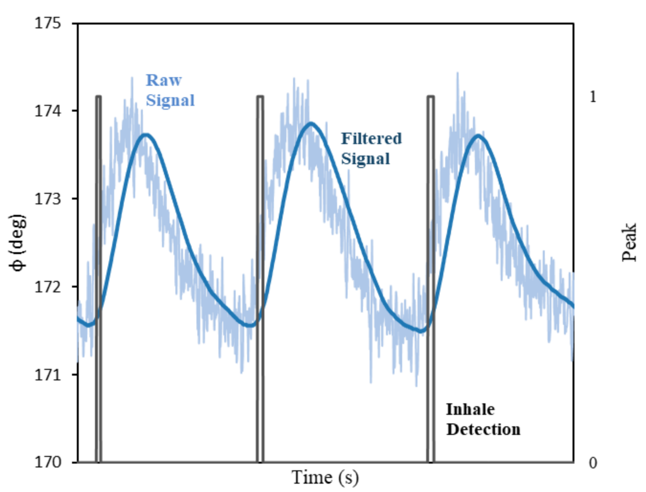

Fig. 4. Roll angle estimation derived from accelerometer reading.

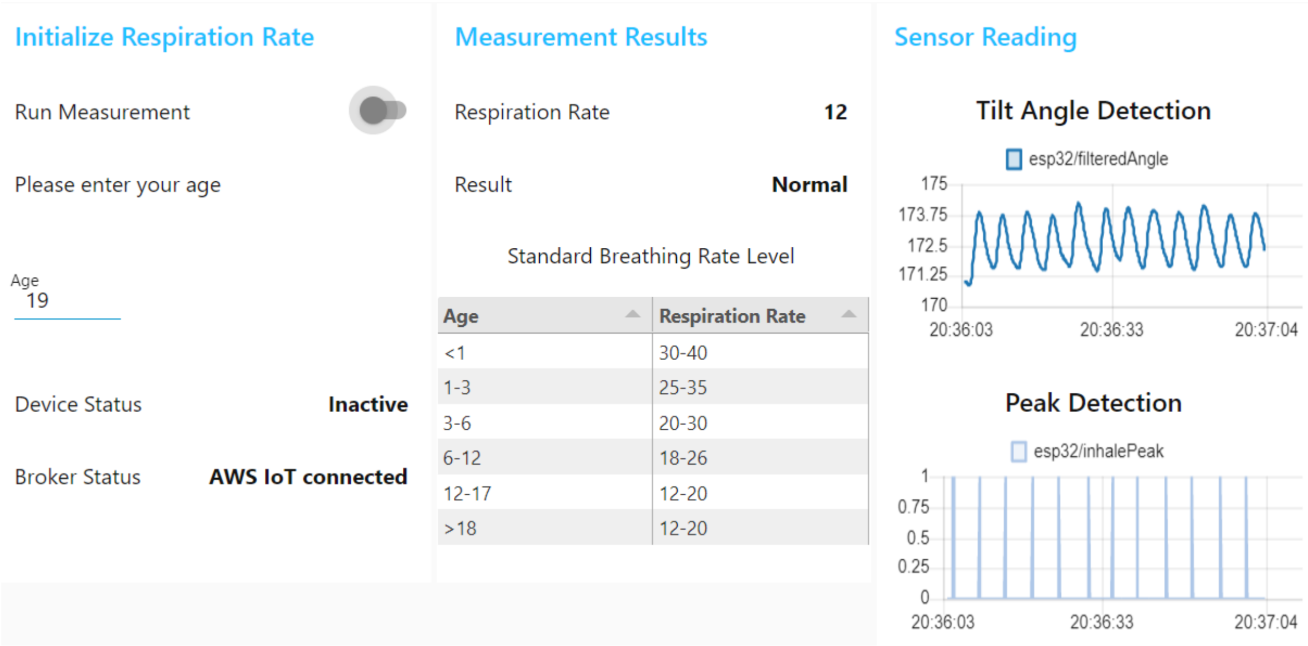

Fig. 5. An example of respiratory rate data from a 19-year old participant displayed on the Node-RED dashboard. For this measurement, the obtained respiratory rate was 12 bpm, which resulted in normal level considering the age of the participant. Roll angle and peak data were also available and plotted in real-time.

to be followed by an automatic pause for approximately 1 second, in which the threshold adapted to this signal. The inhalation process increased the roll angle of the sensor which caused the new datapoint to exceed the threshold. This informed the algorithm about a new respiration cycle. The device accumulated every change in peak signal from 0 to 1 to respiratory rate once the measurement was complete.

To validate the performance of the device, the estimation of respiratory rate using peak detection algorithm was compared to the gold standard (Table I). Of all paired t-tests performed on the respiratory rate of each subject, no significant difference was observed between the two methods ($p>0.05$). The accelerometer-derived respiratory rate values were within ± 1 of the gold standard. Thus, it is elucidated that the proposed work resulted in good accuracy in measurement.

TABLE I
COMPARISON OF PEAK DETECTION ALGORITHM AND GOLD STANDARD FOR RESPIRATORY RATE ESTIMATION

Gold Standard	**Peak Detection Algorithm**				
	S1	***S2***	***S3***	***S4***	***S5***
12	12	13	11	12	11
13	12	14	14	12	13
14	15	14	15	14	14
15	15	15	15	15	14
16	16	16	16	16	15
P-value*	1.00	0.18	0.62	0.37	0.07

* $P<0.05$

Monitoring system of respiratory rate detection was displayed on the Node-RED dashboard (Fig.5). Three groups of nodes were made for initialization using MQTT inputs, measurement results, and sensor reading using MQTT outputs. Roll angle and peak signals were provided so that personnels may track the progress during the test. In our experiment, we experienced high latency when publishing the roll angle data through MQTT. This resulted in an interference with the accelerometer reading. We assumed that the broker required extra processing for such real-time measurement using sampling time of 10 ms. In response, we altered the data transmission rate such that the ESP32 client published one in every five data points. Nonetheless, this did not change the sampling frequency of the device to measure respiratory rate.

Computations including peak detection algorithm and Butterworth filtering were carried out on ESP32. The implementation of the IoT system enabled the visualization of the monitoring interface for respiratory rate signals. These plots may be useful for personnels to detect any abnormal respiration cycle such as irregular pauses or inadequate inhalation and expiration. With the recent COVID-19 pandemic, respiratory rate was a significant metric to predict the risk of infection [24]. Moreover, a noninvasive wearable device with an IoT system is preferable to facilitate respiratory rate monitoring and deter virus transmission.

After completing each test, the device published the total peak detected which represented the respiratory rate. We used the reference values from Shabeeb et al. to categorize the standard respiratory rate level [17]. If the obtained respiratory rate was in accordance with the age range input, the result would be published as normal, whereas abnormal in the opposite manner. That said, this device is able to provide users with a vital clinical parameter as an indicator of fitness and health.

IV. Conclusions

As a vital parameter, respiratory rate contributes as an early indicator of disease progression. An automation of respiratory rate monitoring is imperative to improve the healthcare workflow and reduce transcription errors from manual reading. With the application of IoT, our prototype is capable of combining an accelerometer reading and real-time monitoring system through MQTT protocol. Respiratory rate measurement is derived from filter implementation followed by a peak detection algorithm, in which the progress can be monitored on the Node-RED dashboard. Good performance for respiratory rate estimation is shown by the absence of significant difference compared to the actual value. Researchers are continuing to develop respiratory rate devices and explore the integration of IoT-based monitoring medical devices through the future of healthcare technology. In addition, future studies should certainly be devoted to the developments of these findings.

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