Estimation of Respiration Rate using an Inertial Measurement Unit Placed on Thorax-Abdomen

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***Abstract*—Respiration rate is one of the important measures of any physiological changes in human body. In this paper, an inertial measurement unit (IMU) is used to detect the chest movement and estimate the respiration rate from the real-time signal. A commercial inertial motion sensor chip used in this study that produces linear motion vector as streaming data. The signal from the motion sensor was sampled at 10 Hz. Signal processing was applied to denoise respiration signals from the values of linear motion vectors. Then, an algorithm of calculating respiration rate, was used to estimate breath per minute (BPM). The results were compared with a commercial respiration monitor belt logger sensor as the ground truth. The IMU sensor was tested at 5 different BPMs (12, 15, 20, 24, and 30) to validate the data from the IMU sensor and from the commercial respiration belt using a protocol where different BPM was maintained. The results show high accuracy of the proposed system which is simpler to use, cheaper to protype, and can be integrated with a wearable device and a custom smartphone app using edge computing technique.**

***Index Terms*—Data validation, Inertial measurement unit, Linear motion, Respiration rate, Wearable.**

I. Introduction

Respiration rate (RR) is a vital sign for any physiological changes in human body. Measuring the respiration rate accurately, is an important medical applications as well as health and well-being applications. Like other health measures such as electrocardiography (ECG) and electroencephalography (EEG), RR measurement is also a key aspect in determining human health condition. Human respiratory system delivers oxygen and removes carbon-di-oxide to maintain the partial pressure of oxygen and carbon-di-oxide in arterial blood. Normal breathing is a consecutive sequence of inhale and exhale phases and occurs synchronously with the movement of thorax and abdomen [1]. Respiration rate can vary according to physical activity and illness. In normal condition, an adult person can have a breathing rate between 12 to 20 breath per minute (bpm) [1], [2]. Abnormal respiration rate may occur due to illness in respiratory centers, taking narcotic medicines, metabolic disarrangements or due to muscle weakness [1]. Unusual breathing can indicate either slowness or fastness of breathing rate due to various physiological conditions and diseases. Different disease can lead to the abnormality of the RR such as obstructive sleep apnea (OSA), Chronic obstructive pulmonary disease (COPD), hyperpnea, tachypnea, bradypnea.

As RR measurement possess important information of human health, different wearable sensors have already been developed to estimate RR and detect breathing patterns [3]. As wearable sensors can take advantage of flexibility, RR sensor based on inkjet printing (IJP) technology has been developed that provides some flexibility [4]. In some cases, microwave components such as Doppler radar has been used to measure the breathing pattern remotely [5]. The radar was able to detect the breathing signal as well as, could calculate the respiration rate. RR calculation based on non-contact assessment of breathing has also been developed to benefit people specially, infant and people with infectious disease [6], as the RR detection process does not require any significant contact with the patient. However, this technique limits the movement of the user to a certain region of measurement space, which might not be practical. Wearables have the advantage of unrestricted user mobility. Several breathing rate detection algorithms have already been developed to detect respiration patterns with high accuracy [7]. As many illness can occur due to unusual respiration pattern, intensity of respiration based diseases can be measured through efficient algorithms [8]. Efforts have also been made to show that the respiration disorders with the association of mobile health technology can improve users health with low burden [9].

Inertial measurement unit (IMU) has been widely used for measuring the linear and angular motion [10], [11]. This specific feature can be used to detect the respiration signal by attaching the IMU sensor on the abdomen. Use of IMU for respiration is gaining popularity as it is showing the ability to accurately detect the respiration pattern in different conditions [12].

This paper proposes the use of a single motion processing sensor to detect respiration rate over time. The breathing pattern measuring process incorporates the vector data from a 3-axis accelerometer, which makes the process a lot simpler. Three-axis (x, y and z) data are normalized and then combined together to form a position vector. Finally, a moving average filter with a window size of 10 is used to remove noise from the actual signal. Implementation of all 3 axis makes our proposed device more reliable in terms of various movement during data capture. Also, the traditional commercial sensors such as Spirometer or Respiration belts are heavy and cumbersome to handle. The proposed device is light weight and small in size, which makes it easy to handle. All data has been captured through a specific protocol so that the results are comparable with a commercial RR measurement device.

The paper organization is as follows. Section II gives description of System Design and Architecture including system overview, hardware specification, software implementation and signal processing. Section III and IV describe the protocol and presents the performance of the sensor from the experimental results, respectively. Finally, Section V discusses the conclusion.

II. System Design and Architecture

In this section, overview of the overall system along with the hardware and software description of the proposed work is discussed.

A. System Overview

During breathing, there is a consecutive sequence of breathe in and breathe out phases that occurs synchronously with the movement of thorax and abdomen. The inertial measurement unit (IMU) can capture the movement caused by breathing, if it is placed in thorax or abdomen region. The IMU sensor thus produces movement pattern which is synchronous with respiratory behavior. The overall system data processing procedure is shown in Fig. 1. The IMU unit was attached on the thorax-abdominal region of a human body. A microcontroller (uC) unit was used to process the data from the IMU sensor. The 3-axis accelerometer data was filtered by a moving average filter and then stored in a mutex buffer. The stored data was further processed using MATLAB software and a corresponding RR was estimated.

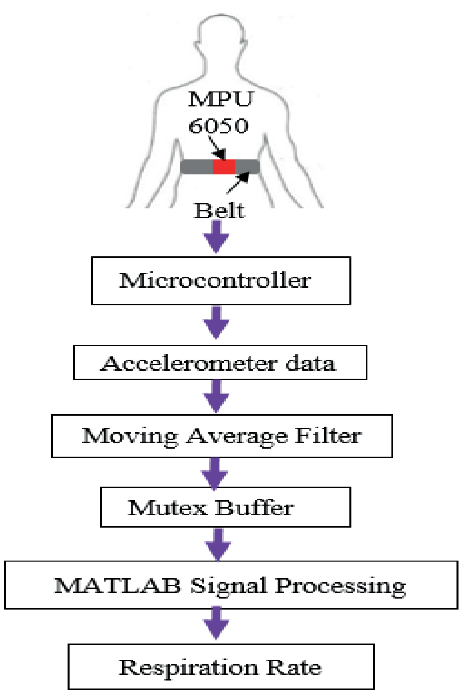

Fig. 1. Signal processing steps of the respiration sensor.

B. Hardware Specification

The key components used were, an ATmega 328 microcontroller connected with an MPU-6050 unit. MPU-6050 is used as the IMU sensor in this work. It is a 6 axis measurement unit containing 3 axis accelerometer, 3 axis gyro meter. The MPU 6050 has 6 dedicated analog to digital converters (ADCs) to digitize the accelerometer and gyroscope data. As per the datasheet of MPU-6050, the user programmable full-scale range of accelerometer is ±2g, ±4g, ±8g and ±16g. Also, the full-scale range of gyroscope is ±250 °sec, ±500 °sec, ±1000 °sec and ±2000 °sec [13]. The uC unit is connected with the MPU-6050 by Inter-Integrated circuit (I^2C) communication.

A respiration monitor belt sensor NUL-236 from NeuLog was used to collect ground truth data, and to compare and verify the MPU-6050 data. The NeuLog belt is attached to the abdomen. The belt can measure the air pressure inside it. The air pressure in the belt changes according to the respiratory behavior of the subject. A practical setup of a user wearing these sensors is shown in Fig. 2 for a reference.

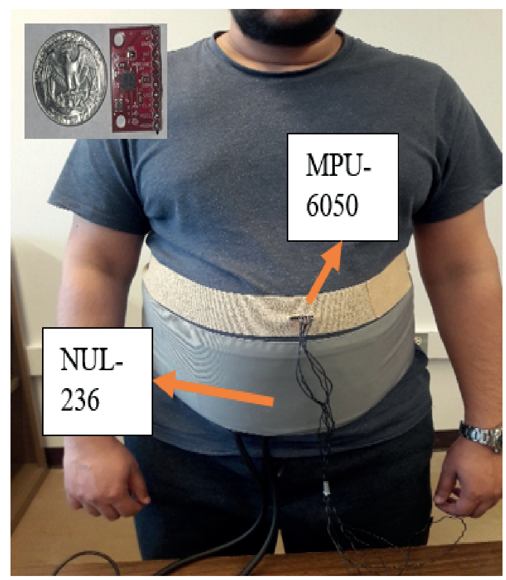

Fig. 2. Practical view of wearing the sensors during data acquisition; (inset) MPU-6050 size compared with a quarter dollar.

C. Software Implementation

A software code was built and run on the uC so that the IMU sensor can provide appropriate data. The 3-axis accelerometer (a_x, a_y and a_z) data have been used to construct a position vector. To form the vector, the data of 3-axis are filtered by a moving average filter of window size 10. The filtered data are saved in a mutex buffer of size 100. For each 100 samples, data was normalized. The normalized data was further processed in MATLAB to compute the RR. Sampling frequency of the IMU sensor was set to 10 Hz. The equation used for moving average filter for x-axis is given as follows,

$$a_{x_{filtered}}\left[n\right] = 1/N \sum_{i=0}^{N-1} a_x\left[n-i\right] \tag{1}$$

Where, $a_{x_{filtered}}$ is filtered value of x-axis of accelerometer and a_x is the raw data coming from x axis of accelerometer. For y- and z-axis, similar equations were applied. The equation used for normalization of x-axis data is as follows,

$$a_{x_{norm}} = (a_{x_{filtered}} - a_{x_{fmin}})/(a_{x_{fmax}} - a_{x_{fmin}}) \quad (2)$$

Where, $a_{x_{norm}}$ is the normalized value for 100 consecutive filtered values of x axis and $a_{x_{fmax}}$ and $a_{x_{fmin}}$ is maximum and minimum values for each 100 consecutive filtered data. For y- and z-axis, similar equations were applied.

D. RR Estimation

The data from the uC is collected and stored in a PC using CoolTerm software. The collected data is processed further to get the respiration rate. At the beginning of this process, data is filtered again using a moving average filter of window size 15. The filtered data is then fed to a curve fitting algorithm. The curve fitting technique used was spline interpolation of *MATLAB®*. From the interpolated curve, the locations and values of the peaks are detected. These peaks represent the peaks formed due to exhale phase of breathing. To calculate the RR, the number of peaks observed in a 1 minute period is taken into account. The following equation is used to calculate the respiration rate,

$$RR(BPM) = nBreath/(s/60minutes) \quad (3)$$

Where, n indicates the number of breaths in s seconds.

III. Protocol For Data Validation

To check whether the data coming from IMU sensor and the NeuLog respiration belt are valid or not, we went through a process of defined protocol and validation. The process uses 3 steps as follows. 1st step is taken to validate the data obtained by Neulog respiration belt. In 2nd step, MPU-6050 data was acquired and validated. In 3rd step, data have been taken simultaneously from NeuLog respiration belt and MPU-6050 sensor, then validated by maintaining a protocol. Each of these 3 steps has been done following specific protocols. The purpose of the protocol is to maintain a fixed RR in a controlled manner. The tested RR by using this protocol is 12, 15, 20, 24 and 30 BPM. To illustrate how the protocol works, let us give an example of the protocol for 12 BPM. For a RR of 12 BPM, there will be 12 inhale and 12 exhale in 1 minute duration. This means that, there will be in total 24 inhalation and exhalation phases over 1 minute. A power point slide is made which contains 24 slides, where each slide moves to next slide automatically after every 2.5 seconds. Moreover, each slide contains an instruction whether to inhale or exhale. A slide for inhale is followed by a slide for exhale until the 1 minute duration completes. The same protocol is constructed for 15, 20, 24 and 30 BPMs. Duration of each slide for 15, 20, 24 and 30 BPMs are 2 s, 1.5 s, 1.25 s and 1 s respectively. Similarly, the total number of slides for 15, 20, 24 and 30 BPMs are 30, 40, 48 and 60 respectively.

IV. Results

In this section, the respiration signal output is represented using the protocol. Moreover, performance of the MPU 6050 in terms of RR estimation is compared with a commercial respiration sensor Neulog NUL-236.

Fig. 3 represents the respiration signal acquired by MPU 6050 sensor. The respiration signal is shown for 12, 15, 20, 24 and 30 BPM. The signals presented are curve fitted by spline interpolation. Number of peaks along with their locations and values are computed from these fitted curve. Then, RR is estimated using equation (3). All of the data have been acquired using the protocol.

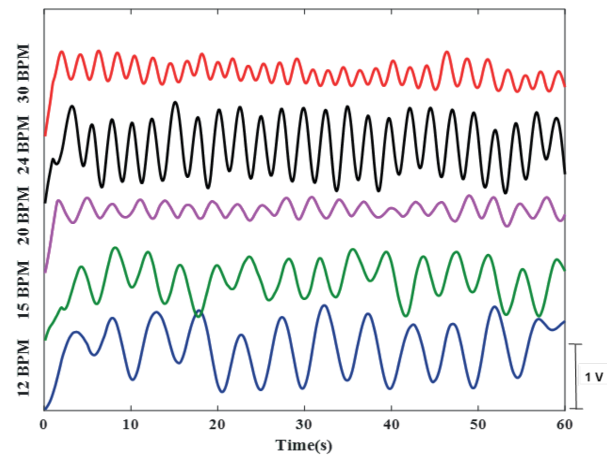

Fig. 3. Respiration signal from MPU-6050 sensor for different BPMs.

Fig. 4, presents the respiration signal obtained by the commercial NUL-236 sensor. The sensor provides raw data. Similar protocol of data acquisition is maintained for 12, 15, 20, 24 and 30 BPM. This step is done to validate the commercial NUL-236 sensor itself. Moreover, the RR is estimated using the same equation (3).

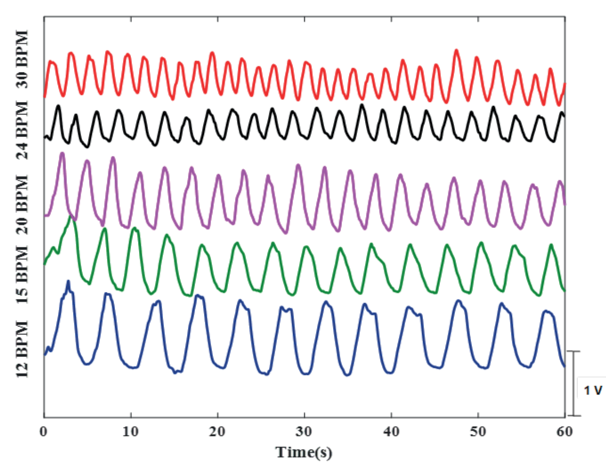

Fig. 4. Respiration signal from NUL-236 sensor for different BPMs.

Fig. 5 shows the respiration pattern where, data from MPU-6050 and NUL-236 are taken simultaneously. The figure shows the pattern for 20 BPM as an example. Data are taken for all of the tested BPMs. For each BPM, 10 different samples are taken so that we have statistically significant results for a conclusion.

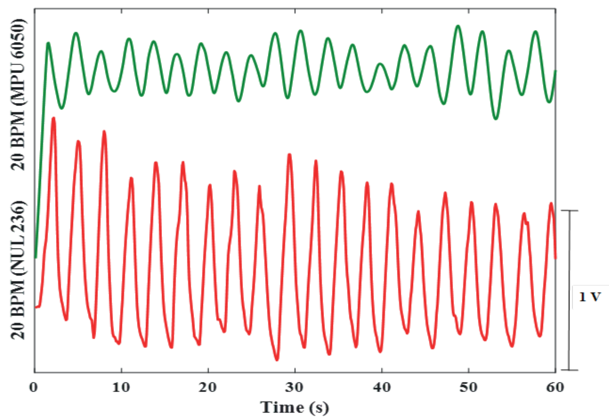

Fig. 5. Simultaneous data acquisition of sensors for 20 BPM.

Fig. 6(a) and Fig. 6(b), depicts the correlation plot for MPU- 6050 and NUL-236 respectively. Fig. 6(c) shows the correlation plot for simultaneous data acquisition of MPU-6050 and NUL-236. For each correlation plot, 10 different samples are taken for every BPMs. For example, there are 10 samples of data acquisition for 12 BPM maintaining the protocol. It is counted as an error if any sample can not estimate 12 BPM. The corresponding error is averaged for 10 samples. Similar procedure is maintained to obtain the errors for 15, 20, 24 and 30 BPM. After having the errors, they are plotted with respect to the actual BPM. According to Fig. 6(a), NUL-236 sensor does not face any error in Respiration signal acquisition. As Fig 6(b), MPU-6050 also promises a good performance having errors in very few cases. As of Fig 6(c), MPU-6050 performs well when compared with NUL-236.

Table I, shows the performances and errors of the MPU-6050 sensor and NUL-236 in different scenario. Data acquisition process is done by strictly following the protocol. For each error, the wrongly estimated RR is also shown.

TABLE I
PERFORMANCE OF MPU-6050 AND NUL-236 FOR DIFFERENT BPMS

Respiration Rate	Number of Error (s), N = 10			
	NUL-236	*MPU-6050*	*Simultaneous Data*	
			NUL -236	*MPU -6050*
12 BPM	0	1 (13 BPM)	0	1 (11 BPM)
15 BPM	0	0	0	0
20 BPM	0	0	0	0
24 BPM	0	1 (26 BPM)	0	0
30 BPM	0	1 (31 BPM)	0	2 (31 & 33 BPM)

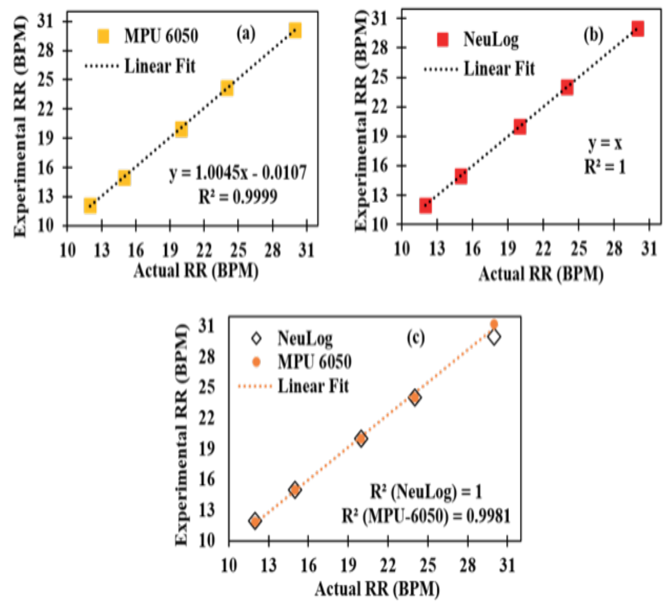

Fig. 6. Correlation plots of (a) MPU-6050, (b) NUL-236, and (c) MPU-6050 and NUL-236 simultaneous data acquisition.

V. CONCLUSION

An inertial measurement unit was used to detect the respiration signal. The sensor could successfully detect the respiration pattern in different BPMs. The detection process we used was simple. Both the IMU and commercial sensor data are validated by a protocol. Moreover, the IMU sensor is compared and verified by taking data simultaneously with NUL-236. The performance of the IMU sensor is reliable enough that it can be a good addition for wearable devices.

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