Extraction of Respiration Rate from Wrist ECG Signals

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***Abstract*—Respiratory behavior is one of the important parameters that indicate any physiological changes in human body. However, using a respiration sensor device for continuous monitoring is inconvenient and expensive. In this paper, an approach to acquire the respiration signal from the wrist electrocardiogram (ECG) is proposed. An analog front end (AFE) sampled at 100 Hz is used to collect ECG signals from the wrist to compute and verify the corresponding heart rate (HR) with a commercial ECG device. Signal processing mechanisms are applied on the raw data to denoise the ECG signal. The captured ECG signal is further processed to extract a breathing pattern to calculate a respiration rate (RR) in breath per minute (BPM). The extracted BPMs are compared with a commercial respiration monitor to validate the data by following a protocol at 5 different BPMs (12, 15, 20, 24 and 30). For each BPM, commercial respiration monitor is validated at first. Then, data are taken simultaneously wearing wrist electrodes and commercial respiratory device to validate the performance of our proposed method at different BPMs. The results indicate high accuracy of the proposed system which is low-cost, simpler to implement, can be integrated with a wearable device and remove the demand of any dedicated sensor for RR measurements.**

***Index Terms*—wearable, electrocardiogram, respiration rate, signal processing, cyber physical system, mobile health**

I. Introduction

Respiration signal is one of the important indications for any physiological changes in human body. Accurate and efficient estimation of respiration rate (RR) is a great concern in the sector of medical application. The respiratory system in a human body delivers oxygen and takes carbon-di-oxide out to maintain the partial pressure of oxygen and carbon-di-oxide in the arterial blood [1]. This breath-in and breath-out phenomenon is termed as inhale and exhale phase respectively. Normal breathing consists of a continuous and successive sequence of inhale and exhale phases and occurs simultaneously with the movement of thorax and abdomen [2]. There can be change in RR due to any kind of physical activity or, illness. Normally, an adult person can have a breathing rate between 12 to 20 breath per minute (bpm) [3]. Abnormality in breathing signal may occur due to several reasons like, weak performance of respiratory centers, taking drugs, metabolic inconsistency or due to muscle weakness [2]. Abnormal breathing can mean either slowness or fastness of breathing due to several fatal diseases. Different diseases can result in the abnormal RR such as obstructive sleep apnea (OSA), Chronic obstructive pulmonary disease (COPD), bradypnea, hyperpnea, tachypnea.

Screening of respiratory signal without the direct use of any breathing sensor can decrease the burden from patient's body. Extracting breathing signal from the subject's ECG signal can serve this purpose. It can be also advantageous in the sector of mobile health monitoring. ECG signal is a representation of changes in the physical activity of the heart muscle over a period of time [4]. Standard placement of ECG electrodes is already established to ensure accurate recording of bio-potential activity around the heart muscle [5] - [6]. ECG signal is generally affected by the electrode movement due to respiratory and non-respiratory behavior [1]. This incident is based on the changes in the orientation of the electrical axis of heart with respect to the electrodes [7], which strongly suggests the amplitude modulation of ECG signal due to respiratory changes. Another way of deriving the RR from ECG is based on the inspecting of frequency modulated ECG caused by respiration activity [8]. The theory of the frequency modulated ECG is based on the changes in heart rate (HR) during the inhalation phase and decrease of the HR at the time of exhalation phase. After several empirical studies, it is observed that the variation in HR has followed approximately the exact RR even after the pulmonary reflexes are removed [9].

As respiratory changes contain important information of physiological health, different wearable sensors have already been developed to estimate RR and detect breathing patterns [10]. Inertial measurement unit (IMU) is a popular sensor for capturing the linear and angular motion [11] - [12]. This feature can be implemented to acquire the breathing pattern by attaching the IMU sensor on the thorax-abdomen [13].In some cases, flexible respiration sensor based on inkjet printing (IJP) technology has been developed that can offer certain amount of flexibility [14]. Moreover, Doppler radar technique has also been implemented to capture the breathing pattern remotely [15]. Different algorithms for detection of breathing rate have already been developed to capture breathing patterns with high accuracy [16] - [18]. Several studies have been established to measure the severity of illness caused by abnormal respiratory behavior [19]. Application based on mobile health monitoring has also been developed to find out the respiratory illness [20].

Non-contact based respiratory analysis have been presented to measure RR to benefit people specially, subjects with infectious disease and infant [21]. Although, this technique does not require any contact with patient, it limits the movement of the subject to a certain area, which might not be practical. However, wearables have the advantage of unlimited subject movability. Ubiquitous smart phone based RR measurment using accelerometer and gyrometer, is constructed where the mobile device is placed on the subject's chest [22]. The performance of both accelerometer and gyrometer is affected by user movements and vibration coming from the environment. Moreover, placement of the mobile device in chest is less user friendly for a subject. In [23], RR has been extracted from chest ECG where the ECG electrodes were placed on a soft clothing. In another work, a modified lead of precordial lead V2 is implemented to extract RR from ECG signal [24]. The modified lead is actually a bipolar surface electrode which mimic the the analog V2 lead. In [25], RR is derived from accelerometer attached at the subject's wrist. We have previously demonstrated respiration rate can be captured using a single inertial measurement unit (IMU) [13].

This paper proposes a method to obtain respiratory signal from an ECG signal using an analog front end. The analog front end captures the electrical activity through the electrodes attached at the wrists of right arm (RA) and left arm (LA). These raw data are applied to a band-pass filter (BPF) to remove the effect of baseline wandering. The filtered signals are further processed through a derivative filter to improve the signal to noise ratio (SNR) of the signal. Afterwards, signals are squared and averaged. Then, adaptive threshold based real time QRS detector is applied to locate the R peaks of ECG signal. Fig. 1 represents a normal ECG signal denoting different beats. After locations of corresponding R peaks are detected, an spline interpolated curve fitting technique is applied to construct a curve with the R peaks. From the fitted curve, new peaks are detected. These new peaks indicate the peaks formed due to consecutive inhalation and exhalation phase of the respiratory system. The proposed method uses ECG that are coming from wrist, which removes the need of dedicated sensor for RR measurement. Also, single lead ECG from wrist, makes the setup more user friendly. The proposed device is light in weight and low cost. The proposed method can detect RR over a wide range varying from 12 BPM to 30 BPM. The data are taken through a protocol and are compared with commercially available devices to validate our result.

The paper organization is designed as follows. The section 2 gives overview of system design and architecture discussing both the hardware specification and software implementation. Section 3 discusses how the protocol is applied to validate the data. In section 4, technical results of the proposed method are presented. Finally section 5 discusses the conclusion.

II. System Design and Architecture

In this section, overall system overview is discussed. Also, specification of corresponding hardware used along with software implementation will be discussed.

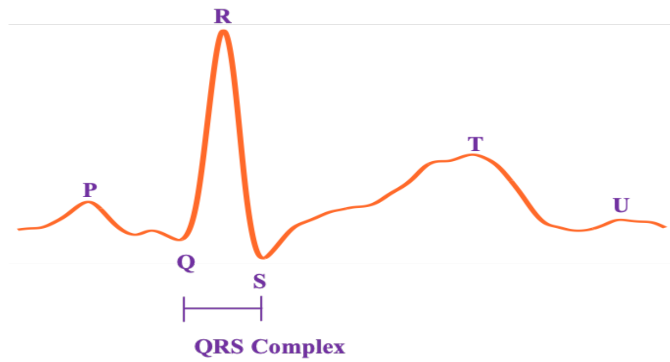

Fig. 1. Different Beats of a normal ECG signal [26].

A. System Overview

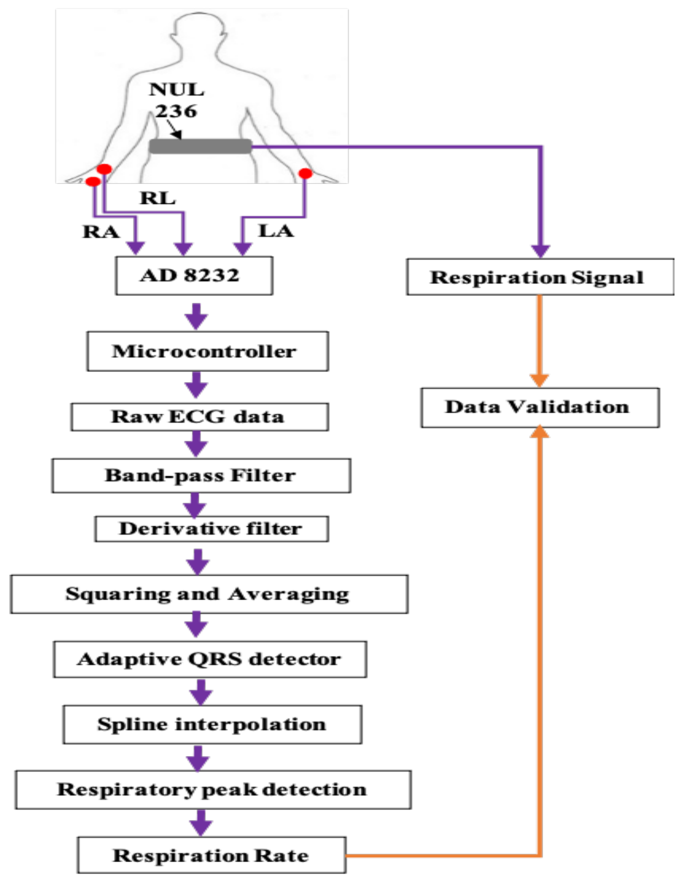

Fig. 2. System overview of the proposed method (shown on left) and validated with a respiration signal capture device (shown on right).

As shown in Fig. 2, AD 8232 is used as an analog front end to capture the ECG signal. Electrodes are connected to RA, LA and right leg (RL). Here, the RL is used for reference. Data from AD 8232 is processed in a micro controller (uC). Raw data from uC is then processed in *MATLAB*® environment. The raw data goes through BPF and derivative filtering. Then data are squared and averaged before locating the R peaks of the ECG signal. An adaptive QRS detector has been applied to get the location of R peak in time domain. After that, spline interpolation is done over the position of the R peaks. As a result, there is a newly fitted curve. This curve represents the breathing signal. To get the respiration rate, location of the peaks of the newly formed breathing signal is detected. At the same time, a commercial device Neulog respiration monitor belt sensor (NUL 236) is used to capture the RR. The extracted RR from ECG is compared with the RR coming from NUL 236 to validate the result.

B. Hardware Specification

The key hardware used in this work are, AD 8232, nRF 52840, *AliveCor*® and NUL-236. AD 8232 is used as an AFE in the proposed work. AD 8232 is a popular AFE used for ECG signal capturing [27]. It implements an instrumentational amplifier(IA) to take input from electrodes. In this work, electrodes were placed on the wrists of RA and LA. To validate the HR obtained from AD 8232, a commercial ECG capturing device *AliveCor*® is used, as shown in Fig. 3. The user can observe the ECG data and know his HR from a mobile device using *AliveCor*® portable device. nRF52840 is a Bluetooth low Energy (BLE) based system on chip(SoC) solution [28]. It incorporates ARM-4 micro-processor. The analog to digital converter (ADC) resolution is 12 bit in this work. The analog signal from AD 8232 is sampled at a rate of 100 Hz. NUL 236 is a commercially available respiration monitor belt. It is attached at the abdominal region of the subject. As consecutive phases of respiration goes on, there are corresponding movements in the abdominal region. The pressure of the belt changes with respect to the respiratory behavior. As a result, NUL 236 gives respiration signal. The raw data from NUL 236 is accessible in different format.

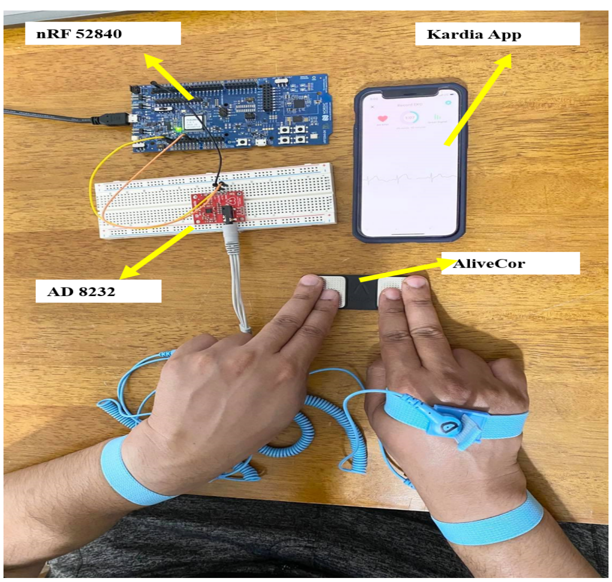

Fig. 3. Hardware setup of ECG data capture validation of AD 8232 against AliveCor

As depicted in Fig. 4, NUL 236 is attached to abdominal region of the subject and wrist electrodes are connected with AD 8232 at the same time to take the data simultaneously.

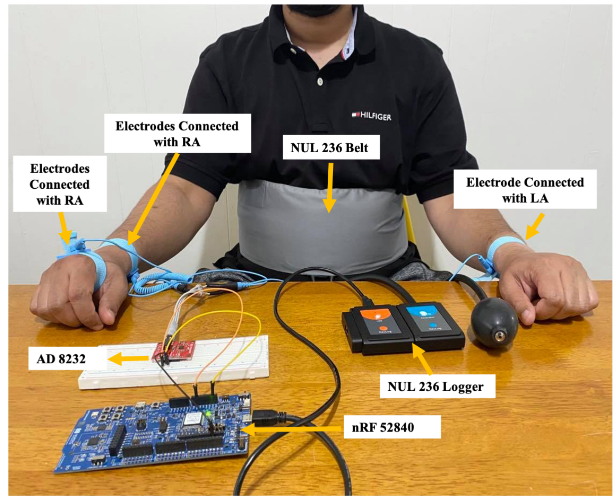

Fig. 4. Hardware setup of validation of RR from ECG captured with AD 8232 against NUL 236

C. Software Implementation

A software code was developed and run on nRF 52840 to acquire raw ECG data from AD 8232 AFE. The code is developed in segger embedded studio (SES). A direct memory access module named as EASYDMA is implemented to gain direct access to data RAM. The sampling rate is set as 100 samples per second. Sampling interval is applied through a timer interrupt based method.

The raw data from nRF 52840 are further processed in *MATLAB*® to extract the RR from ECG signal. At first, a Butterworth BPF of order 3 is applied over the raw signal to remove the baseline wandering from the data. The lower and upper cut-off frequency of the BPF is set as 5 Hz and 15 Hz respectively. Then a derivative filter is applied to improve the SNR of the ECG signal. Then the filtered data are squared to enhance the non-linear dominant peaks. After that, a moving average filter of window size 30 is applied on the squared data. Then an adaptive threshold based method is used to get the position of the R peaks. This technique is beased on a physiological point of view that, no consecutive R to R (RR) peak can occur in less than 200 ms. The adaptive thresholding works with set of thresholds which can automatically select the range of samples where the QRS complex exists. In the training phase, the initial threshold level of the signal is set to 0.25 times the maximum amplitude and the threshold level for the noise is set to 0.50 times the mean of the ECG signal. For each training phase, a time period of 2s is taken into account. As a new corresponding peak is detected the heart rate is updated. The algorithm also checks back for error. The time duration for check back error is set as 360 ms. If no QRS complex is detected in 360 ms of the previous QRS complex, then the method looks for possible T wave. The condition set for identifying T wave checks whether the slope of the waveform is less than 0.50 times the mean slope of the previous R wave. Consecutive detection phases produces a pulse for each QRS complex. As soon as the R peaks are located, the HR in beats per minute (BePM)can be calculated using the following equation,

$$HR\ (BePM) = h\ Beats\ /\ (m\ /60minutes) \tag{1}$$

Where, h denotes the number of beats in m seconds.

As the location of R peak is detected, an spline interpolated curve is fitted over the R peaks of the ECG signal. This fitted curve forms a breathing pattern. The extracted breathing pattern is further analysed to detect the peaks. These peaks indicate the peaks formed due to exhalation phase of respiration system. RR is calculated by the number of peaks observed in a 1 minute period of time. The following equation is used to calculate the RR,

$$RR\ (BPM) = b\ Breath\ /\ (s\ /60minutes) \tag{2}$$

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

III. Protocol for Data Validation

To confirm whether the extracted RR from ECG data is valid or not, the proposed method is checked through several validation steps. The process consists of 3 main steps. 1st step is taken to validate the data obtained by AD 8232 by comparing it with *AliveCor*® commercial device. Fig. 5 represents the collected ECG data from AD 8232 for 30 s.

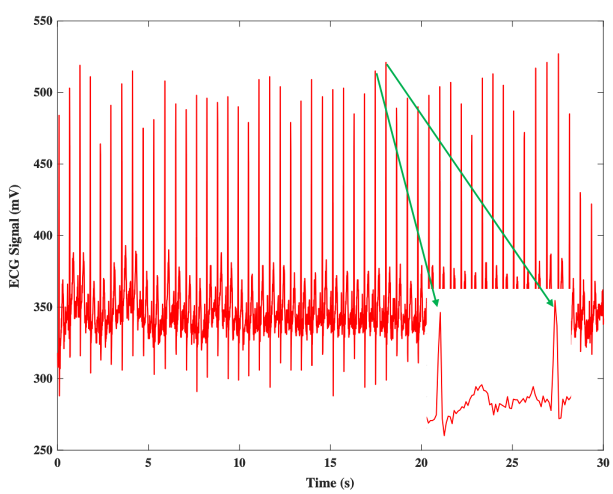

Fig. 5. Collected ECG data from AD 8232, (inset) Zoom in view of two consecutive ECG beats

Once performance of AD 8232 is validated, 2nd step is approached where, commercial sensor NUL 236 is validated. To validate the performance of NUL 236, a specific protocol has been applied. The purpose of the protocol is to ensure a specific RR in a controlled fashion. The protocol is made for a wide range of RR which are, 12, 15, 20, 24, 30 BPM. To demonstrate how the protocol works, an example for 20 BPM is discussed here. For a RR of 20 BPM, there will be 20 inhalation and 20 exhalation phase during 1 minute time period. As a result, there will be altogether 40 consecutive breath-in and breath-out phases over a minute. A timely controlled power point file is made which contains 40 slides, where each slide moves to next slide spontaneously after every 1.5 seconds. Moreover, every slide comes with an instruction whether to breath-in or exhale. A slide for breath-in is followed by a slide for breath-out until it completes the 1 minute time period. The same protocol is made for 12, 15, 24 and 30 BPMs for 1 minute duration. Duration of each slide for 12, 15, 24 and 30 BPMs are set as 2.5 s, 2 s, 1.25 s and 1 s respectively. Also, the number of total slides for 12, 15, 24 and 30 BPMs are 24, 30, 48 and 60 slides respectively.

In 3rd step, ECG data from AD 8232 and respiration data from NUL 236 are taken simultaneously. The same protocol for 12, 15, 20, 24 and 30 BPMs are also followed in this step. ECG data from AD 8232 is used to extract respiration signal. If extracted RR matches with expected RR from protocol and NUL 236, then data are verified. To make the data statistically valid, 10 samples of data are taken for each BPMs.

IV. Results

In this section, performance of the extracted RR (ExRR) from AD 8232 is presented and compared with a commercial respiration sensor NUL 236. Also, to validate the performance of AD 8232, a commercial device *AliveCor*® is used to compare with.

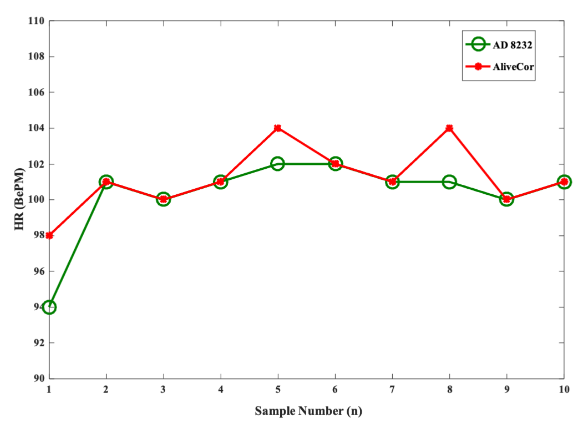

Fig. 6. Performance comparison of AD 8232 against *AliveCor*®

Fig. 6 shows the performance comparison of AD 8232 with *AliveCor*®. A subject wears the setup as shown in Fig. 3. HR is calculated by the ECG coming from AD 8232 using equation (1). At the same time, data from *AliveCor*® is captured in a mobile app. If both data matches, then there is no error. The variation of ECG from AD 8232 over 10 samples of data is presented in Fig. 6. It is seen that, the HR from AD 8232 ECG either matches exactly or closely matches with the HR of *AliveCor*®.

Fig. 7 presents the performance of NUL 236 for different BPMs. Respiration signal for different BPMs are taken using the protocol. 10 samples of data are taken for 12, 15, 20, 24 and 30 BPM respectively. The main purpose of this step is to validate the performance of NUL 236 itself. The RR is calculated using equation (2). If RR does not match with the expected RR from protocol, then an error is considered.

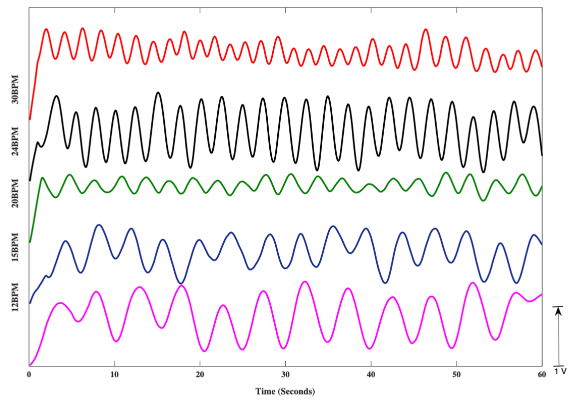

Fig. 7. Respiration signal at different BPMs to validate the performance of NUL 236

Fig. 8 represents the breathing signal which are obtained after extraction from ECG of the subject. The similar protocol is also maintained here for different BPMs. The obtained breathing signal is processed through equation (2) to determine the RR of those extracted signal. These RRs are compared with the RRs obtained from NUL 236.

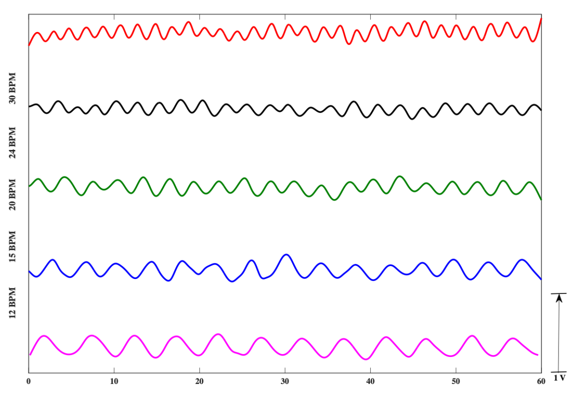

Fig. 8. Extracted respiration signal from the wrist ECG at different RRs

In Fig. 9, simultaneous acquisition of breathing signal from NUL 236 and AD 8232 is presented. In this case, simultaneous acquisition at 24 BPM rate is shown. Similar procedure is implemented for all other BPMs with 10 samples of data for each BPM.

Fig. 10 (a) and (b) shows the correlation plot for NUL 236 and simultaneous data acquisition of NUL 236 and ExRR from AD 8232 respectively. 10 samples of data are taken for every BPM. For example, for 20 BPM there is 10 samples of data acquisition by maintaining the protocol. An error is encountered if the experimental RR is not 20 BPM. The

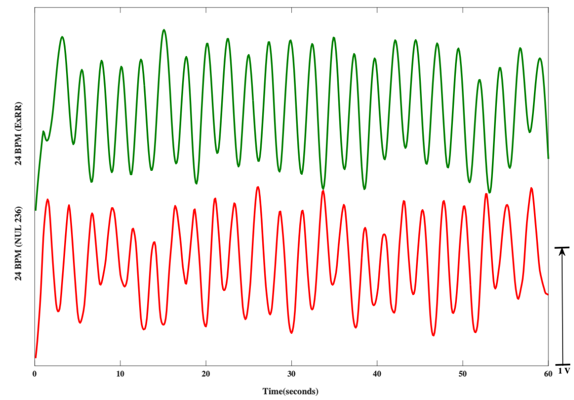

Fig. 9. Simultaneous respiration signal using NUL 236 (red) compared with the proposed ECG extracted RR (green).

corresponding errors are then averaged over the 10 samples. Similar procedure is maintained for other BPMs. After that, the experimental RR is plotted with respect to the actual RR. As shown in Fig. 10(a), NUL 236 faces no error in data acquisition. AS depicted in Fig. 10(b), performance of ExRR from the the wrist ECG is well enough when data are taken simultaneously while wearing the NUL 236.

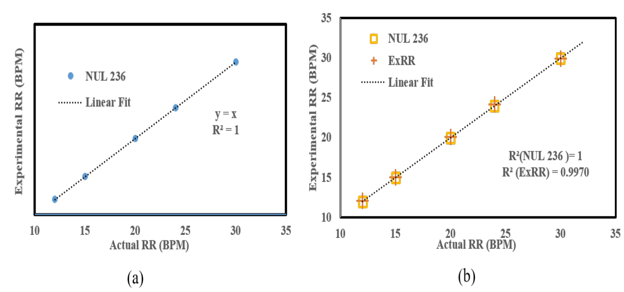

Fig. 10. Correlation plots of (a) NUL-236, and (b) simultaneous data acquisition of NUL-236 and ECG extracted RR.

Table 1 lists performances and errors for NUL 236 and ExRR from AD 8232 at different BPMs. Data acquisition process is completed by following the protocol strictly. For each BPM, errors in estimated RR are also indicated.

TABLE I
PERFORMANCE OF EXRR FROM WRIST ECG AND NUL-236 FOR DIFFERENT BPMS

Respiration Rate	**Number of Error (s), N = 10**		
	Using NUL-236	***Simultaneous Data***	
		Using NUL -236	***Using proposed ExRR method***
12 BPM	0	0	1 (13 BPM)
15 BPM	0	0	0
20 BPM	0	0	1 (21 BPM)
24 BPM	0	0	2 (25 & 25 BPM)
30 BPM	0	0	1 (29 BPM)

V. Conclusion

A method to extract the breathing signal and RR from wrist ECG is implemented in this work. An AFE device AD 8232 is used to capture the ECG signal from wrist. The method to get ExRR is simple. AD 8232 performance is validated by a commercial device AliveCor®. Commercial respiration sensor NUL 236 is also verified by maintaining a protocol. Finally, data are taken simultaneously by wearing NUL 236 and electrodes attached with AD 8232. ExRR is achieved and validated with the NUL 236 at the same time. The performance of the ExRR is promising that the proposed method can be a convenient option for respiration behavior monitoring, while eliminating the need for a dedicated respiration sensor. This work demonstrates the potential of extracting RR from ECG signals which can be useful for minimalistic modality deployment for body signal monitoring. In future, we will explore a flexible wearable ECG device that can compute both body signals for health status monitoring applicable to Smart Health (sHealth) framework.

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