Respiratory Rate Estimation and Monitoring from ECG Signal using IoT

Nawshad Binta Nizam Ananna
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706016@eee.buet.ac.bd

Md. Boktiar Mahbub Murad
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706026@eee.buet.ac.bd

Tamim Ahmed
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706063@eee.buet.ac.bd

Tajwar Al-Mamun
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706039@eee.buet.ac.bd

Md. Al Amin
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706060@eee.buet.ac.bd

Md. Owahiduzzaman
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1706108@eee.buet.ac.bd

Partho Kumar Das
Dept. of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
1606110@eee.buet.ac.bd

***Abstract*—A common problem with current techniques for estimating respiratory rate (RR) from the electrocardiogram (ECG) is that they frequently cannot tell the difference between high- and low-quality input data periods. The inability of these systems to enter clinical practice directly comes from the fragility of current methodologies. The current work suggests a different approach to strengthen the reliability of RR estimation using the ECG. Our work proposes a real-time prototype that is able to exhibit one's bpm(Breaths per minute) within a few seconds. The RR value is shown within a window length of 5 seconds. Using optimum bandpass filters (BPF) and baseline wander elimination techniques the ECG-derived respiratory signal is obtained. For parameter tuning, real-time data is collected and analyzed. This work demonstrates that the use of large publicly-available datasets is essential for improving the robustness of wearable-monitoring algorithms for use in clinical practice.**

***Index Terms*—Respiratory Rate, ECG, Baseline wander, bpm, BPF**

I. Introduction

Respiratory rate(RR) refers to the number of breaths a person takes per minute. Accurately measuring respiratory rate is an essential part of monitoring the health and wellness of an individual. One non-invasive method for measuring respiratory rate is by analyzing electrocardiogram (ECG) signals.

The ECG signal reflects the electrical activity of the heart and can also contain information about respiratory rate. Specifically, the variation in the time interval between successive R-peaks (RR intervals) in the ECG signal can be used to estimate respiratory rate. The availability of cardio synchronous signals from devices such as pulse oximeters and bioimpedance sensors is currently being marketed as being useful only for determining the HR of the subject. But these devices don't show direct respiratory rate. So our prototype presented in the laboratory can resolve this issue by giving a bpm value within a few seconds.

During normal breathing, the respiratory cycle causes small variations in the RR intervals due to the interaction between the heart rate and the respiratory system. These variations are known as respiratory sinus arrhythmia (RSA) and can be quantified by calculating the variability in the RR intervals over time. Several algorithms have been developed to extract respiratory rate information from ECG signals, including time-domain and frequency-domain methods. Time-domain methods involve analyzing the time differences between successive R-peaks, while frequency-domain methods use spectral analysis to identify respiratory-related peaks in the ECG signal. Overall, respiratory rate determination from ECG signals provides a non-invasive and convenient method for monitoring respiratory health and can be useful in a variety of clinical settings, such as in sleep apnea diagnosis, critical care, and monitoring of patients during anesthesia other critical health states.

II. Background Research

Extracting respiratory signals from the Electrocardiogram (ECG) signals is a potential surrogate measurement of RR. In recent years, ECG devices are becoming miniaturised, and sensors have been integrated with sport bands, smartwatches, and other portable monitors. This provides the feasibility and potentiality to design wearable ECG-based RR measurement devices. A plethora of algorithms have been proposed for the estimation of RR from the ECG or PPG. Two independent methods were used to estimate RR from each window in line with the methodology presented in [**?**]. Fourier analysis was used to compute the power spectral density of the signal, as described in [5] and time domain analysis was done in the other method. A first RR estimate was obtained as the frequency corresponding to the maximum power within the range of plausible respiratory frequencies (4–60 bpm). Since frequency domain analysis requires regularly sampled signals, these signals were resampled at a regular frequency of 5 Hz using linear interpolation. Finally, spurious non-respiratory frequencies introduced in the extraction process were eliminated using band-pass filtering within the range of plausible respiratory frequencies (4–60 bpm). Spurious high frequencies arise due to linear interpolation and spurious low frequencies can be caused by physiological changes. Respiration is known to modulate the PPG in different ways. Many methods have been proposed in the literature to address the need for robust estimation of RR from analysis of the PPG signal[1].An evident approach to the problem is to carry out a spectral analysis and look for prominent spectral components of frequencies in the RSA(Respiratory sinus arrhythmia) domain[2]. As an alternative method, we can obtain an accurate RR from a pulse oximeter for saturation of partial pressure oxygen (SpO2), which is user-friendly and economical [4]. Specifically, respiratory information are derived from the non-respiratory measurements taken by such wearables, including the electrocardiogram (ECG), photoplethysmogram (PPG), seismocardiogram (SCG) [3]. Certain fusion strategies were based on selecting or assigning weights to RRs estimated. Progressive software level development in this case is happening. But both software and hardware level development in equal pace is rare nowadays.

III. Overview of The Collected Dataset

To evaluate algorithm performance and for the purpose of parameter tuning 40 samples of ECG signal with a duration of one minute each from 4 different subjects is collected. To obtain ECG data like Fig.2, the AD8232 module and Arduino Uno are used. ArduSpreadsheet tool is used to collect the analog value from the ECG sensor and later stored as CSV (comma seperated value) file format, similar as Fig.1 is generated to feed it to our algorithm. A stopwatch is used for one-minute countdown. To evauluate RR derived from the model breaths per minute (bpm) is counted manually from the number of times ones chest or abdomen rises over the course of one minute[7].

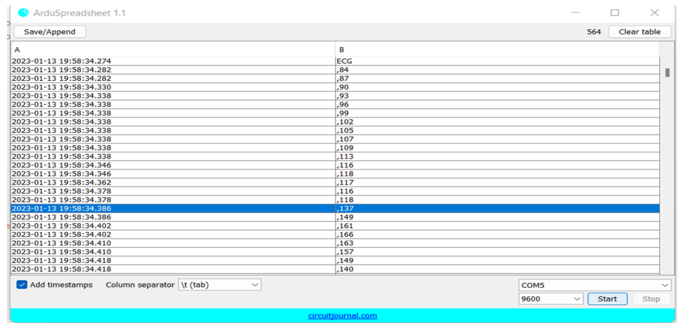

Fig. 1. CSV file from ArduSpreadsheet

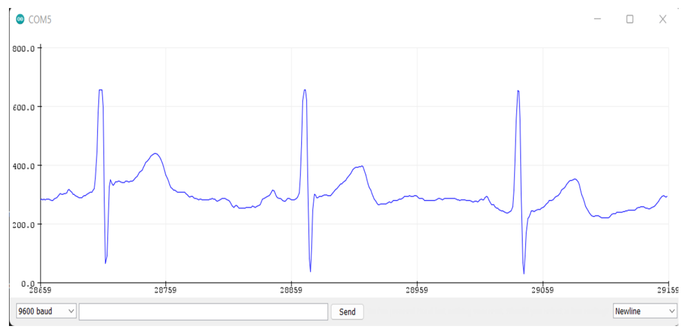

Fig. 2. ECG data in serial plot monitor

IV. Hardware Setup

We've used the AD8232 ECG sensor module to collect the ECG signal in real time.AD8232 is a 3-lead ECG sensor.An ESP8266 Module is used for processing the collected signal and estimating the respiratory rate. Additionally, this module will send the Respiratory rate for each window to the ThingSpeak Server where the Respiratory Rate will be displayed and monitored. An LCD 16x2 display is used to show the Respiratory rate in real-time. A lipo battery is used to power up the whole setup.

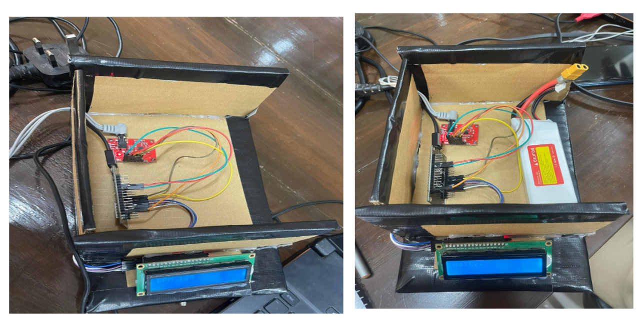

Fig. 3. Hardware Setup

V. Methodology

A. *Preprocessing*

The extracted waveforms from AD8232 module contained periods of high and low (reliable and unreliable) quality, as shown in Fig.5 This is in keeping with the literature, where

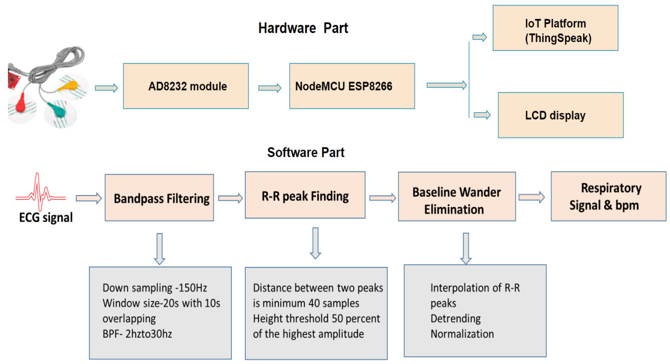

Fig. 4. Block Diagram of the whole model

it is well reported that physiologic signals can be expected to contain periods of artifacts. In our case the filtering part is enough to clean up the data. So we have not used any sophisticated denoising method to retrieve a better signal. The pre-processing procedure involves the use of heart rate variability feature of ECG signal which is observed in QRS complex. Using a bandpass filter with proper lower and upper cut off, R-R peaks are found out.

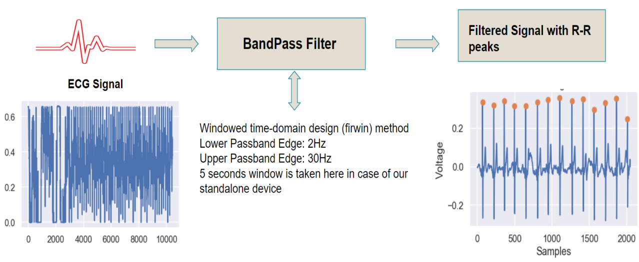

Fig. 5. ECG Signal Preprocessing

B. Respiratory Signal Extraction

Following preprocessing, the denoised signal is subjected to detrending and normalization processes aimed at eliminating the baseline wander. Subsequently, the R peaks are identified from the normalized signal, and the intervals between them, referred to as R-R peaks intervals, are calculated. The peaks are then upsampled with a sampling frequency of 4 Hz and interpolated using the cubic spline interpolation method, resulting in a smooth curve that represents the ECG-derived Respiratory Signal. The peaks of the EDR signal are subsequently located, with each peak indicating either an exhale or inhale phase in the analyzed window.

C. Respiratory Rate Estimation

Considering the memory limitations of ESP8266 modules, a window size of 5 with an overlap of one second was employed. During each loop iteration, the Respiration count for the current window is estimated from the ECG Derived Respiratory signal, and the counts are stored in an array. The

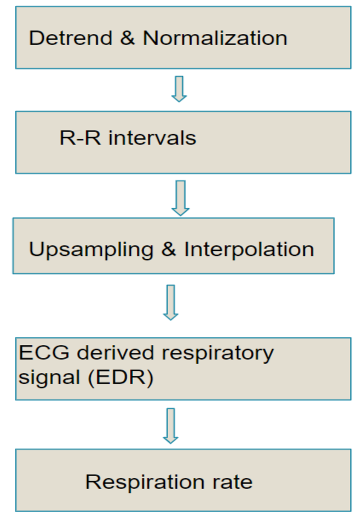

Fig. 6. Respiratory Modulation to derive Respiratory Signal

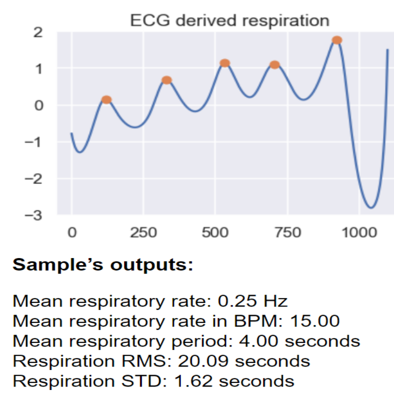

Fig. 7. ECG derived Respiratory Signal

current respiratory rate is then calculated by utilizing the Respiration counts from the previous 11 windows in conjunction with the current window. This yields the respiratory rate per minute, which is subsequently displayed on the LCD screen and transmitted to the IoT Server for continuous monitoring

D. IoT Platform

To visualize data the RR values of every 5 seconds window are uploaded to ThingSpeak. It helps to observe certain fluctuations in bpm over a span of 1 minute.

VI. Results and Discussion

We've collected the data from four subjects. We've experimented with two different approaches, one is our final method, baseline wanders removal and the other one is with Periodogram. Here is the mean absolute error for both cases considering a 20 seconds window size. The results indicate that Baseline wander performs much better and the error is in a considerable range. 20 seconds window gives the best result among all the available window sizes. However, due to

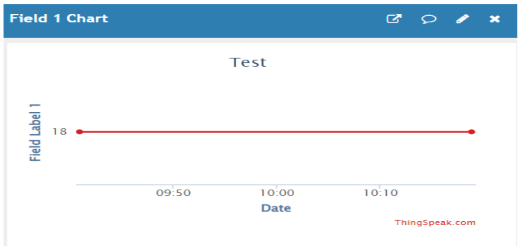

Fig. 8. bpm for each 5 seconds window in for a span of 1 minute

Subject No.	mae(BW)	mae(Periodogram)
1	2.653	7.028
2	3.281	6.275
3	2.733	6.731
4	2.932	4.813

Fig. 9. Mean absolute error for Baseline Wonder and Periodogram method

memory limitations of ESP8266, we used a 5 seconds window. The mean absolute error for 5 seconds window was 3.293.

VII. Cost Estimation

Our whole hardware setup cost is very low compared to the available clinical hardware setups to look over respiratory system. The cost is shown in Fig.7.

Component	Cost (Taka)
1. ESP8266 Wi-Fi module	450
2. LCD Display 16x2	350
3. AD 8232 ECG module	800
4. ECG Leads	710
5. 9-volt battery x 2	120
6. Jumper wires	50
Total=	2480

Fig. 10. Tentative Expenses

VIII. Limitations

Due to hardware usage there are certain boundaries while doing software implementations. Possibly moving to raspberry pi can give access to the usage of machine learning and deep learning usage. Also, the 20 seconds window is not possible to take due to memory and time issues in the case of ESP8266, so we need to take 5 seconds window while showing it in real time.

IX. Future Prospect

The robust estimation of RR in a number of important healthcare-related applications (e-health, m-health, wellness) is a topic in which a substantial amount of work has been done and more development are happening in these days. One of the major reasons that we identified for not translating RR estimation algorithms into clinical practice is the lack of large-scale validation studies using datasets that match the conditions under which a system would be used in practice. The whole hardware setup can be brought to wearable stage by using better sensors. An app can be designed to notify via smart phone.

X. Conclusion

We have presented the development of an algorithm for estimating RR from the ECG which involves the fusion of both hardware and software development. It will make a great contribution to a real-time health monitoring system. Our analysis demonstrated the importance of using alternative datasets for evaluating the performance and generalization ability of proposed methods. Future studies should concentrate on the use of raw data sources as a benchmark for the comparison of new RR estimation approaches. The experiments done on the prototype device based on the proposed model shows that the model performance is satisfactory as the deviation from the ground truth value is very minor and it is compatible with use in real life in terms of portability, cost-efficiency, and simplicity.

Acknowledgment

We would like to thank our course teacher Lecturer Shahed Ahmed sir and Md. Jahin Alam sir for their constant supervision and suggestions.

References

[1] Pimentel, M. A., Johnson, A. E., Charlton, P. H., Birrenkott, D., Watkinson, P. J., Tarassenko, L., Clifton, D. A. (2016). Toward a robust estimation of respiratory rate from pulse oximeters. IEEE Transactions on Biomedical Engineering, 64(8), 1914-1923.

[2] Schäfer, A., Kratky, K. W. (2008). Estimation of breathing rate from respiratory sinus arrhythmia: comparison of various methods. Annals of Biomedical Engineering, 36, 476-485.

[3] Chan, M., Ganti, V. G., Inan, O. T. (2022). Respiratory rate estimation using u-net-based cascaded framework from electrocardiogram and seismocardiogram signals. IEEE Journal of Biomedical and Health Informatics, 26(6), 2481-2492.

[4] Bao, X., Abdala, A. K., Kamavuako, E. N. (2020). Estimation of the Respiratory Rate from Localised ECG at Different Auscultation Sites. Sensors, 21(1), 78.

[5] Pimentel, M. A., Charlton, P. H., Clifton, D. A. (2015). Probabilistic estimation of respiratory rate from wearable sensors. Wearable Electronics Sensors: For Safe and Healthy Living, 241-262.

[6] Lee, S., Moon, H., Son, C. H., Lee, G. (2022). Respiratory Rate Estimation Combining Autocorrelation Function-Based Power Spectral Feature Extraction with Gradient Boosting Algorithm. Applied Sciences, 12(16), 8355.

[7] https://drive.google.com/drive/folders/1m0J4zcdUqhwqIicxMnnhWHpWY42fdIe7?fbclid $_E HQRb6o9tBWMNehEmZj9227rrfF$ – $44P7yuvImyplfx8KgAt3m_7Z4$.