Methods for Extraction of Respiration Rate from Wrist-Worn PPG Sensor and Doppler Radar

(Invited Paper)

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***Abstract*—Respiration rate and heart rate variability (HRV) due to respiratory sinus arrhythmia (RSA) are physiological measurements that can offer useful diagnostics for a variety of medical conditions. This study uses a wrist-worn wearable development platform from Maxim Integrated and Doppler radar sensor developed by Adnoviv, Inc. to non-invasively measure these physiological signals. Six datasets are recorded comprising of five different individuals in varying physical environments breathing at different respiration rates. First, respiration rates are extracted from photoplethysmography (PPG) and accelerometer data and compared to Doppler radar. The average maximum and minimum difference between Doppler radar extracted RR and PPG, HRV RSA, and accelerometer extracted RR is 0.342 b/m and 0.171 b/m, respectively. Then, waveforms for Doppler radar, PPG, and HRV RSA signals are plotted in time domain and an analysis discusses the physical phenomena associated with the phase alignment of the signals.**

***Index Terms*—Accelerometer, Doppler radar, photoplethysmography (PPG), respiration, wearable**

I. Introduction

The adoption of connected, wearable technology is becoming increasingly popular. The consumer market is filled with a variety of smart watches and fitness trackers that can be used to track daily health metrics, such as step count, calories burned, or sleep duration. The increasing use of these metrics by consumers means there is utility in the development of new techniques to extract useful physiological data using commercially available, off-the-shelf hardware.

Commonly measured and useful health metrics include heart rate, heart rate variability (HRV), and respiration rate (RR). This paper focuses on RR and HRV. HRV is a measure of the variation in time between consecutive heart beats. HRV is an important metric that can be used to study cardiovascular health and potentially diagnose a number of medical conditions, such as cardiovascular disease [1], atrial fibrillation [2], or risk of hypertension [3]

The study of RR is equally important. Changes in respiratory rate can assist in diagnosing medical conditions such as sleep apnea [4] or chronic obstructive pulmonary disease (COPD) exacerbation events [5]. Respiratory sinus arrhythmia (RSA) is one way that respiration can affect cardiovascular measurement. RSA is a phenomenon where heart rate varies due to respiration. RSA affects HRV in that the timing between heart beats decreases during inspiration and increases during expiration. This paper will extract RR and calculate HRV due to RSA using data gathered from a wrist-worn photoplethysmography (PPG) sensor using the Maxim Integrated Health Sensor Platform 2.0 (HSP).

Additionally, non-contact Doppler radar allows for the study of physiological signal waveforms. Doppler radar is currently being developed for use in occupancy sensing for smart building applications under Adnoviv, Inc. Doppler radar can be used as a non-contact method to obtain physiological signals such as respiration from the rising and falling motion of a patient's chest. Doppler radar has been previously demonstrated as an accurate and effective reference measurement [6,7]. Coupling the use of a PPG sensor and Doppler radar affords a patient access to comfortable contact and non-contact options that can be used to monitor vital signs.

This research presents the usage of a PPG sensor to sense RR at the wrist. Measurement of RR from a wrist-worn PPG sensor has been demonstrated with various techniques employed [8,9], as well as measurement of HRV from a wrist-worn PPG sensor [10]. Furthermore, PPG has been used previously to extract RSA [11]. This work is unique in that it extracts RR, HRV, and the effects of RSA, along with accelerometer data and Doppler radar data simultaneously for varying RRs using commercially available hardware. One sleep study was performed using 10.5 GHz Doppler radar, PPG, and accelerometer sensing. [12]. No other study found has directly compared 2.4 GHz Doppler radar, PPG, and accelerometer signals using common wearable sensors. No other study has performed a signal analysis in time domain of phase alignment between Doppler, PPG, and HRV RSA signals.

II. Methods

Experiments for this study were conducted according to the Committee on Human Studies (CHS) protocol number 14884, which was approved by the CHS of the University of Hawai'i system. The subject is seated in a chair with arms resting on the arms of the chair to minimize body movement. The HSP is affixed to the wrist just behind the wrist bone as seen in Fig. 1. Maxim Integrated software controls the PPG sensor and logs sensor data to disk via a USB connection. The computer timestamp, PPG ADC counts, and accelerometer data are the

Fig. 1. Placement of HSP watch on subject, plugged in to computer

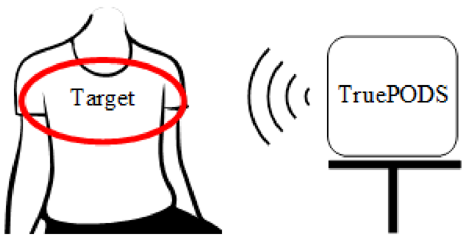

Fig. 2. Doppler radar sensor setup (not to scale)

data points used for this analysis. PPG effective sampling rate is set to 100 samples per second, or 100 Hz.

The Doppler radar sensor is set up about three to five feet away from the subject. The patch antenna is aimed at the chest of the subject as seen in Fig. 2. A Python program reads and saves serial data to a text file and insert timestamps every second, and timestamps for individual samples are calculated. A computer provides one clock source for timestamping both signals, allowing simultaneous data recording from the HSP and Doppler radar sensor.

The app Pro Metronome by EUMLab is installed on a smartphone to assist with maintaining a consistent RR. A test conducted at a RR of 15 breaths per minute (b/m) is set with a tempo of 30 beats per minute at 1/1-time signature. An inhale occurs with the first audible tick of the metronome, then an exhale with the next tick, and so on. The subject practices breathing at the set RR before beginning data collection. During data collection, the subject sits still and breathes with the set RR to the best of their ability. The data collection period can be ended at any time. Data was collected for a duration of four to five minutes for each RRs.

III. Matlab Processing

Data was processed using Matlab R2021a Update 3. Multiple subjects in different environments are evaluated for RRs of 13 b/m (0.217 Hz), 15 b/m (0.25 Hz), 18 b/m (0.3 Hz), and one trial at 10 b/m (0.16667 Hz). With different respiration rates, twenty trials total were recorded.

Doppler radar data is filtered for respiration using the Matlab *bandpass* filter with the passband frequency range set

TABLE I
Comparison of Extracted Respiration Rates, Subject A, Breathing Rate in b/m (Hz)

Breathing Rate	**Doppler FFT**	**PPG FFT**	**HRV RSA**	**Accelerometer (axis)**
13 (0.217)	13.047 (0.217)	13.147 (0.219)	13.089 (0.218)	13.147 (Z) (0.219)
15 (0.25)	14.953 (0.249)	15.066 (0.251)	15.034 (0.251)	15.272 (Z) (0.254)
18 (0.3)	18.072 (0.301)	18.211 (0.303)	18.385 (0.306)	18.211 (Y) (0.303)

from 0.1 to 0.5 Hz, and a FFT is computed to determine the dominant frequencies in the signal. PPG data undergoes filtering and FFT computation is performed to extract the low frequency respiration component from the raw PPG signal.

To determine respiration rate from HRV RSA, the PPG signal must first be filtered to remove low-frequency respiration noise. A 10th order IIR Bandpass Butterworth filter is designed to filter the PPG heart signal with the passband set from 0.8 to 5 Hz. Then, heart peaks are selected and timing between neighboring heart peaks is calculated to extract the peak-to-peak timing variability over time. Finally, the Matlab *bandpass* filter is applied from 0.1 to 0.4 Hz, and the low frequency component corresponding to RR from HRV RSA can be extracted by computing a FFT of the resulting signal

A FFT of the raw accelerometer data is performed to identify the low-frequency respiration component in the raw signal. The accelerometer axis that is selected is dependent on each trial. This is noted in Table I.

IV. Results

Subject A has been chosen to display data as an example. In most trials across subjects, the RR extracted from accelerometer data matches the RR extracted from PPG FFT.

All trials show high agreeability with Doppler radar extracted RR. Across all datasets, the average maximum and minimum difference between Doppler radar extracted RR and PPG, HRV RSA, and accelerometer extracted RR is 0.342 b/m and 0.171 b/m, respectively. The largest maximum difference of 0.781 b/m occurs with Subject E at 13 b/m. The smallest minimum difference of 0.006 b/m occurs with Subject E at 15 b/m.

For Table 1, the smallest maximum difference between Doppler RR and PPG, HRV RSA, and accelerometer methods of 0.01 b/m occurs at 13b/m, and the largest maximum difference of 0.318 b/m occurs at 15 b/m. The smallest minimum difference of 0.042 b/m occurs at 13 b/m, and the largest minimum difference of 0.139 b/m at 18 b/m. It is notable that the HRV RSA RR is closer to Doppler RR in two of three trials

V. Waveform Comparison

A waveform comparison of the filtered Doppler, filtered PPG, and filtered peak-to-peak timing signals in time domain is performed to analyze how physical phenomena can affect

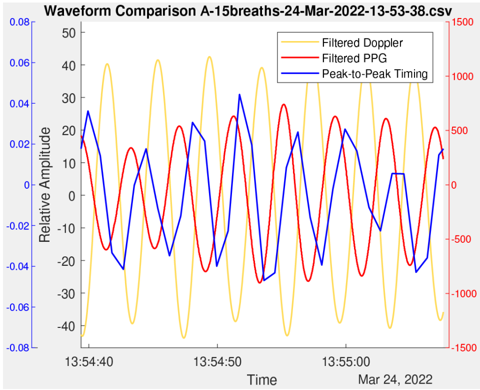

Fig. 3. Waveform comparison for Subject A, 15 b/m

the phase relationship of these signals relative to each other. Four datasets are used for this comparison because Doppler radar data was timestamped. Fig. 3 shows a zoomed-in graph used to study the waveforms.

Each subject exhibited similar characteristics in the waveforms across all trials. However, though some characteristics are shared across subjects, no two subjects' waveforms looked exactly similar, and more similarity exists within individual subjects rather than across subjects.

The strongest relationship exists between the filtered PPG signal and filtered Doppler radar signal across subjects, with the PPG signal generally 180° out of phase with the Doppler signal. This agrees with previous studies, demonstrating blood volume change is consistently affected by respiration [13], and inspiration causing lower skin blood flow [14, 15]

Subjects may exhibit stronger RSA correlations than others. Strong RSA correlation is present when the filtered PPG signal is 180° out of phase with the peak-to-peak timing signal. The closer to in-phase the signals become indicates weak RSA correlation. The strength of RSA is an important health metric to consider because age, cardiac health, or even effective regulation of stress and emotions can affect HRV and the strength of RSA [16]-[18].

For Subject A in Fig. 3, the filtered PPG signal is 180° out of phase compared to the filtered Doppler signal. The peak-to-peak timing signal is slightly out of phase from the filtered Doppler signal, and the peak-peak timing signal phase is closer to the filtered PPG signal across the trial. The filtered PPG and peak-to-peak timing signal RSA correlation is present but not as strong for Subject A at 13 b/m.

VI. Conclusion

Processing methods for PPG and Doppler radar data is discussed. High agreeability is shown from the wrist-based extracted RR rate compared to Doppler radar. A waveform comparison is performed the phase alignment of signals is analyzed.

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References

[1] J. F. Thayer, S. S. Yamamoto, and J. F. Brosschot,"The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors," International Journal of Cardiology, vol. 141, no. 2, pp. 122–131, 2010.

[2] P. K. Stein, P. P. Domitrovich, N. Hui, P. Rautaharju, and J. Gottdiener, "Sometimes higher heart rate variability is not better heart rate variability: Results of graphical and nonlinear analyses," Journal of Cardiovascular Electrophysiology, vol. 16, no. 9, pp. 954–959, 2005.

[3] E. B. Schroeder, D. Liao, L. E. Chambless, R. J. Prineas, G. W. Evans, and G. Heiss, "Hypertension, blood pressure, and heart rate variability," Hypertension, vol. 42, no. 6, pp. 1106–1111, 2003.

[4] Y. Fang, Z. Jiang, and H. Wang, "A novel sleep respiratory rate detection method for obstructive sleep apnea based on characteristic moment waveform," Journal of Healthcare Engineering, vol. 2018, pp. 1–10, 2018.

[5] S. A. Shah, C. Velardo, A. Farmer, and L. Tarassenko, "Exacerbations in chronic obstructive pulmonary disease: Identification and prediction using a digital health system," Journal of Medical Internet Research, vol. 19, no. 3, 2017

[6] O. Boric-Lubecke, V. M. Lubecke, A. D. Droitcour, B.-K. Park, and A. Singh, Doppler radar physiological sensing. Hoboken, NJ: IEEE, Wiley, 2016.

[7] A. D. Droitcour et al., "Non-contact respiratory rate measurement validation for hospitalized patients," 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, Sep. 2009.

[8] S. Nabavi and S. Bhadra, "Design and development of a wristband for continuous vital signs monitoring of COVID-19 patients," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2021.

[9] H.-H. Chang, C.-C. Hsu, C.-Y. Chen, W.-K. Lee, H.-T. Hsu, K.-K. Shyu, J.-R. Yeh, P.-J. Lin, and P.-L. Lee, "A method for respiration rate detection in wrist ppg signal using holo-hilbert spectrum," IEEE Sensors Journal, vol. 18, no. 18, pp. 7560–7569, 2018.

[10] T. Bhowmik, J. Dey, and V. N. Tiwari, "A novel method for accurate estimation of HRV from smartwatch PPG Signals," 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2017.

[11] W. Karlen, C. J. Brouse, E. Cooke, J. M. Ansermino, and G. A. Dumont, "Respiratory Rate Estimation Using Respiratory Sinus Arrhythmia from Photoplethysmography," 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011.

[12] D. Phan, L. Y. Siong, P. N. Pathirana, and A. Seneviratne, "Smartwatch: Performance evaluation for long-term heart rate monitoring," 2015 International Symposium on Bioelectronics and Bioinformatics (ISBB). IEEE, Oct. 2015.

[13] J. Allen, "Photoplethysmography and its application in clinical physiological measurement," Physiological Measurement, vol. 28, no. 3. IOP Publishing, pp. R1–R39, Feb. 20, 2007.

[14] K. E. Pinkerton, P. Gehr, A. Castañeda, and J. D. Crapo, "Architecture and Cellular Composition of the Air–Blood Tissue Barrier," Comparative Biology of the Normal Lung. Elsevier, pp. 105–117, 2015.

[15] K. E. Pinkerton, P. Gehr, A. Castañeda, and J. D. Crapo, "Architecture and Cellular Composition of the Air–Blood Tissue Barrier," Comparative Biology of the Normal Lung. Elsevier, pp. 105–117, 2015.

[16] L. R. Squire, "Autonomic Disorders," in Encyclopedia of Neuroscience, Amsterdam: Elsevier, 2009, pp. 799–808.

[17] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, and B.-H. Koo, "Stress and heart rate variability: A meta-analysis and review of the literature," Psychiatry Investigation, vol. 15, no. 3, pp. 235–245, 2018.

[18] B. Rassler, A. Schwerdtfeger, C. S. Aigner, and G. Pfurtscheller, "'Switch-off' of respiratory sinus arrhythmia can occur in a minority of subjects during functional magnetic resonance imaging (fMRI)," Frontiers in Physiology, vol. 9, 2018.