Respiratory rate estimation using respiratory sinus arrhythmia from photoplethysmography

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, pp. 1201-1204, doi: 10.1109/IEMBS.2011.6090282.

Respiratory Rate Estimation Using Respiratory Sinus Arrhythmia from Photoplethysmography

Walter Karlen*, *Member, IEEE,* Christopher J. Brouse, Erin Cooke,
J. Mark Ansermino, and Guy A. Dumont, *Fellow, IEEE*

***Abstract*—Respiratory rate (RR) is an important measurement for ambulatory care and there is high interest in its detection using unobtrusive mobile devices. For this study, we investigated the estimation of RR from a photoplethysmography (PPG) signal that originated from a pulse oximeter sensor and had a sub-optimal sampling rate. We explored the possibility of estimating RR by extracting respiratory sinus arrhythmia (RSA) from the PPG-derived heart rate variability (HRV) measurement using real-time algorithms. Data from 29 children and 13 adults undergoing general anesthesia were analyzed. We compared the RSA power derived from electrocardiography (ECG) with PPG at the reference RR derived from capnography. The power of the PPG was significantly higher than that of the ECG (182.42 $\pm$ 36.75 dB vs. 162.30 $\pm$ 43.66 dB). Further, the mean RR error for PPG was lower than ECG. Both PPG and ECG RR estimation techniques were more powerful and reliable in cases of spontaneous ventilation than when pressure controlled ventilation was used. The analysis of cases containing artifacts in the PPG revealed a significant increase in RR error, a trend that was less pronounced for controlled ventilation. These results indicate that the estimation of RR from the sub-optimally sampled PPG signal is possible and more reliable than from the ECG.**

***Index Terms*—photo-plethysmogram, respiratory rate, heart rate variability, pulse oximeter, anesthesia, respiratory sinus arrhythmia**

I. INTRODUCTION

Mobile health technology is a rapidly advancing field that holds great promise for improving medical services and changing the way that health care is delivered. A common theme in this area is the use of general purpose consumer devices, in particular smart phones. An increasing number of health care applications use these mobile platforms to interface directly to biomedical sensors, such as blood pressure cuffs, actigraphs, or pulse oximeters. This reduces or eliminates the cost of custom embedded hardware and facilitates the measurement process. However, features such as increased noise level, limited battery and computational resources, and the requirement for real-time processing challenge the accurate, real-time detection of physiological parameters.

Respiratory rate (RR) is an important measurement for diagnosing chronic illnesses, such as sleep apnea. The detection of RR using mobile or wearable sensors is not trivial because gold standard methods such as spirometry or capnometry are too obtrusive and impractical. Other, less direct methods for estimating RR exist. Respiration modulates the heart rate (HR). When subjects are breathing spontaneously, HR decreases on expiration and increases on inspiration. This phenomenon is called respiratory sinus arrhythmia (RSA). RSA is regulated by mechanical effects and changes in vagal and sympathetic tone. [1]. Under positive pressure ventilation, this phenomenon can present large phase shifts and variations [2]. Respiration also modulates blood pressure. This effect can be observed in the photoplethysmogram (PPG) recorded with a pulse oximeter and is more pronounced under positive pressure ventilation [3].

In this paper, we consider the estimation of RR from PPG using the RSA phenomenon. We explore the possibility of estimating RR from its heart rate variability (HRV) measurement. HRV is the time variation between heart beats derived from either the PPG or the electrocardiogram (ECG) signal. Comparison of RR estimation by extracting RSA from the HRV measurement of PPG and ECG to the gold standard RR estimation from capnometry is performed. The primary goal of this work is to identify potential limitations of estimating RR from PPG due to temporal smearing of the distal pulses in the PPG compared to the ECG. Further, we want to assess possible pitfalls when extracting RSA from sub-optimally sampled signals.

A. Background and Related Work

The most common method for assessing HRV is the analysis of ECG signals sampled at high rates (>250 Hz) [4]. The measurement of ECG is standard in the clinical environment, but other methods, such as PPG measurement, are easier to perform and are less obtrusive in the ambulatory setting. Because of this, numerous research groups have tried to assess whether ECG can be replaced with the measurement of PPG [5]–[9] for the estimation of HRV. The major focus of these studies has been to compare the outcome of the HRV over the full frequency spectrum of interest. RR was kept constant using a metronome [5] or ignored [6], [9]. In [8], it was observed that the RSA components of HRV were more pronounced when recorded with PPG compared to ECG. While this positive bias towards RSA power was considered a disturbance for HRV analysis by the authors, it might be beneficial for RR estimation. Other research groups have used inter-beat interval as one of many components to compute RR. For example, an artificial neural network for RR estimation

W. Karlen, C. Brouse and G. Dumont are with the Electrical and Computer Engineering in Medicine group (ECEM), University of British Columbia (UBC), Vancouver, Canada; *Corresponding author, e-mail: walter.karlen@ieee.org

J.M. Ansermino and E. Cooke are with the Department of Anesthesiology, Pharmacology Therapeutics, University of British Columbia (UBC), Vancouver, Canada;

was designed without investigating in detail the contribution of RSA, [10]. More recently, a variable-frequency complex demodulation method was suggested [11].

HRV analysis from PPG has certain limitations. For example, a low sampling rate may alter the spectrum considerably. For ECG analysis, the minimal sampling rate range has been defined as 250 to 500 Hz [4]. For this reason many previous studies of PPG HRV used custom sampling boards that sampled and recorded the waveform at 500 Hz or more. This sampling rate is not available from commercial, non-research devices, and especially not for devices designed for the ambulatory market. Further, common PPG pre-processing steps on commercial pulse oximeters, such as baseline removal with high-pass filters, influence the low frequency components. Often, the end user has no access to alter these settings. For mobile applications where battery power and computational resources are limited, algorithms must be computationally efficient. Algorithms and sampling rates are commonly trimmed in order to achieve computational efficiency. However, this comes at the expense of accuracy and performance, which has to be taken into consideration during HRV analysis. It is therefore important to validate RSA performance under these conditions.

Our goal is to assess the limit to which RR can be estimated using the RSA phenomenon on data obtained from ECG and PPG sensors with lower than recommended sampling rates and low-profile algorithms.

II. Methods

A. Data Collection

Following institutional review board approval and written consent, data was recorded from 29 children (4.8 years $\pm$ 5.4, 18.5 kg $\pm$ 23.4) and 13 adults (46.3 years $\pm$ 9.0, 73.5 kg $\pm$ 24.2) receiving general anesthesia. The recordings obtained included ECG (300 Hz), capnometry (25 Hz), and PPG (100 Hz) signals. All signals were recorded with S/5 Collect software (Datex-Ohmeda, Finland) using a sampling frequency of 300 Hz (PPG and capnometry with lower sampling rates were automatically up-sampled). An 8-min segment of reliable recording of spontaneous or controlled breathing was randomly selected from each case. The segments are available for download from the on-line database CapnoBase.org [12]. All the data processing and analysis was performed using the Matlab (Mathworks, Natick, USA) software framework.

B. Data Processing

The capnogram waveform was used as the reference recording for computing RR. A technician independently validated the reference measurement using the CapnoBase Signal Evaluation Tool [12]. The ECG and PPG waveforms were used to compute the HR. R-peaks and PPG pulse peaks were automatically detected by determining the maximum value of each heart beat peak, and a technician independently validated the detection and corrected errors. In addition, the technician labeled the beginning and end of all potential artifacts in the ECG and PPG waveforms. Pulse peak times were converted into tachograms. For Fourier analysis, data must be evenly sampled and, therefore, the tachogram was resampled onto an even 4 Hz grid using Berger's algorithm [13]. Berger's algorithm is computationally efficient, highly localized and, therefore, ideal for real-time processing. The ECG and PPG tachograms were then transformed to the frequency domain in pseudo real-time. Data were divided into 64 second windows (i.e. 256 sample points, which is optimal for computing the fast Fourier transform (FFT)) for analysis, each sliding 20 seconds (i.e. 44 seconds of window overlap) to simulate real-time analysis. Each 8 minute case was thus divided into n =21 overlapping windows. A Hamming window was applied to minimize the first side lobe of the frequency response, and the tachograms were then converted to the frequency domain using FFT. The resulting power spectrogram of each ECG and PPG tachogram window were then analyzed.

C. Analysis

First, we compared ECG- and PPG-obtained tachogram powers at the reference RR obtained from capnometry to determine if they provide a consistent measure of RSA and, therefore, RR (Figure 1a).

We tested the discrepancy of ECG and PPG RR estimation between the reference RR. For this we measured the deviation ($RRerror$) of the RR frequency at the maximum power that was within the expected RR range (4 to 45 breaths/min or 0.04 to 0.75 Hz) in the spectrogram with the reference RR (Figure 1b). The expected RR range was set to a larger range than the traditional frequency band (HF) attributed to RSA in HRV analysis (0.15 - 0.4 Hz) to account for all possible values of RR. We also computed the ratio of poor RR estimation (> 10 breaths/min), as follows

$$\text{high RR Error} = (\text{count of RR error} > 10)/n. \quad (1)$$

We then tested RR estimation robustness by choosing the maximum power in the RSA frequency range. For this, we measured the ratio of the power of the detected frequency and the next highest peak power spectrogram within the RSA frequency range (Figure 1c). Therefore, a spectrogram with a single, clearly distinguishable power peak will have a higher robustness than one with multiple peaks.

We analyzed the impact of spontaneous and controlled ventilation on the RR estimation. For this we divided the cases into two groups. If a window contained a mixture of controlled and spontaneous breathing, it was considered to be spontaneous breathing. To exclude any bias in the analysis due to artifacts, we excluded cases that contained artifacts in the ECG or PPG. To investigate the impact of the artifacts on the RSA we repeated the mean error measures only for cases that were labeled with artifacts.

All results were tested for Gaussian distribution using the Lilliefors test at a significance level of $p<0.05$. An unpaired t-test was performed at a significance level of $p<0.01$ for all statistical comparisons except where stated otherwise.

III. Results

Twenty cases contained artifacts in the ECG and/or PPG and were not used for the initial analysis. From the remaining

TABLE I
RESULTS FOR ARTIFACT-FREE ECG AND PPG DATA

	Units	ECG		PPG	
		controlled	spontaneous	controlled	spontaneous
RR Power	dB	134.24 ±39.80	185.68 ±31.24	160.82 ± 32.03	200.43 ± 30.16
RR Error	breaths/min	2.38 ± 4.29	0.93 ± 2.98	-0.09 ±5.00	-0.02 ± 3.47
High RR Error	%	2.38	2.38	2.86	1.98
Robustness	unitless	4.41 ± 3.81	9.83 ±12.19	2.71 ± 2.15	7.09 ± 6.29

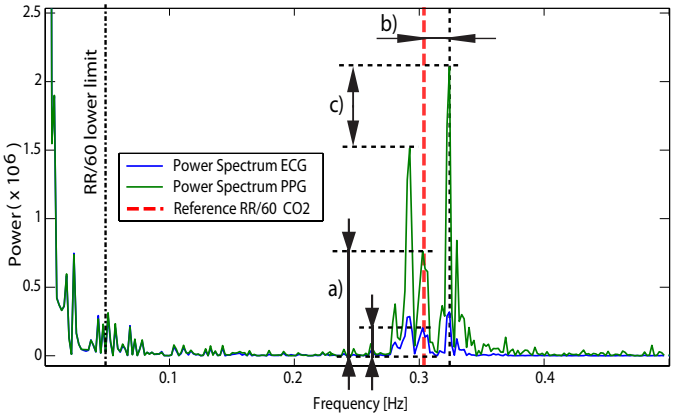

Fig. 1. Performed measures for the analysis and comparison of the power spectrogram obtained from the FFT: a) Spectral power for ECG and PPG at the true RR obtained from capnometry (CO2), b) RR error obtained by the difference between the true RR and the RR at the maximum power, and c) Robustness, which is the ratio between the maximum and the second largest peak in the spectrogram within the RR limits.

22 cases, 12 had spontaneous and 10 had controlled positive pressure ventilation. The mean HR for these cases ranged from 53 to 142 bpm, and the mean RR ranged from 8 to 32 breaths/min. The frequency resolution obtained from the FFT was 0.0152 Hz or 0.9375 breaths/min. All results followed a normal distribution.

The power of the PPG (182.42 ± 36.75 dB) was significantly higher than that of ECG (162.30 ± 43.66 dB) at the reference RR. There was a statistical increase in power content for spontaneous ventilation for both signal sources (Table I). The high RR error rate was lower than 3% for all four configurations.

The mean error in RR detection was -0.05 ± 4.23 breaths/min for PPG, which was significantly lower than 1.59 ± 3.70 breaths/min for ECG. There was no statistical difference between spontaneous and controlled ventilation for the PPG signal source ($p>0.85$, Table I).

The robustness of the PPG (7.37 ± 9.74) was significantly higher than that from ECG (5.10 ± 5.33). For both signals, the controlled ventilation cases showed significantly lower robustness than the spontaneous ventilation cases.

The PPG cases corrupted with artifacts showed a significant increase in RR error (Table II). The increase was less important for controlled ventilation.

IV. DISCUSSION

Overall, the RR estimation from RSA analysis seems to be equally possible using the PPG or the ECG as the signal source. The spectral power at the respiratory frequency was more pronounced for the PPG than for the ECG, which suggests that PPG is the better source for RSA computation and, consequently, RR estimation. Indeed, RR estimation using PPG is more robust and has a lower mean error. This finding is consistent with other research groups that observed a stronger RSA response in the PPG signal [8]. They argued that mechanical respiratory effort influences cardiac output and aortic transmural pressure, which in turn changes pulse wave velocity.

TABLE II
RESULTS FOR ARTIFACT CORRUPTED PPG DATA

	Units	PPG	
		controlled	spontaneous
RR Power	dB	176.09 ± 42.48	180.90 ± 32.99
RR Error	breaths/min	-1.30 ±6.85	5.86 ± 10.44
High RR Error	%	7.79	23.81
Robustness	unitless	3.33 ± 2.79	3.66 ± 4.09

At first glance there is no difference in the RR estimation between controlled and spontaneously ventilation for PPG (Table I). However, RR power and robustness were significantly higher for the spontaneously ventilated cases for both signal sources. This suggests that the RR is easier to estimate during spontaneous ventilation. We investigated this further by dividing the robustness results for each ventilation mode into two classes, one for poor RR estimation ($>$ 10 breaths/min) and one for moderate and good RR estimation ($\leq$ 10 breaths/min), and plotted a histogram (Figure 2). Interestingly, 52.9% of windows during controlled and 80.2% of windows during spontaneous ventilation showed a robustness higher than 1.9 when they had a high RR error, whereas low RR error windows were not present in this range. These results suggest a possible way for improving the RR estimation in the future. Many high peaks in the spectrogram are an indication of poor RSA, so the RR estimation for the corresponding window could be rejected. The application of this principle on our data by rejecting all RR estimations with a robustness $<$1.1 would reduce the high RR error ratio from 1.98% to 1.21% for spontaneous and from 2.83% to 2.61% for controlled ventilation.

In practice, a technician is not able to validate peak detection and label artifacts for a real-time system. Since almost 50% of the cases contained artifacts, any algorithm design will need to account for the presence of artifacts. Such an algorithm might use an artifact detection algorithm to detect and potentially eliminate artifacts. A PPG signal quality estimation might also be useful to reject RR estimations from low quality signals.

Other approaches for estimating RR from the PPG exist. The monitoring of the amplitude modulation of the raw PPG waveform [14] is often explored. Baseline and pulsatile components

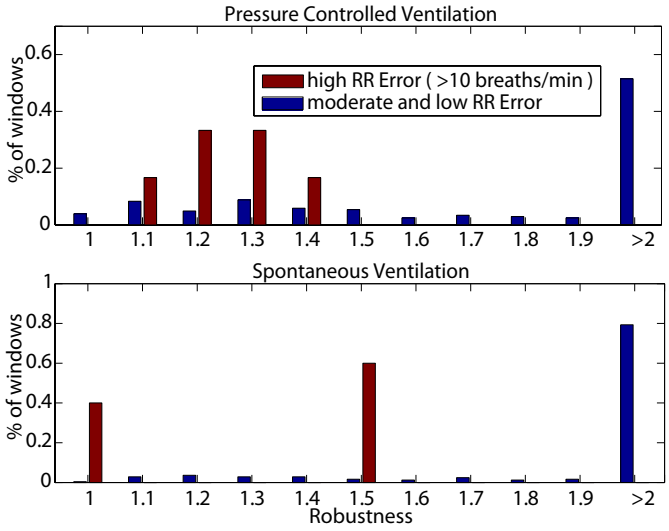

Fig. 2. Histogram comparison of robustness for pressure controlled (top) and spontaneous ventilation (bottom) cases. The histogram bars are divided into windows that showed poor (red) and good and moderate (blue) RR estimation. The histogram bar for robustness=1 groups all tested windows that had multiple peaks in the spectrogram with almost equal power and, therefore, were hard to estimate a single RR.

of the PPG present fluctuations that correlate with RR. This effect is more pronounced with positive pressure ventilation [3]. It might be beneficial to combine this measurement with the RSA method presented here to render the RR estimation more robust, especially for controlled ventilation where robustness was lower. Unfortunately, many commercial pulse oximeters only provide a filtered PPG signal, which has the baseline component removed and the pulsatile variation dampened. To overcome this limitation, custom hardware would be required. This disadvantage of amplitude analysis makes RSA-based RR estimation more universal.

We have not investigated cases with apnea or very low RRs. It is known that other effects, such as Mayer waves [15], share this frequency range with RSA. Further investigations will be necessary to evaluate the impact of these effects.

The proposed algorithms were designed to be ready for real-time analysis on low power devices. Berger's resampling algorithm and the FFT, as well as the maximum peak selection can be easily implemented as real-time algorithms for a mobile device. Future work will include such implementation into a pulse oximeter connected to a mobile phone, such as the *Phone Oximeter* [16], and clinical validation in an ambulatory setting. This would open new possibilities for mobile diagnostic applications involving RR.

V. Conclusion

We have illustrated the estimation of RR using RSA obtained from PPG signals sampled at a sub-optimal sampling rate. The RR estimation was equally good for controlled and spontaneously ventilated patients, but showed to be less robust for controlled ventilation. We believe RSA RR estimation from the PPG is an appropriate and robust approach for RR estimation on mobile devices.

VI. Acknowledgments

This work was supported in part by the University of British Columbia Martha Piper Research Fund and the Canadian Institutes of Health Research (CIHR). The authors acknowledge the contributions of the Department of Pediatric Anesthesia at BC Children's Hospital and the Department of Anesthesia at St. Paul's Hospital for their assistance in conducting the study.

References

[1] G. G. Berntson, J. T. Cacioppo, and K. S. Quigley, "Respiratory sinus arrhythmia: Autonomic origins, physiological mechanisms, and psychophysiological implications," *Psychophysiology*, vol. 30, no. 2, pp. 183–196, Mar. 1993.

[2] A. Van de Louw, C. Médigue, Y. Papelier, M. Landrain, and F. Cottin, "Role of brainstem centers in cardiorespiratory phase difference during mechanical ventilation." *Respiratory physiology & neurobiology*, vol. 174, no. 1-2, pp. 119–27, Nov. 2010.

[3] F. Michard, "Changes in arterial pressure during mechanical ventilation," *Anesthesiology*, vol. 103, no. 2, p. 419, 2005.

[4] M. Malik, T. F. of the European Society of Cardiology, and the North American Society of Pacing Electrophysiology, "Heart Rate Variability : Standards of Measurement, Physiological Interpretation, and Clinical Use," *Circulation*, vol. 93, no. 5, pp. 1043–1065, 1996.

[5] R. Rauh, R. Limley, R.-D. Bauer, M. Radespiel-Troger, and M. Mueck-Weymann, "Comparison of heart rate variability and pulse rate variability detected with photoplethysmography," in *Proceedings of SPIE*, V. V. Tuchin, Ed., vol. 5474. SPIE, 2004, pp. 115–126.

[6] S. Lu, H. Zhao, K. Ju, K. Shin, M. Lee, K. Shelley, and K. H. Chon, "Can photoplethysmography variability serve as an alternative approach to obtain heart rate variability information?" *Journal of clinical monitoring and computing*, vol. 22, no. 1, pp. 23–9, 2008.

[7] N. D. Giardino, P. M. Lehrer, and R. Edelberg, "Comparison of finger plethysmograph to ECG in the measurement of heart rate variability." *Psychophysiology*, vol. 39, no. 2, pp. 246–53, Mar. 2002.

[8] I. Constant and D. Laude, "Pulse rate variability is not a surrogate for heart rate variability," *Clinical Science*, vol. 97, pp. 391–397, 1999.

[9] K. Charlot, J. Cornolo, J. V. Brugniaux, J. P. Richalet, and a. Pichon, "Interchangeability between heart rate and photoplethysmography variabilities during sympathetic stimulations." *Physiological measurement*, vol. 30, no. 12, pp. 1357–69, 2009.

[10] A. Johansson, "Neural network for photoplethysmographic respiratory rate monitoring," *Medical & Biological Engineering & Computing*, vol. 41, no. 3, pp. 242–248, 2003.

[11] K. H. Chon, S. Dash, and K. Ju, "Estimation of respiratory rate from photoplethysmogram data using time-frequency spectral estimation." *IEEE transactions on bio-medical engineering*, vol. 56, no. 8, pp. 2054–63, Aug. 2009.

[12] W. Karlen, M. Turner, E. Cooke, G. Dumont, and J. M. Ansermino, "CapnoBase: Signal database and tools to collect, share and annotate respiratory signals," in *Annual Meeting of the Society for Technology in Anesthesia (STA)*, West Palm Beach, 2010, p. 25.

[13] R. D. Berger, S. Akselrod, D. Gordon, and R. J. Cohen, "An Efficient Algorithm for Spectral Analysis of Heart Rate Variability," *IEEE Transactions on Biomedical Engineering*, vol. 33, no. 9, pp. 900–904, 1986.

[14] K. H. Shelley, "Photoplethysmography: beyond the calculation of arterial oxygen saturation and heart rate." *Anesthesia and analgesia*, vol. 105, no. 6 Suppl, pp. S31–6, Dec. 2007.

[15] C. Julien, "The enigma of Mayer waves: Facts and models." *Cardiovascular research*, vol. 70, no. 1, pp. 12–21, Apr. 2006.

[16] W. Karlen, G. Dumont, C. Petersen, J. Gow, J. Lim, J. Sleiman, and J. M. Ansermino, "Human-centered Phone Oximeter Interface Design for the Operating Room," in *HEALTHINF 2011 - Proceedings of the International Conference on Health Informatics*, V. Traver, A. Fred, J. Filipe, and H. Gamboa, Eds. Rome, Italy: SciTePress, 2011, pp. 4333–7.