Empirical Mode Decomposition for Respiratory and Heart Rate Estimation from the Photoplethysmogram

A Garde[1,2], W Karlen[1,2], P Dehkordi[1,2], JM Ansermino[1,2], GA Dumont[1,2]

[1] Electrical and Computer Engineering in Medicine Group, The University of British Columbia and BC Children's Hospital, Vancouver, BC, Canada
[2] Anesthesiology, Pharmacology & Therapeutics, The University of British Columbia and BC Children's Hospital, Vancouver, BC, Canada

Abstract

We introduce a method based on empirical mode decomposition (EMD) to estimate both respiratory rate (RR) and heart rate (HR) from the photoplethysmographic (PPG) signal obtained from pulse oximetry. The spectral analysis of the EMD applied to the PPG signal was used to extract two signals, the respiratory and cardiac modulations respectively. On these modulated signals, an additional spectral analysis was applied to calculate their frequency peaks. To improve spectral resolution a parametric power spectral analysis based on autoregressive modelling was selected. The frequency peak found in the respiratory and cardiac signals reflects RR and HR, respectively. The PPG signals were analysed using a 1-min sliding window with 50% overlap. The RR and HR estimation accuracy was assessed using the unnormalized root mean square (RMS) error. Median errors (quartiles) were calculated to account for the non-normal RMS distribution. The test dataset consisted of 8-min PPG and capnometric signals from 29 paediatric and 13 adults cases (42 subjects in total) containing reliable recordings of either spontaneous or controlled breathing. A research assistant manually labelled the signals. The reference RR (from capnogram) and HR (from PPG) were manually extracted. The median RMS error (quartiles) obtained for RR was 3.5 (1.1, 11) breaths/min and for HR was 0.35 (0.2, 0.59) beats/min. Therefore, the spectral analysis of the respiratory and cardiac signals extracted through EMD, introduces a useful method to estimate and monitor RR and HR simultaneously from the PPG signal obtained from pulse oximetry.

1. Introduction

Reliable and easy to use methods are needed for monitoring vital signs in the intensive care environment or patients at home with long-term disease with associated instability in respiratory or cardiovascular function. The ability to track heart rate (HR) and respiratory rate (RR) from a simple, low cost, non-invasive sensor will promote and facilitate physiological tele-monitoring (1).

An abnormal respiratory rate is often an early sign of critical illness. For example, the assessment of an elevated respiratory rate (RR > 40 breaths/min)(2) is an essential criterion integrated in guidelines for the diagnosis of pneumonia in children (age 1-5 years). However, clinical measurement of respiratory rate has been shown to have poor reliability and repeatability (3).

Pulse oximetry is widely used in health facilities to monitor physiological vital signs. It is based on an optical technique to measure local variations of blood volume in tissues, providing SpO_2 and photopletysmography (PPG) (4). The PPG signal is a complex signal, composed of the peripheral pulse synchronized to each heartbeat (the AC component), and modulated by a quasi DC component that varies slowly due to respiration, vasomotor activity and vasoconstrictor waves (5). While SpO_2 and HR are well-established parameters derived from the PPG signal, the addition of RR estimation from PPG analysis would provide the ability to obtain multiple vital signs from a single, non-invasive, peripheral sensor. There have been several efforts to extract RR from PPG signal, through the characterization of the PPG cycles morphology in the time domain (6,7), applying time-frequency analysis (8,9) or digital filtering (10).

Empirical mode decomposition (EMD) is an alternative technique that has been successfully applied to reduce motion artifacts in the PPG signal (11), extract respiratory rate from ECG (12), and decompose respiratory sounds (13). The EMD is an adaptive decomposition technique that derives its basis functions from the signal itself. The EMD is especially suitable for analyzing non-linear and non-stationary signals.

In this paper, we propose a method to estimate both RR and HR simultaneously from the PPG signal. Respiratory and cardiac modulations are derived from the spectral

analysis of the EMD applied to the PPG. Consequently the RR and HR are estimated from the spectral analysis of these signals.

2. Methodology

2.1. Dataset

This method was tested using Capnobase, a benchmark dataset that can be downloaded from the on-line database, CapnoBase.org (14). The dataset comprises physiological signals that were recorded from 29 children (4.8 years ± 5.4, 18.5 kg ± 23.4) and 13 adults (46.3 years ± 9.0, 73.5 kg ± 24.2) receiving general anesthesia at the British Columbia Children's Hospital and St. Paul's Hospital, Vancouver BC, respectively. All subjects were studied according to a protocol approved by the institutional Ethics Committee. The recordings included ECG with a sampling frequency of 300 Hz, CO_2 and airflow with a sampling frequency of 25 Hz, and PPG with a sampling frequency of 100 Hz. All signals were recorded with S/5 Collect software (Datex-Ohmeda, Finland) using a sampling frequency of 300 Hz (PPG, CO_2 and airflow with lower sampling rates were automatically up-sampled). A single 8-min segment of reliable recording of spontaneous or controlled breathing was selected for each patient. The CO_2 waveform was used as the reference gold standard recording of RR. A research assistant manually labeled each breath in the capnogram (with support of airflow) and pulse peak in the PPG (with support from the ECG) and validated the derived instantaneous reference RR and HR. This benchmark dataset with reference RR and HR has been previously used to test RR estimation from the PPG (6).

2.2. Empirical mode decomposition

EMD deconstructs non-stationary and non-linear signals into a set of mono-component signals called intrinsic mode functions (IMF). An IMF is a function that represents the oscillation mode embedded in the data signal. An IMF satisfies 2 conditions: the number of extrema and zero crossings must be either equal or differ by one, and the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Similar to wavelet analysis, EMD decomposes the signal into IMFs of different resolution scales. However, in EMD, the basis functions are directly extracted from the data, while in wavelet analysis, a pre-designed mother wavelet is selected before the analysis and determines the basis functions for the different scales. Therefore, IMF can better represent the local characteristics of a signal, and adapt to the signal's oscillation patterns over time. Due to this advantage, EMD is suitable for analyzing nonlinear and non-stationary signals and is thus applicable to PPG analysis (11).

A real valued signal y(t) can be represented as a set of IMFs plus a residual:

$$y(n) = \sum_{k=1}^{N} s_k(n) + r_k(n) \qquad \text{k=1,2,...,N}$$

where $s_k(n)$ are the resulting IMFs and $r_k(n)$ the residual term. In this study, the PPG signals are decomposed into 5 IMFs and a residual.

2.3. Power Spectral Density

The PSD of each IMF is analyzed. To provide a better frequency resolution a parametric power spectral estimation was performed through autoregressive modeling. Each signal $s_k(n)$ is then modeled through an autoregressive model by:

$$s_k(n) = -\sum_{p=1}^{P} a[p] \cdot s_k(n-p) + e(n)$$

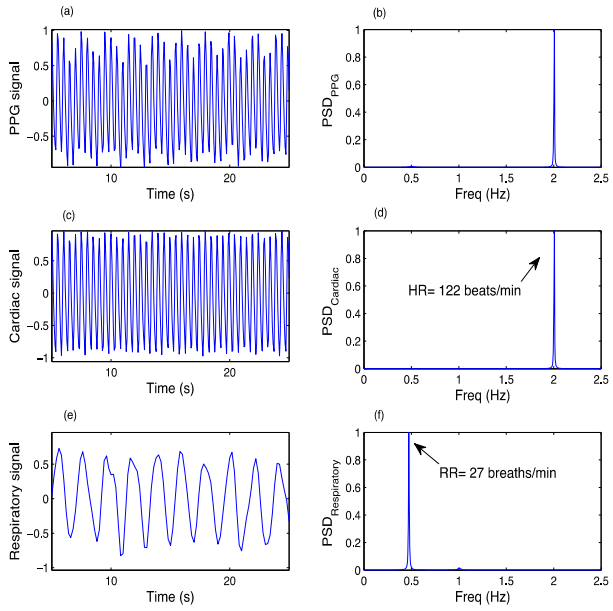
where $e(n)$ denotes zero-mean white noise with variance σ_e^2 , $a[p]$ the AR coefficients and P the model order. Once the autoregressive coefficients and the variance σ_e^2 have been estimated, the PSD of an autoregressive process is computed by means of:

$$P_{AR}(f) = \frac{\sigma_e^2}{\left|1 + \sum_{p=1}^{P} a[p] \cdot e^{-j \cdot 2\pi f p T}\right|^2}$$

with T being the sampling period.
The selection of model order is a trade-off between the frequency resolution and the spurious peaks. The optimum model order was evaluated according to Rissanen's minimum description length criterion $P = 4$.

2.4. HR and RR calculation

Using a sliding window of 1 min with 30s overlap, the PPG signals are divided into segments, decomposed into IMFs and studied in the spectral domain. For each IMF the frequency peak with the highest power is evaluated. The cardiac modulation is estimated by adding the IMFs in which the peak frequency lies within the cardiac frequency range. Similarly, the respiratory modulation is estimated by adding the IMFs in which the peak frequency lies within the respiratory frequency range. A subsequent spectral analysis is applied to these signals to calculate their frequency peaks, reflecting HR and RR (Figure 1).



process. Original PPG segment (a) and its PSD (b); PPG derived cardiac signal (c) and its PSD with the frequency peak reflecting HR (d); derived respiratory signal (e) and its PSD with the frequency peak reflecting RR (f).

Reference cardiac and respiratory frequency ranges are extracted from a review of observational studies that used heart rate data from 143,346 children and respiratory data from 3,881 children (from 2-18 years old) (15). The range in adults is much more restricted but would be included in this range. Based on 99th and 1st centiles for healthy children and young adults, the HR typically ranges from 45 to 145 beats/min (0.75 to 2.4 Hz, respectively) and respiratory rate from 8 to 45 breaths/min (0.14 to 0.75 Hz, respectively). Considering these values, in this study we define the cardiac frequency range from 0.75 to 2.5 Hz and respiratory frequency range from 0.1 to 0.85 Hz.

2.5. Method evaluation

The performance of the EMD-based method is evaluated using the unnormalized root mean square (RMS) error. The RMS error is calculated for each subject, considering all estimations over time.

$$RMS\ error = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(x_i{}^{ref} - x_i{}^{est})^2}$$

where L is the number of observations and x^{ref} and x^{est} are the reference and the estimated values, respectively. The median of the instantaneous reference RR and HR is compared to the estimations for each time window.

3. Results

The median (1st and 3rd quartiles) error obtained for RR is 3.5 (1.1, 11) breaths/min and for HR is 0.35 (0.2, 0.59) beats/min. Figure 2, shows an example output of the method for a subject with an RMS error of 1.13 breaths/min and 0.59 beats/min, estimating RR and HR, respectively. The accuracy of the method per subject is illustrated in Figure 3, where the estimated RR and HR using 1-min sliding window and reference values for each subject are represented as scatter plots.

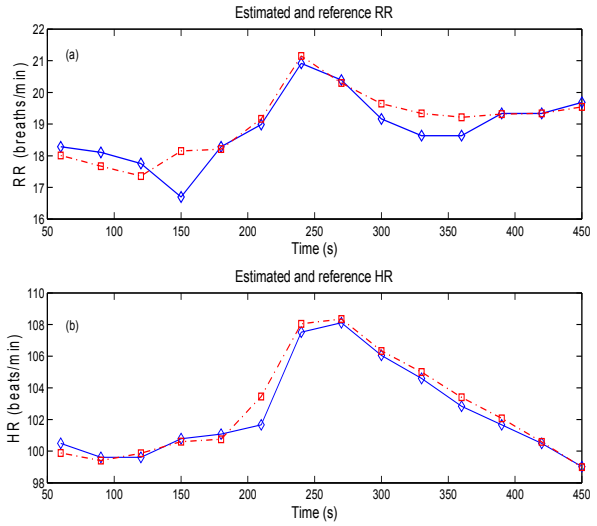


Figure 2. Time-varying estimated (solid blue with ◊ markers) and manually labeled (dotted red with Ω markers) reference RR in (a) and HR in (b). For this subject the RMS error estimating RR and HR are 1.13 breaths/min and 0.59 beats/min, respectively.

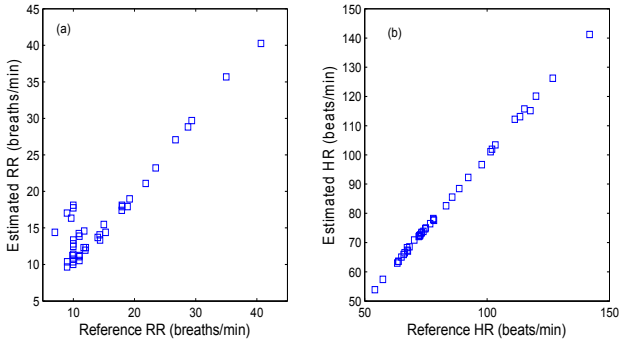


Figure 3. Scatter plot showing the median value of estimated and reference values of (a) RR and (b) HR for each subject using 1-min time window. The respiratory and cardiac frequency peaks are detected around the RR and HR range. Observations with artifacts are included.

4. Discussion

In this study we presented a novel method based on EMD to estimate both RR and HR simultaneously from the PPG. A number of algorithms based on the PPG signal morphology (6,7), time-frequency or spectral analysis (8,9), digital filtering (10), complex demodulation have previously been proposed to detect RR from PPG. Most of these methods were tested only in controlled environments (research laboratories), and their robustness to artifacts (very common in ambulatory environments) has not typically been demonstrated.

The method proposed by Karlen et al. (6) was successfully evaluated in an ambulatory environment using the same benchmark dataset. However, RR estimation was only provided during periods that have an agreement between the three respiratory induced variations, which significantly reduced the number of estimations. In contrast, our EMD-based method can provide a continuous output with very comparable performance.

5. Conclusion

The spectral analysis of the respiratory and cardiac signals extracted through EMD introduces a new method to estimate RR and HR simultaneously from the PPG signal. This method provides an adaptive and robust tool to monitor HR and RR noninvasively from a simple, low cost sensor.

Acknowledgements

This work was supported in part by The Natural Sciences and Engineering Research Council of Canada (NSERC), and the Canadian Institutes of Health Research (CIHR) through the Collaborative Health Research Projects Program.

References

[1] Olsson E, Ugnell H, Oberg P a, Sedin G. Photoplethysmography for simultaneous recording of heart and respiratory rates in newborn infants. Acta Paediatr 2000;89(7):853–61.

[2] WHO. Pocket book of hospital care for children. Guidel. Manag. common illnesses with Ltd. Resour. Geneva, CH. 2005.

[3] Lovett PB, Buchwald JM, Stürmann K, Bijur P. The vexatious vital: neither clinical measurements by nurses nor an electronic monitor provides accurate measurements of respiratory rate in triage. Ann Emerg Med 2005;45:68–76.

[4] Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiol Meas 2007; 28(3):R1–39.

[5] Meredith DJ, Clifton D, Charlton P, Brooks J, Pugh CW, Tarassenko L. Photoplethysmographic derivation of respiratory rate: a review of relevant physiology. J Med Eng Technol 2012;36(1):1–7.

[6] Karlen W, Raman S, Ansermino JM, Dumont G. Multi-parameter Respiratory rate estimation from the photoplethysmogram. IEEE Trans Biomed Eng 2013;(c):1–8.

[7] Lázaro J, Gil E, Bailón R, Mincholé A, Laguna P. Deriving respiration from photoplethysmographic pulse width. Med Biol Eng Comput 2013;51(1-2):233–42.

[8] Chon KH, Dash S, Ju K. Estimation of respiratory rate from photoplethysmogram data using time-frequency spectral estimation. IEEE Trans Biomed Eng 2009;56(8):2054–63.

[9] Orini M, Bail R, Gil E. Estimation of spontaneous respiratory rate from photoplethysmography by cross time-frequency analysis. Computing in Cardiology 2011: 661–4.

[10] Nakajima K, Tamura T, Miike H. Monitoring of heart and respiratory rates by photoplethysmography using a digital filtering technique. Med Eng Phys 1996;18(5):365–72.

[11] Wang Q, Yang P, Zhang Y. Artifact reduction based on Empirical Mode Decomposition (EMD) in photoplethysmography for pulse rate detection. Proc. IEEE Conf Eng Med Biol 2010: 959–62.

[12] Madhav KV, Ram MR, Krishna EH, Komalla NR, Reddy KA. Estimation of respiration rate from ECG , BP and PPG signals using empirical mode decomposition. Instrum Meas Technol Conf 2011: 1–4.

[13] Lozano M, Fiz JA, Jané R. Estimation of instantaneous frequency from empirical mode decomposition on respiratory sounds analysis. Proc IEEE Conf Eng Med Biol 2013: 981–984.

[14] Karlen W, Turner M, Cooke E, Dumont GA, Ansermino JM. CapnoBase: Signal database and tools to collect, share and annotate respiratory signals. Annu Meet Soc Technol Anesth 2005: 25.

[15] Fleming S, Thompson M, Stevens R, Heneghan C, Plüddemann A, Maconochie I, et al. Normal ranges of heart rate and respiratory rate in children from birth to 18 years of age: a systematic review of observational studies. Lancet 2011;377(9770):1011–9.

Address for correspondence:

Ainara Garde
950 West 28th Avenue, V5Z 4H4,
Vancouver, BC, Canada.
Ainara.garde@cw.bc.ca