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Extraction of Respiration from PPG Signals using Hilbert Vibration Decomposition

Hemant Sharma, Ph.D.

Department of Electronics & Communication Engineering

National Institute of Technology Rourkela, India

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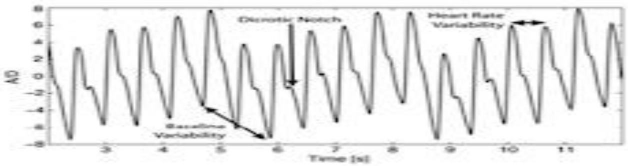
OUTLINE

- Background
- Need for PPG-derived respiration
- Hilbert vibration decomposition (HVD)
- HVD based PPG-derived respiration
- Experiment and results
- Discussion

BACKGROUND



Photoplethysmography (PPG)

- Acquired using pulse oximeter that measures changes in light absorption in tissues
- Primarily used for non-invasive monitoring of blood oxygen saturation
- But it can also be used to monitor other vital signs.
- Simple, feasible, cost-effective process
- Thus, PPG is preferred physiological signal for home-based routine health supervision

Need for PPG-derived respiration

- Respiration is essential to monitor patient deterioration.
- Diagnosis of several health problems including stress, apnea, acute respiratory dysfunction etc.
- Limitations of conventional equipment for respiration measurement
- Feasible for home-based monitoring

Hilbert Vibration Decomposition (HVD)

- It decomposes non-stationary signals into a sum of components with slowly varying amplitudes and frequencies
- Each iteration of HVD includes-
  - Estimation of instantaneous frequency of the largest component
  - Extraction of envelope of largest component (Synchronous detection or Signal mixing)
  - Subtraction of largest component from the composite signal

CONT'D….

- From HVD applied to the input $x(t)$

$$x(t) = \sum_k a_k(t)\cos\left(\int \omega_k(t)dt\right),$$

where,

$a_k(t)$ - envelope of k^{th} component

$\omega_k(t)$ - Instantaneous frequency of k^{th} component

- Energy of $x_k(t)$ > Energy of $x_l(t)$, for $l > k$
- First component of HVD → largest energy component

HVD based PPG-Derived Respiration

- Assumption – Respiratory component in PPG has significant fraction of the total energy of the PPG
- Using HVD, the largest component of PPG corresponds to the respiratory-related variations
- The largest component $x_1(t)$ of PPG $x(t)$

$$x_1(t) = a_1(t)\cos\left(\int \omega_1(t)dt\right)$$

The signal $x_1(t)$ when plotted shows cyclic variations closely resembling the respiration

CONT'D….

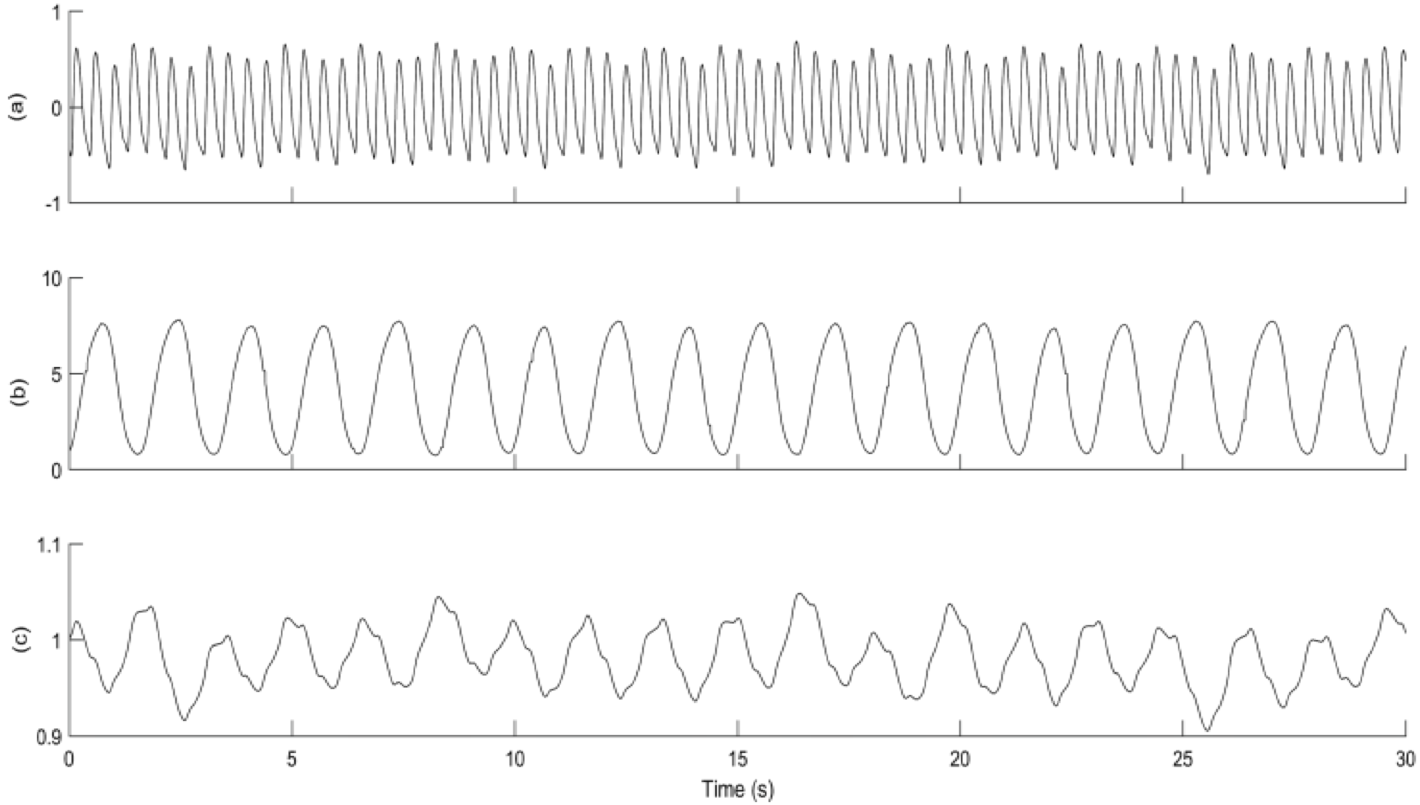


Figure: (a) PPG; (b) Reference respiration; (c) Largest component of PPG $x_1(t)$

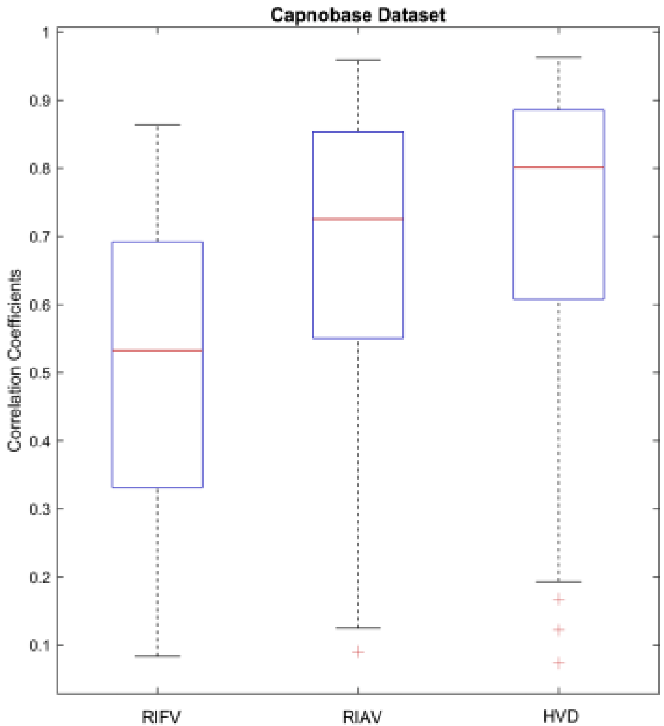
The signal $x_1(t)$ is filtered using a band-pass (0.08 – 0.8 Hz) filter and the output is referred to as the derived respiration

Experiment and Results

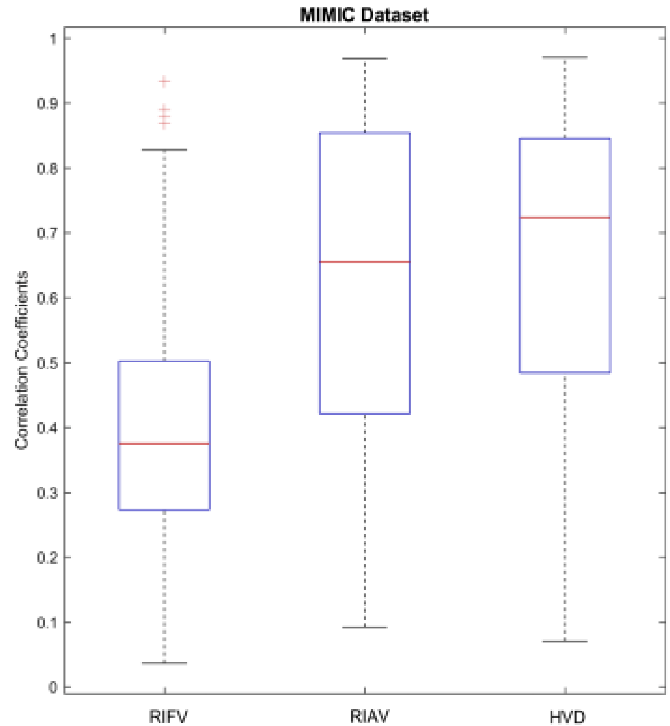
- **Databases**: Capnobase and MIMIC (available at Physionet.org)
- PPG recordings are segmented into equal length epochs of duration 30 seconds each
- A total of 2905 epochs (605 epochs from Capnobase and 2300 epochs from MIMIC) are selected (which are visually uncorrupted)
- Respiratory rate is calculated using fast Fourier transform
- Performance measures
    - Pearson’s correlation coefficient
    - Mean absolute error (MAE)
    - Average percentage (relative) error (PE)
    - Root mean square error (RMSE)

CONT'D….

Pearson's correlation coefficient



RIFV: 0.53; RIAV: 0.73; HVD: 0.80



RIFV: 0.38; RIAV: 0.66; HVD: 0.73

RIFV: Respiratory-induced frequency variation; **RIAV:** Respiratory-induced amplitude variation (Karlen *et al.* 2013)

Karlen et al. 2013. Multiparameter respiratory rate estimation from the photoplethysmogram. IEEE Trans. Biomed. Eng. 60, 1946-1953.

CONT'D….

Capnobase dataset (parameters are shown as median (1st quartile, 3rd quartile))

Techniques	MAE (bpm*)	PE (%)	RMSE (bpm)
RIFV	2.5 (0.4, 4.5)	23.3 (2.7, 38.3)	4.8 (1.1, 7.5)
RIAV	1.9 (0.3, 3.9)	14.6 (2.6, 30.8)	3.3 (0.9, 6.3)
HVD	**0.97** (0.2, 3.3)	**8.8** (0.4, 26.5)	**1.4** (0.3, 5.5)

*bpm = breaths per minute

MIMIC dataset (parameters are shown as median (1st quartile, 3rd quartile))

Techniques	MAE (bpm)	PE (%)	RMSE (bpm)
RIFV	6.5 (3.8, 8.9)	39.6 (28.1, 65.8)	8.1 (6.1, 10)
RIAV	2.2 (1.1, 4.4)	15.1 (6.3, 32)	3.6 (2.2, 6.3)
HVD	**1.8** (0.9, 3.4)	**12.8** (7.1, 20.4)	**3.1** (1.4, 5.9)

CONT'D….

Comparisons with other existing methods (Capnobase data)

Methods	**RMSE (bpm)**	**Epoch Length (sec)**
Proposed work	1.4 (0.3, 5.5)	30
EEMD-PCA (Motin *et al*. 2017)	2.77 (0.50, 5.9)	30
Smart fusion (Karlen *et al.* 2013)	1.56 (0.60, 3.15)	32
Correntropy spectral density (Garde *et al.* 2014)	0.95 (0.27, 6.20)	120
EMD (Garde *et al.* 2013)	3.5 (1.1, 11)	60

Motin *et al*. 2017. Ensemble empirical mode decomposition with principal component analysis: a novel approach for extracting respiratory rate and heart rate from photoplethysmographic signal. IEEE J. Biomed. Health Inform. 99, 766-774.

Karlen *et al*. 2013. Multiparameter respiratory rate estimation from the photoplethysmogram. IEEE Trans. Biomed. Eng. 60, 1946-1953.

Garde *et al*. 2014. Estimating Respiratory and Heart Rates from the Correntropy Spectral Density of the Photoplethysmogram. PLoS ONE. 9, 1-11.

Garde *et al*. 2013. Empirical mode decomposition for respiratory and heart rate estimation from the photoplethysmogram. In *Computing in Cardiology Conference* (2013). 799-802.

Discussion

- A simple but effective approach to estimate the respiration from PPG.
- Computationally efficient
- Reduces the need for detection of fiducial points
- Satisfactory performance over a large number of epochs acquired from two different datasets
- Better resemblance between derived and recorded respiratory signals

Cont'd….

- What if the respiratory component in PPG doesn't appear to be the largest energy component?
    - Add to the initial signal a constant value larger than the peak value.
- *Limitation:* If the muscles noise or artifacts lie in the respiratory band and are of significant magnitude in the PPG signal → erroneous results

Questions?

THANK YOU
FOR
YOUR ATTENTION