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Estimating relative respiratory effort from features of Photo-Plethysmography signal

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Abstract— The gold standard method for measuring respiratory effort (esophageal pressure measurement) is invasive, uncomfortable, and itself can disrupt sleep. As a consequence, majority of sleep studies use an alternate sensor, typically respiratory bands, which, however, do not measure respiratory effort. Typically they indicate changes in thoracic volume, and so are more a secondary sensor of respiratory movement rather than respiratory effort. In this study, we aim to look at how features extracted from finger Photo Plethysmogram (PPG) signals correlate with changes in esophageal pressure signal. Principle component analysis was used to derive the relative respiratory effort signals using pulse to pulse intervals, pulse wave amplitudes, area of pulse and wavelet decomposed band (0.15~0.4 Hz) of PPG signals.

I. Introduction

Photoplethysmography (PPG) is the optical technique of measuring the cardiovascular pulse wave. This pulse wave is caused by the periodic pulsations in arterial blood volume and is measured by the consequential changing optical absorption that this induces. The measurement system consists of a light source (usually infra-red) and a light detector (with a photodiode). Infra-red light is predominantly used since it is relatively well absorbed in blood and weakly absorbed in tissue; blood volume changes are therefore observed with PPG waveform changes by measuring the light transmission through the tissue as a function of time. The PPG measurement is entirely non-invasive and can be applied to any blood bearing tissue [1]. The PPG signal oscillates with the heart cycle period, due to the systolic increase in the tissue blood volume, resulting in a lower transmission of light.

Esophageal catheter pressure (Peso) measurement technique is the standard way to estimate respiratory effort. However, the relationship between Peso signal and photo-plethysmography (PPG) signal has not been investigated. Therefore, the aim of this preliminary study was to develop a model to estimate the relative respiratory effort using PPG signal.

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II. Subjects and Methods

A. Subjects

Overnight PPG (Infrared) and esophageal pressure signals from 10 patients with sleep disordered breathing (SDB) [AHI 10~90] were collected from Charite Hospital in Berlin, Germany and analyzed in this study.

B. Schematic Diagram

Figure 1 shows the schematic diagram to create a model (panel a) using Principle Component Analysis (PCA) and generate the relative respiratory effort using features of PPG signal (panel b). In step 1, features (see Section C) from PPG signal were extracted. Then a band pass filter of 0.15~0.45Hz was used in step 2 to remove other frequencies except the respiratory frequency range. In step 3, Principal Component Analysis (PCA) was used to determine the weight coefficients of PPG features. Finally, the PCA based model was used to generate the relative respiratory effort signal using PPG signal and compare with Peso signal.

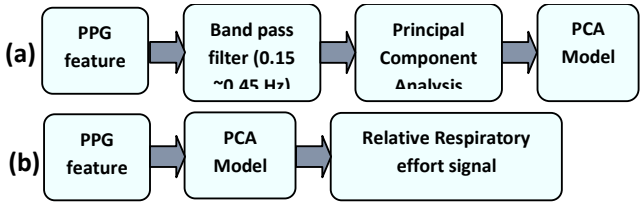

Figure 1. Schematics for relative respiratory effort estimation using PPG features and PCA model.

C. PPG Features

Eight features are extracted from the PPG signal (Figure 2). Brief description of all eight features is given below:

- *Peakamp*: Amplitude of peak point of each pulse.
- *Valleyamp*: Amplitude of trough point of each pulse.
- *PWA*: pulse wave amplitude (vertical distance. between Peakamp and Valleyamp) during systole.
- *ppInterval*: Pulse to pulse time interval.
- *Area*: Triangular area between one Peakamp and two neighboring Valleyamp points.
- *Upslope*: gradient towards Peak.
- *Downslope*: gradient towards Valley.

- *Wv*: Wavelet decomposed level 8.

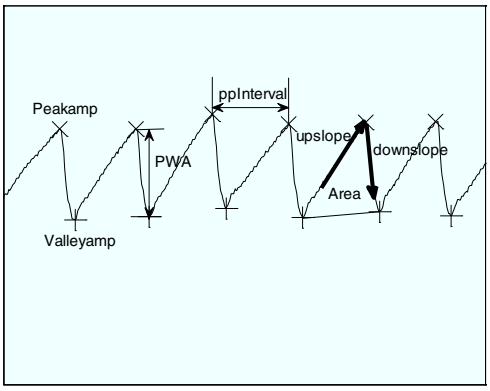

Figure 2. Example of PPG signal and its features

Figure 2 shows an example PPG signal (Infrared) and the time domain features extracted in this study. To evaluate the relationship between the extracted feature and the esophageal pressure, we first filtered the high frequency component of the esophageal pressure by passing Peso signal through a low pass filter (0~1.56 Hz). The original Peso signal and filtered Peso signal is shown in Figure 3.

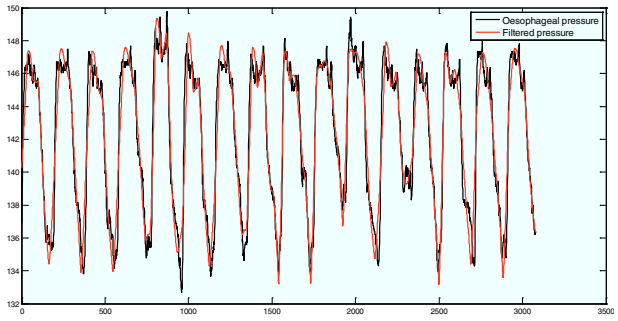

Figure 3. Original Poeso signal and filtered Poeso signal.

C. Principal Component Analysis

Principal component analysis generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data. The full set of principal components is as large as the original set of variables. But it is commonplace for the sum of the variances of the first few principal components to exceed 80% of the total variance of the original data. In this study, we have used the Matlab function "princomp" to find the principal components. We have used all extracted and filtered PPG features (discussed in previous section) to define the principal components. The number of principal components is equal to the number features we have used. However, we have used the second principal component by analysing each components performance on the training set. The second principal component was defined as:

$$Relative\ Effort\ (PPG) = -0.11 * PPInterval\ + 0.84 * PWA\ + 0.06 * PeakAmp - 0.04 * ValleyAmp + 0.00001 * UpSlope - \ 0.0002 * DownSlope + 0.41 * Area - 0.21 * Wv$$

From the above equation, we have selected the features which are multiplied by a weight more than 0.1. As a result, PPInterval, PWA, Area and Wv features were selected for estimating the relative respiratory effort signal.

III. Results

A. Individual Feature

- *PWA*: The extracted PWA feature and mean zero filtered pressure signals are shown in panel (a) of Figure 4. The mean zero filtered PWA feature and mean zeros filtered pressure signals are shown in panel (b) of same figure. From Figure 4 (lower panel) it is obvious that the activity in PWA signal at respiratory frequency is high and it follows the pattern with the increase in negative pressure in Pseo signal.

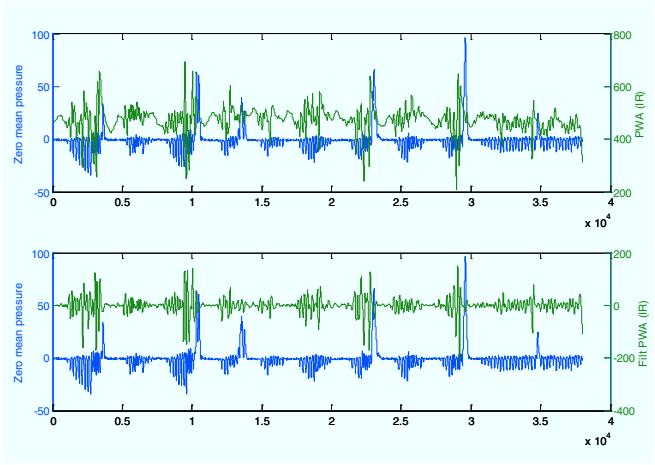

Figure 4. (upper) Zero mean filtered Peso signal (blue) and PWA feature (green) during 10 central apnea events; (lower) Zero mean filtered Peso signal and zero mean filtered (0.15~0.45Hz) PWA feature.

- *ppInterval*: The extracted PPInterval feature and mean zero filtered pressure signals are shown in panel (upper) of Figure 5. The mean zero filtered PPInterval feature and mean zeros filtered pressure signals are shown in panel (lower) of same figure. From Figure 5 (lower panel) it shows the similarity in patterns of PPInterval signal with the increase in negative pressure in Peso signal.

- *Area*: The extracted Area feature and mean zero filtered pressure signals are shown in panel (upper) of Figure 6. The mean zero filtered Area feature and mean zeros filtered pressure signals are shown in panel (lower) of same figure.

- *Wavelet (0.15-0.4Hz):* The mean zero Wv feature and mean zeros filtered pressure signals are shown in Figure 7. Since, the wavelet feature itself represents the activity in respiratory frequency no

further filtering has been used like other time domain features. Wv feature has shown high correlation to the change in Peso signal.

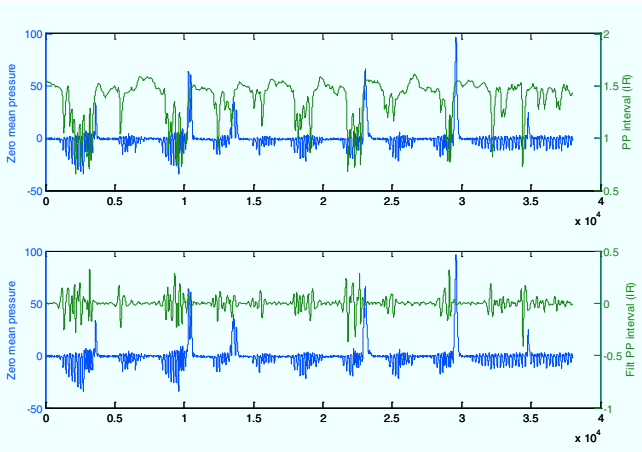

Figure 5. (upper) Zero mean filtered Peso signal and PPInterval feature during 10 central apnea events; (lower) Zero mean filtered Peso signal and zero mean filtered 0.15~0.45Hz) PPInterval feature

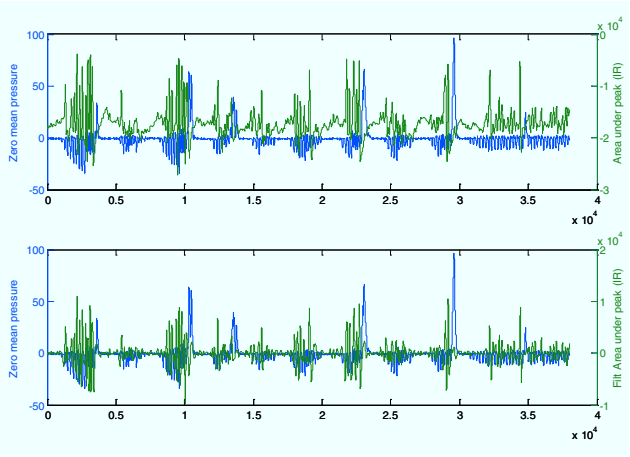

Figure 6. (upper) Zero mean filtered Peso signal (blue) and Area feature during 10 central apnea events (green); (lower) Zero mean filtered Poeso signal and zero mean filtered (0.15~0.45Hz) Area

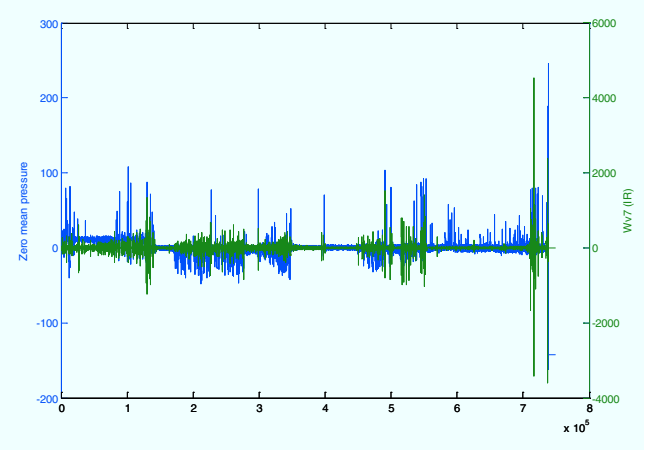

Figure 7. Zero mean filtered Peso signal (blue) and zero mean Wv feature (green) during 10 central apnea events.

B. PCA Model

Relative respiratory signal predicted using developed PCA model and individual features is shown in Figure 8.

IV. Discussion

The different components of the PPG signal, such as its baseline (Peakamp), amplitude (PWA) and period (ppInterval) spontaneously fluctuate in the same low and high frequencies [2]. Peakamp is inversely related to the tissue blood volume, PWA is directly related to the tissue blood volume increase during systole and ppInterval is actually the heart cycle period. The baseline and the amplitude of the PPG signal mainly fluctuate in the low-frequency region, while the fluctuations in the period of the signal are more intense in the high-frequency region, i.e. the respiration rate [2-4]. Since the low-frequency fluctuations of the heart period were found to be mediated mainly by the sympathetic nervous system [5, 6] it is also reasonable to attribute the low-frequency fluctuations in the baseline and amplitude of the PPG signal to the same nervous system [2-4]. Furthermore, the fluctuations in the finger blood volume are due to the constriction and relaxation of the tissue blood vessels which are predominantly affected by the sympathetic nervous system [7]. The low-frequency fluctuations of the PWA curves are due to spontaneous fluctuations in the sympathetic nervous system activity. During high-activity periods of the sympathetic system, greater constriction of the vascular system is induced. Greater vasoconstriction results in lower tissue blood volume and lower compliance (higher rigidity) of the arterial system, which lead to decrease in the PWA values.

Acknowledgment

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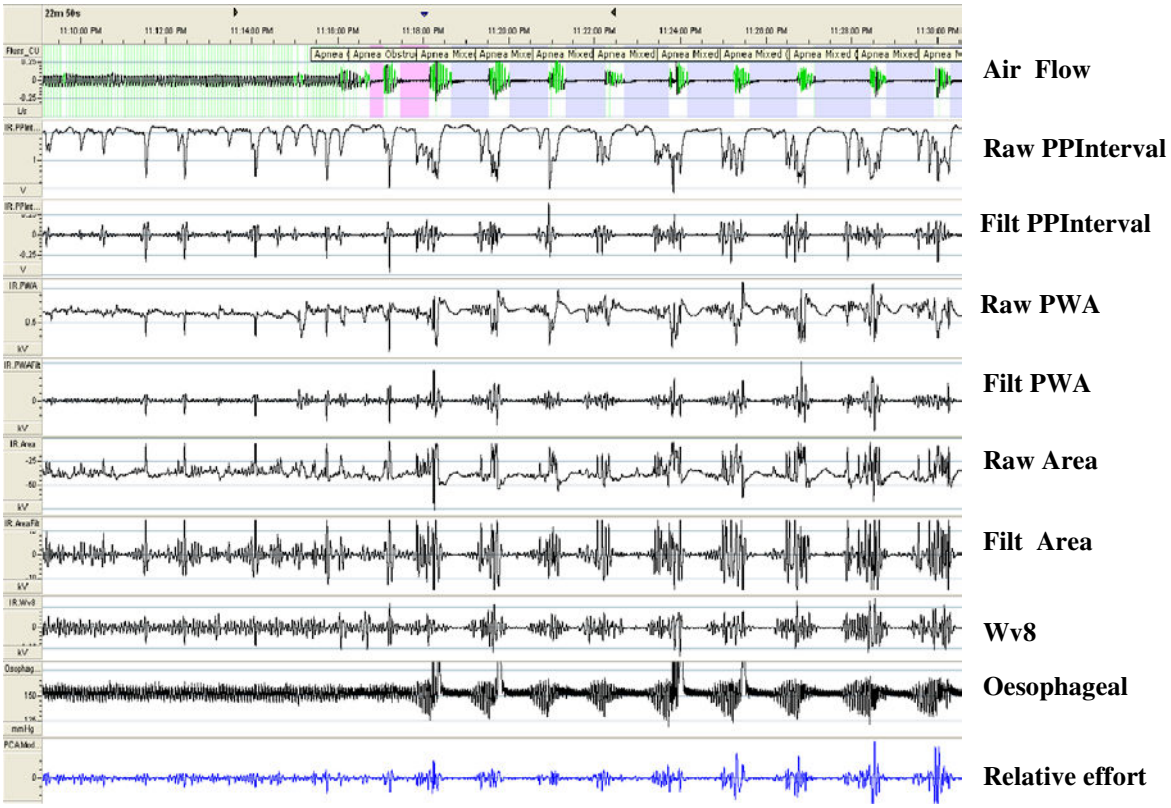

Figure 8. Raw and filtered PPG features during 8 mixed apnea events and relative respiratory effort predicted using PCA model.