Multi-Frequency Model Fusion for Robust Breathing Rate Estimation

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Abstract

Breathing rate (BR) is an important physiological indicator monitored for a variety of chronic diseases. Since direct measurement devices are often cumbersome to wear, we hence aim to obtain an accurate estimation of BR using other monitored signals, such as PPG or ECG. However, derived modulations from these signals are highly dependent on patient and activity type, making the task difficult as to switching among the modulations. We have previously proposed respiration quality index(RQI) based selection method to update the optimal modulation in a realtime manner. A fusion strategy has also been proposed by coupling the RQI with a Kalman smoother to further exploit the sinusoidal waveforms observed from different modulations. In the current study, we further investigate the enhancement of model complexity of the Kalman smoother by introducing multiple frequency dynamics. Performances are compared to reference methods (Pimentel2016, Karlen2013) on the Capnobase Benchmark dataset. In particular, our enhanced KS method achieves a median absolute error and $25-75$ *percentile range of* $0.22(0.16-0.64)$ *bpm, as compared with* $0.35(0.28\ 0.89)$ *bpm from our previous KS fusion method and* $1.1(0.3\ 2.6)$ *bpm from the best reference method in the literature (Karlen et al. 2013).*

1. Introduction

Breathing rate (BR) is one important indicator of physiological deterioration. Abnormal BR prevents unwanted chronic diseases such as renal failure, respiratory or cardiac arrest, pneumonia [1]. Direct measurement by the capnography, impedance plethysmography and flow thermography are often uncomfortable to wear, especially for long-term monitoring[2]. On the contrary, its indirect estimation can be achieved from the photoplethysmography signal (PPG), for which the acquisition is much simpler. Respiration activities also modulate heart rate variability under the name of respiratory sinus arrhythmia (RSA), causing respiration-induced amplitude variations[3], [4].

Indirect estimation of BR from derived modulations is a difficult task due to the noise artifacts and patient-specific activities. It is also based on factors such as age, gender and cardiopulmonary system function [5]. Previous studies have been focused on the development of either the signal quality index (SQI) or the respiratory quality indices (RQI), aiming at selecting *the best* modulation.

We, on the otherhand, believe that merging multiple modulation signals should be more pertinent in terms of information retrieval instead of combining RQI values as in [6] that selects one single modulation for BR estimation. In our previous work [7], we proposed an Kalman smoother with a single-frequency component model to fusion pre-selected modulations with highest RQI scores. Significant improvements have been observed in terms of median and interquartile absolute estimation error. In this paper, we further enhance the model with multiple-frequency component and compare our results with the previous fusion method and reference methods using the benchmark CAPNOBASE.

2. Materials and methods

The flowchart for BR estimation from ECG/PPG signals is presented in Fig. 1. The method consists in extracting and selecting respiratory modulations with highest RQI scores, their fusion using a multi-frequency component model in the Kalman smoother and finally peak and trough detection of the fused modulation for BR estimation. In the following, we will briefly describe the Capnobase dataset used for comparison study, the preprocessing steps (modulation derivation and selection with RQI), detailed in [7, 8] and the BR estimation step on the fused modulation. We focus in this paper on the enhancement of fusion model by including multiple frequency components and its comparison with the single-frequency fusion model in different scenarios .

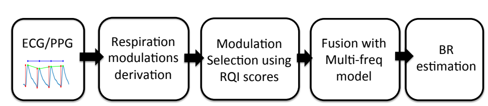

Figure 1: Flowchart of the proposed approach

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2.1. Database

For pertinent performance comparison and easy access of gold standard, the CAPNOBASE dataset was used in our study as previously. It consists of 8min simultaneous PPG and ECG signal and BR reference from the capnography waveforms (http://www.capnobase.org/) recorded from 42 subjects during elective surgery or routine anesthesia. For our analysis, each recording is divided into non-overlapping windows of 32s duration and performances are compared to two reference methods (Karlen *et al*. [9], Pimentel *et al*. 2016 [10])

2.2. Preprocessing and respiration quality

Three derived modulations are extracted from PPG signals (RIIV, RIAV and RIFV) as proposed by [10] or ECG signals (RPA, QRA, RSA, AQRS) [6, 11, 12]. These modulations are calculated for 15 non-overlapping 32s-windows for each 8-min recording in the Capnobase and are then filtered with a 5-th order Butterworth band-pass filter ($[0.083,\ 1]$ Hz) and down-sampled to 4 Hz as in [10] (see typical results in Fig. 2).

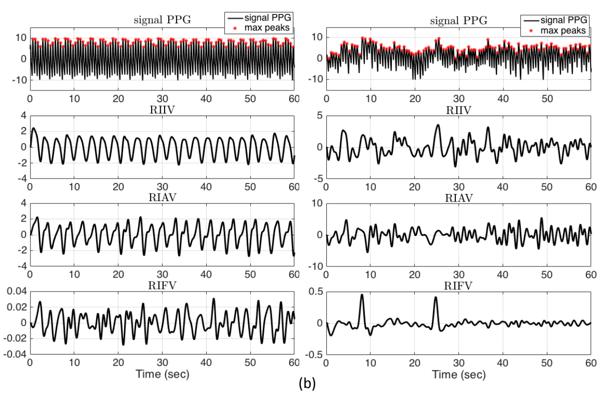


Figure 2: Modulations from PPG (RIIV, RIAV and RIFV), with higher quality (left) and lower quality (right)

The Respiratory Quality Indexes (RQIs) quantify the respiration modulation quality. In the current study, we tested the fourier transform ($\mathrm{RQI_{FT}}$), auto-correlation ($\mathrm{RQI_{ac}}$) proposed by [6] and sinusoidal model index ($\mathrm{RQI_{sinus}}$) from our previous paper [8] based on the normalized mean squared error (NMSE) of the residual error of the sinusoidal model:

$$\mathrm{RQI_{sinus}} = \sqrt{\frac{\sum_{n=0}^{N}\left(y_n - \widehat{A}\cos(2\pi\bar{f}n + \widehat{\theta})\right)^2}{\widehat{A}^2}}, \quad (1)$$

$$y_n = \mathrm{A}\cos(2\pi\bar{f}n + \theta) + b_n, \quad (2)$$

for which $\bar{f} = f_R/f_s$ is the normalized frequency obtained from the periodogram. $\widehat{A}$ and $\widehat{\theta}$ are the maximum likelihood estimates assuming b_n to be *i.i.d.* Gaussian:

$$\widehat{\theta}_{\mathrm{ML}} = \arctan\left\{ -\frac{\sum_{k=0}^{N-1} y_n \sin(2\pi\bar{f}n)}{\sum_{n=0}^{N-1} y_n \cos(2\pi\bar{f}n)} \right\}$$

$$\widehat{A}_{\mathrm{ML}} = \frac{\sum y_n \cos(2\pi\bar{f}n+\theta)}{\sum \cos^2(2\pi\bar{f}n+\theta)} \approx \frac{2}{N}\sum_{n=0}^{N-1} y_n \cos(2\pi\bar{f}n+\widehat{\theta}_{\mathrm{ML}}).$$

Smaller $\mathrm{RQI_{sinus}}$ values suggest closer fit to the sinusoidal model and better periodicity.

As shown in our previous study [7], selection of modulations based on RQI scores is necessary to trade-off between the modulation quality and quantity for the fusion purpose. We adopt the optimized RQI thresholds for easier comparison.

2.3. Fusion with Kalman smoother

The Kalman Smoother algorithm consists of a Kalman filter followed by a fixed interval smoother [13]. The filter algorithm recursively updates the estimation of a state process $\boldsymbol{X}_n$, given observation $\boldsymbol{Y}_n$ of the dynamic system:

$$\boldsymbol{X}_{n+1} = \mathbf{F}\boldsymbol{X}_n + \boldsymbol{W}_n \quad (3)$$

$$\boldsymbol{Y}_n = \mathbf{H}\boldsymbol{X}_n + \boldsymbol{V}_n \quad (4)$$

where $\boldsymbol{X}_n$ is the state vector and $\boldsymbol{Y}_n$ the measurement vector containing all selected modulations in our application. The random processes $\boldsymbol{W}_n$ and $\boldsymbol{V}_n$ are supposed independent, zero-mean white Gaussian: $\boldsymbol{W}_n \sim \mathcal{N}(0, \mathbf{Q})$ and $\boldsymbol{V}_n \sim \mathcal{N}(0, \mathbf{R})$. In the current application, we choose a time invariant formulation for which the state transition matrix $\mathbf{F}$, the measurement matrix $\mathbf{H}$ as well as covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ do not change in time within the 32s segment. The Kalman filter minimizes the squared error expectation of the estimated state vector by calculating the conditional expectation $\widehat{\boldsymbol{X}}_n = \mathrm{E}[\boldsymbol{X}_n|\boldsymbol{Y}_{1:n}]$ in a filtered manner. With a reversed order, the fixed interval smoother further refines the estimation based on all available observations $\boldsymbol{Y}_{1:N}$ by calculating the posterior conditional expectation $\widehat{\boldsymbol{X}}_n = \mathrm{E}[\boldsymbol{X}_n|\boldsymbol{Y}_{1:N}]$. We have studied and validated the fusion method with the KS algorithm in [7] based on a single-frequency component model for the i-th selected modulation: $y_n^i = A^i\cos(2\pi\bar{f}n+\theta^i)+o_n^i+b_n^i$. Significant improvements are observed with comparison to the state-of-the-art methods, independently of the RQI chosen.

Compared to the single-frequency component fusion method, the key difference here is to consider the i-th selected modulation containing two frequency components: $y_n^i = A_1^i\cos(2\pi\bar{f}_1n+\theta_1^i)+A_2^i\cos(2\pi\bar{f}_2n+\theta_2^i)+o_n^i+b_n^i$ with $\bar{f}_1,\ \bar{f}_2$ the normalized frequencies, A_1^i, A_2^i the amplitudes, θ_1^i, θ_2^i the phases, b_n^i the observation noise and o_n^i the baseline wonder. Note that all input modulation signals are modeled with the same frequencies as a result of respiration modulations but differ in amplitudes and phases. This model is motivated from the spectral representations of typical respiration signals illustrated in Fig. 3, for which multiple frequency modes lie in the band of $[0.083,\ 1]$ Hz.

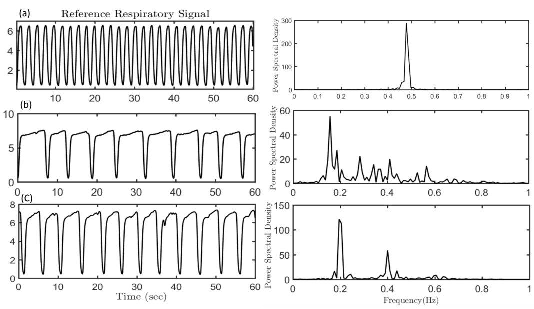


Figure 3: Examples of respiration signals (left) and its PSD (right).

We deduce in the following the case of 2-input fusion without loss of generality. First we define the state vector: $\boldsymbol{X}_n = [\cos(2\pi\bar{f}_1 n), \sin(2\pi\bar{f}_1 n), \cos(2\pi\bar{f}_2 n), \sin(2\pi\bar{f}_2 n), o_n^1, o_n^2]^t$ The transition matrix $\mathbf{F}$ can be directly deduced from $\boldsymbol{X}_{n+1} = \mathbf{F}\boldsymbol{X}_n + \boldsymbol{W}_n$:

$$\mathbf{F}=\begin{bmatrix} \cos(2\pi\bar{f}_1) & -\sin(2\pi\bar{f}_1) & 0 & 0 & 0 & 0 \\ \sin(2\pi\bar{f}_1) & \cos(2\pi\bar{f}_1) & 0 & 0 & 0 & 0 \\ 0 & 0 & \cos(2\pi\bar{f}_2) & -\sin(2\pi\bar{f}_2) & 0 & 0 \\ 0 & 0 & \sin(2\pi\bar{f}_2) & \cos(2\pi\bar{f}_2) & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Allowing a 10% variation on each component of $\boldsymbol{X}_n$ through $\boldsymbol{W}_n$ yields the covariance matrix:

$$\mathbf{Q} = \begin{bmatrix} 0.1^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.1^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & (0.1 \times o_n^1)^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & (0.1 \times o_n^2)^2 \end{bmatrix}$$

The observation matrix $\mathbf{H}$ links the observation (modulation) vector $\boldsymbol{Y}_n = [y_n^1, y_n^2]^{\mathrm{t}}$ and the state vector $\boldsymbol{X}_n$ as defined in the multi-frequency model:

$$\mathbf{H} = \begin{bmatrix} A_1^1 \cos\theta_1^1 & -A_1^1 \sin\theta_1^1 & A_2^1 \cos\theta_2^1 & -A_2^1 \sin\theta_2^1 & 1 & 0 \\ A_1^2 \cos\theta_1^2 & -A_1^2 \sin\theta_1^2 & A_2^2 \cos\theta_2^2 & -A_2^2 \sin\theta_2^2 & 0 & 1 \end{bmatrix}$$

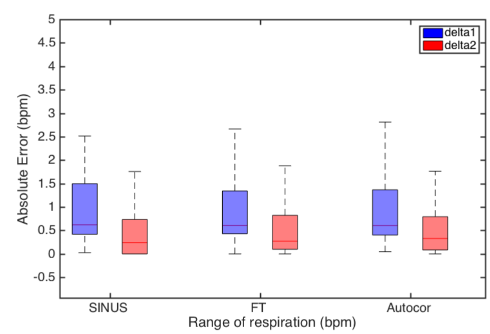
The observation noise covariance matrix $\mathbf{R}$ is supposed to be diagonal by assuming independent noise/artefact influences in different modulation signals.

To initialize the Kalman smoother for each 32s-segment, we need to update $\{\bar{f}_1, \bar{f}_2, A_1^i, A_2^i, \theta_1^i, \theta_2^i, \sigma_1^2, \sigma_2^2\}$ to construct $\mathbf{F}$, $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{R}$. As in the calculation of $\mathrm{RQI}_{\mathrm{sinus}}$, frequencies can be estimated using the periodogram on the modulation with highest RQI scores whereas amplitudes and phases are the ML estimates and MSE of model residuals can be used for noise variance estimations.

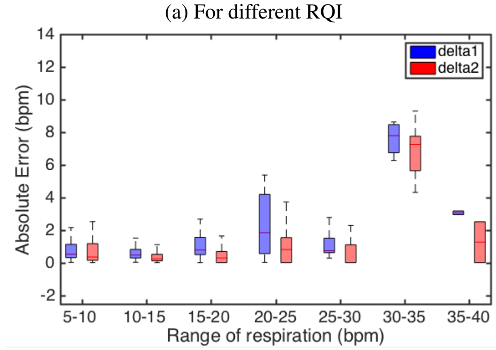
3. Results

3.1. Enhancement due to the KS

First of all, we are interested in proving the exact improvements made by the Kalman smoother fusion. To do this, we compare final BR estimation results with those obtained from the KS initialization step, where $\bar{f}_1, \bar{f}_2$ are calculated using the periodogram on the modulation with highest RQI score. In Fig. 4, Δ_1 represent absolute errors from the initialization while Δ_2 those from the fused modulation. It is noteworthy that the reduction in AE is systematic for all tested RQI and the main improvements occur in the range of $10-30$ bpm, that stands for the majority of Capnobase recordings.



(a) For different RQI



(b) for different BR range (with $\mathrm{RQI}_{\mathrm{FT}}$)

Figure 4: Absolute error before (Δ_1) and after (Δ_2) KS

3.2. Comparison with reference methods

We report the BR estimation performance comparison with two state of the art methods in the literature [9, 10] and our previous paper [7] in Tab. 1 for both PPG and ECG signals from the Capnobase. We note that no comparable results are reproduced in the literature for ECG signals, for which we have implemented and optimized the reference methods. The best obtained results are from the smoothing with 2-frequency model using RQI_{ac}, with a median and 25–75 percentile range of $0.26(0.12-0.61)$ bpm for PPG and $0.22(0.16-0.64)$ bmp for ECG signals.

Median and $25-75$ percentile AE (bpm), PPG		
	1 Freq model	**2 Freq model**
Prop method		
$\mathrm{RQI}_{\mathrm{SINUS}}$ + KS	0.32 (0.17-0.52)	0.26 (0.12-0.61)
$\mathrm{RQI}_{\mathrm{FT}}$ + KS	0.34 (0.19-0.73)	0.27 (0.13-0.57)
$\mathrm{RQI}_{\mathrm{AC}}$ + KS	0.54 (0.33-0.54)	0.26 (0.12-0.61)
Ref methods		
Pimentel (2016)	0.9 (0.5-3.5)	
Karlen (2013)	1.1 (0.3-2.6)	

(a)

Median and $25-75$ percentile AE (bpm) on ECG		
	1 Freq model	**2 Freq model**
Prop method		
$\mathrm{RQI}_{\mathrm{SINUS}}$ + KS	0.36 (0.25-0.55)	0.27 (0-0.63)
$\mathrm{RQI}_{\mathrm{FT}}$ + KS	0.34 (0.25-0.51)	0.24 (0.15-0.41)
$\mathrm{RQI}_{\mathrm{AC}}$ + KS	0.35 (0.28-0.89)	0.22 (0.16-0.64)
Ref methods		
Pimentel (2016)	1.4 (0.8-3.6)	
Karlen (2013)	1.1 (0.3-2.6)	

(b)

Table 1: BR estimation error (median and interquartile in bpm) with PPG (a) and ECG (b) from the CAPNOBASE.

4. Discussion/ Conclusion

The extraction of BR is directly related to the periodicity in the derived modulations. Different methods have been proposed in the literature for estimating BR based on derived PPG/ECG modulations.

In this paper, we propose to further develop the periodic modulation waveform model to include up to two frequency components in the Kalman smoother. We have shown the benefits from the KS, and the model complexity separately from previous studies. We emphasize that in addition to the apparent performance gains achieved with the Capnobase, our proposed methods do not depend on specific parameter tuning on any database. This property is consistant with our previous paper [7], in which performance improvements are significant across different databases.

This method represents an important step towards future challenging works, including ambulatory physical activity and neonatal monitorings. Its validation in both ECG and PPG signals is essential from the point of information fusion under highly artifacted environments.

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