Improved Respiration Rate Estimation Using a Kalman Filter and Wavelet Cross-Coherence

Alistair E W Johnson[1], Sharath R Cholleti[2], Timothy G Buchman[2], Gari D Clifford[1]

[1] University of Oxford, Oxford, United Kingdom
[2] Emory University, Atlanta, GA, United States
[3] Emory University Hospital, Atlanta, GA, United States

Abstract

Introduction: Respiration rate is a common measurement in the intensive care unit (ICU) which is well correlated with patient severity. However, automated estimation of the respiration rate, especially when the patient is not intubated, is prone to large errors. Here we present a method of merging respiration estimates from the electrocardiogram (ECG) merged based on a novel signal quality index.

Methods: Four lead electrocardiograms (ECGs) and capnograms were recorded for 133 patients admitted to a mixed ICU during a spontaneous breathing trial. An average of 2.93 $\pm$ 0.53 hours of data was recorded for each patient. Respiration was derived using four methods based upon respiratory sinus arrythmia and ECG amplitude modulation by respiration. A novel signal quality index (SQI), based upon the Wavelet Transform coherence (WTC) between two respiration waveforms, was used to reflect the quality of each signal. This SQI was used with a Kalman filter to provide a single robust respiration estimate for each ECG lead. These respiration estimates were compared with the reference extracted from the capnogram.

Results: The root mean square error of the new approach ranged between 5.4-6.1 breaths per minute across ECG leads. These errors were statistically significantly better than all component respiration estimates.

Conclusions: Respiration rate can be robustly estimated from ECG leads during a spontaneous breathing trial. The use of a novel SQI within a Kalman filter allows for proper assessment of the accuracy of each component respiration estimate, even though the estimates are derived from the same underlying ECG lead.

1. Introduction

Respiration rate is a commonly measured physiological parameter correlated with patient severity. In the intensive care unit (ICU) it is routinely measured for intubated patients as the ventilator provides a measurement of end tidal CO2 content for each breath (capnography) which tracks respiration. As not all patients in the intensive care unit are ventilated capnography is not always available, and the acquisition of respiration rate for these patients' would provide useful prognostic information for the attending physician. As the electrocardiogram (ECG) is almost ubiquitously measured on ICU patients, extraction of the respiration rate from the ECG is a promising direction. Furthermore, there exist many well validated methods of extracting the respiration rate from the ECG, which take advantage of the different modulations of the ECG by respiration. First, the R-R interval frequency is modulated by respiration due to sympathetic and parasympathetic responses (respiratory sinus arrythmia or RSA), increasing upon inspiration and decreasing upon expiration [1]. Second, the R amplitude is modulated by chest movements during respiration causing impedence changes [2]. However, these methods can be corrupted both by pathology and noise. For example, RSA is absent in patients with a pacemaker and is dampened in the elderly [3]. Modulation of the R peak amplitude by respiration is susceptible to high frequency noise, ectopy, and large baseline wander. The combination of these methods would help to alleviate their sources of error assuming they are mostly independent. In this work we use a Kalman filter to fuse the various estimates of respiration, and evaluate the quality of these estimates using a novel signal quality index (SQI). The SQI developed is based upon the Wavelet Transform Coherence (WTC) between two respiration estimates. The performance of the robust respiration estimate is compared to the component respirations for four ECG leads.

2. Methods

2.1. Data

Data for 133 patients undergoing a spontaneous breathing trial (SBT) in a mixed ICU unit was used for evaluating the model. Standard waveforms recorded at 240 Hz were the ECG (leads I, II, III, V) and the capnogram. Waveform recording commenced 60 minutes before the SBT and stopped 60 minutes after the SBT. The average recording lasted 2.93 $\pm$ 0.53 hours, and the average SBT lasted 55.61 $\pm$ 31.86 minutes.

2.2. Respiration waveform derivation

Prior to deriving respiration waveforms, R peaks were detected in each ECG lead using the open source detector *eplimited* [4]. From the detected R peaks, four respiration waveforms were derived: RSA, RA, RS, and QRSArea. RSA was derived by taking the difference between consecutive R peak detection times. RA was derived by extracting the ECG amplitude at each detected R peak. RS was derived by first determining the S point (minimum 50ms following the R peak), and extracting the ECG amplitude at the R peak minus the ECG amplitude at the S troph. Finally, QRSArea was derived by calculating the energy in a fixed window of 50ms around the R peaks. All four of these methods result in a respiration waveform whose dominant frequency should correspond to respiration. In order to provide even sampling intervals, all respiration waveforms were resampled at 4 Hz.

2.3. Respiration rate derivation

Respiration rate was derived from the four respiration waveforms (for each ECG lead) using an autoregressive (AR) model previously described and validated [5]. AR models are particularly advantageous for respiration detection as they are capable of resolving peaks given low amounts of data. The AR model predicts the value of a function at the next time step, given a set of previous time values plus the error.

$$x_n = \sum_{k=1}^{P} a_k x_{n-k} + e_n \tag{1}$$

where P is the order of the model, i.e. the number of previous time values used to predict the future value. in the z-domain, the model can be described using the transfer function $H(z)$:

$$X(z) = H(z)E(z) \tag{2}$$

$$H(z) = \frac{1}{1 - \sum_{k=1}^{P} a_k z^{-k}} \tag{3}$$

Thus a common interpretation of the AR model is as a filter which transforms the error into the measured time values. The learning of the model coefficients was done using the Maximum Entropy Method [6], as it produces the minimum bias solution. The result of the AR model process is a set of paired complex conjugate poles which each correspond to a distinct resonant frequency. After excluding poles in unphysiological breathing ranges (<4 breaths/minute and >70 breaths/minute), the pole with the smallest angle whose magnitude was above the 95th percentile provided the breathing rate frequency estimate. The autoregressive model was applied on 30 second segments of the respiration waveforms derived from the ECG with a 15 second overlap.

2.4. Wavelet transfer coherence SQI

Wavelet transfer coherence (WTC) is a method for assessing how coherent to time series signals are in both magnitude and phase [7]. It has an advantage over wavelet cross spectral power in that it does not require that the two time signals both have high power in certain bands, only that they vary similarly. The continuous wavelet transform of time series $X(x[n], n = 1, ..., N)$ is the convolution of the signal with a normalized wavelet, or mathematically [7]:

$$W_m^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n=1}^{N} x_n \psi_0 \left[(n-m) \frac{\delta t}{s} \right] \tag{4}$$

The wavelet power can be defined as $|W_m^X(s)|^2$, and the cross-wavelet power of two time series (X and Y) can be defined as $|W^{XY}| = |W^X W^{Y*}|$, where $*$ indicates the complex conjugate. From these definitions, WTC is defined as:

$$WTC_n(s) = \frac{\left| S(s^{-1} W_n^{XY}(s)) \right|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)} \tag{5}$$

where S is a smoothing operator, realized in this work as a rectangular window integration. The WTC can thus be thought of as a squared correlation coefficient between continuous wavelet transforms of the two time series. Further, the WTC is naturally normalized to the range [0,1].

The WTC SQI is derived by averaging the WTC values in an adaptive band. For each respiration rate, two waveforms are required for the WTC SQI. Furthermore, the respiration rate for one of these waveforms determines the location of the adaptive band (RW_{band}). The other respiration waveform is used as a comparison respiration waveform (RW_{cmp}). Table 1 shows the respiration waveforms used to calculate the WTC SQI for each respiration method. An ideal RW_{cmp} is not corrupted by the same type of noise as the RW_{band}, preventing the WTC SQI from detecting correlation due to noise.

Method	RW_{band}	RW_{cmp}
RSA	RSA	RS
RS	RS	RSA
RA	RA	RS
QRSArea	QRSArea	RSA

Table 1. List of the respiration waveforms used to derive the WTC SQI for each respiration estimate.

An example WTC and respiration estimate used to acquire the adaptive band is shown in Figure 1

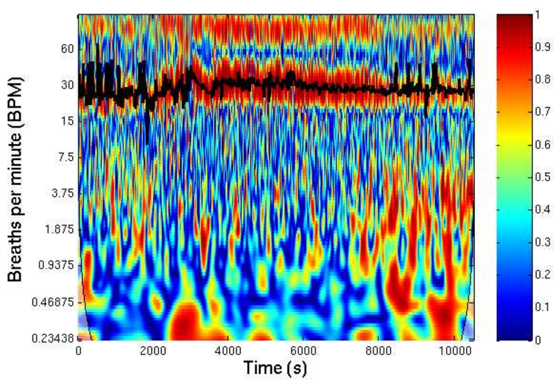

Figure 1. WTC for RSA and RS waveforms. The background is shaded according to the WTC, and the RSA respiration is overlayed in black. The WTC SQI is calculated by averaging a square window centered on the respiration rate of the RW_{band}, in this case RSA.

2.5. Kalman filter

The Kalman filter implemented in this work is based upon that of Nemati *et al* [8]. Briefly, a Kalman filter provides a more robust estimate of a certain variable by combining both a historical value (the state) and the current measured value (the measurement). The weighting of the state and measurement is a controllable parameter of the Kalman filter, and is usually related to the covariance of the parameter in question. More concretely, the Kalman filter estimates the state of a signal, x, given measurement data z, in the presence of noise. The state and measurement variables are controlled by two difference equations:

$$x_n = Ax_{n-1} + w_{n-1} \tag{6}$$

$$z_n = Hz_{n-1} + v_n \tag{7}$$

where w and v represent independent white noise ($p(w) \sim N(0,Q)$ and $p(v) \sim N(0,R)$). A is the state trainsition matrix, and H is the ideal (noiseless) connection between the measurement and the state. The proposed SQI is then combined with the Kalman filter by modifying the measurement noise covariance R as shown in the following equation:

$$R_n \leftarrow R_n e^{SQI_n^{-2}-1} \tag{8}$$

Large values of the SQI will cause the measurement noise covariance to be very large, causing the current state to depend more on the previous state than the current measurement. The Kalman filter is used for each respiration estimate independently, and are fused in a final step according to:

$$X_n = \sum_{r=1}^{R} \left(\frac{\prod_{i=1,i\neq n}^{R} SQI_{n,i}^2}{\sum_{r=1}^{R} \left(\prod_{j=1,j\neq i} SQI_{n,j}^2 \right)} x_{n,r} \right) \tag{9}$$

where R is the total number of respiration estimates, and X_n is the final fused estimate from all respiration estimates. Equation 9 essentially weights each respiration estimate based upon its corresponding SQI. Further detail is provided in [8,9].

2.6. Performance evaluation

The reference for the respiration rate was automatically extracted from a simultaneously measured capnogram. First, instantaneous respiration was derived using an energy detector and an adaptive threshold. As it is not possible to calculate instantaneous respiration from the ECG, an average respiration was calculated in non-overlapping 15 second windows across the capnogram.

The derived ECG respiration estimates were compared to these capnography respiration estimates using the root mean square error (RMSE), defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(RESP_n^{capn} - RESP_n^{ECG})^2} \tag{10}$$

The overall approach of respiration fusion is as follows. First, four respiration waveforms are derived. The breathing rate is estimated using an 11-order AR model in 30 second windows with a 15 second overlap. A set of WTC SQIs are also calculated by averaging the WTC of two selected respiration waveforms in a band centered on the estimated breathing rate.

The four respiration rate estimates are matched with their corresponding SQIs, and fused using the Kalman filter. The resultant respiration rates are compared to the reference capnogram estimates, and RMSE values are reported.

3. Results

Table 2 shows the RMSEs of the respiration estimates and the Kalman filter for each lead of the ECG. Each lead is fused independently of one another.

Lead	RSA	RS	RA	QRSArea	Kalman filter*
I	10.32	6.67	7.59	7.36	5.82
II	10.75	7.16	8.52	7.29	6.13
III	10.15	6.71	8.40	7.54	5.87
V	9.66	6.83	7.83	7.08	5.43

Table 2. Performance of the component respiration estimation methods as compared to the Kalman filter, which fused these estimates using the WTC SQI. Values presented are root mean square errors of breath per minute estimates every 15 seconds.
*Signficantly different from all components at the 0.05 level.

4. Discussion

In this work we have fused respiration estimates derived from the ECG of ICU patients undergoing a SBT. As is shown in Table 2, the Kalman filter improves upon the component respiration estimates for all ECG leads by approximately 0.9 BPM, even though the best method is not known a priori. This is novel in many respects. First, the use of respiration fusion during a SBT shows that the these estimates can be robust even if the underlying signals are difficult. The ECGs analyzed contained many artefacts including electromyographic noise, large baseline wander, inverted T waves, pacing artefact, lead inversion, ectopy, and other abnormalities influencing ECG morphology. The use of the Kalman filter to fuse estimates allows for the marginalization of noise which contaminates one respiration estimate but not others (e.g. pacing removing RSA). Furthermore, the validation of the estimates in the ICU contexts demonstrates that it is possible to acquire respiration estimates for patients who are not intubated, and that these estimates are not overly corrupted by patient agitation.

While previous work has been done on developing SQIs to reflect ECG noise levels [10], these were inappropriate for this application as each respiration estimate was derived from the same underlying ECG. The use of the WTC SQI allowed for accurate reflection of the veracity of each respiration estimate even though each was derived from the same underlying ECG. Furthermore, the WTC SQI was robust as it assessed both the magnitude and phase matching of the two underlying respiration waveforms.

5. Conclusion

The use of a Kalman filter provided more robust estimates of respiration for ICU patients undergoing a SBT. Furthermore, a novel SQI allowed for accurate reflection of the quality of the respiration estimates by assessing correlation both in frequency magnitude and phase. The work here presents a robust way to estimate respiration rate from patients using only the ECG, and would be useful for monitoring physiologic derangement in general ICU patients who are not intubated.

Acknowledgements

AJ acknowledges the support of the RCUK Digital Economy Programme grant number EP/G036861/1 (Oxford Centre for Doctoral Training in Healthcare Innovation).

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Address for correspondence:
Alistair Johnson
Institute of Biomedical Engineering
Oxford, OX3 7DQ, UK
alistair.johnson@eng.ox.ac.uk