Segmentation of 24-hour Cardiovascular Activity Using ECG-based Sleep/Sedation and Noise Metrics

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Abstract

A method to segment cardiovascular time series is proposed using ECG-derived metrics. Segmentation of cardiovascular time series into quasi-stationary and low noise segments is important for the construction of models (based around fixed operational points) and the evaluation of a variety of indices, including cardiovascular (such as HRV) and signal quality-based metrics. Noise and activity-related segments are excluded using beat classification and ECG spectral thresholding. ECG-based cardiorespiratory and cardio-pulmonary coupling (CRC/CPC) metrics are used to determine periods of deep sleep or sedated states, amenable to model fitting and cardiovascular metric evaluation (which require quasi-stationary time series). Performance tests using a realistic 'perfectly sedate/deep sleep' ECG model over a range of coloured $1/f^{\beta}$ Gaussian noise sources ($0 \leq \beta \leq 2$) show that the CPC metric is extremely robust to high levels of realistic noise with only a 7% error in classification of deep sleep/sedated states at a signal-to-noise ratio of -20dB ($\beta = 2$), 0dB ($\beta \leq 1$). In vivo murine tests reveal a correlation between CRC and HR, and an anti-correlation with noise and activity metrics. Tests on human ECGs recorded in an intensive care unit show a similar relationship. The techniques presented in this paper may therefore provide a robust set of metrics for segmenting cardiovascular signals into quiescent and noisy/active states.

1. Introduction

The RR-interval time series extracted from the ECG can be accurately modelled by a series of segments of varying length with a given mean (operating point) and variance [1], where the lengths are distributed with a f^{-1} frequency scaling [2].However, the exact point at which a particular normal (non-arrhythmic) nonstationary shift in the ECG occurs is highly unpredictable, since it is induced by a complex variety of endogenous and exogenous factors including natural changes in the autonomic nervous system and shifts in activity. In order to analyse this type of time series, many methods (such as spectral analysis and model-fitting) require the segmentation of the time series at these changes. Furthermore, shifts in stationarity are often accompanied by an increase in artifact density [3]. Not only can the identification and removal of artifactual sections help reduce error in studies, but the frequency of artifact (or lack of artifact) is useful information [3]. The distribution of the length of stationary segments has also been shown to be useful as a health metric [4]. In particular, epoch distribution during wakefullness differs significantly from that during sleep [5], and recent studies have shown that cardiovascular analysis during sleep can lead to improved metric sensitivity [6].

Segmentation schemes for long term cardiovascular time series have already been proposed [7] but with limited success since they are based only upon the statistical nature of the RR interval time series. However, much more activity-related information can be derived from the ECG than just the sequence of beat-to-beat intervals. In this paper we present a novel method of segmenting the ECG into quiescent states using a set of ECG metrics based upon direct spectral ratios, the density of artifactual beat classifications, ECG-derived respiration (EDR), heart rate variability (HRV) and the coupling between the EDR and HRV. The method is calibrated for a spectrum of noise powers and colours using a realistic artificial ECG [8, 9]. Tests on murine ECG are compared to activity metrics derived from an independent visual movement metric. Finally, tests on intensive care unit (ICU) data are compared to the Riker scale, a clinical scale for sedation and agitation.

2. Methods

2.1. Cardiorespiratory coupling

Respiratory sinus arrhythmia (RSA), or increases in heart rate with inspiration (and decreases with expiration)

is *partly* due to the Bainbridge reflex, the expansion and contraction of the lungs and the cardiac filling volume caused by variations of intra-thoracic pressure [10].

Respiratory rate may be derived from the body surface ECG (EDR) by measuring the fluctuation of the mean cardiac electrical axis [11] or peak QRS amplitudes which accompany respiration. This fluctuation is due to changes in the observation axis or thoracic impedance caused by the expansion and contraction of the chest during respiration.

The frequency coupling of RSA and EDR has been shown to be correlated to sleep stability in humans [12]. Coupling between these two signals is more evident or easily obtainable when the subject is at rest (or in deep sleep) where there are fewer factors that may significantly influence changes in the respiratory rate or heart rate. Furthermore, the strongest coupling frequency is directly correlated with respiration, which is a good index of activity.

Following [12], frequency coupling is measured using the cross-spectral density between RSA and EDR. Two slightly different measures of cross-spectral density are obtained: coupling frequency with respect to magnitude of the sinusoidal oscillations $A(f)$ and the consistency in phase of the oscillations $\Theta(f)$ are separately calculated such that $A(f) = \mathcal{E}\ [\ |P^i_{xy}(f)|^2\ ]$ and $\Theta(f) = |\mathcal{E}[\ P^i_{xy}(f)\ ]|^2$ where $\mathcal{E}[.]$ denotes averaging across all the $i = 1, .., N$ segments and $P^i_{xy}(f)$ is the cross-periodogram of the i^{th} segment. A measure of RSA and EDR coupling which we call the *cardiorespiratory coupling* (CRC_{index}), is then given by

$$CRC(f) = \frac{A(f)}{\max[A(f)]} * \frac{\Theta(f)}{\max[\Theta(f)]} \qquad (1)$$

which ranges between 0 and 1. A low CRC indicates poor coupling and therefore increased activity. A high CRC (> 0.4) indicates decreased activity that can be interpreted as sleep or sometimes sedation. It should be noted that this method, used on the murine data, is a slight modification of the one used in [12] (called Cardiopulmonary Coupling, or CPC), where the squaring of the phase is taken before the averaging. This method is used on the artificial and human ECG and does not appear to lead to significant differences in the metric as a predictor of stable (coupled high frequency) activity. Furthermore, in CPC, the cross-power is thresholded at different frequencies to produce an output of wakefullness/REM sleep (W-R), light/cyclic alternating pattern (CAP) sleep, or restfull/non-CAP (NC) sleep. NC sleep is correlated with low Riker scores and W-R is correlated with medium to high Riker scores.

2.2. Power thresholding & artifact density

Increase in noise in the ECG signal is a strong indication of an increase in the level of physical activity. This noise can either be measured by direct spectral measures or by counting the number of false positives of any ECG analysis algorithm. For a direct spectral estimation, Welch's averaged periodogram method is used on 30 second segments of linearly detrended ECG. The signal is then divided into eight sections with 50% overlap. A Hamming window is applied to each section, then zero padded to the next power of two and the eight periodograms are then averaged.

The energy in the clean murine ECG is mostly confined between 1 Hz to 200 Hz. A noisy murine ECG usually results in an increase in energy in the low (< 3 Hz) frequency range which corresponds to baseline wander of the ECG. Surprisingly, noise in the ECG signal, which includes movement and muscle artifacts, does not seem to manifest itself as a significant increase in energy above 200 Hz. For this reason and due to the fact that mouse heart rate can drop below 120 bpm (below 2 Hz), ECG noise will be measured primarily by baseline wander (energy below 1 Hz). The ECG index is given by

$$ECG_{index} = \frac{Power > 1\ Hz}{Total\ Power\ (0 - 250\ Hz)} \qquad (2)$$

Since human ECG has significant non-activity related information in the sub 1Hz region, we cannot use this threshold as an indicator of activity. However, a previous study [3] has demonstrated that the density of abnormal beats in a given window can be indicative of sudden changes in activity. We extend this idea and postulate that extremely active subjects will have persistent artifacts on the ECG significantly above the normal expected levels and inactive subjects will exhibit few artifacts. We therefore propose to use an artifact count in a given 60s window as a metric of activity. Low counts are interpreted as inactivity.

2.3. Non-ECG comparison metrics

In the case of the artificial ECG, no *gold standard* metric is needed, since the model is designed such that a stationary, synchronized (deep sleep) output will result from any activity metric. For the murine ECG we devised a simple activity metric derived from a fixed webcam which captured an image of the mouse at 1Hz. The activity metric was taken as the mean squared difference between each frame. Given two N x M images X_{ij} and Y_{ij}, where i and j are coordinates for the ith and jth pixel respectively, motion M_n is calculated as

$$M_n = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} (Y_{ij} - X_{ij})^2 \qquad (3)$$

Increased level of activity results in $M_n \gg 0$ while minimum activity decreases M_n towards 0.

Table 1. Percentage correct CPC sleep staging for model ECG exhibiting only deep sleep (NC=100%) with decreasing SNR (coloured noise; $0 \leq \beta \leq 2$).

β	SNR	CAP	NC	β	SNR	CAP	NC
2	-2	2	98	1	27	0	100
2	-4	2	98	1	24	0	100
2	-6	2	98	1	21	0	100
2	-8	3	97	1	18	0	100
2	-10	2	98	1	15	0	100
2	-12	4	96	1	12	0	100
2	-14	5	95	1	9	2	98
2	-16	6	93	1	6	3	97
2	-18	4	96	1	3	5	95
2	-20	5	95	1	0	6	93
0	18	1	99	0	12	2	98
0	15	1	99	0	0	3	97

For the ICU data, the Riker scale [13] (a standard sedation/agitation scale routinely recorded by nursing staff approximately once per hour) was used; see [13] for definitions. Although the Riker scale is broken down into seven classes, we consider only three distinct classes; sedated (≤ 3), awake and alert (4) and agitated (≥ 5).

2.4. Data

Three types of data are used in this study; artificial ECG, murine ECG and human ECG recorded from an ICU. The ECG model, described in [8] and [9] is designed to produce a constant phase relationship between the RS amplitude changes and the RR interval changes (since the latter drives the former). The mouse data is described in [14] and the ICU data is described in [15].

3. Results

Table 1 presents details of the application of a realistic 'perfectly sedate/deep sleep' ECG model over a range of coloured $1/f^{\beta}$ Gaussian noise sources ($0 \leq \beta \leq 2$). The CPC metric is extremely robust to high levels of realistic noise with only a 7% error in classification of deep sleep/sedated states at a signal-to-noise ratio of -20dB ($\beta = 2$), -0dB ($\beta = 1$).

Figure 1 illustrates a typical relationship between the mean heart rate HR_{mean}, ECG spectral quality ECG_{index}, web-cam derived motion index (M_n) and the CRC_{index}. Notice that regions where CRC_{index} is greater than 0.4 correlate with low HR_{mean} and high ECG_{index}. Moreover, the corresponding frequencies are around 3 Hz, which is the normal breathing frequency. This observation indicates that CRC may be used as a good index of mouse activity.

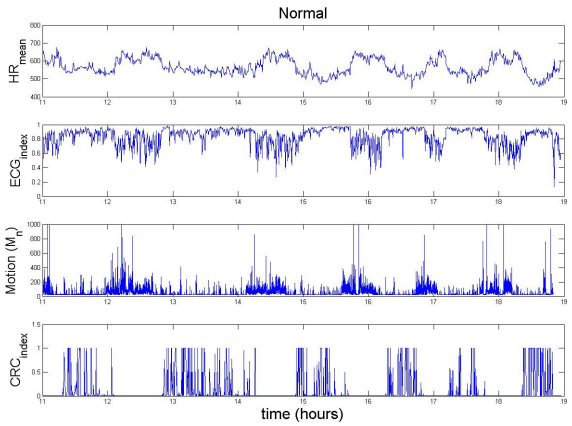

Figure 1. From top to bottom: mean heart rate HR_{mean} (bpm), ECG spectral quality ECG_{index}, motion (M_n) and CRC_{index}. Each metric is computed on a 30 second window and sliding the window by 15 seconds.

It is important to note that frequency components of RSA and EDR signal can only be obtained if heart rate is high enough to prevent sub-Nyquist frequency undersampling and therefore extreme bradychardia can result in frequency aliasing. Furthermore, the noise metric does not perform well on humans, even when scaled by the *usual* [14] factor of 10, since there can be significant power < 0.1Hz for sedated or sleeping patients. It may be appropriate to reduce this frequency threshold.

Figure 2 illustrates an application of the CPC algorithm to human data. The sleep/wake values are derived from thresholding on the cross-spectral density (see [12]). The Riker values recorded just before the onset of this record and just after the end of the recording were 3 (sedated) and 4 (calm and cooperative) respectively. This is typical of the results observed so far; Riker scores of 3 and below map to stationary coupled CPC activity The sudden shift in the dominant cross-spectral coupling frequency from 0.5Hz to 0.3Hz may be due a change in ventilator settings. Note also that other arousals also appear in the time series, but no corresponding Riker measurement is available at these times. This undersampling is an inherent problem with the use of the Riker scale and prevents the complete validation of this technique within the ICU with this scale. Furthermore the times at which Riker scores are recorded are subject to non-systematic inaccuracies. A more stringent method for recording agitation (such as actigraphy) is therefore more appropriate. It should also be noted that observations of the periodogram time series in figure 2 indicate that ECG measurements of power in the low end of the spectrum (< 0.5Hz) may prove redundant, since the CRC or CPC indices include this information.

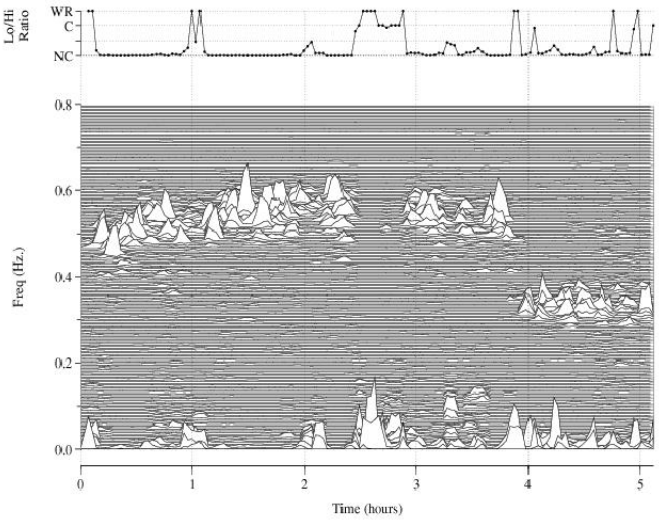

Figure 2. CPC-derived sleep staging and the associated HR-EDR cross spectra. Note the arousal at hour 2.5 and the shift in respiratory frequency (from 30 to 18 rpm) around hour 4.

4. Conclusion

Performance tests using a realistic 'perfectly sedate/deep sleep' ECG model a range of coloured $1/f^{\beta}$ Gaussian noise sources ($0 \leq \beta \leq 2$) show that the CPC metric is extremely robust to high levels of realistic noise with only a 7% error in classification of deep sleep/sedated states at a signal-to-noise ratio SNR of -20dB ($\beta = 2$), -0dB ($\beta = 1$). In vivo murine tests reveal a correlation between CRC and HR, and an anti-correlation with noise and activity metrics. Preliminary tests on human ECGs recorded in an ICU show a similar relationship. The fusion of ECG-derived metrics presented in this paper may therefore provide a robust set of metrics for segmenting an ECG into quiescent and noisy/active states.

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