Real-Time Estimation of Heart Rate Variability Parameters From Passband Filtered Interbeat Interval Series

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Abstract

Real-time heart rate variability (HRV) analysis provides means to measure neural system responsiveness and has recently been found useful in cardio-resynchronization therapy optimization.

Computationally efficient methods for LF and HF power estimation are proposed. The methods are based on interbeat interval series decomposition into LF and HF components using short, infinite impulse response filters. The LF and HF instantaneous powers are computed for time windows of adaptive lengths of duration of LF and HF cycles respectively.

The proposed methods outperform considerably the spectral methods in applications requiring fast tracking of HRV parameters.

1. Introduction

Heart rate variability (HRV) is a measure of beat-to-beat variations in the length of the RR interval. It is a marker of autonomic nervous system modulation of the sinus node activity. The intensity of influences coming from sympathetic and parasympathetic nervous systems and their balance are reflected in the low (0.04-0.14Hz) and high (0.14-0.4Hz) frequency components of the HRV power spectrum.

Instantaneous analysis of HRV provides information about the coupling of the nervous system with the mechanisms controlling the heartbeat activity. The aim of the conducted research is to propose algorithms for fast detection of changes in HRV. Such HRV analysis tool can find application in studying patients' responses to various effort and tilt tests. What is more quick detection of LF power changes is believed to be useful in optimization of electrode placement during cardio-resynchronization therapy [1].

There have been a number of methods proposed for time-frequency HRV analysis including the Short Term Fourier Transform (STFT), the wavelet transform [2], bilinear time-frequency distribution [3], and Kalman filtering of auto-regressive (AR) coefficients [4]. The simplicity in decomposition of AR spectrum into LF and HF components results in high popularity of AR modelling in HRV analysis. However, a large number of parameters are required to be set prior to the analysis, which makes this spectral method less effective in the instantaneous HRV analysis.

The suggested approach is based on interbeat interval series decomposition into LF and HF components using short, infinite impulse response filters. The LF and HF instantaneous powers are computed directly from the decomposed signals for time windows of adaptive lengths of duration of LF and HF cycles respectively.

2. Methods

All the recordings were performed using a 12-lead ECG recorder – Medea Kardio PCMu (12 bits, 500Hz). The algorithm was prototyped in Matlab and its real-time version was implemented in C++.

2.1. HRV series determination

The QRS complexes are detected using digital filters based on the Haar wavelet [5]. A Haar filter of 20-th order is a bandpass linear-phase filter whose passband is centered at f=18.5Hz (for sampling frequency fs=500Hz), while its first and second zeros correspond to 0Hz and 50Hz respectively, which suppresses power network interference and baseline wandering. Interbeat interval (IBI) series is determined. Artefacts including ectopic beats, missed and false detections are located by applying thresholding to the second derivative of the IBI series and then removed [6]. In order to obtain uniformly sampled series, the result is interpolated using cubic splines method and re-sampled with a frequency of 4 Hz in accordance with the HRV analysis guidelines [7].

2.2. Bandpass filtering

The obtained series is split into LF and HF components with passband digital filters of cut off frequencies corresponding to LF and HF band limits. Both filters are 4^{th} order infinite impulse response filters of Butterworth type. This ensures smooth, constant amplitude, nearly linear phase responses within the passbands (figure 1) and buffering delay equal to 0.5 s. The group delay equals to approximately 5.5 s and 1.65 s for the passband of LF and HF filter respectively.

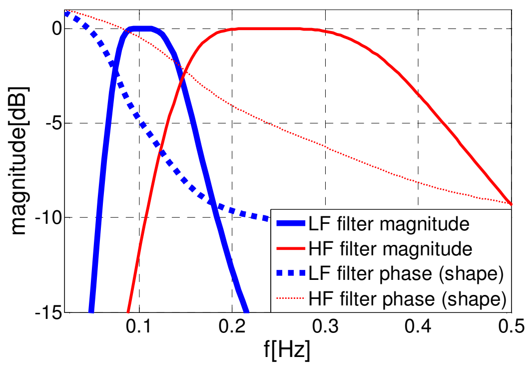

Figure 1. Frequency characteristics of the designed bandpass filters.

2.3. Determination of power components

The instantaneous LF and HF powers of IBI series are computed (1) for time windows of adaptive lengths corresponding to duration of LF (~10 s) and HF (~3 s) cycles respectively.

$$P(n) = \sum_{m=n-L_n+1}^{n} \frac{rr_{filt}{}^2(m)}{L_n}, \qquad (1)$$

where $P(n)$ is the instantaneous power at the arrival of the *n-th* sample, $rr_{filt}(m)$ is a value of the *m-th* sample of the filtered interbeat interval series, and L_n is the length of the current cycle in samples.

The length of the current cycle is determined as the distance between the two last successive zero crossings of the filtered LF or HF signal components correspondingly (figure 2).

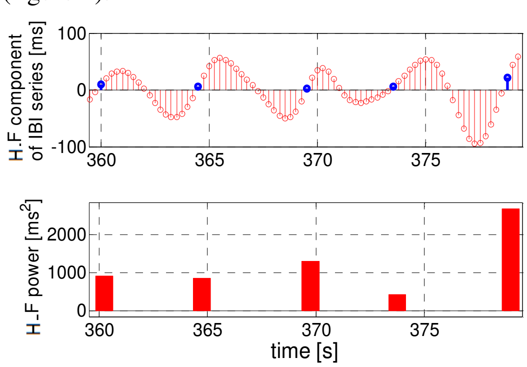

Figure 2. IBI series after HF bandpass filtering and zero-crossing detection indicated by bold, blue samples (upper panel) and the instantaneous HF power determined for the successive cycles.

Since there is a longstanding controversy on the validity of sharp limits between the LF and the HF bands [8], the HF cycle length can be computed alternatively, from the breathing signal. The respiration wave is established from ECG amplitude modulation occurring due to distance changes between the heart and the V6 precordial electrode during breathing (figure 3).

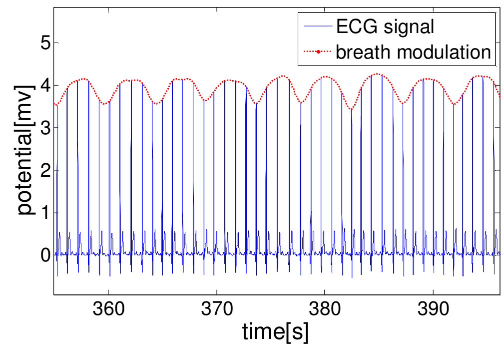

Figure 3. ECG amplitude modulation occurring due to distance changes between the heart and the V6 electrode during breathing.

With such an approach, the instantaneous HF power can be computed for windows of the computed length taken directly from the IBI series (without bandpass filtering) with the 1st order trendline subtracted for each window.

3. Results

The elaborated algorithms were applied to ECG recordings taken for ten healthy patients during body position changes (standing, sitting, supine – each for five minutes), hand grip test (one minute grip followed and preceded by two minutes supine rest), deep breath tests and a test during metronome paced breathing.

3.1. Comparison to spectral methods

In order to validate the results obtained using the proposed algorithms, the computed instantaneous LF and HF powers were averaged over periods for which the state of the patient did not change and then compared to the powers computed using classical Fourier periodogram method and parametric AR modeling over the same regions. Correlation coefficients are listed in table 1.

Table 1. Correlation coefficients of sets of LF and HF powers computed using reference classical methods and the tested bandpass filtering (A) with breathing cycles (B)

	Periodogram	AR modelling
LF power (A)	99.3%	94.3%
HF power (A)	99.6%	96.8%
HF power (B)	99.2%	94.4%

3.2. Simulation

The proposed algorithms were also verified with the use of simulated HRV series. The heart beat events were generated from the input being a sum of two sinusoids of frequencies: f_{LF}=0.1 Hz and f_{HF}=0.25 Hz corresponding to simplified LF and HF contributions and an offset of A_0=900, corresponding to the mean value of HRV (2).

$$in_{rr} = A_0 + A_{LF}\sin(\omega_{LF}t) + A_{HF}\sin(\omega_{HF}t) \qquad (2)$$

where:

$$\frac{A_{LF}^{\ 2}}{2} = \begin{cases} 500 \leftrightarrow t < 2\,\mathrm{min} \\ 400 \leftrightarrow t \geq 2\,\mathrm{min} \end{cases}, \qquad (3)$$

and

$$\frac{A_{HF}^{\ 2}}{2} = \begin{cases} 250 \leftrightarrow t < 4\,\mathrm{min} \\ 300 \leftrightarrow t \geq 4\,\mathrm{min} \end{cases} \qquad (4)$$

The simulated HRV series was designed so that the LF and HF powers were initially equal to 500 ms^2 and 250 ms^2 respectively with a 20% decrease of LF power at 2min and a 20% increase of HF power at 4min. The results of analysis of such a simulated signal are shown in figure 4. The changes of LF and HF component contributions are clearly detected by the algorithm. Slight amplitude fluctuations visible in the plots of instantaneous powers are caused by signal leakages due to soft transition slopes of the bandpass filters. Another reason is a different arrangement of samples within the cycles.

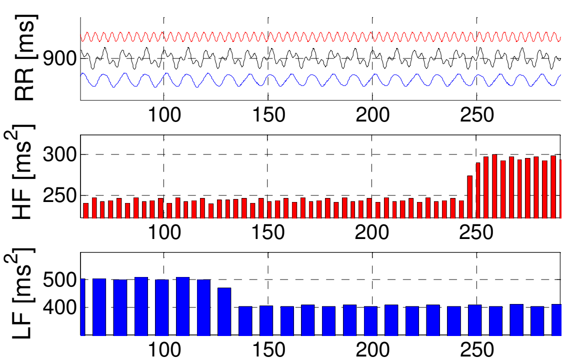

Figure 4. The results of instantaneous HRV analysis performed on the simulated HRV series. The blue (upper) and red (lower) plots in the uppermost figure represent filtered LF and HF components of the HRV series. Their mean is 0, the offset is added for better visualization only.

3.3. Real-time tests

To check the algorithm's validity on ECG recordings, several test were performed including body position change tests, hand grip tests and paced breathing tests. Generally, the obtained results stay in accordance with clinical interpretation of phenomena occurring in the human body during such exercises.

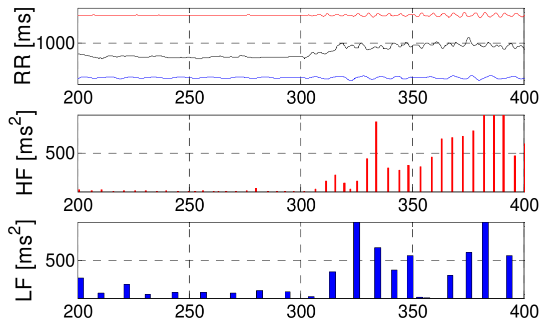

Figure 5. The results of a body position change test performed on a healthy 23 year-old woman. The change from standing to sitting took place at time t=300 s.

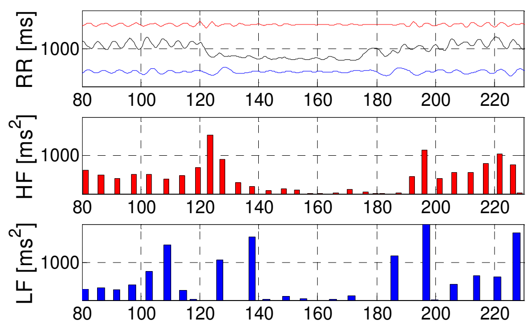

Figure 6. The results of a hand grip test performed on a healthy 28 year-old man. The test started at time t=120 s. The grip was released after one minute.

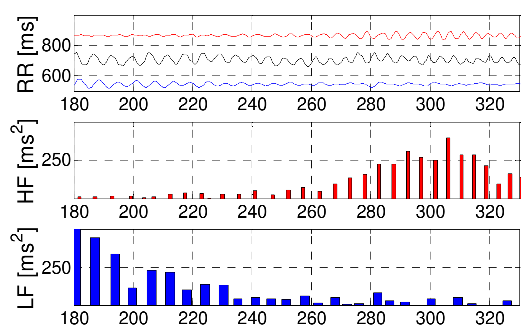

Figure 7. The results of a test with metronome paced breathing. A healthy 21 year-old man controlled his breath according to a metronome which gradually increased its pace from 0.1 Hz to 0.3 Hz. The increase of HF power at the cost of LF power occurs due to strong respiration arrhythmia forced to traverse through the boundary between LF and HF bands.

4. Conclusions

The proposed approach allows to assess HRV parameters with a delay equal to the sum of: LF/HF cycle duration, interpolation, filter order lags (order of seconds) and the computational delay (order of milliseconds). Correlation coefficients for the mean LF and HF powers computed by means of the proposed algorithms and the classical periodogram estimation as well as the widely used parametric autoregressive modeling range from 94,3% to 99,6%. However, the spectral methods need much longer analysis periods for a sufficient spectral resolution [9]. This preliminary work shows that the proposed methods outperform considerably the spectral methods in applications requiring fast tracking of HRV parameters. A larger number of ECG recordings are currently collected for the purpose of this study.

Acknowledgements

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