Time-Frequency Analysis of Cardio-Respiratory Response to Mental Task Execution

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Abstract

Heart rate, heart rate variability (HRV), and respiratory effort have been proposed in numerous studies with the goal of correlating physiological parameters with mental workload.

Aim of this study was to analyze the cardio-respiratory response to a mental task (Sternberg Task) from a single lead ambulatory ECG recording, in healthy subjects. Under no assumptions on stationarity, HRV was analyzed in the time-frequency domain by means of the Hilbert-Huang Transform (HHT). A surrogate respiratory signal was also extracted from the ECG recording, by means of an established principal component analysis (PCA) based method, and its spectrum was analyzed.

A sharp decrease in low frequency (LF) components of HRV during the execution of the mental task with respect to the resting intervals was generally observed. In some subjects, an increase in the peak-power respiratory rate was also observed during task execution.

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1. Introduction

Heart rate and heart rate variability (HRV) have been proposed in numerous studies [1, 2] in neuroergonomics with the goal of detecting physiological parameters correlating with mental workload. Studies [3,4] have also shown the role of the respiratory signal (breathing rate and depth) in characterizing the physiological response to mental workload.

To limit the obtrusiveness of measurements, the electrocardiogram (ECG) is recorded by means of a single lead ambulatory setup. Based on this assumption, aim of this study was to analyze the cardio-respiratory response to mental workload induced by Sternberg's high-speed memory scanning task [5], relying only on a single lead ECG recording.

In the analysis of mental workload, frequency domain parameters of HRV such as low frequency (LF: 0.04-0.15 Hz) power are generally used, though stationarity verification is often overlooked. In this study a time-frequency analysis of HRV requiring no assumptions on stationarity was adopted: the Hilbert-Huang Transform (HHT). Results were then compared with the power spectral density (PSD) estimate based on Welch periodogram.

A surrogate respiratory signal (SRS) was extracted from the ECG by means of the principal component analysis (PCA) based method proposed in [6], and its spectrum was computed in the range 0-0.5 Hz for respiratory rate and power estimation.

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2. Methods

2.1. Data acquisition

Fourteen healthy subjects, aged 29 ± 6, participated in this study. The experimental protocol was approved by the ethical committee of the Department of Electronics, Computer Science and Systems of the University of Bologna. All participants provided informed consent before undergoing the experiment.

The ECG was continuously recorded while subjects were sitting at the desk, performing four sessions of modified Sternberg memory-scanning task [5]. Each session consisted in 90 trials. For each a memory set of digits was displayed on the screen for 1500 ms, followed by a screen blank of 500 ms after which a probe symbol would appear, prompting subjects to judge whether the symbol was part of the original set. Response timeout was set to 1500 ms.

Two difficulty levels were defined: easy, for memory sets of three items, difficult, for memory sets of eight items. Sessions were presented in the order: easy-difficult-difficult-easy, each one taking approximately 04:20 (mm:ss) and followed by a short rest. Recording duration was fixed (31:00) for all subjects, as well as the start time for the four sessions (03:00, 10:00, 17:00, 24:00).

The ECG was acquired from a modified lead two (MLII) single-lead setup. Data were acquired using g.Tec gMO*BILab*+ ™ . The ECG signal was sampled at 256 samples/s, 16 bits/sample, with an amplitude resolution of 0.19 µV. Reaction time and error rate were recorded for analysis.

2.2. Time-frequency HRV analysis

To assess HRV without introducing any assumptions on stationarity of the inter-beat interval series, HHT was used. Empirical mode decomposition (EMD) into intrinsic mode functions (IMF) was carried out according to [7]. The convergence criterion adopted for the j-th IMF was:

$$SD = \sum_{t=0}^{T} \frac{\left|h_{j(k-1)}(t) - h_{j(k)}(t)\right|^2}{h^2_{j(k-1)}(t)} \leq 0.1 \qquad (1)$$

where T is the duration of the input time-series, $h_{j(k)}$ is the j-th IMF at the k-th iteration of the sifting process.

The evenly resampled inter-beat interval series (tachogram), can be expressed as:

$$x(t) = \sum_{j=0}^{n} h_j + r_n \qquad (2)$$

where n is the number of empirical modes the input series is decomposed into, and r_n is the residual, which can either be a mean trend or a constant.

After performing the Hilbert Transform on each IMF, the input series can be expressed as:

$$x(t) = \sum_{j=0}^{n} a_j(t) e^{i \int \omega_j(t) dt} \qquad (3)$$

where a_j and ω_j are the instantaneous amplitude and frequency, respectively. The residual r_n may be discarded [7].

The expression in (3) may be interpreted as a generalized Fourier expansion, where amplitude and phase coefficients are time-varying.

The HHT amplitude spectrum was approximated in this study by evenly discretizing the instantaneous frequency and the time axes and by computing for each square of the grid the sum of the magnitude squared (energy spectrum) of all IMFs contributions. The discretization criterion can be summarized as:

$$E(i, j) = \sum_{k, \omega, t} \left|IMF_k(\omega, t)\right|^2 \qquad (4)$$

where E(i,j) is the energy of the (i,j)-th element of the discretized time-frequency grid, IMF_k is the k-th IMF, and indices k, ω, t range in [1,n], [f_j, f_j+ ΔF], [t_i, t_i+ ΔT], respectively, while ΔT is the discrete time and ΔF the discrete frequency axis resolution.

The discrete approximation of the HHT marginal spectrum (HHT-MS) is derived from (4) by assigning the interval [t_i, t_i+ ΔT] to a constant value.

2.3. Frequency domain HRV analysis

Traditional HRV spectral analysis was also carried out as per [8]. Welch periodogram was used (arbitrarily) assuming wide sense stationarity of the input data. The inter-beat interval series was evenly resampled at 4 Hz. A 96 s sliding window with 50% overlap was used for computation of PSD of the tachogram. Only low (LF: 0.04-0.15 Hz) and high (HF: 0.15-0.40 Hz) frequency bands were considered for power computation.

2.4. SRS analysis

Beat detection on the raw ECG data was performed by means of the open-source algorithm proposed in [9].

The PCA-based method proposed in [6] was then adopted for SRS extraction.

Preliminary low-pass filtering (6th order Butterworth, cut-off frequency of 35 Hz) on the ECG signal was performed to reduce the impact of muscular noise and power-line coupling which was empirically found to affect PCA results severely. Also accurate R-peak localization for each beat was performed. A window of 50 ms preceding the R peak and 60 ms following it was used, thus P and T wave were left out (only normal sinus rhythm beats were found in all recordings). SRS was extracted from the first principal component coefficient series (PC1) over a 96 s sliding window (as for HRV) by converting the beat index of each PC1 coefficient into the R-peak time of the corresponding beat. This unevenly sampled time series was evenly resampled at a sampling frequency of 4 Hz. Figure 1 shows an example of R-peak aligned beats for PCA computation and the extracted SRS.

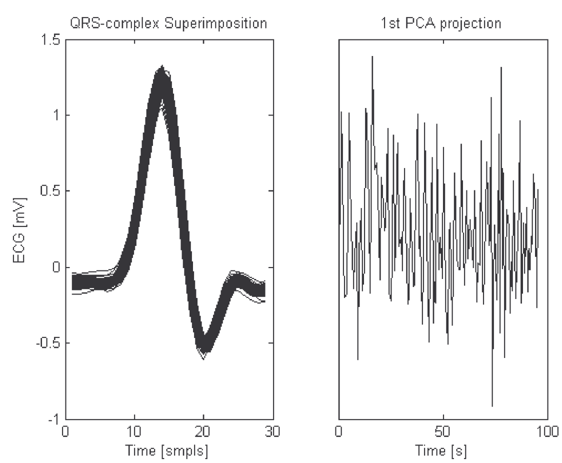

Figure 1. Superimposition of consecutive QRS complexes (left) and SRS extracted from PC1 coefficients (right).

3. Results

3.1. HRV

Regardless of the task difficulty level, a marked decrease of LF during task execution with respect to the resting intervals was observed in most subjects.

Figure 2 shows a typical PSD spectrum and the evolution of the corresponding LF, HF components of HRV. Figure 3 represents the HHT energy spectrum for the same subject.

In the Fourier representation, the existence of energy at a frequency ω means that a component persisted through the time span of the data, whereas in HHT the existence of energy at ω means only that, in the whole time span of the data, there is a higher likelihood for such wave to have appeared locally. In spite of this conceptual difference, normalized PSD-LF power and HHT-LF energy exhibit remarkably similar pattern over time, as shown in figures 2 and 3.

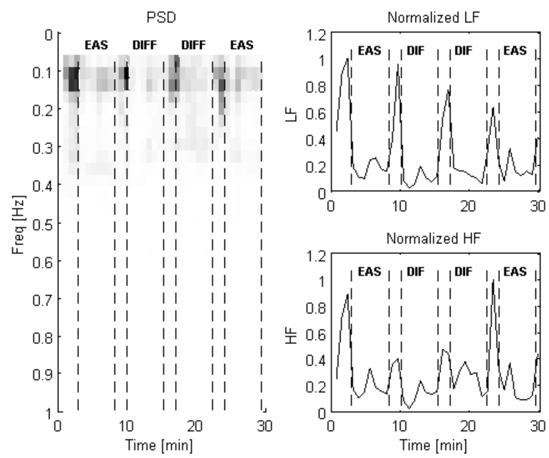

Figure 2. PSD computed over 96 s sliding window (left), and normalized LF, HF evolution (right). EAS=Easy task, DIFF=Difficult task.

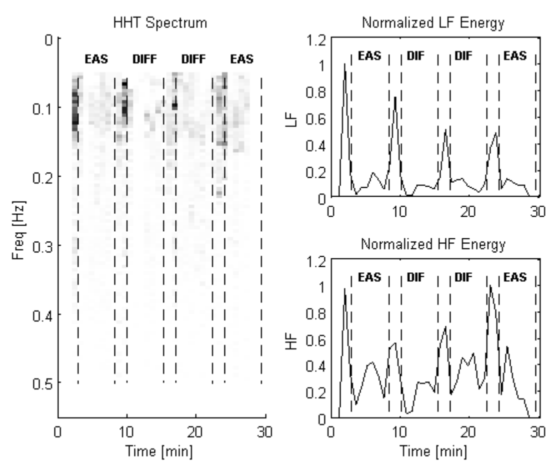

Figure 3. HHT energy spectrum computed over the entire recording (left), and normalized LF, HF energy evolution (right). EAS=Easy task, DIFF=Difficult task.

Table 1 shows linear regression of PSD-LF and HHT-LF components and of PSD-HF and HHT-HF, for all 14 subjects

Table 1. PSD vs. HHT linear regression for LF and HF

	Normalized LF		Normalized HF	
Subject	r^2	RMSE	r^2	RMSE
S1	0.90	0.07	0.62	0.15
S2	0.69	0.13	0.46	0.14
S3	0.73	0.15	0.23	0.18
S4	0.44	0.17	0.48	0.16
S5	0.70	0.14	0.58	0.14
S6	0.38	0.17	0.54	0.17
S7	0.68	0.12	0.54	0.13
S8	0.79	0.10	0.82	0.10
S9	0.66	0.17	0.56	0.14
S10	0.42	0.17	0.62	0.10
S11	0.59	0.17	0.69	0.10
S12	0.37	0.18	0.91	0.05
S13	0.75	0.12	0.49	0.14
S14	0.74	0.12	0.15	0.18

3.2. SRS

Figure 4 shows PSD evolution over a 96s sliding window (50% overlap) for one subject. A dominant respiratory rate between 0.25 Hz and 0.35 Hz (15 rpm and 20 rpm, respectively) can be observed. In proximity of the start of the 2nd, 3rd and 4th task a transient lower frequency component (0.15-0.20 Hz) with higher power is also noticeable. Figure 5 shows HHT approach to the SRS of the same subject. A large spread in respiratory rate can be observed and the low frequency-high power phenomenon is not evident except for the 3rd task start.

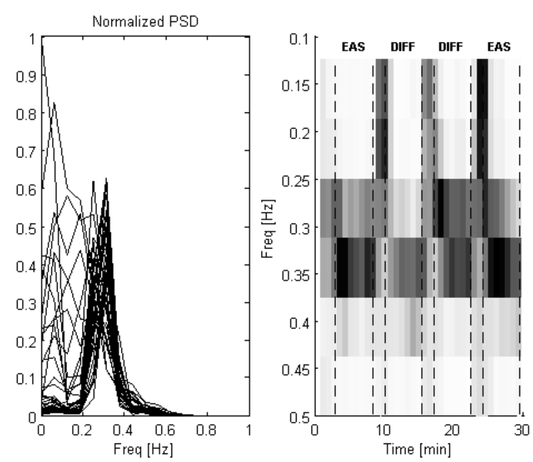

Figure 4. Overlapped PSD spectra of SRS, each one computed over a sliding 96 s window (left), and time-frequency PSD plot (right). EAS=Easy task, DIFF=Difficult task.

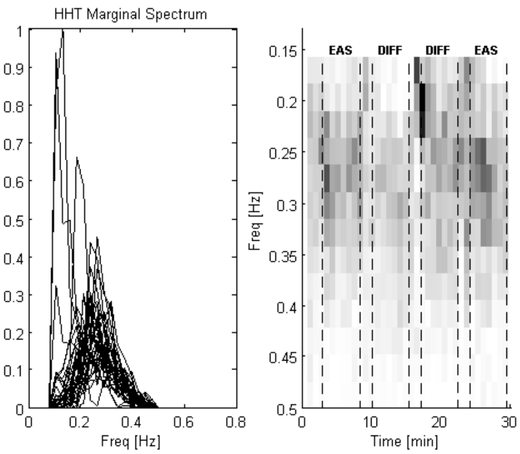

Figure 5. Overlapped HHT marginal energy spectra of SRS, each one computed over a sliding 96 s window (left), and HHT energy spectrum (right). EAS=Easy task, DIFF=Difficult task.

4. Discussion and conclusions

HRV and SRS from a single lead ambulatory ECG recording were analyzed with the goal of characterizing the cardio-respiratory response to a mental task in healthy subjects. A time-frequency approach was used for HRV analysis based on HHT, making no assumptions on inter-beat series stationarity. Results were then compared to traditional PSD-based frequency domain analysis. A sharp decrease in LF was found in most subjects during task execution with respect to the resting intervals, as shown in figure 2 and 3. A remarkable correlation in PSD power and HHT energy time evolution was found for normalized LF in most subjects (r^2=0.63±0.17), as shown in Table 1. Normalized HF component showed slightly lower correlation (r^2=0.54±0.20). Average reaction time was significantly higher ($p<0.05$) for all subjects in the difficult tasks with respect to the easy, also error rate was higher. The difficulty level of the task could not be observed from LF evolution, except for one subject where the LF peak was higher for the two difficult tasks.

Respiratory rate and power were analyzed by means of SRS from an established PCA-based method. A frequency domain analysis based on PSD showed a dominant respiratory rate between 0.20 Hz and 0.35 Hz (12 rpm and 20 rpm, respectively) in most subjects, which in some cases was associated with a transient lower frequency component (0.15-0.20 Hz) with higher power in proximity of the task start, as shown in figure 4. HHT approach to the SRS was also adopted to account for non-stationarity in SRS. A large spread in respiratory rate was generally observed and the low frequency-high power phenomenon was not evident as in PSD approach, except in few cases. However, SRS frequency and time-frequency behavior was found sensitive to the PCA component choice, to R-peak alignment, to the time window of the ECG segments (i.e. the portion of the heart beat) considered for PCA, to muscular and power-line noise on the ECG signal, and perhaps to the subjective respiratory mechanics.

In conclusion, HRV analysis in the time-frequency domain and in the frequency domain lead to similar results in terms of normalized LF and HF components, the first being more evident and also the most relevant to the characterization of the cardio-respiratory response to a mental task in healthy subjects. On the other hand, SRS analysis requires further investigation as the results are potentially affected by numerous factors.

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