Estimating Respiratory Frequency from HRV during Treadmill Exercise Testing

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Abstract

The indirect extraction of respiratory frequency during exercise testing is very interesting and challenging. In this work we propose a method to estimate respiratory frequency during exercise testing from heart rate variability (HRV) analysis. Empirical mode decomposition is first applied to HRV signal to obtain the intrinsic mode functions (IMF). The combination of different IMF is studied and a criterion is proposed to select the one which best represents respiratory information. Finally, time-frequency analysis is applied to the combination of IMFs and respiratory frequency is selected as the largest peak of the spectrum within a restricted frequency band and given that the spectrum is sufficiently peaked.

The proposed methodology is applied to a database consisting of the instantaneous RR interval series of 23 healthy and sportive volunteers recorded during treadmill exercise testing. Estimated respiratory frequency shows a relative error close to 3% with respect to the respiratory frequency simultaneously recorded by a gas analyzer system.

1. Introduction

Indirect extraction of respiratory information from other physiological signals is particularly interesting in situations where respiration recording is unavailable or cumbersome, by instance, during exercise testing. Different methods have been presented to derive respiratory information from biosignals including heart rate (HR) extracted from from the electrocardiogram (ECG), blood pressure, and pulse photoplethysmography [1, 2]. HRV Spectral analysis at rest reveals, at least, two main components: one in the Low Frequency (LF) band ($f \in [0.04, 0.15]\,Hz$) that is associated with sympathetic and parasympathetic activity, and another regarding High Frequency (HF) band ($f \in [0.15, 0.40]\,Hz$) of parasympathetic origin that is mainly due to respiratory sinus arrhythmia and is synchronous with respiration [3].

However, estimation of the respiratory frequency grounded on HRV analysis faces several restrictions during exercise testing. Parasympathetic activity on the heart is dramatically reduced during exercise. However, a mechanical effect has been observed when the exercise intensity is high, which modulates HRV at respiratory frequency [4].

The fact that respiratory frequency is not restricted to the classical HF band during exercise testing makes necessary to redefine the HF band [5]. Besides, it has been reported the appearance of a component in HRV during exercise testing centered at pedaling frequency or running stride frequency, when exercise is cycling or running, respectively [6] which can mislead estimation of respiratory frequency from HRV. Moreover, the respiratory frequency during exercise is in itself a highly dynamic quantity and changes with effort and work load [6].

To overcome this issue, several approaches to non-stationary analysis of HRV have been proposed in the literature including time-frequency analysis, time-varying autoregressive models, and empirical mode decomposition [7].

This paper proposes a methodology for continuously assessing respiratory frequency from HRV during exercise testing. Empirical mode decomposition (EMD) is carried out as preprocessing stage of HRV to enhance its representation. Since the respiratory frequency moves through time over a wide range of frequencies, selection of combinations of pairwise of intrinsic mode functions (IMF) is also proposed. The methodology is applied to a database consisting of the RR interval series of 23 healthy and sportive volunteers performing a treadmill exercise test.

2. Methods

2.1. HRV enhancement using EMD

EMD is an adaptive method decomposing a time series into a set of IMF under the following conditions: *i*) the amount of zero crossing and local extremes is the same or differs at most by one; and *ii*) at any point the mean value between the superior envelope defined by the local maxima and the inferior envelope defined by the local minima is zero. A time series can be represented by EMD as follows:

$$x_{\text{HRV}}(t) = \sum_{k=1}^{K} c_k(t) + r_K(t), \tag{1}$$

where $\{c_k(t)\}$ is the set of IMF, $r_K(t)$ is the remainder, and K is the number of the IMF extracted from original data. The first IMF is related to the highest frequency and the last one to the lowest, i.e. EMD presents a filter bank structure, as described in [8]. More detailed sifting process description of the IMF extraction can be found in [9].

After the EMD decomposition, a set of main IMF is defined as $\mathscr{C} = \{c_j(t) : j = 1, \ldots, K'\}$, where each c_j has most of its frequency information above a fixed threshold Δ_ε and $K' \leq K$. Due to the respiratory frequency moves through time over a wide bandwidth, its information is not contained just by one $c_j(t)$. Therefore, another neighboring IMF, $c_{j+1}(t)$, should be included, i.e., $c_{j,j+1}(t) = c_j(t) + c_{j+1}(t)$. So, the following set of pairwise combinations is considered: $\mathscr{C}' = \{c_{j,j+1}(t) : j = 1, \ldots, K'-1\}$. Yet, only one of these combined components is to be selected as the one holding the respiratory frequency information. To this end, cross power spectral density (CPSD) is used, noted $P_{xy}(\omega)$, as the similarity measure between the original signal $x_{\text{HRV}}(t)$ and each $c_{j,j+1}(t)$, but within the frequency band of interest $[\omega_1, \omega_2]$.

The selection criterion is as follows:

i) The CPSD $P_{x_{\text{HRV}},c_{\text{j,j+1}}}(\omega)$ is computed between $x_{\text{HRV}}(t)$ and $c_{j,j+1}(t)$, for each $c_{j,j+1}(t) \in \mathscr{C}'$.

ii) For all the $P_{x_{\text{HRV}},c_{\text{j,j+1}}}(\omega)$, the power over the band of interest is estimated as:

$$\kappa_{x_{\text{HRV}},c_{\text{j,j+1}}} = \int_{\omega_1}^{\omega_2} P_{x_{\text{HRV}},c_{\text{j,j+1}}}(\omega) d\omega \tag{2}$$

iii) Assuming that $|\kappa_{x_{\text{HRV}},c_{\text{j,j+1}}}| < \infty$, the finite set $\mathscr{C}_\kappa = \{\kappa_{x_{\text{HRV}},c_{\text{j,j+1}}} | c_{j,j+1} \in \mathscr{C}'\}$ has a maximum, noted as $\kappa_{x_{\text{HRV}},c_{\text{m,m+1}}}$. So, the IMF combination $c_{m,m+1}(t)$ is selected initially as the one holding the respiratory frequency.

iv) However, due to the dyadic filter bank structure, $c_j(t)$ is expected to have a larger bandwidth than c_{j+1}, therefore, aiming to remove most of non related information with the respiratory frequency, if $|\kappa_{x_{\text{HRV}},c_{\text{m,m+1}}} - \kappa_{x_{\text{HRV}},c_{\text{n,n+1}}}| < \rho$, and $n > m$, then $c_{n,n+1}(t)$ is selected for the extraction task, where $\kappa_{x_{\text{HRV}},c_{\text{n,n+1}}}$ is the maximum of $\mathscr{C}_\kappa - \{\kappa_{x_{\text{HRV}},c_{\text{m,m+1}}}\}$.

Thus, the pair $c_{m,m+1}(t)$ or $c_{n,n+1}(t)$ having the CPSD with highest power within the band of interest is selected, for the further extraction task.

2.2. Respiratory frequency estimation

The respiratory frequency $\hat{f}(k)$ estimation is carried out stepwise [10]: power spectrum estimation of $x_M(t)$ where $x_M(t)$ could be the HRV signal or a combination of IMFs, as it will be later explained, and computation of peak location. In the former procedure, at k-th running time interval of T_s second duration, spectrum $S_k(\omega)$ results from averaging the power spectra obtained from sub-intervals of length T_m with $T_m/2$ overlapping. Each spectrum is estimated every t_s. Further, within the frequency interval $[\omega_1, \omega_2]$, an averaged version $\overline{S_k(\omega)}$ over time is computed by an introduced "peak-conditioned" averaging that is performed only on those $S_k(f)$ regarded as sufficiently peaked, where "peaked" means a certain percentage of the spectral power in an interval centered around the largest peak. In the latter procedure, the respiratory frequency $\hat{f}(k)$ is estimated as the largest peak of $\overline{S_k}(\omega)$, but narrowing down the search interval to only include frequencies within the 2δ interval centered at a reference frequency $f_\omega(k)$: $[f_w(k) - \delta, f_w(k) + \delta] \cap [\omega_1, \omega_2]$. Lastly, the needed reference frequency is obtained as an exponential average of previous estimates, as follows:

$$f_\omega(k+1) = \beta f_\omega(k) + (1-\beta)\hat{f}(k), \tag{3}$$

where β denotes the forgetting factor.

For evaluation purpose of the considered respiratory frequency estimation, the relative error is used and defined as:

$$\varepsilon = \left|\hat{f}(k) - f_R(k)\right|^2 / |f_R(k)|^2, \tag{4}$$

where $f_R(k)$ is the actual respiratory frequency measured on the exercise test using an open-circuit sampling system (Oxycon Pro, Jaeger-Viasys Healthcare).

3. Experimental setup

The used treadmill exercise database holds 23 males physically active [6]. During acquisition, all *R–R* intervals were recorded beat-to-beat using the HR monitor (RS800, Polar Electro Oy), with the $1000\,Hz$ sampling frequency of the input ECG signal, providing $1\,ms$ accuracy of *R–R* interval series. The HR monitor also recorded every second HR and running stride frequency. Synchronization between the open-circuit sampling system and the HR monitor measurements was assessed using the HR recorded by both devices.

Extraction of the HRV signal from the R–R sequence during exercise stress testing, is carried out according to the integral pulse frequency modulation model with time-varying threshold explained in [11]. The HRV signal $x_{\text{HRV}}(t)$ is sampled at 4 *Hz* for the assumed respiratory frequency below 1 *Hz*. From the whole exercise test recording. Only the exercise phase, lasting 9.40 ± 3.64 minutes, is considered in this study. It must be quoted that recordings numbered as 11, 18, and 25 were removed.

3.1. Results and discussion

Since the stop criterion of the sifting process is the standard deviation, initially, each HRV recording is statistically normalized to be further decomposed by the EMD that yields the selected IMF set $\mathscr{C} = \{c_1(t), c_2(t), c_3(t)\}$, given a threshold $\Delta_\varepsilon = 0.2$ *Hz*, according to the proposed approach explained in § 2.1. Afterward, the respiratory frequency is computed following the procedure explained in § 2.2, for which the needed parameters, T_s, t_s, T_m are fixed as $40, 5\,s$ and $16\,s$, respectively, where T_m is selected as a power of 2 for computational reasons, and the frequency band of interest as $[\omega_1, \omega_2] = [0.3, 0.95]$ *Hz*. In addition, optimal values of parameters δ and β Eq. (3) are fixed heuristically for each extraction task, as shown in Table 1.

The respiratory frequency is extracted according with five different scenarios, where the difference is in the signal to which the respiratory frequency estimation algorithm of §2.2 is applied: *i*) as baseline $x_{\text{HRV}}(t)$, *ii*) $c_{1,2}(t)$, *iii*) $c_{2,3}(t)$, *iv*) selecting IMF from $\mathscr{C}' = \{c_{1,2}(t), c_{2,3}(t)\}$ heuristically, and finally *v*) selecting IMF combination from $\mathscr{C}' = \{c_{1,2}(t), c_{2,3}(t)\}$ using the criterion as described in § 2.1, where the CPSD parameter is fixed as $\rho = 0.045$.

Table 1 shows the relative error of each recording for the five considered scenarios, where the notation $\{\cdot\}^\circ$ stands for heuristically IMF selection, $\{\cdot\}^\diamond$ for the criterion in § 2.1. The values achieving same performance for both, selections of IMF combinations are noted in bold letter. The introduction of HRV Enhancement using EMD allows achieving better error performance using scenario *iv* (2.86) and *v* (2.93). However, the mere introduction of EMD combinations is not enough. So, other EMD based scenarios without a selecting criterion get lower error performance even that the baseline scenario *i*.

Generally, the CPSD-based selection criterion matches all the heuristically selected ($c_{1,2}(t)$ or $c_{2,3}(t)$) except for the recording $\#14$, for which the frequency estimated over $c_{1,2}(t)$ performs an error close to the estimated from $c_{2,3}(t)$ (5.17% and 5.22% respectively). In this concrete case, literal iv) of the selection criterion is carried out.

To make clear the influence of the introduced preprocessing, Fig. 1(b) shows the time-frequency representation of the baseline scenario *i* (left side) and the proposed methodology scenario *v* (right side), for the recording labeled as 24 and 12, respectively.

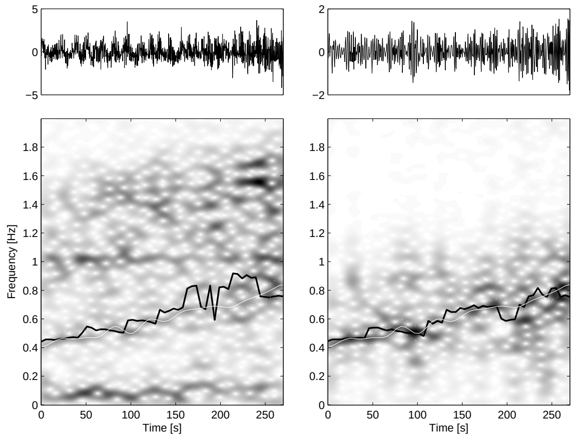
Table 1. Relative error from the estimated respiratory frequency, the mean, standard deviation of all recordings, and the optimal parameters

Record	Relative error [%]				
	$\mathbf{x}_{\text{HRV}}$	$\mathbf{c}_{1,2}$	$\mathbf{c}_{2,3}$	$\{\mathbf{c}_{1,2}, \mathbf{c}_{2,3}\}^\circ$	$\{\mathbf{c}_{1,2}, \mathbf{c}_{2,3}\}^\diamond$
1	1.76	8.83	**1.68**	1.32	1.32
2	1.34	1.94	**2.55**	1.62	1.62
3	5.15	8.20	**2.75**	1.83	1.83
4	0.17	**0.16**	1.31	0.16	0.16
5	4.73	**4.19**	8.36	4.19	4.19
6	9.55	10.10	**8.02**	5.16	5.16
7	9.95	7.65	**6.67**	4.89	4.89
8	1.20	**1.07**	2.09	1.09	1.09
9	6.42	**6.16**	9.33	6.20	6.20
10	2.05	2.05	**2.95**	4.13	4.13
12	0.95	**2.86**	6.86	2.91	2.91
13	0.24	**0.59**	0.96	0.59	0.59
14	5.42	5.17	5.22	5.21	6.71
15	6.58	**3.97**	16.76	3.96	3.96
16	4.67	**0.03**	4.05	0.03	0.03
17	5.39	**2.74**	4.65	3.71	3.71
19	2.22	**0.55**	6.54	0.52	0.52
20	4.42	**3.13**	5.77	3.13	3.13
21	4.61	**5.15**	10.53	5.16	5.16
22	4.33	**5.24**	4.82	5.44	5.44
23	1.58	**1.16**	6.39	1.16	1.16
24	2.18	2.21	**0.55**	0.55	0.55
mean	**3.86**	**3.78**	**5.40**	**2.86**	**2.93**
std	**2.76**	**2.97**	**3.79**	**2.02**	**2.13**
δ	**0.19**	**0.11**	**0.18**	**0.11**	**0.11**
β	**0.50**	**0.40**	**0.50**	**0.30**	**0.30**

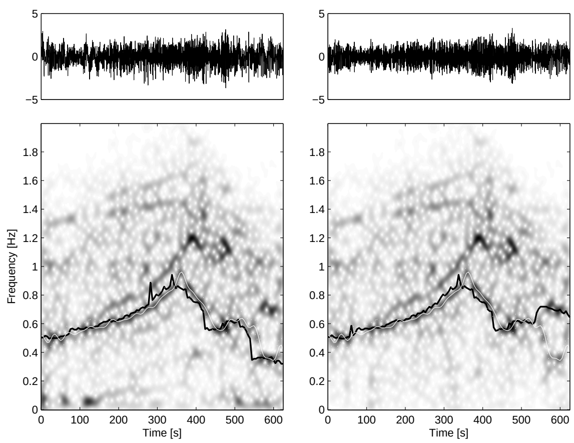
In the Fig. 1(a), respiratory frequency estimation is better when selecting the IMF $c_{2,3}(t)$ combination as the most powerful, which removes not only muscular noise bellow 0.2*Hz*, but also an undesired component above 1*Hz*. However, EMD decomposition is very sensitive to the presence of those components having frequency very close the respiratory frequency, as shown in as shown in Fig. 1(b). During the last $50\,s$ a strong time-variant frequency component that is non-related respiratory affects negatively performance of the estimation.

4. Conclusions

The proposed methodology lies on the hypothesis that providing preprocessing to accomplish an appropriate spectral decomposition, it is possible to detect the respiratory frequency with improved accuracy. So, the EMD decomposition is used, but, the respiratory frequency, moves through time over a wide range of frequencies, therefore is not contained only in one IMF, then, a methodology to extract information over combined IMF is proposed. The methodology selects the appropriate combinations of IMF improving the respiratory frequency detection in comparison to the baseline. As future work, it would be interesting to deal with other kind of power spectrum estimation,



(a)Recording # 24



(b)Recording # 12

Figure 1. Acquired time recordings and their time frequency representations of the baseline scenario *i* (left) and after introduction of HRV Enhancement using EMD (right). The white line shows the reference measurement and the black line the estimated respiratory frequency.

in order to suitable decomposes the main dynamics of the signals, allowing enhance the respiratory frequency estimation.

Acknowledgments

This work is supported by "*Jóvenes Investigadores e Innovadores*", the project "*Grupo de Control Y Procesamiento Digital de Señales 20501007205*", financed by Colciencias and Universidad Nacional de Colombia Sede Manizales, and by Ministerio de Economía y Competitividad (MINECO), FEDER, under project TEC2010-21703-C03-02 and by CIBER de Bioingeniería, Biomateriales y Nanomedicina through Instituto de Salud Carlos III, and by Grupo Consolidado GTC (T-30) from DGA and European Social Fund (EU).

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