ASSESSMENT OF CARDIOVASCULAR AUTONOMIC CONTROL BY THE EMPIRICAL MODE DECOMPOSITION

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Abstract:. RR intervals variability is an interesting tool for assessing cardiac autonomic system control, but nonstationarities raise problematic issues. We propose to use the recent method of Empirical Mode Decomposition, so as to analyze the cardiac sympathovagal balance on automatically extracted modes. Using this method and visualizing the result in the time-frequency plane, we can identify local events due to changing position, and we can assess a (time-varying) HF vs. LF discrimination without resorting to some fixed high-pass/low-pass filtering.

Keywords: Empirical mode decomposition, heart rate variability, sympathovagal balance.

I. INTRODUCTION

The analysis of fluctuations in heart rate or in the intervals between consecutive heart-beats (RR intervals, RRI) has become increasingly important in physiological studies because it could provide information about cardiovascular neural regulation [1]. The support for using heart rate variability (HRV) as an index of autonomic cardiovascular control comes from data demonstrating that HRV is virtually abolished after parasympathetic and sympathetic blockades. Human and animal studies support the hypothesis that the low frequency (LF) component of RRI could be used as a marker of sympathetic modulation to the heart, high frequency (HF) component of RRI as a marker of cardiac vagal modulation and the LF/HF ratio of RRI as a marker of cardiac sympatho-vagal balance [2, 3]. Dynamical states like standing position, are accompanied by an increased sympathetic activity characterized by a shift of the LF/HF balance in favor of the LF component; the opposite occurs during presumed increases in vagal activity [2, 4]. Thus, spectral analysis of heart rate variability has been a widely used non-invasive tool to assess sympathovagal drive to the heart. The most commonly used method of spectral analysis of HRV are the (fast) Fourier transform and autoregressive models. However these methods are limited by implicit assumptions of linearity and stationarity. Biological oscillators rarely meet these requirements. Thus it is necessary to develop a more appropriate approach for biological non-stationary processes.

We propose here to make use of a new data analysis method developed by Huang et al [5] based on the *Empirical Mode Decomposition* (EMD) method, which generates a collection of intrinsic mode functions.

II. METHODOLOGY

II.1. *From spectral to time-frequency analysis*

In order to investigate the regulating action performed by the autonomic nervous system in the heart, we analysed the RR intervals in healthy adult men recruited for voluntary participation in the present investigation. The acquisition was done continuously during three periods (Fig. 1): *proned* position (about 10 min) followed by *seated* position (about 10 min) and finally *standing* position (about 10 min). These postural changes provoke instantaneous changes in heart rate mainly resulting of autonomic modifications [3].

This figure evidences a number of variations in the signal history, including a very low-frequency trend. This makes difficult (from both points of view of computation and interpretation) the extraction of frequency informations from a standard spectrum analysis. This can nevertheless be tempted for each of the three periods (see Fig. 2) leading — in addition to a very low-frequency contribution below, approximately, 0.04 Hz — to a gross characterization of two main frequency bands: a low frequency band (LF, from 0.04 to 0.15 Hz) related to sympathetic activity and a high frequency band (HF, from 0.15 to 0.4 Hz) related to parasympathetic activity [1].

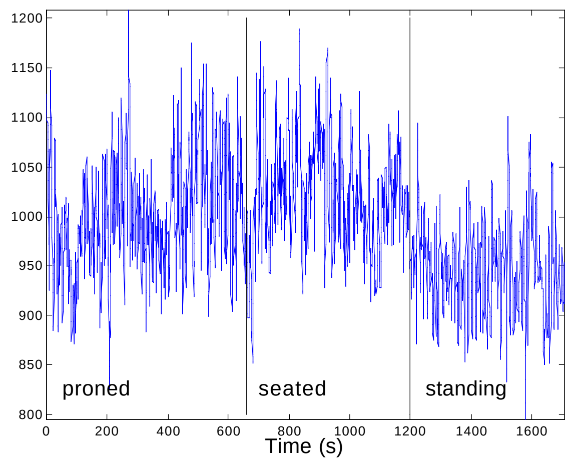

Fig. 1: RR intervals in time

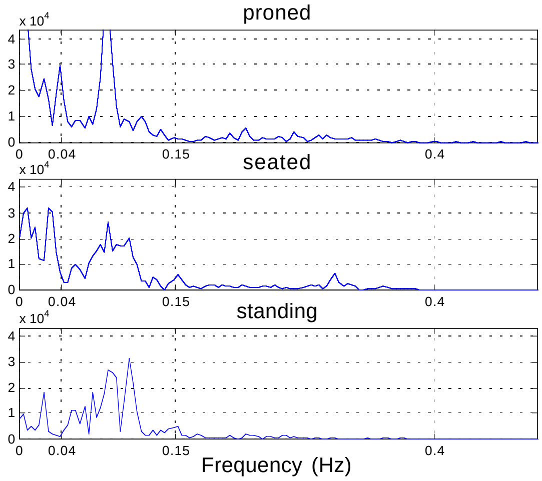

Fig. 2: RR intervals in frequency

The issue of nonstationarity, which conveys the key information about the evolution of the system, can be better addressed by resorting to a time-frequency technique, as the one used in Fig. 3 (although more elaborated methods could be used, the figure has been produced by computing a simple spectogram for a sake of simplicity [7]. It has to also be noted that, for improving readability of the diagram, the very low frequency contribution, associated in particular to "trends", has been removed by rejecting all frequencies below 0.04 Hz).

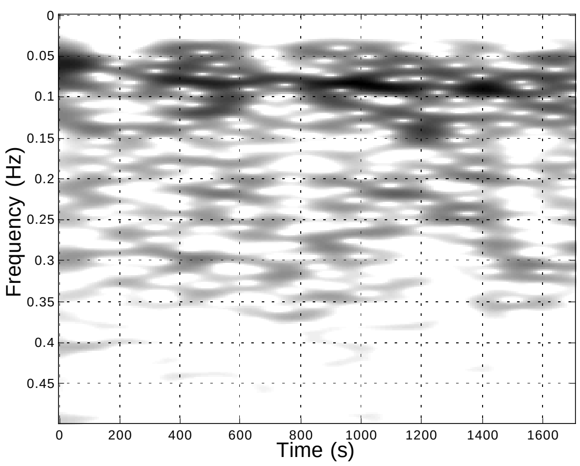

Fig. 3: RR intervals in time-frequency

In this case, it becomes apparent that the two main frequency bands involved in Fig. 2 are in fact related to the time evolution of two bandpass components. Determining the precise frequency support of these two bands (a pre-requisite for filtering them) is however difficult, and extracting corresponding AM-FM features also requires some extra post-processing (e.g., tracking of local maxima, or of local centroïds). Those difficulties suggest a different (*pre-processing*) approach which would first isolate in some way each of the two components, to which standard tools (such as instantaneous frequency estimation via the Hilbert transform) could be further applied. This point of view is the one put forward by Huang *et al*. [5], and referred to as "Empirical Mode Decomposition" (EMD).

II.1. *Empirical Mode Decomposition*

The starting point of EMD is to consider oscillations at a very local level. In fact, if we look at the evolution of a signal $x(t)$ between two consecutive extrema (say, two minima m_- and m_+, occurring at times t_- and t_+, respectively), we can heuristically define a (local) high-frequency part $d(t)$, or local detail, which corresponds to the oscillation which terminates at the two minima and which passes through the maximum M which necessarily exists in between m_- and m_+. For the picture to be complete, one still has to identify the corresponding (local) low-frequency part $m(t)$, or local trend, so that we have $x(t) = m(t) + d(t)$ for $t_- < t < t_+$. Assuming this is done in some proper way for all the oscillations composing the entire signal, the procedure can then be applied on the residual consisting of all local trends. Constitutive components of a signal can therefore be iteratively extracted this way, the only definition of such a so-extracted "component" being that it is *locally* (i.e., at the scale of one single oscillation) in the highest frequency band. Given a signal $x(t)$, the effective algorithm of EMD is as follows [5]:

1. identify all extrema of $x(t)$
2. interpolate between minima (resp. maxima), ending up with some "envelope" $e_n(t)$ (resp. $e_M(t)$)
3. compute the average $m(t) = (e_n(t) + e_M(t))/2$
4. extract the first "mode" as $d(t) = x(t) - m(t)$
5. iterate on the residual $m(t)$

In practice, the above procedure has to be refined by first iterating steps 1 to 4 upon the detail signal $d(t)$, until this latter can be considered as zero-mean according to some stopping criterion [5]. Once this is achieved, the detail is considered as the effective mode, the corresponding residual is computed and step 5 applies.

By construction, the number of extrema is decreased (on the average, by a factor of 2) when going from one residual to the next. Modes and residuals are determined on spectral arguments, but it is worth stressing the fact that their high vs. low frequency discrimination applies only locally and corresponds by no way to a pre-determined sub-band filtering (as, e.g., in a wavelet transform). Selection of modes rather corresponds to an automatic and adaptive (signal-dependent) *time-variant* filtering.

III. RESULTS

Application of EMD to the RRI signal of Fig. 1 is illustrated in Fig. 4.

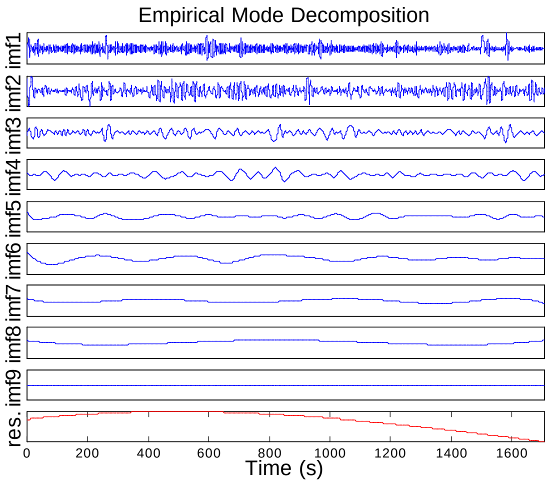

Fig. 4: EMD of RR intervals

Alternative ways of displaying the same information consists in evaluating partial reconstructions, either from coarse to fine (i.e., by adding more and more details to low frequency modes), or from fine to coarse. This is given in Figs 5 and 6. One specific interest of the fine to coarse reconstruction of Fig. 6 is that it allows for a quantitative approximation of the overall signal by means of a limited number of essential modes. In the considered case, comparing the time-frequency representation of the overall "detrended" signal (see Fig. 3) with that of the partial reconstruction built on the 3 first intrinsic modes (Figure 7) reveals a striking agreement, thus justifying that most of the LF and HF structure of the signal has been captured.

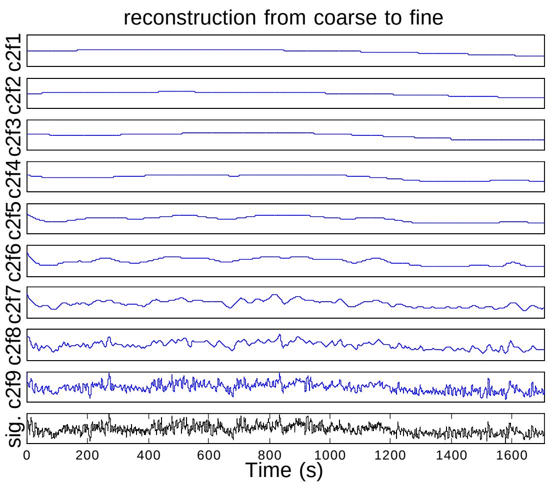

Fig. 5: Coarse to fine reconstruction of RR intervals

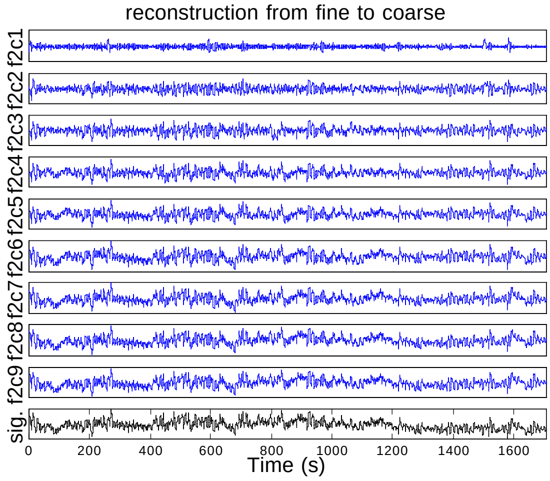

Fig. 6: Fine to coarse reconstruction of RR intervals

Moreover, it turns out that the obtained representation does not suffer from any arbitrary high-pass filtering aimed at removing the very low-frequency component attached to trends. This component is indeed adaptively removed (in a time-varying way) while not perturbating the adjacent LF component we are interested in. As a result, we can consider that the effective, time-varying, HF component identifies to the first intrinsic mode of the decomposition, while the LF component is correctly described by the superposition of the second and third intrinsic modes.

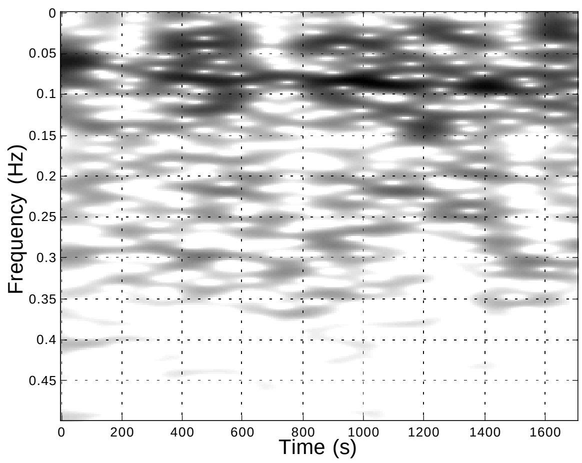

Fig. 7: 3 first modes of RR intervals in time-frequency

This identification achieved, it becomes possible to process independently each of the two components, either by evaluating their AM-FM features, or by computing the LF/HF ratio of RRI as a marker of cardiac sympatho-vagal balance. The HF vs. LF separation is of particular importance if we consider in closer detail Figs. 3 and 7, where it appears that, at the precise time instant (namely, t = 1200 s) where the position is changed from *seated* to *standing*, the most energetic contribution does not clearly belong to what is usually referred to the LF band (0.04-0.15 Hz) or the HF band (0.15-0.4 Hz), but rather sits on the borderline 0.15 Hz. Figure 8 displays the time-frequency representations of both HF and LF components of RR intervals, evidencing the fact that this contribution is considered by the EMD as belonging to the HF part of RRI. The consequence of this identification is that the LF/HF ratio is likely to be diminished as compared to what would have been obtained with a crude filtering which would have attached part of the energy below 0.15 Hz to the LF component. The overall signal being nonstationary, and especially at changing points (with respect to position), this observation stresses the limitation of any conventional fixed filtering in a time-varying situation.

IV. CONCLUSION

A link appears to exist between cardiac vagal or sympathetic activity and HF or LF oscillations of RRI. A number of approaches are currently available for analysing periodic components of RRI like the (fast) Fourier transform or autoregressive models. These methods can provide valid estimates of periodic components of HRV when the target rhythm is sinusoidal and the data is stationary. In recent years the study of data analysis has tended to focus far more on the methods that do not need linearity and periodicity of the signal. This comes from the fact that it has been quite difficult to satisfactorily handle the nonstationary mechanisms regulating the cardiovascular system using conceptualisations based on stationarity. In order to cope with nonstationarity issues and to adaptively separate the (time-varying) HF and LF components of RRI, we proposed here to make use of the recently introduced method of Empirical Mode Decomposition (EMD), so as to analyze the cardiac sympathovagal balance on automatically extracted modes. Using this method and visualizing the result in the time-frequency plane, we can identify local events due to changing position, and we can assess a (time-varying) HF vs. LF discrimination without resorting to some fixed high-pass/low-pass filtering.

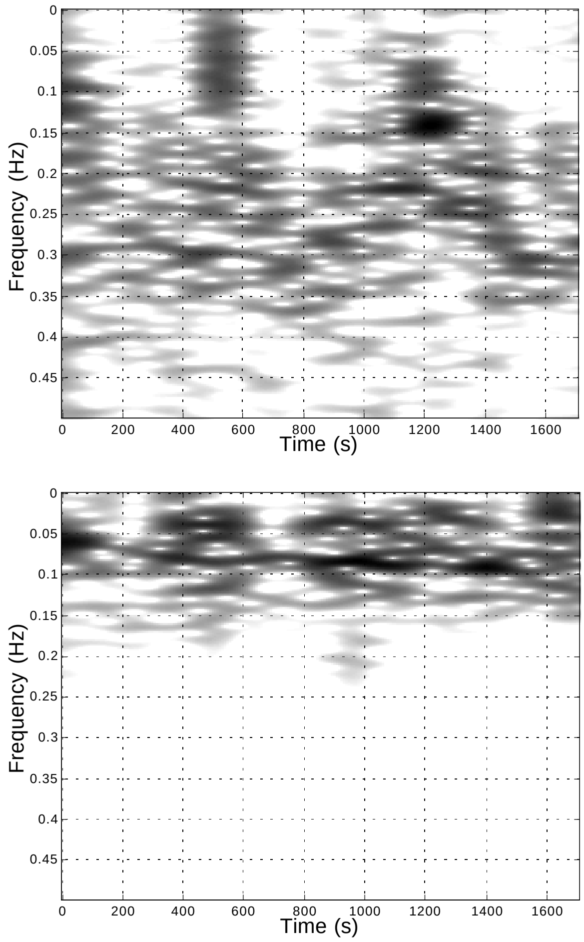

Fig. 8: HF (top) and LF (bottom) components of RR intervals in time-frequency, identified as intrinsic mode 1 and intrinsic modes 2+3 of the EMD, respectively

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