Interpreting Power-Spectral-Measures Extracted from Sympathetic Nerve Activity: Possibilities and Pitfalls

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Abstract

This paper discusses the possibilities and potential pitfalls associated with interpretations based on the low-frequency power (LFP), the high-frequency power (HFP) and their ratio: PR=LFP/HFP, computed from muscle sympathetic nerve activity (MSNA). Segments of MSNA from several subjects were analyzed by Capon's minimum variance distortionless response (MVDR) method. The power spectra revealed peaks within [0-0.5] Hz, apart from the peak at the cardiac-related frequency (CF). Our investigations reveal that: (1) the presence of nearly periodic (groups of) bursts can produce strong harmonics that affect the HF component and hence the accuracy of HFP and PR, (2) changes in the strong CF-component can affect the components within the lower frequency range, and (3) small changes in the location of the needle electrode can affect the spectral-measures.

1. Introduction

Spectral analysis of sympathetic nerve activity (SNA) has attracted significant attention over more than a decade [1],[2],[3],[4],[5],[6],[7],[8],[9]. This has been motivated, if not entirely, by the extensive research on non-invasive assessment of sympatho-vagal interaction within the autonomic nervous system, based on power-spectral measures of cardiovascular signals such as heart rate variability (HRV) [10],[11],[12]. The spectral-measures of interest are the low-frequency (LF~0.1 Hz, attributed primarily to the sympathetic system) power (LFP), high-frequency (HF~0.2 Hz, attributed to the parasympathetic system) power (HFP) and their ratio, PR (LFP/HFP, considered to be an index of sympatho-vagal balance [11],[12], although controversies exist [13],[14]). The advent of microneurography providing a direct access to MSNA has naturally led to studies involving the spectral measures, on the lines of the analysis of cardiovascular signals. Accordingly, spectral analysis of SNA has been of immense utility for validating the interpretations based on the analysis of cardiovascular signals [2],[7],[8] and studying possible relationships among the oscillatory components within the two signals [1],[9],[4],[6],[8], apart from its value in understanding the role of SNA in cardiovascular regulation [15]. In particular, power-spectral measures are being used to study the relationship between cardiovascular signals and SNA [4],[6],[9] .

Clearly, the analysis of SNA on the lines of the spectral analysis of cardiovascular signals is well motivated. However, cardiovascular signals such as HRV and the integrated SNA are of different characteristics. While HRV is band-limited (with limited variations), the integrated SNA is a train of groups of bursts (*cf.* [16]). Consequently, investigations are essential – from a signal processing perspective – before attempting to interpret the power-spectral measures computed from SNA, as discussed below.

2. Methods

Power spectrum estimation: We use Capon's minimum variance distortionless response (MVDR) method for estimating the power spectrum (PS) [17],[18]. The method treats the problem of estimating the power at a frequency ω, as one of designing a unity gain, narrow-band filter centered at ω, and measuring its output power. The design involves finding a finite impulse response (FIR) filter $\boldsymbol{h}$ according to the optimization criterion [18]:

$$\boldsymbol{Min.}\ P_O(\omega) = \boldsymbol{h}^T \boldsymbol{R}\boldsymbol{h}, \quad \boldsymbol{Sub:}\ \ \boldsymbol{v}^* \boldsymbol{h} = 1 \qquad (1)$$

where $\boldsymbol{v} = [1 \ \ e^{j\omega}\ e^{j2\omega} \ \ldots\ e^{jM\omega}]^{\mathrm{T}}$, M is the *order* of the filter and $\boldsymbol{R}$ is the correlation matrix. The output power of the optimum filter at frequency ω is given by [18]:

$$P_{MVDR}(\omega) = \frac{1}{\boldsymbol{v}^* \boldsymbol{R}^{-1} \boldsymbol{v}} \qquad (2)$$

Free of the assumptions associated with a model, the MVDR PS has a resolution higher than that of Fourier transform-based methods [18], though lower than that of autoregressive (AR) power spectrum *density* (PSD). However, the MVDR method gives a *power spectrum*, so that the power at a dominant frequency can be read-off – unlike the AR approach, in which the power must be estimated by numerical integration of the PSD over an interval, for which there is no clear guidance (nevertheless, area-based estimate is more tolerant to the noise-strength and model-order than that based on the residue method [19]). In contrast, the MVDR estimator

involves an implicit narrow-band, data adaptive & frequency-dependent window. Further, the variability of the MVDR-estimate of PR is lower than that of AR-estimate (at low orders) [19],[20]. Note that the MVDR PS can be efficiently computed through its relation to the AR coefficients [21]:

$$P_{MVDR}(\omega) = \frac{1}{\sum_{k=-M}^{M} \mu(k) e^{j\omega k}} \qquad (3)$$

where, the MVDR coefficients $\mu(k)$ are given by a linearly weighted correlation of the AR coefficients $\{a_k, k = 0, 1,\ldots, M\}$:

$$\mu(k) = \frac{1}{E_M} \sum_{i=0}^{M-k} (M+1-k-2i) a_k a^*_{i+k}, \quad k = 0,\ldots,M$$
$$= \mu^*(-k), \qquad k = -1,\ldots,-M \qquad (4)$$

In (4), E_M is the AR prediction-error-variance. The AR coefficients are computed efficiently by Levinson-Durbin algorithm, and the FFT is employed to evaluate the PS.

Pre-Processing: As the integrated MSNA was sampled at 1 KHz (except for one record at 400 Hz), each 2 min. segment had 120000 samples. To alleviate the difficulty arising from the requirement of large orders and to reduce the processing-time, the MSNA records were low-pass filtered (10 Hz cutoff) and decimated to 100 Hz. The processed waveforms were visually indistinguishable from the original.

Spectral analysis was performed on the MSNA of 7 healthy subjects recorded in *supine* and 60° *head-up-tilt* positions, on two different days. The PS of a 2-min. segment of each of the subjects was examined over [0-2.5] Hz.

3. Results

The power spectra of MSNA segments revealed peaks within [0.-0.5] Hz, and also the cardiac-related frequency (CF) component. Although peaks similar to those typical in HRV spectra appeared within the [0.05-.5] Hz range, multiple and/or smeared peaks were also observed in several cases. Further, while the CF-peak was prominent and narrow in many cases, it was often split and/or stretched and/or smeared. The preceding observations indicate the potential difficulties in interpreting the spectral measures of LFP, HFP and PR extracted from integrated MSNA, as explained subsequently.

We start by recalling that integrated MSNA is a train of bursts that often occur in groups; these constitute a non-sinusoidal (pseudo-) periodicity, the predominant source of the LF component. A consequence of such a periodicity is the presence of harmonics (multiples of the fundamental frequency, f_F) in the PS. To illustrate this point, consider the PS of a periodic train of pulses (in noise) of "noisy" period and height (Fig. 1). Note the presence of harmonics, shifted slightly from the multiples of f_F. The PS of a 2-minute segment of MSNA (Fig. 2) displays a similar harmonic structure (f_F ~ 8/60 = .135 Hz), as expected from the nearly regular groups of bursts in the MSNA. Thus, the significant harmonics due to strong LF-groups interfere with the detection and estimation of the HF component, as the latter is expected to be located within the frequency-range of the former. This illustrates the difficulty in interpreting HFP and PR, in the presence of strong "LF periodicity" (not narrow-band).

We now consider the effects of a varying CF component in MSNA. From an understanding of HRV, it is reasonable to expect the value of CF to vary. Firstly, note that such a variation renders the data non-stationary. Next, to gain an impression of the manifestation of variations in CF, we conducted simulation experiments involving a sinusoid of frequency varying about 1 Hz. We found that, in general, such variations result in (i) shifted and smeared signal-peak, and (ii) potential spurious peaks over the lower frequency-range. An example is shown in Fig. 3(a). In general, the location and the strength of the spurious peaks depend upon the extent and degree of variations in CF. In Fig. 3(b), the PS of a 2 minute segment of MSNA is displayed. Notice the split and spread CF component. To find out about the possible variations in the CF component, the CF was extracted from consecutive 5 sec. segments spaced 1 sec. apart. The peaks in the 5 sec. segments were generally unlike the split/spread CF-peak in Fig. 3(b), except possibly over intervals of strong variation. The result of tracking the value of CF, shown in Fig. 3(c), confirms variation.

Finally, we discuss the sensitivity of the MSNA PS to the position of the electrode. The spectra associated with the two records of MSNA of a subject in supine position in the same experimental session, corresponding to two slightly different electrode-positions, are shown in Fig. 4. Notice the difference in the spectra within [0–0.5] Hz. Incidentally, the harmonic structure of the PS in (a) interferes with the detection of the HF component (HFC). From its prominence and proximity to the HFC in (b), the peak to the right of the largest wihtin [0-.5] Hz was taken to be the HFC. The values of PR for the two cases were 1.2 and 2.6 respectively. The difference in the values of PR may very well be due to the power added to the HF range by the harmonics of LF periodicity.

4. Conclusion

Spectral analysis of integrated MSNA of several subjects exhibited dominant components within [0-0.5] Hz, indicating the possibility of interpretations based on power-spectral measures. However, examples exposing the factors that can affect the accuracy of the spectral measures suggest the potential pitfalls associated with interpretations based on the measures. The factors

discussed in this paper should be considered before arriving at conclusions based on the spectral measures extracted from MSNA.

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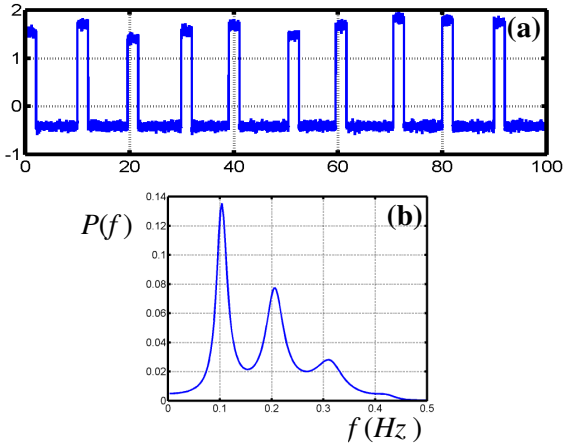

Fig. 1 (a) A 100 sec. waveform of nearly periodic (10 s) train of pulses of slightly perturbed amplitudes, and (b) its PS.

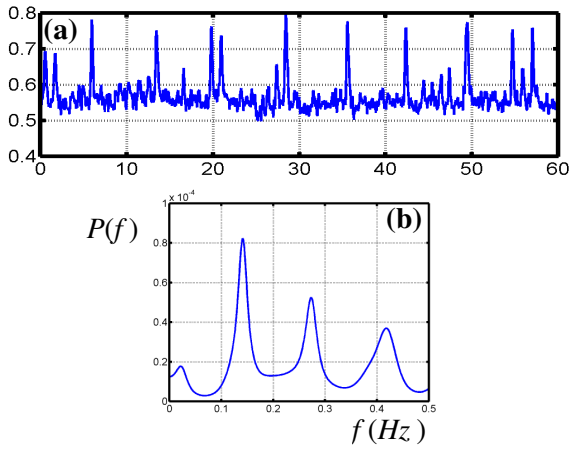

Fig. 2: (a) A 1 min. segment of MSNA with about 8 significant (groups of) bursts, and (b) its PS.

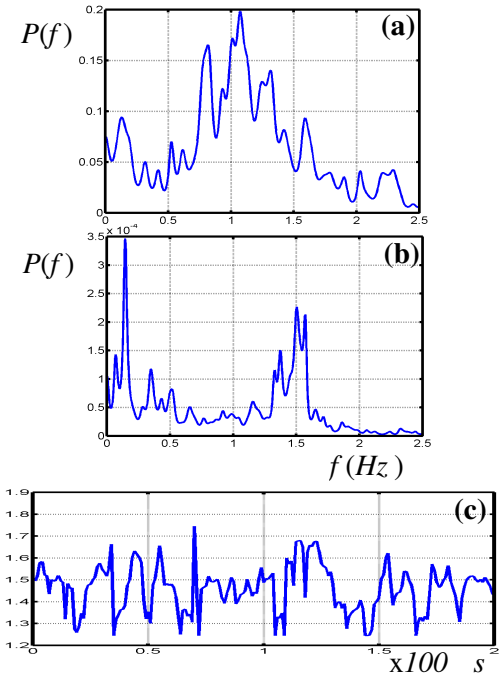

Fig. 3: (a) PS of a sinusoid in noise, with (sinusoidal) variations in the frequency (about 1 Hz). (b) PS of a 2 min. segment of MSNA, showing a split and spread CF-peak. (c) Variations in CF as a function of time.

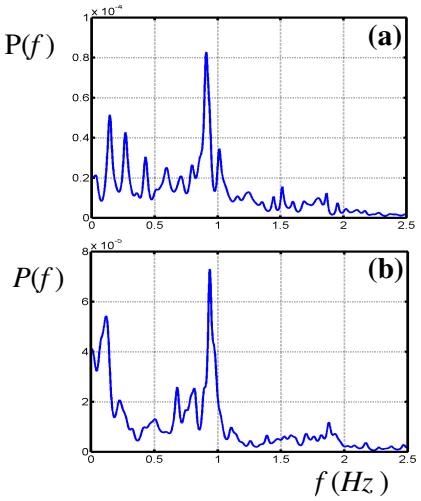

Fig. 4: The power spectra of 2-min. segments recorded from the same subject during the same session, at slightly different electrode-positions. PR: (a) 1.2, and (b) 2.6.

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