A Unified Framework for Investigating Aperiodic and Periodic Components in the Hearbeat Dynamics Spectrum: a Feasibility Study

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***Abstract*— Heart Rate Variability (HRV) series is a widely used, non-invasive, and easy-to-acquire time-resolved signal for evaluating autonomic control on cardiovascular activity. Despite the recognition that heartbeat dynamics contains both periodic and aperiodic components, the majority of HRV modeling studies concentrate on only one component. On the one hand, there are models based on self-similarity and $1/f$ behavior that focus on the aperiodic component; on the other hand, there is the conventional division of the spectral domain into narrow-band oscillations, which considers HRV as a combination of periodic components. Taking inspiration from a recent parametrization of EEG power spectra, here we evaluate the applicability of a unified modeling framework to quantitatively assess heartbeat dynamics spectra as a mixture of aperiodic and periodic components. The proposed model is applied on publicly-available, real HRV series collected during postural changes from 10 healthy subjects. Results show that the proposed modeling effectively characterizes different experimental conditions and may complement HRV standard analysis defined in the frequency domain.**

I. Introduction

The analysis of heart rate variability (HRV) series is an important tool for studying the impact of autonomic nervous system (ANS) control on cardiovascular activity [1]–[4]. It has been established that such an ANS control is influenced by the interplay between sympathetic and vagal activities to regulate sinus node activity, producing time-varying heartbeat dynamics, which also reflects the influence of respiration, blood pressure, and functional brain-heart interplay [1], [5].

Pathological processes can arise from dysfunction in ANS control and can affect the cardiovascular system with, e.g. hypertension [6] and heart failure [7], as well as may affect other physiological systems (e.g. in case of diabetes and obesity [8], and mood disorders [5]).

Quantitative assessment of ANS control on cardiovascular activity is usually performed through HRV analysis in the frequency domain [1], [2], which mainly reflects heartbeat linear dynamics. The spectral analysis of HRV typically involves the identification of three main oscillatory components: high frequency (HF) $[0.15, 0.4]Hz$, whose power may be a biomarker of respiratory sinus arrhythmia and vagal activity in case the respiratory frequency is in the same band [9]; low frequency (LF) $[0.04, 0.15]Hz$, which may be associated with blood pressure regulation, vasomotor tone, and sympathovagal activity [2], [3]; and very low frequency (VLF) $[< 0.04Hz]$, less employed, whose physiological correlates are not clarified yet. While spectral power within the aforementioned bands are widely used in research, especially LF power is not specific to a single ANS activity [2], [3]. This indeed limits the reliability of a HRV frequency domain analysis, especially in case of clinical applications. Besides linear dynamics, nonlinear and complexity analysis of HRV series have provided powerful computational tools to discern, e.g., healthy vs. pathological heartbeat dynamics [10]. Nevertheless, physiological correlates of heartbeat nonlinear and complex dynamics are unknown and quite hard to be uncovered [10], [11].

In light of the above, there is the need for devising novel methodological framework accounting for heartbeat nonlinear dynamics, while being linked to cardiovascular physiology, i.e., to a frequency domain analysis. To this end, in this study we evaluate the applicability of a unified methodological framework accounting for periodic and aperiodic components of HRV spectra.

We took inspiration from a recent methodology proposed by Donoghue et al., who demonstrated that, in the frame of a frequency domain analysis, electrophysiological signals may be modelled as an aperiodic component showing an exponentially decreasing power across increasing frequencies, on which a number of oscillations are superimposed as narrowband peaks of power [12], [13]. Indeed, in heartbeat dynamics, the spectrum is known to manifest a similar profile, with $1/f$-like behavior [14]–[16], and multiple known oscillations [3]. Note that, in presence of a spectral power change, the usual interpretation is an associated oscillation drift, i.e., changes in the linear dynamics of the system. However, the same analytic band power change might be due to several factors, as true oscillatory power variation, alterations in the aperiodic components, shifts in the cental frequency of the oscillation, or others [12].

Here, we assess the applicability of the aforementioned algorithm, also known as *SpecParam* [12], in benchmark experimental series gathered during tilt-table tests in healthy subjects. The aim is to quantitatively characterize variations in heartbeat dynamics by taking into account both periodic and aperiodic parameters.

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II. Materials and Methods

A. Experimental Dataset

The "Physiologic response to changes in posture" dataset [17] was used to test the proposed SpecParam algorithm in real HRV series. This dataset is publicly accessible on Physionet [18] and consists of data collected from ten healthy volunteers (five males and five females, with an average age of 28.7 ± 1.2 years). The participants provided informed written consent for the procedure, and the signals were obtained using a standard clinical ECG device. The experimental protocol included a 5-minute resting state followed by a series of postural changes, specifically two fast head-up tilts (75° head-up tilt over 2 seconds) each maintained for 3 minutes. The experimental procedure was approved by the local ethical committee and additional details can be found in [17].

The ECG data were analyzed using the Pan-Tompkins algorithm [19] to identify the R-peaks and derive the HRV series. Such series were also preprocessed using a point-process based model [20] to eliminate ectopic and erroneous heartbeats and then interpolated to a frequency of $4Hz$. Power spectral density (PSD) estimation was calculated using the standard Burg's method [21], with order 30. Canonical LF and HF powers estimation were performed through the analytic integral of the extracted PSD in the associated frequency bands, i.e. $[0.04, 0.15]Hz$ and $[0.15, 0.4]Hz$, respectively.

B. SpecParam model for periodic and aperiodic components of the HRV spectrum

The SpecParam model proposed in [12], [13] formalizes the PSD as a combination of an aperiodic component, counting for $1/f$-like profile, that covers the entire frequency spectrum, and multiple periodic components, corresponding to narrow-band oscillations referred to as "peaks". The model operates in a semi-log space, with frequency represented on a linear scale and PSD on a logarithmic scale. The PSD formulation is the following:

$$PSD = A + \sum_{i=1}^{N_p} P_i \tag{1}$$

where A is the aperiodic component, and the sum of N_p peak functions P_i models the periodic one. For each of the N_p peaks identified in the power spectrum, a P_i Gaussian function is defined as follows:

$$P_i = \rho \times \exp\left(\frac{-(\hat{f} - \mu)^2}{2\sigma^2}\right) \tag{2}$$

where $\hat{f}$ is the frequency vector, ρ is the peak power as $\log_{10}$(power), μ is the central tendency frequency expressed in Hz, and σ is the Gaussian's standard deviation, also expressed in Hz.

Furthermore, a Lorentzian function is employed to model the aperiodic component, A, as follows:

$$A = \phi - \log(k + \hat{f}^{\chi}) \tag{3}$$

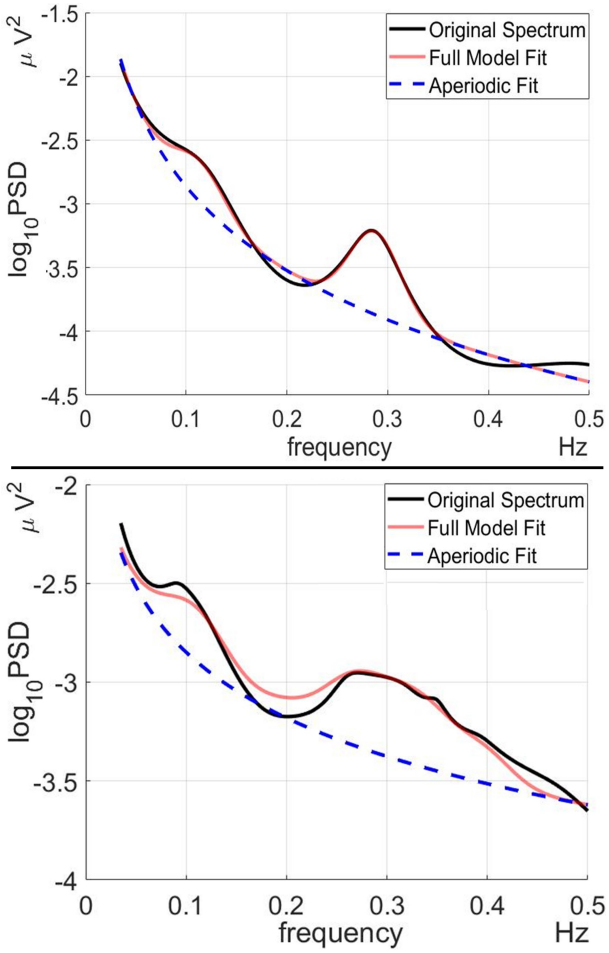

Fig. 1: Exemplary SpecParam model fitting on HRV spectra, with black line indicating the original spectrum, blue dotted line representing the aperiodic component, and red shaded line reporting the complete model fitting (combination of the aperiodic and two periodic components). Top panel refers to HRV series from an exemplary subject, subject 1, in the resting state, whereas bottom panel refers to median spectrum across all subjects during the resting state.

where $\hat{f}$ is the frequency vector; χ is the exponent; ϕ is the broadband offset; and k is the so-called "*knee*" parameter, formally the point of inflection of the exponential function (i.e., when $k = 0$ the exponential collapses to a line in $\log - \log$ space). Fitting the k parameter allows for a better characterization of the aperiodic component in a broad frequency range, e.g. in the HF frequency band. Figure 1 shows an exemplary model fit for both subject specific (i.e., subject 1, on the top panel), and group-wise (i.e., median across subjects, on the bottom panel) spectra recorded during the resting state.

The algorithm described in [12] and accessible on *https://github.com/fooof-tools/fooof* provides output of the best-fit parameters for the aperiodic component (ϕ and χ) and the N_p identified Gaussian peaks. For each periodic component, the algorithm outputs: i) the central frequency

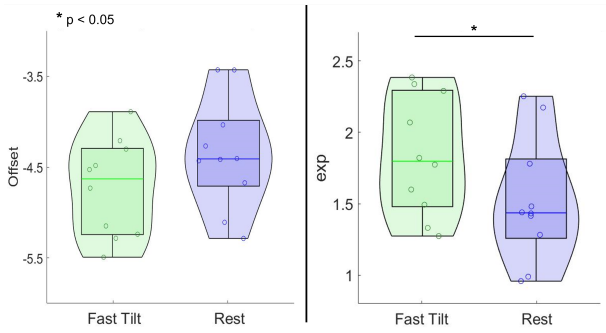

Fig. 2: Boxplot statistics of the aperiodic components extracted from the model fitting for both fast tilt (green boxes) and resting state (green boxes) experimental conditions. Left sub-panel refer to the offset parameter; right sub-panel refers to the exponent parameter. Asterisks indicate statistical differences with p-value < 0.05.

μ, ii) the adjusted power, which is the distance between the peak of the Gaussian and the aperiodic fit, associated to ρ, and iii) the bandwidth, represented by 2σ (see Eq. 2).

The model can accurately compute these parameters even in the presence of overlapping oscillations, reducing their confounding effect, and automatically identify them when present, without relying on narrow-band definitions. As an example, if a subject does not exhibit peaks in the HF frequency band, the algorithm will not consider periodic components in that band, unlike canonical HRV analysis which may still estimate HF even if an oscillation is not present. As a result, the number of peaks N_p identified as periodic components may serve as a potential biomarker for the analyzed time series.

Experimental results refer to the application of the SpecParam model for the parametrization of periodic and aperiodic components of the HRV spectrum on data gathered during fast tilt and related resting state. The model is then applied subject-wise to fit each spectrum derived from each subject and experimental condition. Results then refer to feature inferential statistics between sessions.

III. Results

The figure 2 presents the results on the HRV aperiodic component, which is characterized by the offset parameter ϕ in equation 3 and the exponent parameter χ. A non-parametric Wilcoxon sign-test was used to perform statistical analysis on paired samples. In the fast tilt condition with respect to the resting state, while the offset parameter showed an increased trend ($p = 0.08$), the exponent parameter showed a significant reduction ($p = 0.009$).

The HRV periodic component was characterized by the number of peaks observed in each experimental condition, as displayed in Table I. The Stuart-Maxwell's test, a statistical test for two categorical paired samples [22], showed a p-value of 0.0327, indicating a statistically significant increase in the number of peaks from the resting state to the fast tilt phase.

TABLE I: Occurrences for each number of periodic components identified in the two experimental conditions. Rows refer to the fast tilt phase, whereas the columns refer to the resting state. The element on the *i-th* row, *j-th* column depicts the number of subjects having the *i-th* number of periodic components identified during fast tilt and the *j-th* number of periodic components identified during rest.

		rest		
		1 peak	2 peaks	3 peaks
FT	1 peak	1	2	0
	2 peaks	0	2	1
	3 peaks	2	2	0

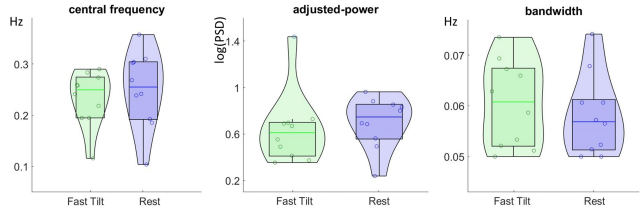

Fig. 3: Boxplot statistics for the model periodic components extracted from the model fitting for both fast tilt (green boxes) and resting state (blue boxes) experimental conditions. Left sub-panel refer to the central frequency parameter (μ); central sub-panel refers to the adjusted-power parameter (ρ); right sub-panel refers to the bandwidth parameter (2σ).

Figure 3 illustrates the experimental results for the periodic component identified through model fitting in both experimental conditions. This component is defined by the peaks identified by the algorithm in equation 2, including the central frequency (μ), the adjusted-power parameter (ρ), and the bandwidth parameter (2σ). No statistically significant differences were found in the parameters of the HRV periodic component between sessions, apart from the previously noted differences in the number of peaks detected.

Figure 4 illustrates the experimental results for the canonical LF (left sub-panel) and HF (right sub-panel) estimation given from the integral of the PSD in the associated frequency bands, in both experimental conditions. While trends are in agreement with expected changes (i,e., reduced vagal activity during fast tilt), no statistically significant differences were found using these canonical powers, as already reported in previous studies [2].

IV. Discussions and Conclusion

This paper presents a feasibility study to demonstrate the potential of a novel formulation for modeling the PSD of heartbeat dynamics. The SpecParam model, originally proposed in [12] for fitting the PSD of neural dynamics, has been adapted to fit the PSD of HRV series. The model represents the spectrum as a combination of an aperiodic and multiple periodic components in a semi-log space, providing a more comprehensive analysis compared to the traditional HRV spectral analysis.

The model was applied to a benchmark dataset of cardiovascular series obtained during postural changes [17].

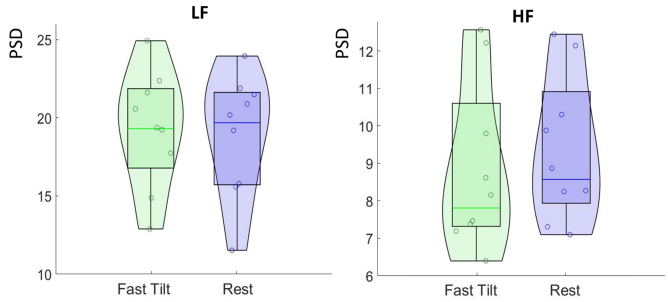

Fig. 4: Boxplot statistics for the canonical LF (left sub-panel) and HF (right sub-panel) power estimation on both fast tilt (green boxes) and resting state (blue boxes) experimental conditions.

Despite important sympathovagal changes occuring during postural changes with respect to the resting state [2], [17], canonical spectral power analysis and narrow-band division in HF and LF has failed in finding significant differences in such a limited dataset [2]. Our experimental results showed significant differences between fast tilt and resting state sessions in terms of the aperiodic component, specifically the exponent parameter χ, as well as in the number of periodic components N_p. A possible explanation might be that the canonical bands estimations may be greatly influenced by the shape of the spectra in different experimental conditions. Narrow-band power analysis or $1/f$-like behavior analysis alone might not capture all aspects of the underlying autonomic control phenomena.

In terms of the algorithm's application to heartbeat dynamics series, further development may be required to comprehensively characterize heartbeat dynamics, such as accounting for the total power of the periodic component, which was currently not included in this feasibility study. Limitations include the potential influence of the PSD estimation procedure on the extracted aperiodic or periodic parameters, which requires further investigation in future studies on both heartbeat and neural series.

In conclusion, the described model is feasible for heartbeat dynamics analysis and requires further application to diverse datasets to understand the physiological implications of the extracted parameters in both physiological and pathological conditions.

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