PHASE-RECTIFIED SIGNAL AVERAGING METHOD APPLIED TO HEART RATE VARIABILITY SIGNALS FOR ASSESSMENT OF THE CHANGES IN SYMPATHOVAGAL BALANCE DURING REST AND TILT

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ABSTRACT

The phase rectified signal averaging (PRSA) method is a technique initially developed to evaluate the acceleration and deceleration of the cardiac rhythm when applied to long-term-recordings of heartbeat intervals [1]. Because PRSA enables better cancellation of non-periodic or/and intermittent components, artifacts and impulsive noise, the quasi-periodic components are enhanced compared with classical Fourier analysis. Thus provides a higher accuracy for the detection of the most important frequencies.

We propose to quantify the changes in sympathovagal balance by characterizing the PRSA power spectrum of heart rate variability (HRV) signals during rest and tilt. Synthetic and clinical HRV signals of short-term recordings are considered. The results demonstrate the PRSA capacity to significantly discriminate rest and tilt in terms of dominant frequencies. The bias and standard deviation of the estimated sympathovagal balance are also computed and compared with those obtained with a classical spectral method.

1. INTRODUCTION

The heart rate variability (HRV) signals are defined as the fluctuation time-series in the beat-to-beat RR-intervals. Over the past two decades, power spectral analysis of HRV signals has become a commonly used tool, for assessing the effect of the sympathetic and parasympathetic modulations of the RR-intervals in a non-invasive manner [2, 3, 4, 5, 6].

The HRV power spectrum is usually divided into different spectral bands [2, 4]. The boundaries of the most commonly used frequency bands are referred to as the very low frequency (VLF) band ($<$ 0.04 Hz), the low frequency (LF) band (0.04Hz - 0.15 Hz) and the high frequency (HF) band (0.15Hz - 0.4 Hz). These boundaries may fluctuate around these ranges. Parasympathetic activity is thought to influence the HF components whereas both sympathetic and parasympathetic activities have an effect on the LF components. The measure of the ratio of the LF and HF component powers (LF/HF ratio) has been used as an index of the balance between the effects of the sympathetic and parasympathetic systems, which is referred to as the sympathovagal balance.

Unfortunately, HRV signals are non-stationary and often contaminated by impulsive noise and artifacts due to abnormal beats, unevenly sampled or/and missing data. The cancellation of these artifacts and noise using classical spectral methods is never perfect and it requires assumptions of models and special rules. Moreover, phantom beat replacement can deteriorate the estimation accuracy of the power spectral density (PSD), even at low levels of artifacts [7]. Therefore, the development of an insensitive method to such artifacts and abnormal beats is a need for HRV signal processing.

In [1, 8, 9], authors proposed a non-linear signal transformation, called the phase-rectified signal averaging (PRSA), the principle of which is very easy and they applied it to HRV signals. The center deflection of the obtained PRSA curve efficiently characterizes the average capacity of the heart to decelerate or accelerate the cardiac rhythm. Later, the PRSA method was applied to a variety of other applications to enhance quasi-periodic components embedded in non-stationarity. For example, the PRSA method was applied to electrocardiogram signals to perfectly cancel the ventricular component [10, 11]. In [12], a new time-frequency representation based on the PRSA principle was defined to analyze electroencephalogram signals.

In the present paper, we aim at better quantifying the sympathovagal balance using the PRSA method. The investigation is performed by a spectral analysis of the PRSA curves. This can provide a higher sensitivity for the detection of the dominant frequencies related to sympathetic and parasympathetic activities during rest and tilt. Because of its properties: elimination of non periodic components, cancellation of artifacts and reducing impulsive noise, PRSA can allow a better accuracy of the LF/HF ratio estimation of both situations. The potential of PRSA is demonstrated through experiments both on synthetic and clinical HRV signals. A comparison with a parametric autoregressive (AR) spectral method is also provided.

The paper is organized as follows. The PRSA principle, a classical parametric spectral method and the HRV signal data set are described in section 2. A deflection criterion is also introduced to help compare the performance of the PRSA with the classical parametric spectral method. Results and discussions of assessing the LF/HF ratio based on the PRSA method are provided in section 3 for synthetic and real data HRV signals. The final section concludes with a summary and some progress on our study.

2. METHODS

Two different methods PRSA and a classical parametric spectral method are compared in the assessment of the changes in the LF/HF ratio, expected during a stand-test. In a first step, comparisons were conducted in simulated conditions and in a second step, those were conducted in RR real data.

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2.1 PRSA method

The basic idea of PRSA is the averaging of selected segments of a discrete time signal y_n corrupted by artifacts and noise. These segments are symmetric regarding to so-called anchor points, samples at which the instantaneous phase of the signal is close to zero. In the simplest version of PRSA [1, 8, 9], the anchor points coincide with the increases in the signal y (Fig.1(b)), i.e. instants n such that $y_n > y_{n-1}$.

Assuming a total of M anchor points indexed by n_m, $m = 1,\ldots,M$, segments of length $2L+1$ are centered on these anchor points (Fig.1(b-d)),

$$[y_{n_m-L}, y_{n_m-L+1}, \ldots, y_{n_m}, \ldots, y_{n_m+L-1}, y_{n_m+L}]. \quad (1)$$

All these segments are averaged, which leads to the PRSA signal $\tilde{y}_\ell$

$$\tilde{y}_\ell = \frac{1}{M}\sum_{m=1}^{M} y_{n_m+\ell}, \quad \text{for} \quad \ell = -L, -L+1, \ldots, L. \quad (2)$$

Finally, a classical PSD estimation technique is applied to $\tilde{y}_\ell$. Figure 1 displays the steps of the PRSA method for a simulated signal.

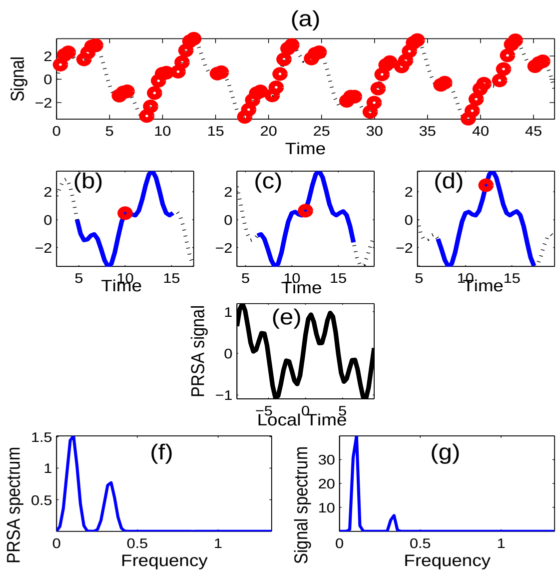

Figure 1: Principle of PRSA: (a) signal $y_n = \sin(2\pi 0.23n) + 1.5\sin(2\pi 0.097n)$ (dotted line), anchor points (circle). (b)-(d) Segments of length $2L+1 = 29$ centered on anchor points. (e) PRSA signal $\tilde{y}_\ell$ (2), (f) PRSA spectrum and (g) signal spectrum. The sampling frequency is 2.7 Hz.

When the signal is corrupted by noise and artifacts, the potential quasi-periodic components which are hidden in a classical Fourier transform of the signal y_n, appear more clearly in the spectrum of PRSA signal (2). This is illustrated in Fig.2 for a simulated example. The signal considered is a pure tone at the frequency 0.097 Hz contaminated by an impulsive noise. As can be observed, the peak frequency at 0.097 Hz is clearly enhanced using the PRSA method (Fig.2(b)) while this peak is hidden in the classical signal spectrum (Fig.2(c)). Actually, the averaging process removes correlated or nonperiodic components of the signal (such as noise and artifacts) while phase resetting helps enhance the existing local-periodicities. Other examples illustrating the potential of the PRSA as a tool to improve the estimation of existing periodicities are provided in [10, 11, 12].

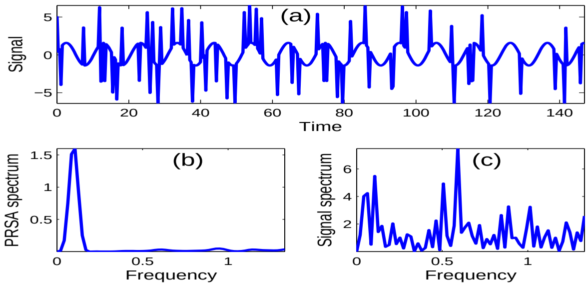

Figure 2: Enhancement of existing quasi-periodic components in signals using PRSA method: (a) studied signal $y_n = 1.5\sin(2\pi 0.097n)$ embedded in impulsive noise, (b) spectrum of PRSA signal (2) and (c) signal spectrum.

2.2 Parametric spectral estimation

Although the assumption of HRV signal stationarity required by classical spectral methods is rarely realistic, these methods are still commonly used to investigate the power alteration in the LF and HF bands in different situations [2, 4, 6]. One standard spectral parametric method among others is the Yule-Walker autoregressive (AR) method. The estimation of the Yule-Walker AR parameters is achieved by evaluating a biased estimate of the signal's autocorrelation function, and solving the least squares minimization of the forward prediction error. The Yule-Walker equations can be solved efficiently via Levinson's algorithm and the obtained AR model is always a stable all-pole model. However it is important to note that this method depends on selecting the appropriate order of the AR model. Therefore, we evaluate the minimum description length criterion (MDL) to determine the model order [13].

2.3 HRV data set

Here, we describe the procedure to generate synthetic HRV signals and we specify the characteristics of the clinical HRV data.

2.3.1 *Synthetic HRV signals*

Simulated signals are generated following typical spectra. We have used two AR models that approximately match the PSD at supine rest and after tilt described in [3]. The true model order in both cases is $p = 7$. The AR model coefficients a_k and the variance σ_r^2 of the driving white noise are reported in Table 1 for a sampling rate of 1 Hz. The noise is zero mean and the PSD of the AR model is given by [3]

$$PSD(f) = \frac{\sigma_r^2}{\left|\sum_{k=0}^{p} a_k \; e^{j2\pi f}\right|^2}. \quad (3)$$

A very low frequency trend, additive white Gaussian noise (AWGN) and impulsive noise are then added to the simulated signals in order to obtain realistic artificial HRV signals.

Table 1: Coefficients and noise variance of the AR models.

Coeff.	Rest	Tilt
a_0	1	1
a_1	-1.6265	-1.8149
a_2	1.8849	2.1365
a_3	-1.8327	-2.1703
a_4	1.2970	1.7194
a_5	-0.7758	-0.9221
a_6	0.4133	0.5311
a_7	-0.2136	-0.3262
σ_r^2	$404\ 10^{-6}$	$137\ 10^{-6}$

2.3.2 Clinical HRV signals

HRV real data are collected from experiments in 11 healthy human subjects during a classical stand-test by means of a Holter device at a sampling frequency equal to 1000 Hz. The mean, bias and STD of the change in the LF/HF ratio are provided in paragraph 3.2.

2.4 Deflection criterion

In order to decide between the two techniques: PRSA method and Yule-Walker AR spectral method, in terms of which technique provides the best measurement of the LF/HF ratio, we propose to use the deflection criterion [14, 15, 16]. Actually, this criterion is well-known in detection procedures to discriminate between two hypotheses. So, let the null hypothesis H_0 be the rest situation and the alternate hypothesis H_1 be the tilt position. The deflection D is defined as follows,

$$D = \frac{\left|\mathrm{E}\left[r\right]_{H_0} - \mathrm{E}\left[r\right]_{H_1}\right|}{\sqrt{\mathrm{STD}\left[r\right]_{H_0}\ \mathrm{STD}\left[r\right]_{H_1}}}, \tag{4}$$

where r is the estimate of the LF/HF ratio. $\mathrm{E}\left[.\right]_{H_0}$ and $\mathrm{E}\left[.\right]_{H_1}$ design the mean expectations under hypothesis H_0 and $H1$ respectively. It is of course assumed that r is such that all these quantities are finite. It is also worth noting that the deflection definition of eq.(4) is a symmetric version of that discussed in [14].

3. RESULTS AND DISCUSSIONS

In order to ascertain the potential of the PRSA, realistic artificial HRV signals are initially used. The results are compared to those obtained by the Yule-Walker AR spectral method. Both methods are then tested on real data to demonstrate consistency with the simulated results.

3.1 Synthetic HRV signal

Figure 3(a) shows a simulated HRV signal composed of a rest period of 500 samples followed by a tilt period of 600 samples (7 order AR models specified in Table 1 are used). The signal is embedded in an additive white Gaussian noise (SNR=30 dB), a very low frequency trend in the rest period and impulsive noise. The probability of positive or negative spike occurrence within 100 samples is equal to $p = 0.01$. Figures 3(b) and (c) display the Yule-Walker AR PSD estimate during rest and tilt respectively. The model orders estimated using MDL are 5 and 6. The PRSA spectra during rest and tilt are depicted in Fig.3(d) and (e) respectively. All spectra were normalized to have a total energy equal to one.

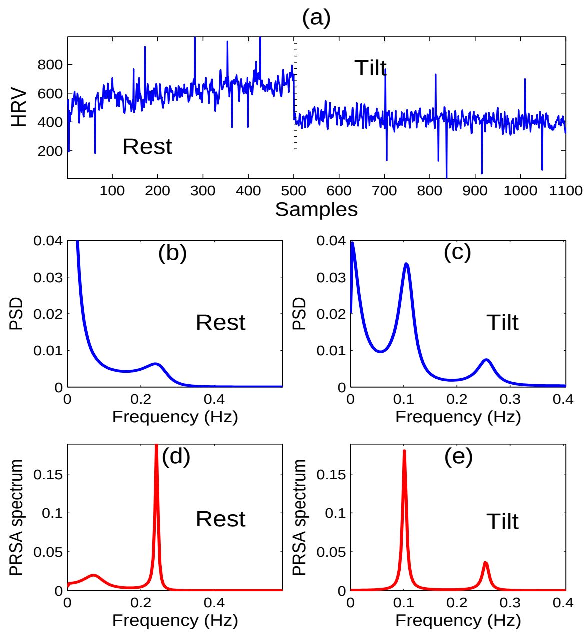

Figure 3: HRV signal analysis: (a) Simulated signal (7th AR model 1). The signal is composed of a rest period (500 samples) followed by a tilt period (600 samples), embedded in an additive white Gaussian noise (SNR=30 dB), a very low frequency trend in the rest period and impulsive noise. A positive or negative spike occurs within 100 samples with a probability equals to $p = 0.01$. The parametric PSD estimation during rest (b) and tilt (c). The spectra of PRSA signal (2) during rest (d) and tilt (e).

From Fig.3(d), one can observe that the significant power during rest is located in the HF band while the LF band is almost absent from the PRSA spectrum. In the opposite, PRSA method clearly enhances the LF components during tilt with respect to the power of the HF components. Additionally, application of the PRSA allows the cancellation of the very low frequency trend which clearly appears in the parametric PSD estimate.

To statistically report on the application of the PRSA for assessing the LF/HF ratio, we consider two cases described as follows.

• **Case 1**: Signal of Fig.3(a) is embedded in AWGN. We run 2000 random realizations of zero mean AWGN with a signal to noise ratio (SNR) varying from 0 to 30 dB. The mean and standard deviation (STD) of the LF/HF ratio estimate are evaluated for each SNR value. The results obtained using PRSA and the AR spectral method are depicted in Fig.4.

For high SNR (10 to 30 dB), the mean of the LF/HF ratio estimated during tilt is about 6 times bigger than that obtained during rest when the PRSA method is used. This factor is about 2 when the LF/HF ratio is estimated by the Yule-Walker AR spectral method with a fixed model order equal to 7. However, both methods exhibit the same STD behavior: a small and almost constant STD is observed for all SNR values during rest whereas a high STD is obtained for high SNR during tilt.

Figure 5 shows the deflection computed using the PRSA method. The results are compared with those obtained by the Yule-Walker AR spectral method using a model order se-

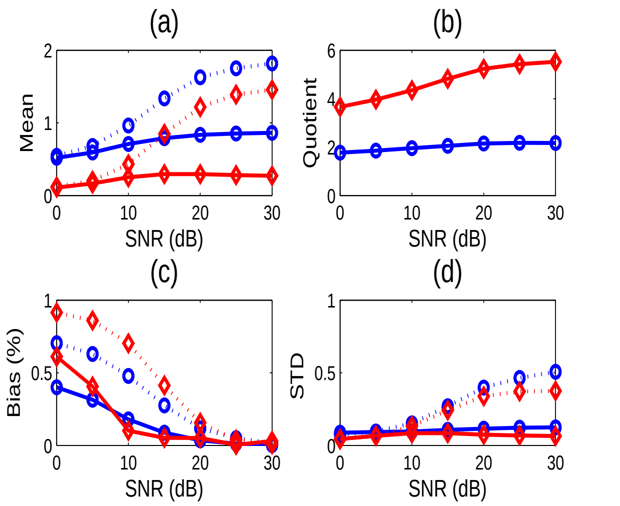

Figure 4: (a) Mean, (c) bias and (d) STD of the LF/HF ratio estimate: (solid line) rest and (dotted line) tilt, (⋄) PRSA, (o) Yule-Walker AR spectral method. The AR model order is assumed to be known and fixed equal to 7. (b) Mean quotient: the LF/HF ratio during tilt normalized by the LF/HF ratio during rest.

lected by the MDL criterion and the Yule-Walker AR spectral method using a model order fixed to 7.

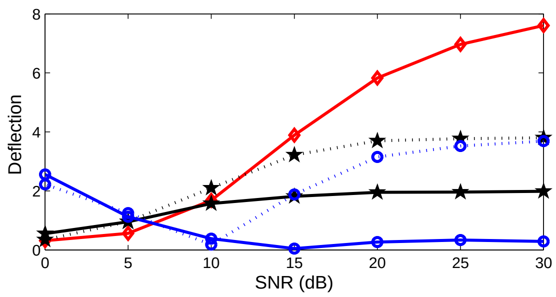

Figure 5: Deflection for different SNR: (–⋄) PRSA, ($\star$) Yule-Walker AR spectral method with a model order fixed equal to 7 and (o) Yule-Walker AR spectral method with a model order selected by MDL, (dotted line) a preprocessing (median filter) is employed to remove impulsive noise from data and (solid line) raw data are used (no preprocessing).

As one can observe, the deflection values computed using the classical techniques are smaller than the values obtained by PRSA for SNR varying from 10 to 30 dB. The PRSA performance is reduced when the SNR tends to zero. However PRSA is still perform much better than the classical AR method especially when the model order is not known and is selected with the MDL criterion.

• **Case 2**: Signal of Fig.3(a) is embedded in impulsive noise. The spikes occur with a probability varying from 0.002 to 0.15. A spike probability equals 0.01 means that one spike may occur within 100 samples. We run 2000 random realizations of impulsive noise for each spike probability. The deflection (4) is evaluated for each spike probability. Curves plotted on Fig.6 show that the PRSA method provides the best deflection value. Actually, the over / or under-estimation of the model order impacts on the accuracy of the estimation of the power in LF and HF bands when using the parametric PSD estimate. However, thanks to the averaging process included in the PRSA steps, less inclusion of noise is impacting the PRSA spectrum and thus provides a more accurate quantification of the most spectral dominant power.

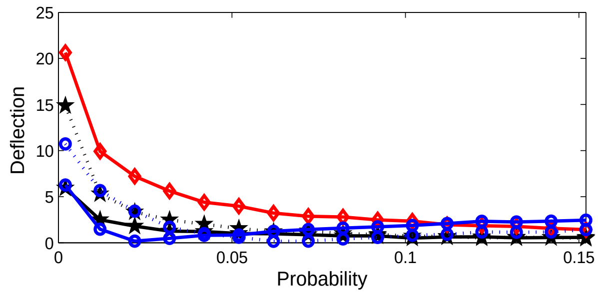

Figure 6: Deflection when the probability of spike occurrence is varying: (–⋄) PRSA, ($\star$) Yule-Walker AR spectral method with a model order fixed equal to 7 and (o) Yule-Walker AR spectral method with a model order selected by MDL, (dotted line) a pre-processing (median filter) is employed to remove impulsive noise from data and (solid line) raw data are used (no preprocessing).

3.2 Analysis of HRV real data

An example of a real HRV is depicted in Fig.7. The PRSA spectrum and the PSD AR estimate are also provided. We observe the same results as expected with synthetic signals.

Based on the 11 subjects, the mean values of the LF/HF ratio are 0.2300 and 3.2768 using the PRSA, 0.7774 and 2.4831 using the PSD AR estimate, in rest and tilt positions, respectively. The STD values of the LF/HF ratio estimate are 0.1846 and 2.4052 using the PRSA, 0.3459 and 1.8090 in rest and tilt positions, respectively.

Despite its good performance, it is important to mention some limitations regarding the PRSA method. First, this technique requires the choice of the length L. In all the example shown in this paper, $2L+1$ is chosen equal to 29. The small length of PRSA signal may impact the computation of the power spectrum of the PRSA signal (2). Second, few theories about PRSA were developed. Nevertheless, the potential of this technique is obvious when it is applied to quasi-periodic components corrupted by impulsive noise. The PRSA especially cancels the very low frequency trend and impulsive noise. There is no need for artificial signal preprocessing to achieve better accuracy of the LF/HF ratio compared to classical spectral methods.

4. CONCLUSION AND PERSPECTIVES

The phase-rectified signal averaging method is a simple definition tool that computes a short-term PRSA signal from the studied signal. The quasi-periodic components, which are initially hidden in a classical Fourier analysis, are enhanced in the PRSA signal spectrum. Indeed, artifacts, correlated non-periodic components, noise and especially impulsive noise are canceled thanks to the averaging process and to the phase synchronization. The noise impact to the accuracy of the frequency estimation is much reduced.

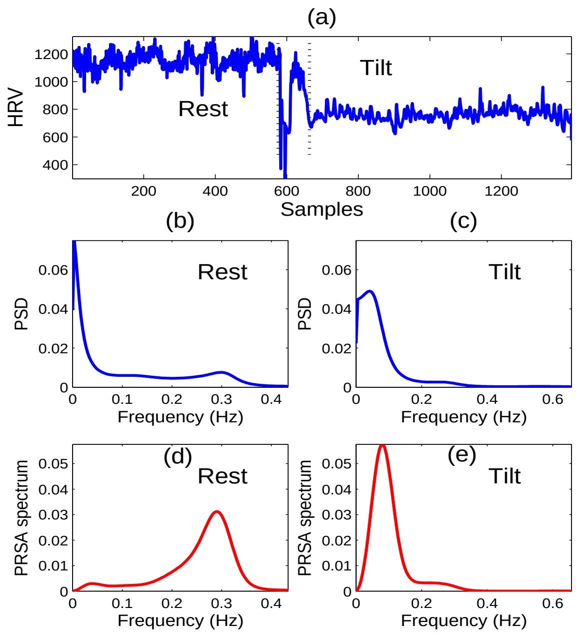

Figure 7: (a) HRV real data from experiments in healthy human subjects during rest followed by tilt. The PSD AR estimate during rest (b) and tilt (c). The model order in both cases is computed based on the MDL criterion. The spectrum of PRSA signal (2) during rest (d) and tilt (e).

In the present paper, the analysis of HRV signals was considered based on the PRSA method. The aim was to improve the characterization of the response of autonomic system to the change from laying to standing. Since the LF /HF power values are required to measure the LF/HF ratio, which is a quantity reflecting the change in the sympathovagal balance, we proposed to evaluate these powers and the LF/HF ratio using the PRSA signal spectrum.

Synthetic HRV signals and HRV real data obtained from experiments in human healthy subjects including rest and tilt are considered. Results observed show the PRSA method capable of efficiently extracting the LF components while the HF components are decreased during tilt and vice versa during rest. The comparison with the conventional spectral analysis, the PSD AR estimate, shows the discrimination between rest and tilt to be particularly significant using the PRSA method. Indeed, the deviation of LF/HF ratio during rest from the one during tilt is three times bigger with the PRSA method.

This analysis suggests that the PRSA method may facilitate the detection of impairment in the sympathovagal balance, when it occurs, in a noninvasive way. This will be addressed in further works. We also aim to study the impact of individual time dependent boundaries of the LF and HF bands developed in [4].

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