

Bispectral Analysis of Heart Rate Variability Signal

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ABSTRACT

This article explores the potential of third-order statistics to analysis of heart rate variability (HRV) signal. Bispectral analysis of short-term HRV signals, obtained from a group of healthy subjects under various experimental settings, showed the HRV activity to be located on specific bifrequency regions of the magnitude bispectrum. Nine *strength* measures were defined and were found to respond selectively to induced perturbation of sympathetic-vagal control of heart rate. In general the measures contained the spectral information and provided complementary information.

Keywords: Heart rate variability, higher order statistics, signal processing

1 INTRODUCTION

A common experimental procedure to study the control mechanism of heart rate (HR) is to perturb the the sympathetic-parasympathetic balance of autonomous nervous system through various interventions [1, 2, 3]. Frequency domain representations of short-term HRV recordings, such as power spectral density (PSD), are the currently used techniques for this purpose [4, 5, 6].

PSD exploits second order statistics, which could fully characterize the signal only if it had a Gaussian distribution. When this is not the case, higher order statistics, such as high order spectra [7, 8, 9], could be advantageous.

Bispectrum and bicoherence [10, 11], which employ up to the third order statistics, could be used to reveal information not present on the spectral domain and detect quadratic phase coupled harmonics (arising from nonlinearities of generating mechanism). Tests of Gaussianity and linearity [12] were also obtained, which are blind to signal correlation.

In this article we explore the analysis of the HRV signal on bifrequency domain. The HRV signals were first tested for Gaussianity and found to be mainly non-Gaussian. Based on observations of magnitude bispectra (MB), as well as PSD, we defined nine measures of MB strength. The measures were found statistically able to characterize various physiological states of the

autonomous control system of heart rate and to provide available and additional information on HRV.

2 THEORY

The cumulants of a random variable x are obtained from the coefficients c_k of the Taylor's series expansion of the logarithmic of moment generating function $M_x(n) = E[e^{nx}]$:

$$C_x(n) \triangleq \ln(M_x(n)) \quad (1)$$

The k -th order cumulant spectrum of a signal is defined as $(k-1)$ -th dimensional discrete-time Fourier transform of the k -th order cumulant $c_{k,x}(\tau_1, \dots, \tau_{k-1})$:

$$C_{k,x}(\omega_1, \omega_2, \dots, \omega_{k-1}) \triangleq \sum_{\tau_1} \cdots \sum_{\tau_{k-1}} c_{k,x}(\tau_1, \dots, \tau_{k-1}) \sum_{i=1}^{k-1} \exp(-i\omega_i \tau_i) \quad (2)$$

For values $k = 2$ and $k = 3$ we obtain respectively *spectrum* $C_2(\omega)$ with domain $\Omega = \{|\omega| \leq \pi\}$ and *bispectrum* $C_3(\omega_1, \omega_2)$ with $\Omega = \{|\omega_1| \leq \pi, |\omega_2| \leq \pi, |\omega_1 + \omega_2| \leq \pi\}$.

Normalized bispectrum, or *bicoherence function*, to be referred later on is

$$P_3(\omega_1, \omega_2) = \frac{C_3(\omega_1, \omega_2)}{\sqrt{C_2(\omega_1)C_2(\omega_2)C_2(\omega_1 + \omega_2)}} \quad (3)$$

We defined *regional strength*(S) on magnitude bispectrum (MB) as

$$\Xi_k = \sum_{\omega_i, \omega_j \in \Omega_k} |C_3(\omega_i, \omega_j)|, \quad k = 1, 2, \dots, K \quad (4)$$

where $\Omega_k \subseteq \Omega$ are partitions of the principal region $\Omega = \{0 \leq \omega_2 \leq \omega_1 \leq \pi\}$ and K is the number of partitions. The additional constraint $\{\omega_1 + \omega_2 \leq \pi\}$ delineates the principal non-redundant domain.

Integral strength(IS) Π would refer to Ξ_k over Ω . *Relative regional strengths* (RS) are then defined as $Q_k = \Xi_k/\Pi$. The measures above would be used subsequently as measures of signal non-Gaussian activity.

3 HRV MODEL

The HRV rhythmical activity is cast into the nonlinear model

$$y(n) = g[h(n) + \nu(n)] + \eta(n), \quad (5)$$

where g is a static nonlinearity,

$$h(n) = \sum_{i=1}^p a_i \exp(\omega_i n + \psi_i) \quad (6)$$

is a deterministic harmonic signal, $\nu(n)$ a random process and $\eta(n)$ quantization noise of HRV signal due to sampling of ECG signal. The random signals are assumed stationary under analysis time-window.

The cumulant bispectrum (2) would be blind to the symmetrical and iid quantization noise $\eta(n)$ (5). Further if phases ψ_i in (6) were random, $h(n)$ would be zero. Interaction of the harmonics components (ω_k, ϕ_k) , (ω_l, ϕ_l) , as when passing through a nonlinear system, might give rise to other harmonic components such as $(\omega_k + \omega_l, \phi_k + \phi_l)$ having same frequency and phase relations. In such cases the bicoherence (3) would peak at (ω_k, ω_l) . The model (5) illustrates that in general the HRV signal might contain phase-coupled harmonics, nonlinear random components and a mixture of the above.

4 SIMULATIONS

Here we assess (a) the effectiveness of MB-based measures in providing information beyond PSD and (b) the power of Gaussianity test for data length $L = 512$ —about the length of seven minutes HRV recordings.

First, we generated the correlated signals

$$x(n) = 0.5x(n-1) + \nu(n) \quad (7)$$

$$y(n) = x(n)^2 \quad (8)$$

where $\nu(n)$ is white Gaussian noise. Variances of both signals were set equal.

(a) Direct estimation of MB, for various combination of estimation parameters (number of segments M 4–32 and frequency box-car window size B 3–9) yielded an average IS value 9.1 for non-Gaussian signals (8) and 2.7 for Gaussian ones (7).

(b) Under the null hypothesis that the bispectrum is zero (i.e. the signal is Gaussian), the magnitude squared bicoherence function (3) $|P_3(\omega_1, \omega_2)|^2$ is central and χ^2 distributed. The Hinich Gaussianity test [12] could not reject the null hypothesis for white Gaussian signals $x_G(n)$ (estimation parameters $M = 1$ and $B = 41$). White signals $x_\Gamma(n)$ with Gamma distribution $\Gamma(2, b)$ were correctly classified non-Gaussian for $b > 8$ and Gaussian for $b \leq 8$ —the distribution skewness increases with b .

Table 1: Number of HRV signals and their frequency components classified as non-Gaussian (in percentage)

Freq. bands	R (17)	T (15)	RS (9)	TS (8)	RP (5)	TP (2)	RX (4)
HRV	53	60	67	63	60	50	75
VLF	88	93	100	88	80	100	100
LF	82	93	56	88	100	100	50
VLF-LF	100	100	89	100	100	100	100
HF	50	80	56	75	100	100	100

5 BISPECTRAL ANALYSIS OF HRV

The following questions are addressed: (i) does bispectrum provides additional information to PSD? (ii) can meaningful features be defined in it? (iii) are the features correlated to underlying physiological phenomena? The supporting data set consists of HRV records from subjects in rest(R) and tilt(T) positions, prior to and after inducement of sympathetic(S), parasympathetic(P) and total (X) autonomic blockades, see [13] for details.

(i) The HRV data are tested for Gaussianity using Hinich test [12]. Bicoherence function was estimated from single records by direct method of estimation [14](four segments, 50% overlapping and no bifrequency smoothing). Considering that HRV is composed of at least two main physiological components [16], which have different characteristics, analysis of VLF, LF, HF and VLF-LF bands were also included in analysis. Table 1 summarize the results.

(ii) As the HRV signal was found to be predominantly nonGaussian we would expect to obtain additional information on bispectral domain. Similarly to PSD, where power is distributed on very low, low and high frequency (VLF, LF and HF) regions, we observed that magnitude bispectrum(MB) $|C_3(\omega_1, \omega_2)|$ was distributed along the diagonal of bifrequency plane with coordinates VLF-VLF (V2), LF-LF (L2) and HF-HF(H2), as well as bifrequency regions with co-ordinates VLF-LF (VL), VLF-HF (VH) and LF-HF (LH). The components V2, L2, and H2 would be referred to as self-component whilst VL, VH, LH as cross-components.

Figure 1 show MB on the first symmetry region (with the non-redundant region delineated) of HRV signals from a healthy subject in supine resting position(a) and head-up tilting position(b). PSD are shown upside-down on top of the figures. Text insets show the measures S, RS, and IS on the specific regions described subsequently.

Based on observation of MB obtained from the whole data set the bifrequency plane was partition on regions of interest Ω_k as shown in Figure 2. The frequency boundaries (ω_1, ω_2) were chosen (on somewhat restrictively) equal to those in PSD. The shaded rectangle is referred to as 'the nonlinear region'—the activity here

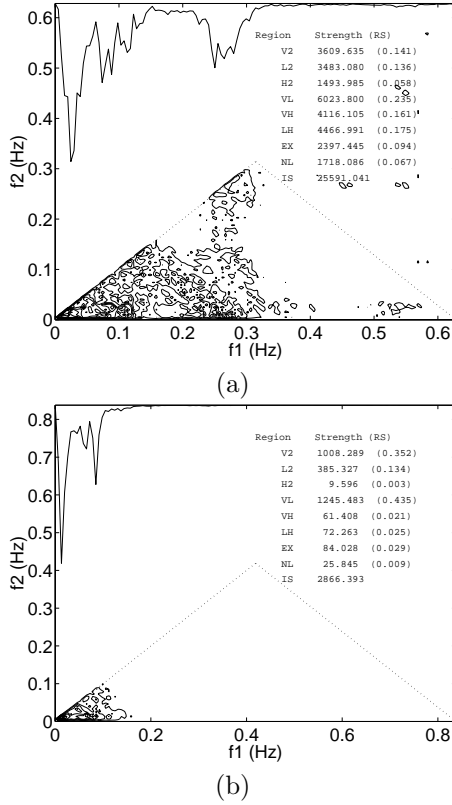


Figure 1: Bispectra of HRV of a normal subject in baseline supine rest (a) and head-up tilt positions (b)

would be negligible if the signal was linear. An extra activity beyond VHF is delineated by the leftmost vertical strip. Note that some of the regions overlap. On each partition Ω_k defined above we calculate the measures S and RS , as well as IS .

(iii) MB of short-term HRV signals from subjects in baseline supine rest position and subjects in other experimental settings show that in the later the MB strengths concentrate towards the V2 and VL regions, become more accentuated and identifiable—quantification of apparent phase coupling from the detection point of view is not considered here.

To statistically evaluate these changes we applied Wilcoxon’s signed ranks test for matched pairs to measures S , RS , and IS . Table 2 summarizes the statistical results. Thick/thin arrows indicate respectively statistically-significant absolute/relative changes. Non-significant changes are not entered on the table. Significance level was set $p < 0.05$. On the following a sentence like ”relative/absolute change of VL” would read change of S/RS on the VL region”. The results in Table 2 should be interpreted as changes on the degree of ’deviation from Gaussianity’ and considered complementary to PSD changes in Table 3.

Based on observations of related behavior the re-

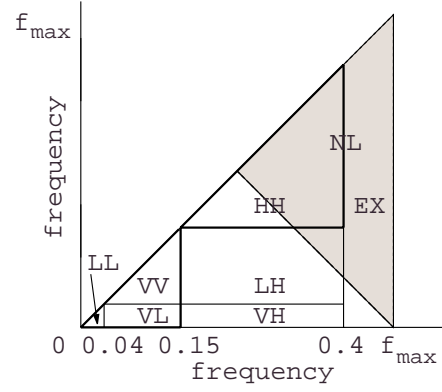


Figure 2: Delineation and labeling of bispectral regions

Table 2: Bispectral AS alterations from baseline rest and tilt positions

Procedure	Group I			Group II			IS	Group III	
	V2	L2	VL	H2	VH	LH		EX	NL
vs. R	T	↑	↑	↑	↓	↓		↓	↓
	RP	↑		↑	↓	↓	↓	↓	↓
	RS		↓			↓	↑	↑	↑
	RX			↑	↓	↓	↓	↓	↓
vs. T	TP		↓		↓	↓			
	TS	↑			↑	↑		↓	↑

gions are clustered in three groups: group I (V2,L2,VL), II(H2,VH,LH) and III (EX,NL).

The upper and lower parts of Table 2 shows respectively S and RS changes from baseline rest and tilt position due to various experiments. Table 3 shows results of an analogous spectral analysis.

Tilting (T) suppresses the components of group II (not LH) and III; their relative decrease seems associated with a relative increase of group I. Parasympathetic blockade (RP) suppresses absolutely all components and IS (not L2). Similarly to tilting, a relative increase of V2 and VL might have counterbalanced the relative de-

Table 3: PSD alterations from baseline rest and tilt positions

Procedure	VLF	LF	HF	IP	VHF
vs. R	T	↓	↑	↓	↓
	RP	↑	↓	↓	↓
	RS	↑	↓	↑	↑
	RX	↑	↓	↓	↓
vs. T	TP		↓	↓	
	TS	↑	↑		

crease of group II. In sympathetic blockade (RS) an increase of IS is observed due to the absolute increase on group III. L2 and VH have a relative decrease to match the relative increase of EX. The total autonomic blockade (RX) suppresses absolutely groups II (not LH) and III. Relative increase of on VL is associated with relative decrease of H2 and LH. Lower part of table 2 shows RS changes relative to baseline tilt position. Parasympathetic blockade (TP) seems to have suppressed absolutely L2 and relatively group II. Sympathetic blockade (TS) increases absolutely V2, group II (not LH) and decreases absolutely EX.

The following features of interest are observed from Table 2 (i) LH component does not in general follow group II response, (ii) L2 does not respond to parasympathetic blockade, (iii) groups I and II are almost indifferent to the sympathetic blockade.

We observe quite a similarity when comparing the self-components V2, L2, H2, IS and EX with corresponding spectral counterparts VLF, LF, HF, IP, and VHF.

6 Conclusions

Bispectral analysis of the HRV signal has shown that HRV activity is mainly located on few specific regions of magnitude bispectra.

The effects of tilting and inducement of parasympathetic, sympathetic and total autonomic blockade were to shift the MB components toward lower bifrequency regions (V2, VL, L2) and enhance their activity.

The proposed method indicated that bispectral self-components contained information readably available from spectral domain. On the other hand supplementary cross-components and intra-group differences provided complementary information.

Some of the features of interest observed were: insensitivity of L2 to parasympathetic blockade and of Group I and II to sympathetic blockade, the absolute increase of group II due to sympathetic blockade during tilt and a peculiar behavior of LH. Gaussianity and linearity tests based on bicoherence classified the HRV signal and its components to be basically non-Gaussian.

7 Discussion

Self-components of bispectral analysis of HRV signals contained basically the information of PSD analysis. Cross components and intra-group variations seem to be of special interest. Correlating the later to physiological mechanism, as tentatively attempted here, might provide further insight to HRV control.

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