Comparison of higher order spectra in heart rate signals during two techniques of meditation: Chi and Kundalini meditation

Ateke Goshvarpour · Atefeh Goshvarpour

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Abstract The human heartbeat is one of the important examples of complex physiologic fluctuations. For the first time in this study higher order spectra of heart rate signals during meditation have explored. Specifically, the aim of this study was to analysis and compares the contribution of quadratic phase coupling of human heart rate variability during two forms of meditation: (1) Chinese Chi (or Qigong) meditation and (2) Kundalini Yoga meditation. For this purpose, Bispectrum was estimated by using biased, parametric and the direct (FFT) method. The results show that the mean Bispectrum magnitude of heart rate signals increased during Kundalini Yoga meditation, but it decreased significantly during Chi meditation. However, in both meditation techniques phase-coupled harmonics are shifted to the higher frequencies during meditation. In addition, it has shown that not only there are significant differences between rest and meditation states, but also heart rate patterns appear to be influenced by different types of meditation.

Keywords Bispectrum estimation · Heart rate variability · Meditation

Introduction

The word ‘meditation’ can be derived from the Latin word ‘meditatio’, which referred to an exercise originally not predefined between intellectual and physical. In both ways it points to the center (lat. ‘Medium’ = ‘center’) of either

the body or the mind. The word ‘medium’ again is rooted in the Indo-Germanic stem ‘*me (d)’, meaning ‘to ambulate’ or ‘to measure’. Today, ‘meditation’ is related to various practices aiming to alter the state of consciousness, therefore belong with a more spiritual context closer associated with the term ‘contemplation’ (Fell et al. 2010).

Meditation refers to a family of mental training practices that is designed to familiarize the practitioner with specific types of mental processes (Brefczynski-Lewis et al. 2007). In addition, meditation is a physiological state of demonstrated reduced metabolic activity—different from sleep—that elicits physical and mental relaxation and is reported to enhance psychological balance and emotional stability (Jevning et al. 1992).

There has been an explosion of popular and scientific interest in the potential health benefits of various types of meditative protocols (Goshvarpour and Goshvarpour 2012a). However, the comparative physiological effects of different forms of meditation remain incompletely explored.

Heart rate variability (HRV), the variation over time of the period between consecutive heartbeats, is predominantly dependant on the extrinsic regulation of the heart rate (HR). HRV is thought to reflect the heart’s ability to adapt to change circumstances by detecting and quickly responding to unpredictable stimuli (Acharya et al. 2006). HRV analysis is the ability to assess overall cardiac health and the state of the autonomic nervous system (ANS) responsible for regulating cardiac activity.

The human heartbeat is one of the important examples of complex physiologic fluctuations. The neural control of the cardiovascular system exhibits the complex nonlinear behavior. One form of nonlinear behavior is the continual interaction between the sympathetic and parasympathetic nervous activities to control the spontaneous beat to beat dynamics of heart rate (Bai et al. 2008). The interactions

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A. Goshvarpour (✉) · A. Goshvarpour
Department of Biomedical Engineering, Mashhad Branch,
Islamic Azad University, Mashhad, Iran
e-mail: ateke.goshvarpour@gmail.com

are believed to be nonlinear because physiological conditions would most likely involve autonomic nervous system regulation based on dynamic and simultaneous activity of the sympathetic and vagal responses to physical environmental stresses (Akselrod et al. 1981; Levy 1971; Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology Circulation 1996).

Different measures of biological signals are designed to reflect different aspects of these signals and thus do not always provide the same information about the system under the study (Gao et al. 2011; Dimitriadis et al. 2012; Schinkel et al. 2007). Over the past years, to reveal nonlinear characteristics of HR signals, dynamic methods of heart rate analysis have been proposed. For this purpose, nonlinear features such as Poincare plots (Goshvarpour et al. 2011), Lyapunov exponents (Goshvarpour and Goshvarpour 2012b, c), Recurrence plots (Goshvarpour and Goshvarpour 2012d), approximate entropy (ApEn) (Goshvarpour and Goshvarpour 2012b) have been studied. In addition, The HRV signal can be analyzed using different higher order spectra (HOS) (also known as polyspectra) that are spectral representations of higher order moments or cumulants of a signal (Nikias and Raghuveer 1987).

Quantification of nonlinear coupling of physiological time series has been of considerable interest during recent years. In Zgallai (2012), the Bispectral contour matching technique was used to identify the signatures of both the maternal and fetal QRS-complexes. Bai et al. (2008) investigated whether autonomic nervous system imbalance imposed by pharmacological blockades and associated with acute myocardial infarction (AMI) was manifested as modifications of the nonlinear interactions in heart rate variability signal using Bispectrum method. In another study (Zhang et al. 2010), the Bispectrum was estimated using an autoregressive model, and the frequency coupling of the Bispectrum was extracted as a quantitative measure to classify normal and congestive heart failure (CHF) subjects. Toledo et al. (2001) applied the Bicoherence function, which provides an estimate of the correlation between three spectral peaks, to determine the relations between the very high frequency (VHF) peaks and other peaks of heart rate variability. They used a statistical approach to determine a threshold which discerns true Bispectral peaks from spurious ones for any required level of significance.

For the first time in this study higher order spectra of heart rate signals during meditation have explored. The present study was designed to further characterize heart rate dynamics during different forms of meditation and to compare them to the rest state by using higher order spectra.

The outline of this study is as follow. In the next section, the signals and methods used in this study are briefly described. Then, the results of analysis on data sets are presented. Finally, the differences between meditation states (Chi meditation and Kundalini meditation) and rest state are discussed.

Methods

Data selection

Two specific meditation techniques were studied: (1) Chinese Chi (or Qigong) meditation (as taught by Xin Yan) (Peng et al. 1999) and (2) Kundalini Yoga meditation (as taught by Yogi Bhajan) (Peng et al. 1999).

Chi meditation

The Chi meditators (Peng et al. 1999) were all graduate and post-doctoral students. They were also relative novices in their practice of Chi meditation, most of them having begun their meditation practice about 1–3 months before this study. The subjects were in good general health and did not follow any specific exercise routines.

The eight Chi meditators, 5 women and 3 men (age range 26–35, mean 29 years), wore a Holter recorder for about 10 h during which time they went about their ordinary daily activities. At approximately 5 h in the recording each of them practiced 1 h of meditation. Meditation beginning and ending time were delineated with event marks.

During these sessions, the Chi meditators sat quietly, listening to the taped guidance of the Master. The meditators were instructed to breathe spontaneously while visualizing the opening and closing of a perfect lotus in the stomach. The meditation session lasted about 1 h. The sampling rate was 360 Hz. Analysis was performed offline and meditation beginning and ending times were delineated with event marks.

Kundalini Yoga meditation

The Kundalini Yoga (Peng et al. 1999) subjects were considered to be at an advanced level of meditation training. The four Kundalini Yoga meditators, 2 women and 2 men (age range 20–52, mean 33 years), wore a Holter monitor for about one and a half hours. 15 min of baseline quiet breathing were recorded before the 1 h of meditation. The meditation protocol consisted of a sequence of breathing and chanting exercises, performed while seated in a cross-legged posture. The beginning and ending of the various meditation sub-phases were delineated with event marks. The sampling rate was 360 Hz.

Bispectrum estimation

The Bispectrum quantifies the relationship among the underlying sinusoidal components of the signals. Specifically, Bispectrum analysis examines the relationship between the sinusoids at two primary frequencies, f_1 and f_2 , and a modulation component at the frequency $f_1 + f_2$. This set of three frequency components is known as a triplet (f_1 , f_2 , and $f_1 + f_2$). For each triplet, the Bispectrum, $B(f_1, f_2)$, a quantity incorporating both phase and power information, can be calculated as described below (Nikias and Raghuveer 1987). Strong phase coupling implies that the sinusoidal components at f_1 and f_2 may have a common generator, or that the neural circuitry, they drive may, although some nonlinear interaction, synthesize a new dependant component at the modulation frequency, $f_1 + f_2$.

$$B(f_1, f_2) = |X(f_1) \cdot X(f_2) \cdot X^*(f_1, f_2)| \quad (1)$$

where $B(f_1, f_2)$ is the Bispectrum at frequencies f_1 and f_2 , $X(f_1)$ and $X(f_2)$ are discrete Fourier transform coefficients at frequencies f_1 and f_2 respectively. X^* is the complex conjugate of X . This multiplication is the heart of the Bispectrum determination: if at each frequency in the triplet, there is a large spectral amplitude (a sinusoid exists for that frequency) and if the phase angles for each are aligned, then the resulting product will be large; if one of the component sinusoids is small or absent or if the phase angles are not aligned, the product will be small.

Finally, the complex Bispectrum is converted to a real number by computing the magnitude of the complex product.

To ensure statistical accuracy a long signal length is divided into P epochs and the Bispectrum of each epoch $B_i(f_1, f_2)$ is formed. The Bispectrum of the total signal is then the averaged value of these Bispectra:

$$B(f_1, f_2) = (1/p) \sum B_i(f_1, f_2) \quad (2)$$

$X(t)$, $t = \pm 1, \pm 2, \pm 3, \dots$ is a real stationary process that characterized with its' moment. The expectation, $E(\cdot)$ is defined by equation (3):

$$E(x(t)) = \lim_{n \rightarrow \infty} 1/(2N + 1) \sum x(t) \quad (3)$$

The first moment is defined by equation (4):

$$\mu = E(x(t)) \quad (4)$$

The first moment of X , is called the mean. It is convenient for define the higher order cumulants under the assumption of zero mean, $\mu = 0$. The second moment of X is defined by equation (5):

$$\sigma^2(t_1) = E(x(t)x(t + t_1)) \quad (5)$$

The third moment of X is defined by equation (6):

$$\gamma(t_1, t_2) = E(x(t)x(t + t_1)x(t_1 + t_2)) \quad (6)$$

The second moment at $t_1 = 0$ is called variance and the third moment at $t_1 = t_2 = 0$ is called skewness. The skewness is usually defined by $\gamma(0, 0)/\sigma^3$.

The Fourier transform of second moment is called power spectrum $P(f)$ and the Fourier transform of third moment is called Bispectrum $B(f_1, f_2)$.

$$\sigma^2(t_1) = \int e^{2\pi i t_1 f} P(f) df \quad (7)$$

$$\gamma(t_1, t_2) = \int e^{2\pi i(t_1 f_1 + t_2 f_2)} B(f_1, f_2) df_1 df_2 \quad (8)$$

For $t_1 = t_2 = 0$:

$$\sigma^2(0) = \sigma^2 = \int P(f) df \quad (9)$$

$$\gamma(0, 0) = \gamma\sigma^3 = \int B(f_1, f_2) df_1 df_2 \quad (10)$$

σ^2 is variance and σ^3 is skewness. Bispectrum can be estimated through several techniques. In this paper biased, parametric and the direct (FFT) method is used.

Bispectrum estimation using the direct (FFT-based) method

In Bispectrum estimation using the direct (FFT-based) method, the data are segmented into possibly overlapping records; the mean is removed from each record, and the FFT computed; the Bispectrum of the k th record is computed as (11).

$$B_K(m, n) = X_K(m) \cdot X_K(n) \cdot X_K^*(m + n) \quad (11)$$

where X_K denotes the FFT of the k th record. The Bispectrum estimates are averaged across records and an optional frequency domain smoother is applied.

Bispectrum estimation using the parametric method

In Bispectrum estimation using the parametric method, AR parameters should be estimated (Ning and Bronzino 1990). The AR order corresponds with the index at which the singular values show the maximum drop (Swami et al. 1998). In this study, to estimate the Bispectrum using parametric method, an AR order of 10 is used.

Bispectrum estimation using biased method

Let $y(n)$, $n = 1, \dots, N$ denote the time series. Let M denote the number of samples per segment. Let O denote the percentage overlap between segments. Let $M1 = M - M * O / 100$. Then, the time series, y , is segmented into K records of

M samples each, where $K = (N - M * O/100)/M$. The k th record or segment of X consists of the samples

$$y_k(i) = y(i + (k - 1) * M1), i = 1, \dots, M, k = 1, \dots, K. \quad (12)$$

The sample mean is removed from the k th record, and sample estimates of the cumulants are computed (Swami et al. 1998). For example, sample estimates of third-order cumulants are obtained as,

$$C_{3y,k}(m,n) = \frac{1}{M(m,n)} \sum_{i=1+\max(0,-m,-n)}^{M-\max(0,m,n)} y_k^*(i)y_k(i+m)y_k(i+n) \quad (13)$$

where $M(m,n) \equiv M$ for biased estimates, and $M - \max(0,m,n) + \min(0,m,n)$ for unbiased estimates.

$$C_{3y}(m,n) = \frac{1}{K} \sum_{k=1}^K C_{3y,k}(m,n) \quad (14)$$

The final estimate is given by Second- and fourth-order cumulant estimates are obtained similarly (Swami et al. 1998).

Statistical analysis

In this study, the t test of the null hypothesis that the data in the vector x are a random sample from a normal distribution with mean 0 and unknown variance, against the alternative that the mean is not 0 is performed. The result of the test is returned in p value. p value $\rightarrow 0$ suggests a rejection of the null hypothesis at the 5 % significance level ($p < 0.05$). p value $\rightarrow 1$ shows a failure to reject the null hypothesis at the 5 % significance level.

Results

Bispectrum of each signal is estimated through three techniques: biased, parametric and the direct (FFT) methods using the MATLAB toolbox. In Bispectrum estimation using the biased and direct (FFT-based) methods, the FFT length is 128 and 512, respectively and the percentage overlap between segments is set to zero for both techniques. In parametric method, an AR order of 10 is used and the percentage overlap between segments is set to zero. The results of the Bispectrum analysis of heart signals during two forms of meditation were compared to before meditation. The sample Bispectrum estimations are shown in Figs. 1, 2 and 3 (record Y2 of Kundalini Yoga meditation).

The Bispectrum estimations of heart rate signals before, and during meditation through the direct method (FFT

Fig. 1 Bispectrum estimation of heart rate signal of a Kundalini Yoga meditation subject (record: Y2) through the direct method. **a** Before meditation, **b** during meditation

based) are shown in Fig. 1 and the results of parametric method are shown in Fig. 2. Figure 3 demonstrates the results of the Bispectrum estimations using biased method.

The color represents the relative change in amplitude of Bispectrum; red suggesting the greatest rise and blue suggesting the greatest decrease. According to Fig. 1 the phase-coupled harmonics are less than 2.25 Hz before meditation and the phase-coupled harmonics are below 12 Hz during meditation. The Bispectrum shows sharp peaks at around (1, 2.25) Hz and (2.25, 1) Hz (and symmetric locations) before meditation and it shows sharp peaks approximately between 5 and 10 Hz (and symmetric locations) during meditation.

Power spectrums of heart rate signals (record Y2) are shown in top-left panels of Fig. 2. Before meditation, the maximum value of the power spectrum is about 0.1 but it is about 10^{-3} during meditation. Therefore, it depicts that the power spectrum of the signal is decreased during meditation.

Singular values of heart rate signals (record Y2) are shown in the top-right panels of Fig. 2. Before meditation,

Fig. 2 Power spectrum, singular values and estimated parametric Bispectrum of heart rate signal of a Kundalini Yoga meditation subject (record: Y2). **a** Before meditation, **b** during meditation

Fig. 3 Estimated biased Bispectrum of the heart rate signal of a Kundalini Yoga meditation subject (record: Y2). **a** Before meditation, **b** during meditation

there are seven significant singular values (Fig. 2a) and there are thirteen significant singular values during meditation (Fig. 2b), corresponding with one quadratically coupled triplet.

In this study, to estimate the Bispectrum using the parametric method, an AR order of 10 is used. As shown in Fig. 2a, before meditation the dominant peak is at $(f_1, f_2) = (1.36, 1)$ Hz. According to Fig. 2b, during meditation the dominant peak is at $(f_1, f_2) = (5.76, 0)$ Hz. The dominant peaks indicating the presence of a second harmonic are about 1 Hz before meditation and 5 Hz during meditation. According to Fig. 2 the phase-coupled harmonics are

less than 3 Hz before meditation and the phase-coupled harmonics are below 10 Hz during meditation.

The contour plot in Fig. 3 reveals the basic symmetry of third-order cumulants. The color represents the relative change in amplitude of Bispectrum using biased method.

As shown in Fig. 3, the patterns of Bispectrum counters are different in two conditions. Before meditation the cool colors are dominant (blue colors) suggesting the greatest decrease in Bispectrum amplitude; while during meditation the colors tend to warm coloring (red colors) which suggests the greatest rise in Bispectrum amplitude. In addition, during meditation phase coupling tends to higher frequencies than

Table 1 Average value of maximum magnitudes of Bispectrum estimation through parametric method before and during two forms of meditation

	Maximum bispectrum	
	Before meditation	During meditation
Chi meditation	1.09×10^4	0.26×10^4
Yoga meditation	0.91×10^4	1.97×10^6

$P < 0.05$

that of before meditation. These results are confirmed with two other Bispectrum estimation techniques, parametric and the direct (FFT) methods (Figs. 1, 2).

The average values of maximum magnitude of Bispectrum estimation through parametric method is shown in Table 1.

Different meditation techniques had different effects on the maximum Bispectrum of heart rate signals. According to Table 1, in comparison with before meditation, maximum Bispectrum of heart rate oscillations were increased during Yoga meditation, while it was significantly decreased during Chi meditation. However, during meditation both techniques induced phase coupling in higher frequencies than that of before meditation.

The results suggest that different forms of meditation appear to alter differentially specific components of heart rate signals. Furthermore, the small value of p indicates that at least one sample mean is significantly different from the other sample means.

Discussion

There are situations in practice where, because of interaction between two harmonic components of a process there is contributing to the power at their sum and/or difference frequencies. Such a phenomenon which could be because of quadratic nonlinearities causes certain phase relations called quadratic phase coupling (Nikias and Raghuveer 1987).

In certain applications it is needed to find out if peaks at harmonically related positions in the power spectrum are, in fact, coupled. Since the power spectrum suppresses all phase relations, it cannot provide the answer. The Bispectrum, however, is capable of detecting and quantifying phase coupling. Therefore, the Bispectrum is very useful for analyzing non-Gaussian signal and detecting the quadratic phase coupling between distinct frequency components in a signal. Thus, it reflects the interaction of subcomponents exhibiting oscillations at different frequencies.

The main goal of this study was to examine the phase coupling of heart rate signals in the specific psychophysiological state. For this purpose, the Bispectrum of heart rate

signals during two forms of meditation (Chi meditation and Kundalini Yoga meditation) was estimated.

The results show that the maximum value of the power spectrum is decreased during meditation (Fig. 2). The mean Bispectrum magnitude of heart rate signals is increased during Yoga meditation, but it is significantly decreased during Chi meditation. Besides that phase-coupled harmonics are shifted to the higher frequencies during meditation in both techniques.

In a previous study (Goshvarpour and Goshvarpour 2012c), to quantify and compare the contribution of non-linear and chaotic dynamics of human heart rate variability during two forms of meditation, Poincare plots, Lyapunov exponents and Hurst exponents of heart rate variability signals were analyzed. It has shown that different types of meditation induced different reflection on heart rate features.

Other studies have shown that Bispectrum techniques can offer useful information for the study of the cardiac function. Zgallai (2012) has shown that the ECG Bispectral contour template matching technique is effective in detecting the occurrence of the fetal heartbeats in the frequency domain even when it is completely buried in noise. In another study (Zhang et al. 2010), the results of the Bispectrum amplitude showed that the strength of the frequency coupling was not as strong in the normal subjects as in the congestive heart failure cases.

The results indicate that the Bispectral analysis of the heart rate signals can reveal extra information non obtainable from the power spectrum and may provide insights regarding the formation of cardiac signals in different psychological states (before, and during meditation) and in different meditation techniques.

There is plenty of room for research in this area with several lines of investigation to be pursued. For example, one could study the use of trispectrum estimation and the estimating of fourth-order cumulants through AR and ARMA models for phase estimation.

Conclusion

The results suggest that quadratic phase coupling indices may serve as a quantitative measure for psychophysiological states such as meditation. In addition, different forms of meditation appear to alter differentially specific components of HRV signals, and they may have their specific benefits to improve health.

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