Contents lists available at ScienceDirect





Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Fractal scaling behavior of heart rate variability in response to meditation techniques



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ARTICLE INFO

Article history: Received 17 October 2016 Accepted 9 March 2017

Keywords: Mindfulness meditation R/S analysis Long-range correlations Breakdown

ABSTRACT

The rescaled range (R/S) analysis was used for analyzing the fractal scaling properties of heart rate variability (HRV) of subjects undergoing premeditation and meditation states. Eight novice subjects and four advanced practitioners were considered. The corresponding pre-meditation and meditation HRV data were obtained from the Physionet database. The results showed that mindfulness meditation induces a decrement of the HRV long-range scaling correlations as quantified with the time-variant Hurst exponent. The Hurst exponent for advanced meditation practitioners decreases up to values of 0.5, reflecting uncorrelated (e.g., white noise-like) HRV dynamics. Some parallelisms between mindfulness meditation and deep sleep (Stage 4) are discussed, suggesting that the former can be regarded as a type of induced deep sleep-like dynamics.

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1. Introduction

Eastern meditation techniques (e.g., yoga) are increasingly used as a psychological intervention to deal with a diversity of disadvantageous conditions, including stress, chronic pain and anxiety [1,2]. The aim of mindfulness meditation is to modulate the present thinking by reducing analytical burden, as well as blocking obsessive and discursive thoughts [3]. Quieting thinking and practicing self-control, two key elements of mindfulness meditation, can have large effects in mind and body, leading to important reductions of stress and anxiety that are detectable by, e.g., changes in skin conductivity [4]. A hypothesis considered in the recent decades is that mindfulness meditation induces important changes in the physiological condition of practitioners [2]. The pioneering work by Wallace [5] provided evidence that meditation is accompanied by changes in oxygen consumption, heart rate, skin resistance, and power of certain EEG frequencies. Subsequent research efforts have focused on finding the functional links between mindfulness meditation and the activity of the autonomic nervous system (ANS) via fMRI monitoring [4], heart rate variability analysis [6], sleep studies [7], endocrine system response [8], among others. Despite these efforts, the clarification of the immediate and

http://dx.doi.org/10.1016/j.chaos.2017.03.026 0960-0779/© 2017 Elsevier Ltd. All rights reserved. long-term effects of mindfulness meditation training and the underlying physiological mechanisms is still an open problem.

Indexes related to the activity of the ANS are commonly considered as biomarkers for monitoring meditative states [4,9,10]. These indexes include heart rate/heart rate variability (HRV) parameters, skin conductance/resistance responses, respiratory amplitude/rate, and EEG frequencies modulation. Although neuro-imaging techniques are highly efficient methods for monitoring dynamics of meditation, they are expensive and disturbing during the meditation process. In contrast, the measurement of such ANS indexes seems lees complicated and marginally invasive. The general hypothesis behind the use of ANS indexes is that mindfulness meditation changes some physiological state through autonomic control actions [11]. Basically, the ANS regulates the heart rate dynamics via sympathetic and parasympathetic efferent networks. The parasympathetic influence on heart rate dynamics, primarily mediated by the vagus nerve, provokes a rapid increase in the duration of the cardiac cycle. It is primarily responsible for the respiratory sinus arrhythmia (RSA) fluctuations and the high frequency variability of the heart rhythm [12]. On the other hand, the sympathetic control primarily driven by the release of norepinephrine, also becomes indirectly manifested in the short-term fluctuations of the heart rhythm [13].

Accordingly, the HRV data appear as ANS signals that can be easily obtained with standard, ambulatory and inexpensive

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technologies (e.g., Holter monitors). The availability of HRV signals as indicators of the ANS activity has motivated their use for monitoring different stages of mindfulness meditation. Thus, extracting information to gain insights in the physiological mechanisms associated with the beneficial effects of different meditation techniques has been the focus of diverse research efforts. Fourier spectral analysis is commonly used to show the displacement of HRV dynamics towards the manifestation of high-frequency components [14]. In turn, this effect has been interpreted as a signature of the dominance of the parasympathetic (i.e., vagal) tone over the sympathetic activity [15,16]. Wavelet transform has been applied as well to extract the low- and high-frequency features of HRV series during meditation [17]. The reduction of the largest Lyapunov exponent during meditation has been also reported [18]. Other study indicated that the width of the multifractal singularity spectra is significantly narrower than those obtained in premeditation, indicating that the HRV signals become more regular and that their multifractality degree decreases during meditation [19]. Decrements in the high-frequency modulation connected with short-term correlations and the complexity of HRV signals were also detected using scaling analysis and entropy estimates [20]. The Shannon entropy showed that the complexity of HRV signal decreases in meditation in comparison with a pre-meditative state [21].

The aim of this work is to characterize the HRV time-variant dynamics before and during mindfulness meditation. To this end, rescaled range (R/S) analysis implemented over a sliding window was used to monitor the behavior of the Hurst exponent in the transition from pre-meditation to meditation states. HRV data was obtained from the Physionet meditation database involving eighth novice subjects and four advanced practitioners undergoing two meditation techniques.

2. Subjects

All HRV data were gathered from the Physionet database that provides heart period RR sequences obtained at the Beth Israel Deaconess Medical Center (Boston, USA). The experimentation procedure and details of the subjects were described by Peng et al. [22]. For completeness in presentation, a brief description of the meditation techniques and subjects participating is described below. Chinese Chi and Kundalini Yoga meditation techniques were considered. The Chi practitioners were postdoctoral and graduate students that were relatively novices in the practice of meditation. Most of these subjects were introduced in the Chi meditation practice about 1–3 months before the study. The Chi meditation group consisted of 5 women and 3 men (age 26-35 years with mean of 29 years). The subjects carried Holter recorders for about 10 h under normal daily activities. At the fifth hour of recording, the subjects practiced meditation during an hour of meditation. The practitioners sat quietly while listening to a taped guidance. The control of spontaneous breathing was instructed to meditators while visualizing an opening/closing cycle of a lotus in the stomach. The Chinese Chi subjects were coded as C1 to C8, following the Physionet database numbering.

Four subjects (2 women and 2 men, aged range 20–52 with mean of 33 years) also participated in Kundalini Yoga sessions. This group was considered to have an advanced level in the meditation practice. Subjects carried a Holter by approx. 1.5 hours before meditation. Also, 15 minutes of baseline quiet breathing were recorded just before the meditation session. The protocol consisted of sequences of controlled breathing and chanting exercises, performed while seated in a cross-legged posture. The Kundalini Yoga subjects were coded as Y1 to Y4, following the Physionet database numbering.

3. Methodology

HRV signals exhibit complex patterns of stochastic nature. An interesting question that should be addressed is whether sequences of HRV contain long-term correlations. For a given sequence $X_N = \{x_k\}_{k=1}^N$, the corresponding runoff auto-correlation function C(s) describes how persistence decays in time. If the elements of a time-series x_k are uncorrelated, C(s) is zero for all scales s. If correlations exist only up to a certain number of events s^* , the auto-correlation function will vanish from s*. By contrast, for long-term correlations, C(s) decays by a scaling power-law C(s) = $\langle x_k x_{k+s} \rangle \approx s^{-\gamma}$. For large values of *s*, a direct calculation of *C*(*s*) can be hindered by noise and by data non-stationarities. If the timeseries is stationary, one can use standard spectral analysis techniques and calculate the power spectrum E(f) of the time-series as a function of the frequency f. For long-term correlated data, one has that $E(f) \approx 1/f^{\beta}$, where $\beta = 1 - \gamma$. However, if the time-series is not stationary, conventional spectral analysis can yield significant bias in the estimation of the correlation strength. The rescaled range (R/S) analysis is a method used to estimate autocorrelation properties of time series. The R/S analysis, developed by Hurst [23], is intended to distinguish completely random time series from correlated ones. Rigorous robustness and stability analysis of the R/S method were later provided by Mandelbrot and Wallis [24].

The main idea behind the R/S analysis is that one looks at the scaling behavior of the rescaled cumulative deviations from the mean, or the distance the system travels as a function of time. For an independent system, the distance covered increases, on average, by the square root of time. If the system covers a larger (resp., smaller) distance, it cannot be considered as independent by definition, and changes must be influencing each other, so that they become correlated (resp., anti-correlated). The R/S statistic is the range of partial sums of deviations of sequences from its mean, rescaled by its standard deviation. For a given time series $X_N = \{x_k\}_{k=1}^N$, consider a *M*-dimensional subsequence $Y_M = \{y_k\}_{k=1}^M \subset X_N$, where M < N. Then, the R/S statistic is estimated by computing the subsample mean $\bar{y}_M = \frac{1}{M} \sum_{k=1}^M y_k$, the sequence from partial summations $z_i = \sum_{k=1}^i (y_k - \bar{y}_M)$, the range $R_M = \max\{z_i\} - \min\{z_i\}$ and the rescaled range $(R/S)_M = R_M/\sigma_M$, where the sample standard deviation is given by

$$\sigma_{M} = \left[\frac{1}{M} \sum_{k=1}^{M} (y_{k} - \bar{y}_{M})^{2}\right]^{1/2}$$
(1)

These steps can be summarized in the following equation [24]:

$$(R/S)_{M} = \frac{1}{\sigma_{M}} \left[\max_{1 \le i \le M} \sum_{k=1}^{i} (y_{k} - \bar{y}_{M}) - \min_{1 \le i \le M} \sum_{k=1}^{i} (y_{k} - \bar{y}_{M}) \right]$$
(2)

The value $(R/S)_M$ corresponds to the maximum possible distance that a walker can travel with the sequence of steps Y_M . The rescaled range is estimated over a sufficiently large number of non-overlapping sub-vectors (namely, [N/M]) Y_M with different sizes or scales M (given in number of events) and then averaged over a sufficiently large number of sample sub-vectors over the whole fractal domain N. The recommended time-scale range to assess is from 10 to N/5. If the stochastic process associated to the sequence X_N is scaling over a certain domain $M \in (M_{\min}, M_{\max})$, the R/S statistic follows a power-law

$$(R/S)_M = bM^H \tag{3}$$

where *b* is a constant and *H* is the Hurst exponent, which is a fractal-like scaling measurement of the time series autocorrelations. A log-log plot of $(R/S)_M$ as a function of the scale *M* Download English Version:

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