The Effect of Chi Meditation on the Multifractal Nature of Heart Rate Variability

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***Abstract*—Heart rate variability (HRV) analysis is fast emerging as a noninvasive research and clinical tool for assessing cardiac and autonomic nervous system function. The variations in the heart rate are the consequences of multiple and complex mechanisms, making the heart rate dynamics nonlinear in nature. So, nonlinear analysis of HRV provides more appropriate information for understanding and interpretation of the physiological problems associated with cardiovascular system. In this paper, multifractal detrended fluctuation analysis of HRV signals pertaining to pre-meditation and during meditation conditions is worked out. We observed a right shift in the peaks of multifractal spectra for the subjects during meditation, which represents an increase in multifractal nature of HRV. This result clearly shows that there will be an improvement of health in the cardiovascular system functioning during meditation.**

***Index Terms*—heart rate variability, multifractal detrended fluctuation, meditation, nonlinear analysis, multifractal spectra**

I. Introduction

Biological signals are both nonlinear and non-stationary, i.e., their statistical character changes slowly or intermittently as a result of variations in background influences [1]. Furthermore, very often there exist smaller amplitude fluctuations at shorter time scales. The idea of having hidden information in physiological time series created a growing interest in applying the concepts and techniques from statistical physics, for a wide range of biomedical problems [2], [3].

Heart rate variability (HRV) analysis is fast emerging as a noninvasive research and clinical tool for assessing cardiac and autonomic nervous system function, and it refers to the beat-to-beat alterations in the heart rate. Various investigations confirmed that long-term heart rate variability (HRV) fluctuations are not random, but exhibit long-term correlations that do not exhibit any characteristic scale, but are rather "scale invariant". Scale invariance of a time series means that there is no specific scale of time can be identified in the data. This type of scale invariant variability is also known as fractal and the methodology employed to evaluate it is often called fractal analysis. In geometrical terms a fractal object is a self-similar structure, which means that looking closely at smaller regions reveals a scaled version of the whole object. The word 'fractal' was first used by Mandelbrot [4]. In case of a time series, the similarity is not structural but statistical. The fractal time series look same when viewed in different time scales (scale invariant).

Analysis of fractal scaling exponents by detrended fluctuation analysis (DFA) is one such method which describes the fractal correlation properties of biological time series. Breakdown of short-term fractal organization in human Heart rate (HR) dynamics, has been observed in various disease states, such as in heart failure [5], [6] and during atrial fibrillation [7]. Fractal analysis methods differ from the traditional measures of HRV because they measure the qualitative characteristics and correlation features of HR behavior instead of the magnitude of variability. Briefly, a scaling exponent obtained by the DFA method quantifies the relations of HR fluctuation at different scales. Low-exponent values correspond to dynamics where the magnitude of beat-to-beat HR variability is close to the magnitude of long-term variability. Conversely, high-exponent values correspond to dynamics where the magnitude of long-term variability is substantially higher than the beat-to-beat variability [8]. Fractals can be classified into two categories: monofractals and multifractals. Monofractals are those, whose scaling properties are the same in different regions of the systems and multifractals are complicated self-similar objects consisting of differently weighted fractals with different non-integer dimensions. As a result, multifractal system is a generalization of a fractal system in which a single scaling exponent is not enough to describe its dynamics; instead a continuous spectrum of exponents (the so called singularity spectrum) is needed [2], [9], [10].

The width and shape of the multifractal spectrum can also differentiate between the heart rate variability from patients with heart diseases like ventricular tachycardia, ventricular fibrillation and congestive heart failure [11], [12]. The multifractality has also been reported in heart

Manuscript received December 15, 2014; revised March 20, 2015.

doi: 10.12720/ijsps.4.2.128-132

rate fluctuations of healthy individuals [13]. The multifractal analysis has become a useful tool to detect long-range correlation in heartbeat fluctuations for the diagnosis of heart failure [14]. The multifractal structure of heart rate variability is therefore suggested to reflect important properties of the autonomic regulation of the heart rate.

II. Methodology and Data

A. Multifractal Detrended Fluctuation Analysis

The simplest type of multifractal analysis is based upon the standard partition function multifractal formalism, which has been developed for the multifractal characterization of normalized, stationary measures [15]–[17]. Unfortunately, this standard formalism does not give correct results for nonstationary time series that are affected by trends or that cannot be normalized. Thus, in the early 1990s an improved multifractal formalism has been developed, the wavelet transform modulus maxima (WTMM) method [18], which is based on wavelet analysis and involves tracing the maxima lines in the continuous wavelet transform over all scales. An alternative approach based on a generalization of the DFA method is proposed by Kantelhardt *et al* [19]. This multifractal DFA does not require the modulus maxima procedure, and hence does not involve more effort in programming than the conventional DFA.

The generalized multifractal DFA (MFDFA) procedure consists of five steps. The first three steps are essentially identical to the conventional DFA procedure [20], [21]. The procedure of MFDFA as described by Kanthelhardt, *et al.* [19] is as follows.

Let us suppose that $x(i)$ is a non-stationary time series of length N. The mean of the series $x(i)$ is given by

$$\langle x \rangle = \frac{1}{N}\sum_{i=1}^{N} x(i) \tag{1}$$

Step 1: Compute the integrated time series (profile)

$$Y(i) = \sum_{k=1}^{i} [x(k) - \langle x \rangle] \qquad i = 1, \dots, N. \tag{2}$$

Subtraction of the mean $\langle x \rangle$ is not compulsory, since it would be eliminated by the later detrending in the third step

Step 2: The profile $Y(i)$ is divided into $N_s = \text{int}(N/s)$ non-overlapping segments of equal length s.

Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of the profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Thereby, $2N_s$ segments are obtained altogether.

Step 3: The local trend for each of the $2N_s$ segments is calculated by a least –square fit of the series. Then determine the variance

$$F^2(v,s) = \frac{1}{s}\sum_{i=1}^{s} \{Y[(v-1)s + i] - y_v(i)\}^2 \tag{3}$$

for each segment v, $v = 1, \dots, N_s$ and

$$F^2(v,s) = \frac{1}{s}\sum_{i=1}^{s} \{Y[(N - (v - N_s)s + i] - y_v(i)\}^2 \tag{4}$$

for $v = N_s + 1, \dots, 2N_s$.

where $y_v(i)$ is the least square fitted polynomial in segment v.

$$y_v(i) = \sum_{k=0}^{m} C(k) i^{m-k} \tag{5}$$

Here $C(k)$ are the set of coefficients. Linear, quadratic, cubic, or higher order polynomials can be used in the fitting procedure (conventionally called DFA1, DFA2, DFA3, …).

Step 4: Averaging all the segments to obtain the qth order fluctuation function

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(v,s)]^{q/2} \right\}^{1/q} \tag{6}$$

where, the index variable q can take any real value except zero (for $q = 0$, see step 5). For $q = 2$, the standard DFA procedure is retrieved. As we are interested in how $F_q(s)$ (generalized q dependent fluctuation functions) depend on the time scale s for different values of q. Hence, we must repeat steps 2 to 4 for several time scales s. It is apparent that $F_q(s)$ will increase with increasing s. Of course, $F_q(s)$ depends on the DFA order m. By construction, $F_q(s)$ is only defined for $s \geq m + 2$.

Step 5: The scaling behavior of the fluctuation functions by analyzing log–log plots $F_q(s)$ versus s for each value of q is determined as shown in Figure 1. If the series $x(i)$ are long-range power-law correlated, $F_q(s)$ increases, for large values of s, as a power-law,

$$F_q(s) = s^{h(q)} \tag{7}$$

If such a scaling exists ln $F_q(s)$ will depend linearly on ln s, with $h(q)$ as the slope. For very large scales, $s > N/4$, $F_q(s)$ becomes statistically unreliable because the number of segments N_s for the averaging procedure in step 4 becomes very small. Thus, scales $s > N/4$ are excluded from the fitting procedure to determine $h(q)$, usually. In general, the exponent $h(q)$ in Eq. (7) depends on q. For stationary time series, $h(2)$ is identical to the well-known Hurst exponent H [15]. Thus, the function $h(q)$ can be called as generalized Hurst exponent. The plot of q versus $h(q)$ is shown in Fig. 1(D).

The value of $h(0)$, which corresponds to the limit $h(q)$ for $q \to 0$, cannot be determined directly using the averaging procedure in Eq. (6) because of the diverging exponent. Instead, a logarithmic averaging procedure has to be employed,

$$F_0(s) = \exp\left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln[F^2(v,s)] \right\} \sim s^{h(0)} \tag{8}$$

Note that $h(0)$ cannot be defined for time series with fractal support, where $h(q)$ diverges for $q \to 0$.

For monofractal time series with compact support, $h(q)$ is independent of q, since the scaling behavior of the

variances $F^2(v, s)$ is identical for all segments v, and the averaging procedure in Eq. (4) will give just this identical scaling behavior for all values of q. If we consider positive values of q, the segments v with large variance $F^2(v, s)$ (i.e., large deviations from the corresponding fit) will dominate the average $F_q(s)$. Thus, for positive values of q, $h(q)$ describes the scaling behavior of the segments with large fluctuations. On the contrary, for negative values of q, the segments v with small variance $F^2(v, s)$ will dominate the average $F_q(s)$. Hence, for negative values of q, $h(q)$ describes the scaling behavior of the segments with small fluctuations. Usually the large fluctuations are characterized by a smaller scaling exponent $h(q)$ for multifractal series than the small fluctuations.

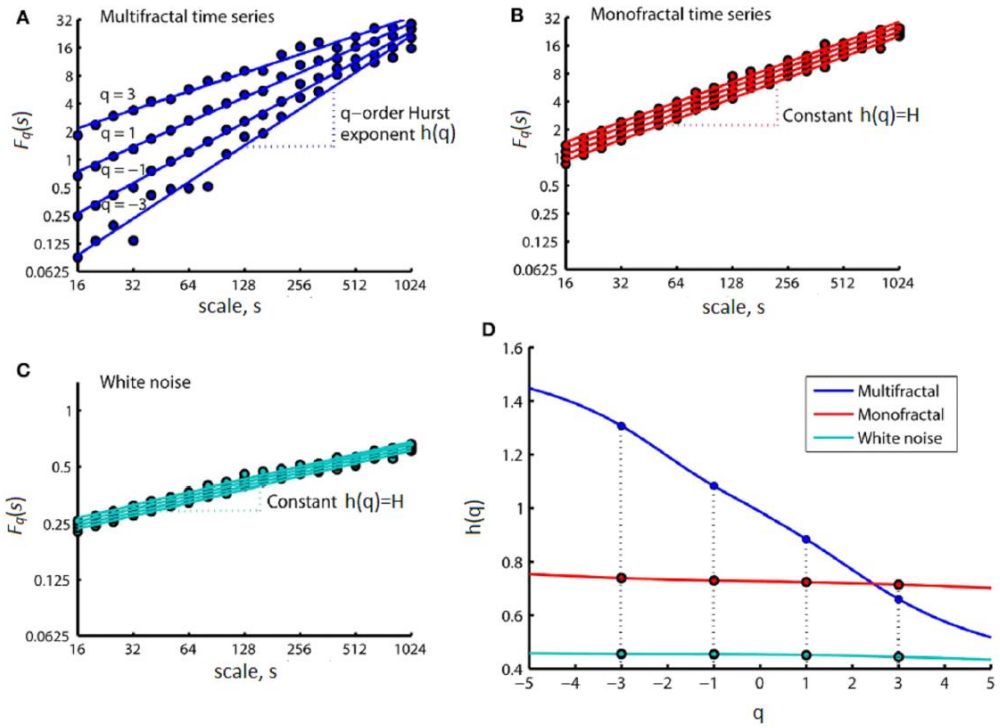

Figure 1. The MFDFA fluctuation functions $F_q(s)$ are shown versus the scale s in log-log plot for A) multifractal time series, B) monofractal time series and C) white noise. Part (D) shows the q dependence of the scaling exponent $h(q)$ for multifractal, monofractal time series and white noise.

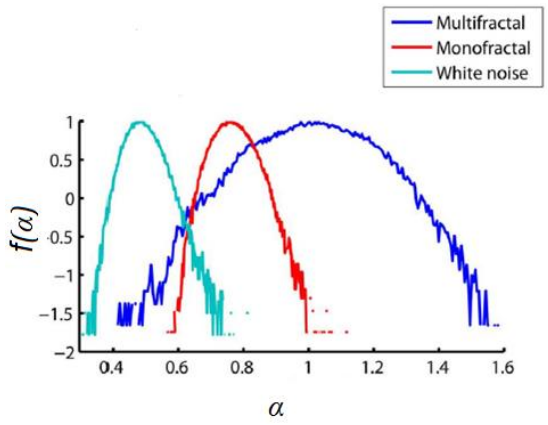

Figure 2. An example of singularity spectrum

The generalized Hurst exponent $h(q)$ of MFDFA is related to the classical scaling exponent $\tau(q)$ by the relation

$$\tau(q)=qh(q)-1 \quad (9)$$

A monofractal series with long range correlation is characterized by linearly dependent q order exponent τ(q) with a single Hurst exponent H. Multifractal signal have multiple Hurst exponents and $\tau(q)$ depends non-linearly on q .

The singularity spectrum f (α) is related to h(q) by

$$\alpha = h(q) + qh(q) \quad (10)$$

$$f(\alpha) = q[\alpha - h(q)] + 1 \quad (11)$$

where α is the singularity strength or Holder exponent and f (α) specifies the dimension of subset series that is characterized by α. The singularity spectra for an example multifractal, monofractal time series and white noise is shown in Fig. 2.

B. Data

In this paper, Multifractal spectrum ($f(\alpha)$) is computed on the HRV signals acquired during meditation. Instead of taking the RR intervals directly for the analysis, the first order difference of RR intervals is used in the study, so as to make the time series look more like noise. The noise like series can be converted into random walk type series using step 1 in the MFDFA procedure. It is customary to convert the time series to a random walk like time series before employing DFA [3]. The plots of RR interval and RR interval differences is shown in Fig. 3.

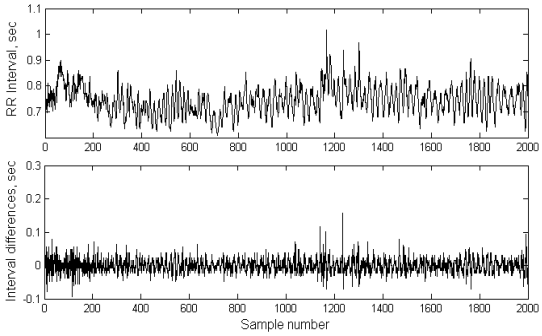

Figure 3. RR intervals (upper) and corresponding RR interval differences (lower).

The data analyzed in this paper is a widely used RR inter-beat interval database for research studies (www.physionet.org) consisting of data before and during meditation, collected from eight healthy Qigong meditation (Chi meditation) subjects (aged 29-35) (more information on the dataset and the meditation method are described in [22]). The length of the time series varied between 50 and 80 minutes.

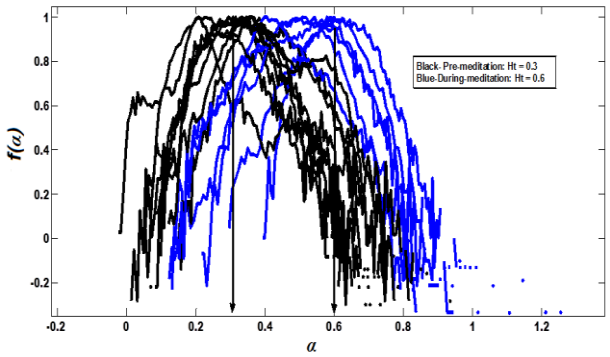

Figure 4. Multifractal spectra of HRV signals taken before and during meditation

III. Results and Conclusion

It can be seen from the Fig. 4 that the peaks of Multifractal spectra are shifted towards the right during meditation. The peaks of pre-meditation data are centered at α = 0.3 and during meditation at α = 0.6. Meyer M. *et al* discriminated heart failure patients from healthy based on the parameter α_{mode} and found that the shape of the singularity spectrum different for pathological conditions (cardiac transplantation vs. ventricular tachycardia) [23]. Magrans, *et al.* [24] applied this method to study HRV before, during, and after ischemia generated by the percutaneous transluminal coronary angioplasty procedure. The results in this study, clearly shows the shifting of the Multifractal spectrum towards right side from pre-meditation to during meditation. The width of the Multifractal spectra increase from white noise to monofractal to multifractal time series and the peak of the spectrum also shifts from white noise to multifractal time series as shown in Fig. 2. Healthy heart rate regulation is a complex process and generates a multifractal signal. It is already proved that complexity of HRV decreases with disease [25]. That means there is a loss of multifractality from healthy condition to disease condition. The results of this study reveal that there is an increase of multifractality from pre-meditation to during meditation. This proves that meditation improves health condition of a person.

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