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Editorial

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Can Fractal Analysis on Heart Rate Variability Reflect Physiological Causes for Cardiorespiratory Interaction?

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Editorial

It is well accepted that Heart Rate Variability (HRV) is a result from complex cardiorespiratory dynamics including heart rate, blood pressure, and respiration rate. Respiratory Sinus Arrhythmia (RSA) is a well-known phenomenon due to cardiorespiratory interaction [1]. Obstructive Sleep Apnea (OSA), one of RSA-related disorders, is the repeated, temporary cessation of breathing during sleep caused by intermittent airway obstruction, and OSA is considered as an independent risk factor for hypertension, ischemic heart attacks, and stroke [2-4]. The underlying mechanisms leading to cardiovascular disease in OSA are complex and not fully understood. However, it is believed that changes of the cardiac autonomic regulation should be involved in the development of cardiovascular disease for OSA patients [5]. In this Editorial, I would like to comment on the understanding of complex cardiorespiratory interaction through sophisticated math like fractal analysis must be careful in clinical applications.

The sympathovagal balance from HRV, supported by numerous data, can be depicted by the spectral analysis. The high-frequency rhythm (HF, 0.15-0.40 Hz) associated with respiration rate covers rapid variations in heart rate due to vagal modulation; therefore, RSA is a result of cardiorespiratory dynamics. The low-frequency rhythm (LF, 0.04-0.15 Hz) often shows a peak at about 0.10 Hz, which is a marker of sympathetic modulation. Low-/high-frequency power ratio (LF/HF) has been a traditional linear index to describe the sympathovagal activity [6]. Recently, Perakakis et al. [7] used a fractal measure, i.e., Detruded Fluctuation Analysis (DFA) [8], to analyze HRV in young adults (14 university students aged 20-23 years), who were instructed to breathe at specific frequencies (0.1 Hz, 0.2 Hz, and 0.25 Hz). One of their findings was that the short-term DFA exponent is significantly reduced when breathing frequency rises from 0.1 Hz to 0.2 Hz. Therefore, they suggested that there are important methodological questions regarding the application of fractal measures to HRV.

Shiau clearly addressed that the short-term DFA exponent (α index, determined from 4 to16 beats) should be strongly correlated with LF/HF through various viewpoints, including physiological and theoretical models [9-11]. Increasing (decreasing) sympathetic activity indicates low-frequency oscillations (LFOs) of HRV will be enhanced (reduced), thus LF/HF should be correspondingly increased (decreased). Moreover, it is known that the spectral density can be approximately expressed as a power-law distribution $f^{-\beta}$, where β is an exponent. And α and β indices obey $\beta = 2\alpha-1$. When Gaussian white noise of that band is considered, $\beta=0$ and, therefore, $\alpha=0.5$. If it is increased over zero (0.5), it indicates LFOs are predominant in the original data, thus LF/HF will be correspondingly increased.

Montano et al. [12] used spectral power to analyze HRV in healthy subjects during graded orthostatic tilt. Their results reflected that the LF component in normalized units becomes largely predominant during 90^0 tilt, which is referred to the effect of gravitation. Moreover, a strong positive (negative) correlation was found between the degree of tilt incline and LF (HF). Using $f^{-\beta}$ to fit spectral power from LF to HF bands, it may find that β would be smaller than 1 in 0^0 tilt, but f^{-1}-like characteristic can be observed in 90^0 tilt. The central peak of the LF component seems to be quite stable around 0.10 Hz, no matter how the change of the degree of tilt inclines. However, the central peak of the HF component will move to a higher frequency when tuning the tilt angle to become 0^0, where it has been known that respiratory rate is synchronized with the HF component. Interestingly, the similar spectral-power distribution as well as the location of the central peak in LF (or HF) rhythm also can be found in healthy subjects during relaxed normal breathing, which were clearly illustrated in the work by Perakakis et al. [7]. Therefore, it could hypothesize that the underlying physiological mechanisms for HRV in healthy subjects during graded orthostatic tilt and relaxed normal breathing could be the same. In 0^0 (90^0) tilt sympathetic

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modulation would be reduced (enhanced) and the central peak of respiratory rate will shift to a higher (lower) frequency, hence a faster (slower) RSA will be induced. Thus, a negative correlation would be found between LF/HF and respiratory rate. In different types of spontaneous breathing Perakakis et al. showed that a faster (slower) RSA will make α exponent to be a smaller (larger) value. Compared to above-mentioned results, we may conclude that α exponent is a result of sympathovagal balance which, of course, will be influenced by breathing frequencies.

The relation between α exponent and sympathovagal balance can be further used to explain the performance of professional athletes. For example, Zhuang et al. [13] reported that shooting athletes get significantly larger α values during exercise compared to those obtained at rest. In particular, an elite athlete displayed the widest alternation in α values from rest (0.5) to exercise (0.9). It is well known that shooting athletes would control their breathing into a slower respiration for prevention of shaking of the gun during exercise. Thus, a larger α exponent would be expected. On the contrary, at rest a faster respiration will show up and a smaller α exponent would be obtained consequently. A complete relaxation at rest as well as a full concentration on the target during exercise would be two key factors for professional athletes. Owing to that, it would be expected that the widest alternation in α values can be detected from elite athletes.

It is well known that DFA is one of powerful methods to detect self-similar scaling exponents (i.e., nonlinear indices) embedded in no stationary biomedical signals. However, in fact, the clinical interpretation of changes in these indices is quite difficult. One of the possible reasons is that they compress cardiorespiratory dynamics including heart rate, blood pressure, and respiration rate in a single numerical index, thus it is not easy to determine physiological relationships between the change in the index and the physiopathological causes. Perakakis et al. demonstrated that changes in breathing frequency produce significant alterations in the short-term DFA exponent that were related to effects of RSA behaving as a sinusoidal trend rather than to autonomic cardiac control. Therefore, they suggested that it is essential to consider both respiration and heart rate in order to correctly interpret short-term HRV scaling behavior. I think it is a very good suggestion which would be very useful to correctly differentiate the underlying meanings of the short-term DFA exponent in clinical applications. In fact, HF and LF could merge into one single dominant oscillation when the breathing frequency (e.g., 0.1 Hz) is close to the LF rhythm. Thus, the concept of sympathovagal balance through LF/HF ratio will be breakdown in this case. Owing to this, using controlled breathing to maintain the frequency of respiration above the LF range would be a possible condition for HRV analysis.

Unfortunately the similar situation also can be observed in OSA, where the respiratory cycle, including apnea and hypopnea, of OSA frequently falls in the LF band that is classically thought to be a non-respiratory marker of sympathetic modulation. Therefore, OSA patients with higher sympathovagal modulation (LF/HF) would be questionable via spectral analysis as well as fractal measure. Thus, developing new indices to correctly characterize the influences of cardiorespiratory interaction in OSA would be essential in near future. In addition, the understanding of the physiological basis of these indices should be an important ingredient for future applications, rather than considering them as numerical indices supported by clinical studies in large-scale database.

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