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The Effect of Yoga Meditation and Metronomic Breathing on Physiological Parameters: A Study of Heart Rate Variability

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ABSTRACT

Introduction: Despite the pervading application of different meditation techniques in treating physical and mental ailments, the effects on neuroautonomic function and physiological parameters have not been extensively researched. This study examined some indices from empirical mode decomposition (EMD) of heart rate variability (HRV) signals during meditation. Specifically, this manuscript aimed to evaluate the modes existing in HRV signals during Yoga meditation and compare them with the corresponding indices before Yoga, metronomic and spontaneous breathing. The validity of the HRV was studied using four Yoga meditators, eight healthy subjects, and eight volunteers during metronomic breathing.

Material and Methods: Intrinsic mode functions (IMFs) and their power spectrums were characterized utilizing entropy and statistical measures. Moreover, the frequency bands of HRV signals were extracted using wavelet transform to obtain more insight into autonomic differences. Wilcoxon test was used for statistical evaluations.

Results: Our results revealed that there are significant differences in very-low-frequency and high-frequency indices between Yoga and other conditions ($p < 0.05$). The most variation in IMFs of HRV signals occurred during Yoga, in which the range of six IMF values was between 15 and 63. Additionally, the IMF patterns in both before Yoga and Metronomic breathing were similar. Significantly lower IMF indices were obtained for normal breathing ($p < 0.05$). The average wavelet entropy value of IMFs is about 10^6 for metronomic breathing and before Yoga, -0.5×10^6 for Yoga, and -2.5×10^6 for normal breathing.

Conclusion: The proposed EMD-based measures can be efficiently exploited in differentiating the HRV signals of meditators.

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Introduction

Despite the pervading application of distinctive kinds of meditation in treating physical and mental ailments [1], its effect on neuroautonomic function and physiological parameters has not been extensively explored.

Heart rate is known as an indicator of autonomic regulation. Since meditation is considered a mind-body health technique [2], some scientists focused on the physiological reactions of the meditative heart through signal-processing approaches. Among the cardiac measures, heart rate variability (HRV) analysis is a promising way to examine cardiac functions [3].

To evaluate sympathetic and parasympathetic activities, the spectral components of the HRV in four frequency bands: ultra-low-frequency (ULF), very-low-frequency (VLF), low-frequency (LF), and high-frequency (HF) are studied [4]. Some meditation literature was conducted based on time and frequency techniques [5-6]. Prominent low-frequency heart rate oscillations or elevated mean resting heart rates were observed during different meditative/breathing protocols.

Considering the chaotic nature of the HRV signals, some nonlinear features, such as Poincare indices, Lyapunov exponents, and Hurst exponents, have been studied previously. Implementing Hilbert transform [7], a greater HRV amplitude was observed during meditation compared to the pre-meditation baselines and the other control groups. In contrast, a decreased dynamical complexity of HRV was concluded in meditation [8]. The width of lagged Poincaré plots of heart rate signals during meditation has been evaluated [9]. The results indicated that the width of the Poincaré plot tended to increase as the lag increased during meditation. In subsequent research, the authors evaluated other lagged Poincare plot measures [10]. The team also reported a decreased chaotic behavior of HRV during the performance of meditation by analyzing recurrence plots [11], Lyapunov exponents (LE), and Hurst exponents [12]. Examining Bispectrum indices [13], heart rate patterns appear to be influenced by different types of meditation. The degree of chaos and the existence of fractal patterns in the meditative HRV was

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investigated by Kamath [14]. Meditation resulted in an elevated chaos level. In addition, lower fractal dimensions were found during meditation. A similar result has been reached by other scholars, where a limited degree of multi-fractality [15] and a reduced fractal scaling [16] were testified. Recently [17], two similarity measures of the meditative HRV signals, including correntropy and Cauchy-Schwarz divergence, were extracted and scrutinized. More recently, the dynamics of HRV signals during meditation have been evaluated through LE, Lempel-Ziv complexity (LZ), Lagged Poincare indices, four entropy measures [18], and the matching pursuit (MP)-based indices [19]. All emphasized the significant difference between HRV responses from different non-meditator and meditator groups.

As an instantaneous amplitude and frequency tracking problem, the modes existing in a signal have been evaluated by some researchers. To this effect, the empirical mode decomposition technique has been introduced. In some literature [20], EMD has been employed on the HRV signals. The authors attempted to classify the sleep stages utilizing different HRV characteristics (one of which was EMD). The signal was decomposed into four levels, and each IMF was quantified with sample entropy and approximate entropy.

Accurately examining the signals will provide more efficacy of meditation as an intervention for various health conditions. For the analysis of the HRV signals, most of the previous studies have separately examined time, frequency, and nonlinear measures. However, we hypothesized statistical and nonlinear feature extraction methods can be combined to extract better results. Consequently, the contribution of this work is extracting the informative meditation-related patterns of HRV using a combination of the EMD method and some spectral and nonlinear indices. This study attempts to investigate the possible effects of meditation on HRV from a signal-processing perspective using some indicators from frequency-based techniques, discrete wavelet transform (DWT), and empirical mode decomposition (EMD) methods. We tested the hypothesis that the HRV responses of non-meditators and meditators are different and dissimilar in meditators pre and during meditation practice.

Materials and Methods

Data selection

The current study assessed the effect of Kundalini Yoga meditation (as taught by Yogi Bhajan) on heart rate signals [7]. In the study [7], participants engaged in Kundalini Yoga, who were at an advanced level of meditation training, included four subjects: two females and two males, with an age range of 20 to 52 years (mean age of 33). They were outfitted with Holter monitors for approximately one and a half hours. A 15-minute baseline of quiet breathing was recorded prior to the hour-long meditation session. The meditation protocol involved breathing and chanting exercises while seated in a cross-legged posture. The commencement and conclusion of the distinct meditation sub-phases were denoted with event marks.

To compare the benefits of Yoga meditation on cardiac functioning, two healthy, non-meditating control groups were also examined: 1) a spontaneously breathing group consisting of 8 healthy subjects during sleeping hours and 2) a healthy group of 8 subjects during supine metronomic breathing at a determined rate of 0.25 Hz. It is mentioned that 11 participants in normal breathing (8 women and three men; age range 20–35, mean 29) and 14 participants in metronome breathing (9 women and five men; age range 20–35, mean 25) are available in the database. We randomly used the identical eight participants from each group (the total number of signals in pre and on-meditation). The overall general health conditions of all three groups (Yoga meditation, Spontaneous nocturnal breathing, and metronomic breathing) were comparable [7].

Wavelet analysis

A signal is decomposed using a different ‘mother’ wavelet, scaled, and translated in time. The selection of suitable wavelets and the number of decomposition levels are crucial in the analysis of signals. Based on the dominant frequency components of the signal, the number of breakdown levels is selected. It has been shown that the Daubechies 4 (db4) function was suitable for analyzing heart rate signals [21]. Therefore, the discrete Daubechies 4 wavelet basis has been chosen. The main reason for using the db4 wavelet is the similarity of its wavelet function to the QRS complex (the composition of three of the graphical deflections, the Q wave, R wave, and S wave, on a typical electrocardiogram (ECG), which represents ventricular depolarization) of the ECG signal. Wavelet decomposition was done at level 5, and the wavelet coefficients of the HRV signals in three frequency bands, VLF, LF, and HF, were calculated. These parameters are summarized as follows:

- VLF {0–0.0375 Hz}: A5 coefficient
- LF {0.0375–0.15 Hz}: D4–D5 coefficients
- HF {> 0.15 Hz}: D1–D3 coefficients.

Empirical mode decomposition

Empirical Mode Decomposition (EMD) is a cutting-edge algorithm utilized for data processing in non-stationary and nonlinear time series [22]. This innovative technique aims to decompose complex time series into a constrained number of Intrinsic Mode Functions (IMFs). An IMF must satisfy two conditions: firstly, the number of zero crossings and extrema must be either equal or differ by one; secondly, its envelopes, which are defined by local maxima and minima, must exhibit local symmetry around zero. The extraction of an IMF from the data involves calculating the mean of the upper and lower envelopes, while connecting the extrema using a cubic spline method. It is important to note that there is a limitation to the number of IMFs that can be extracted from a complex time series. As a result, a residue signal with a monotonic pattern will still remain. Finally, the original time series can result in N IMFs and the residue signal by the following equation:

$$X(t) = \sum_{n=1}^{N} C_n + r_n \tag{1}$$

where X(t) represents the original signal and C_n is the n^{th} IMF. The residue after n decomposing operations is represented by r_n.

We obtained possible IMF levels for each time series. Then, to homogenize the analysis in all the HRVs, we considered the minimum IMF levels for all the signals. Several features can be extracted from IMFs to depict the differences between normal, metronomic, and meditative HR signals. In the current study, the minimum, mean, maximum, and wavelet entropy of each mode of the EMDs (IMFs), and the minimum, mean, and a maximum of the power spectrum of the IMFs were examined.

Wavelet entropy

The Shannon entropy provides a beneficial criterion for evaluating and comparing probability distribution, it provides a measure of any distribution.

Consider the wavelet coefficients as *Cj(k)*.The energy at each resolution level *j = -1, …, -N* is calculated as Eq.(2),

$$E_j = \sum_k \left|C_j(k)\right|^2 \tag{2}$$

and the energy at each sampled time *k* is obtained as (3).

$$E_j = \sum_k \left|C_j(k)\right|^2 \tag{3}$$

The total energy is found by (4).

$$E_{tot} = \sum_{j<0} \sum_k \left|C_j(k)\right|^2 = \sum_{j<0} E_j \tag{4}$$

The relative wavelet energy (5), defined by scales the probability distribution of the energy for the resolution level *j = -1, -2, …, -N.*

$$p_j = \frac{E_j}{E_{tot}} \tag{5}$$

where $\sum_j p_j = 1$. The distribution $\{p_j\}$ is a time–scale density [23].

The WE is defined by (6) [24]:

$$S_{WT} = -\sum_{j<0} p_j . \ln[p_j] \tag{6}$$

The WE performs as a measure of the degree of order/disorder of the signal, so it can communicate valuable information about the underlying dynamics of the data.

Power spectrum

Applying the Fast Fourier transform (FFT), the power spectral density (PSD) of the IMFs of heart rate signals was estimated during normal breathing, metronomic, and the Yoga meditation technique. The following features were utilized as indices of HRV signals:

- Minimum PSD of the intrinsic mode functions
- Mean PSD of the intrinsic mode functions
- Maximum PSD of the intrinsic mode functions

Statistical analysis

In the present study, we conducted the Mann-Whitney U-test (Wilcoxon). This test compares two vectors to determine if they are independent samples from the same continuous distribution with equal medians. The null hypothesis assumes equal medians, while the alternative hypothesis suggests unequal medians. Applying the Wilcoxon test, two vectors can occupy different lengths. The result of the test is returned in p.

In the present study, signal processing was carried out utilizing MATLAB R2014a. In addition, the CEEMDAN toolbox has been used to simulate EMD [25].

Results

The introduced features were extracted from HRV signals in various conditions: prior to and during Yoga, metronomic and normal breathing. As a reminder, the features were minimum, mean, maximum, and wavelet entropy of each IMF, and minimum, mean, and a maximum of the power spectrum of the IMFs. Wilcoxon statistical test was performed to examine the significance of the features. The results of the statistical test for each feature are presented in Table 1.

First, to provide greater insight into autonomic differences in different conditions (i.e. prior to and during Yoga, metronomic and normal breathing), the frequency bands of HRV signals are extracted based on wavelet coefficients (refer to section 2). It is comprehensible from Table 1 that there are significant differences in VLF and HF indices between Yoga and other conditions.

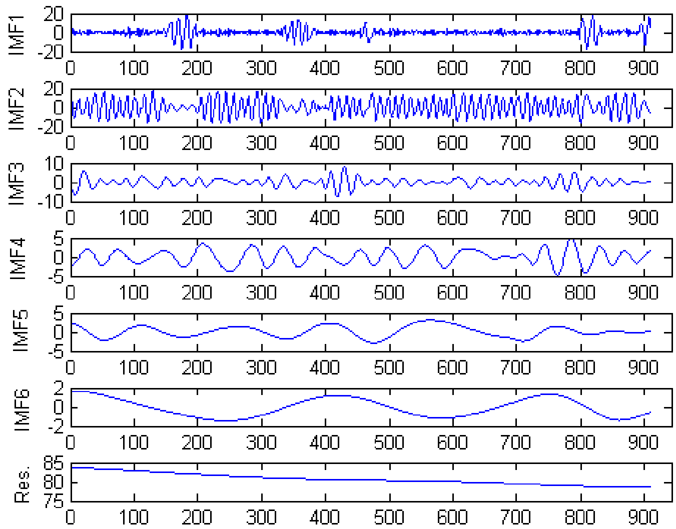

Figure 1. An example of empirical mode decomposition of the HRV signal during Yoga (subject 3). The x-axis shows the samples, and the y-axis represents the amplitude of each signal mode. IMF1 to IMF6 refers to the first six levels of EMD modes (the first intrinsic mode function to the sixth intrinsic mode function), and Res. shows the residue of the algorithm.

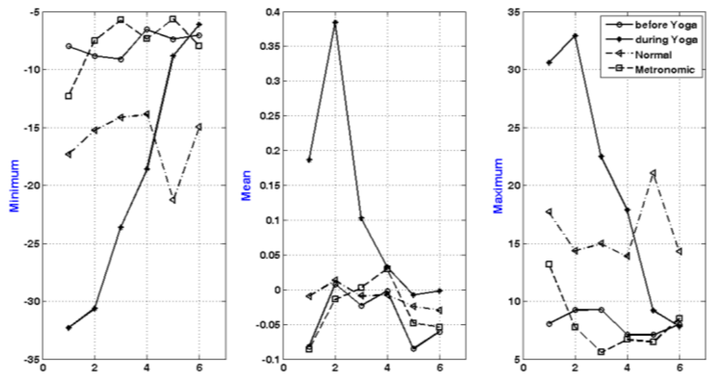

Figure 2. Minimum, mean, and a maximum of the IMFs. X-axis represents IMF's numbers (IMF1 to IMF6). The y-axis represents the feature values

Next, implementing the EMD algorithm, the IMFs of each signal are calculated. The number of intrinsic modes for HRV signals was estimated. The results showed that the number of HRV intrinsic modes for metronome breathing and yoga is lower than that of the other states (for more information, refer to the supplementary results, Table S1). In these two conditions, the number of inherent modes changes between 6 and 8. While for Chi meditation, their number is between 9, and 11 and for normal is between 13 and 17. Additionally, the minimum IMF level for all the signals is 6. Consequently, all analyses have been done on 6 IMFs of the data.

Figure 1 exemplifies the IMFs of an HRV signal.

The following features of each mode are extracted to quantify the IMFs, minimum, mean, maximum, wavelet entropy of the IMFs, minimum, mean, and maximum of the PSD of the IMFs.

Results for the time indices (minimum, mean, and maximum) of the IMFs are presented in Figure 2.

It can be perceived in Figure 2 that the most variation in IMFs of HRV signals has occurred during Yoga and that the IMF patterns in both before Yoga and Metronomic breathing are similar.

The PSD of the IMFs was calculated in different conditions. Figure 3 illustrates an example of it. The frequency-based indices (minimum, mean, maximum of the PSD) of the IMFs are extracted (Table 2) to quantify the PSDs. The Wilcoxon test for statistical evaluations of PSDs has been reported in Table 1. The table shows that PSDs are significantly different in the conditions. Using IMF indices based on PSD evaluation, there are significant differences between normal and Yoga/metronomic breathing states (Table 2). In addition, the HRV indices before Yoga meditation are highly different from the normal, which means the effect of Yoga practice on HRV baseline and behavior.

As shown in Figure 3, the frequency of each mode differed from the others and tended to decrease for higher IMFs. As a result, for the higher IMFs, the PSD tends to lower frequencies, and its area is reduced.

Figure 4 shows the wavelet entropy of the IMFs. Again, a similar pattern is observed in both before Yoga and Metronomic breathing, but it is significantly different from normal and Yoga conditions. Altogether, results indicate the significant differences between Yoga and other states (Figure 4, Table 1, and Table 2).

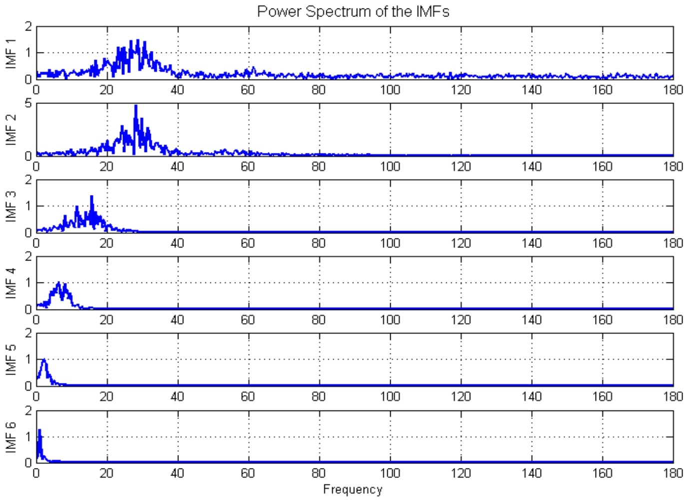

Figure 3. The power spectrum of the IMFs for a meditative HRV (subject 3). The x-axis shows the frequency (Hz), and the y-axis represents the amplitude of each mode in the corresponding frequency.

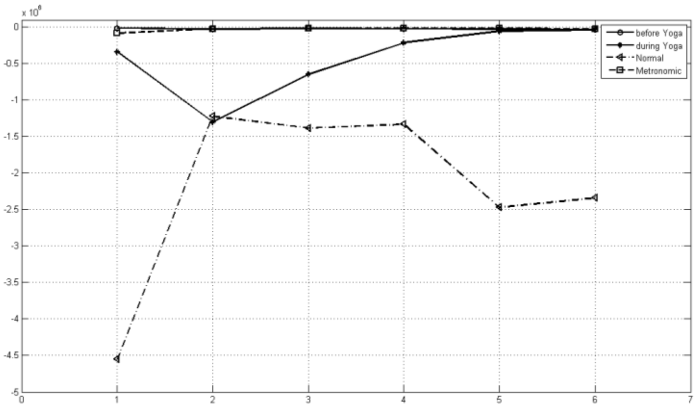

Figure 4. Wavelet entropy of the IMFs. The x-axis represents IMF's numbers (IMF1 to IMF6). The y-axis represents the feature values.

Table 1. A statistical test (Wilcoxon) to determine the significance of extracted features between different conditions of the HRV signals

Feature		Yoga vs pre Yoga	Yoga vs normal	Yoga vs metronomic	Metronomic vs normal
Wavelet	VLF	8.72×10^{-41}	2.53×10^{-89}	7.94×10^{-37}	0.1115 NS
	LF	0.86 NS	0.8614 NS	0.84 NS	0.730 NS
	HF	5.85×10^{-4}	0.0010	0.50 NS	0.1136 NS
Wavelet Entropy	IMFs	0.0043	0.0152	0.0087	0.0022
Power	IMF 1	3.8×10^{-18}	0	0.0205	0
	IMF 2	1.25×10^{-57}	0	1.45×10^{-131}	0
	IMF 3	5.38×10^{-53}	0	2.38×10^{-149}	9.41×10^{-302}
	IMF 4	0.1131 NS	0	8.59×10^{-102}	0
	IMF 5	9.68×10^{-77}	0	0.0025	0
	IMF 6	5.35×10^{-7}	0	6.02×10^{-27}	0

Note: $p < 10^{-302}$ considered as 0. NS: Not Significant

Table 2. The mean ± standard deviation (SD) of the PSD measures of the IMFs, and the statistical test (Wilcoxon) results in defining significant differences between different conditions of the HRV signals.

Feature	Before Yoga	Yoga	Normal	Metronomic
Minimum of PSD				
IMF 1	$4.1\times10^{-3}\pm1.4\times10^{-3(2)}$	$6.5\times10^{-3}\pm5\times10^{-3(2)}$	$1.05\times10^{-4}\pm1.12\times10^{-4\,(1,3,4)}$	$5\times10^{-3}\pm3.4\times10^{-3(2)}$
IMF 2	$0.7\times10^{-3}\pm0.5\times10^{-3(2)}$	$1.7\times10^{-3}\pm2\times10^{-3(2)}$	$0.19\times10^{-4}\pm0.12\times10^{-4(1,3,4)}$	$1.1\times10^{-3}\pm1.5\times10^{-3(2)}$
IMF 3	$1.3\times10^{-3}\pm0.18\times10^{-3(2)}$	$1.4\times10^{-3}\pm1.5\times10^{-3(2)}$	$0.04\times10^{-4}\pm0.02\times10^{-4(1,3,4)}$	$0.6\times10^{-3}\pm0.9\times10^{-3(2)}$
IMF 4	$4.1\times10^{-3}\pm4\times10^{-3(2,3)}$	$1.8\times10^{-3}\pm2\times10^{-3(2)}$	$0.04\times10^{-4}\pm0.05\times10^{-4(1,3,4)}$	$1.1\times10^{-3}\pm1.1\times10^{-3(2,4)}$
IMF 5	$5.9\times10^{-3}\pm6.4\times10^{-3(2)}$	$1.2\times10^{-3}\pm0.7\times10^{-3(2)}$	$0.11\times10^{-4}\pm0.14\times10^{-4(1,3,4)}$	$2.1\times10^{-3}\pm1.8\times10^{-3(2)}$
IMF 6	$4.2\times10^{-3}\pm5.4\times10^{-3(2)}$	$1.6\times10^{-3}\pm1.5\times10^{-3(2)}$	$0.22\times10^{-4}\pm0.4\times10^{-4(1,3,4)}$	$4\times10^{-3}\pm4.8\times10^{-3(2)}$
Mean of PSD				
IMF 1	$0.12\pm0.03^{(2)}$	$0.19\pm0.15^{(2)}$	$0.03\pm0.01^{(1,3,4)}$	$0.15\pm0.05^{(2)}$
IMF 2	$0.09\pm0.02^{(1,2)}$	$0.24\pm0.11^{(2,3,4)}$	$0.014\pm0.005^{(1,3,4)}$	$0.06\pm0.02^{(1,2)}$
IMF 3	$0.06\pm0.02^{(2)}$	$0.13\pm0.09^{(2,3)}$	$0.012\pm0.004^{(1,3,4)}$	$0.04\pm0.01^{(1,2)}$
IMF 4	$0.05\pm0.03^{(2)}$	$0.07\pm0.05^{(2)}$	$0.009\pm0.002^{(1,3,4)}$	$0.04\pm0.009^{(2)}$
IMF 5	$0.04\pm0.03^{(2)}$	$0.03\pm0.02^{(2)}$	$0.0085\pm0.002^{(1,3,4)}$	$0.03\pm0.01^{(2)}$
IMF 6	$0.04\pm0.03^{(2)}$	$0.02\pm0.02^{(2)}$	$0.006\pm0.002^{(1,3,4)}$	$0.03\pm0.02^{(2)}$
Maximum of PSD				
IMF 1	$0.61\pm0.1^{(2)}$	0.86 ± 0.62	$0.29\pm0.16^{(3,4)}$	$1.12\pm0.68^{(2)}$
IMF 2	$0.78\pm0.18^{(1,2)}$	$3.67\pm0.83^{(2,3,4)}$	$0.13\pm0.06^{(1,3,4)}$	$0.56\pm0.22^{(1,2)}$
IMF 3	$0.72\pm0.32^{(1,2)}$	$2.87\pm1.46^{(2,3,4)}$	$0.2\pm0.06^{(1,3,4)}$	$0.61\pm0.24^{(1,2)}$
IMF 4	$1.2\pm0.47^{(2)}$	$1.89\pm0.90^{(2,3)}$	$0.23\pm0.05^{(1,3,4)}$	$0.82\pm0.22^{(1,2)}$
IMF 5	$1.69\pm0.70^{(2)}$	$1.65\pm0.45^{(2,3)}$	$0.37\pm0.14^{(1,3,4)}$	$1.01\pm0.43^{(1,2)}$
IMF 6	$2.3\pm1.54^{(2)}$	$1.51\pm0.5^{(2)}$	$0.45\pm0.15^{(1,3,4)}$	$1.35\pm0.60^{(2)}$

Note:
(1)Significantly different from Yoga
(2)Significantly different from Normal
(3)Significantly different from Metronomic
(4)Significantly different from before Yoga

Discussion

The current study attempted to answer the following assumptions. 1) The potential of the proposed features (EMD-based measures) for studying meditation effects. 2) Whether there are any differences between Yoga and metronomic breathing. 3) The lingering effect of Yoga practice on cardiac function. For this purpose, the HRV was compared between the resting condition of Yoga meditators (before Yoga) and non-meditators (normal breathing). To this effect, some features, namely minimum, mean, maximum, wavelet entropy of the IMFs, minimum, mean, and maximum of the PSD of the IMFs, were extracted. They were compared in different conditions, including before and during Yoga, metronomic, and normal breathing.

The results indicated that simple indices extracted from the EMD technique are beneficial for differentiating between Yoga and other conditions (Pre Yoga, Metronomic and normal breathing). Besides, the frequency bands of HRV signals were extracted using DWT instead of calculating them with conventional spectral analysis. It can be apparent from Table 1 that the significant differences between Yoga and the other conditions occurred in the VLF and HF bands ($p < 0.05$). This finding is confirmed by the previous one utilizing spectral analysis [26], where HRV spectral measures in the Samadhi, which is the state of one-pointed concentration or successful meditation, and the Non-Samadhi states were remarkably different. A higher HF power during meditation was revealed [26], which means the synchronization of the HRV to the respiratory rhythm. In a few cases, the VLF-resonant peak was also observed during meditation [26], where thermoregulation and humoral regulation are possible reasons. However, further examination still needs to prove this issue.

Statistical analysis of intrinsic modes indicated a significant difference between normal breathing and all other groups. Furthermore, some extracted parameters showed significant differences between the pre and on-Yoga. These results are in line with some previous findings. In [19], meaningful differences between the HRV parameters of non-meditators and meditators were reported utilizing Matching pursuit analysis. The authors also concluded a significant difference between before and during meditation for most MP coefficients. A recent study [27] evaluated heart rate asymmetry (HRA) using a conventional Poincare plot for meditators and non-meditators groups. The results emphasized significant differences between the HRA index of meditators and non-meditators. Deka and Deka [28] proposed the standard deviation of second-order differences of RR intervals to characterize HRV dynamics for the distinction between meditative and pre-meditative states. The statistical t-test showed a significant difference in six out of the eight suggested features between the two states before and during meditation. More recently [29], a generative adversarial network-based approach was designed to identify the meditation effect on the HRV. The results pointed out that meditation exercise influences cardiac dynamics significantly.

Another substantial result of the current study is that the EMD indices of both before Yoga and Metronomic breathing HRV signals are similar (Figure 2 and Figure 4). It may be signified that the baseline HRV signals of Yogic are altered due to meditation practice and tend to the pattern of metronomic breathing. Therefore, it can be concluded that regular meditation practices can be applied as an intervention for various health conditions, for example, in respiratory disorders.

Some proposed features have not been considered in the previous studies of meditation. Our results proved a hybrid of the EMD, statistical, spectral, and entropy measures is pertinent to study the physiological reactions of non-meditators and meditators. In addition, these indices can be valuable in understanding the beneficial health of meditation techniques.

We used an open database [7], where a limited number of signals are presented. On the other hand, the number of time series is unequal for the groups. Reliable validation of the findings should be assessed utilizing bulky and balanced signals in the future.

Conclusion

This paper investigated the effect of meditation on HRV parameters utilizing EMD indices. Different indices were extracted from the data modes (IMFs) for two groups of meditators and non-meditators. The Wilcoxon rank-sum test was implemented for statistical evaluations of the physiological reactions between the groups. The results imply a meaningful difference between Yoga and the other conditions in the VLF and HF bands. Additionally, significantly lower IMF indices were obtained for normal breathing. In conclusion, our results established the efficiency of the proposed EMD-based measures in differentiating HRV signals of meditators.

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