TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 09/18 pp325–332
DOI: 10.26599/TST.2021.9010030
Volume 27, Number 2, April 2022

Heart-Rate Analysis of Healthy and Insomnia Groups with Detrended Fractal Dimension Feature in Edge

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Abstract: Insomnia, whether situational or chronic, affects over a third of the general population in today's society. However, given the lack of non-contact and non-inductive quantitative evaluation approaches, most insomniacs are often unrecognized and untreated. Although Polysomnographic (PSG) is considered as one of the assessment methods, it is poorly tolerated and expensive. In this paper, with the recent development of Internet-of-Things devices and edge computing techniques, we propose a detrended fractal dimension (DFD) feature for the analysis of heart-rate signals, which can be easily acquired by many wearables, of good sleepers and insomniacs. This feature was derived by calculating the fractal dimension (FD) of detrended signals. For the trend component removal, we improved the null space pursuit algorithm and proposed an adaptive trend extraction algorithm. The experimental results demonstrated the efficacy of the proposed DFD index through numerical statistics and significance testing for healthy and insomnia groups, which renders it a potential biomarker for insomnia assessment and management.

Key words: insomnia; fractal dimension; adaptive signal separation; hypothesis testing

1 Introduction

To date, a large proportion of the population suffers from insomnia disorder, including situational, recurrent, or chronic symptoms. Insomnia, or sleep disorder, will lead to medical or psychiatric disorders, such as pain and depression in the daytime, whereas persistent insomnia will cause many other comorbid diseases, such as hypertension and cardiovascular disease (CVD). Since 2009, nearly up to 10% of the population met the diagnostic criteria for insomnia syndrome, and about a third experienced insomnia symptoms at any given moment, resulting in a heavy burden for the patients and health-care systems[1]. Although insomnia can be characterized by dissatisfaction with the sleep duration or quality and difficulties in initiating or maintaining sleep, it is often unrecognized and untreated because of the difficulties in quantitative evaluation and management[2, 3]. Polysomnography (PSG) is one of the assessment methods, that can show objective indicators of sleep quality (e.g., fall asleep time, sleep duration, and respiration); however, this process is poorly tolerated, inconvenient, and expensive[4]. Furthermore, the severity of insomnia may mismatch the patient's complaint of poor sleep. Recently, many deep-learning-based models have been proposed to assist clinicians in diagnosing sleep insomnia. Shahin et al.[5] applied deep learning on a set of 57 electroencephalography (EEG) features to accurately differentiate between patients with insomnia or controls with no sleep complaints. Sun et al.[6] proposed a snore detection network to detect early symptoms of obstructive sleep apnea-hypopnea syndrome. However, these kinds of approaches often have high computational complexity and present difficulty in achieving home-based monitoring and long-term prognosis observation. Furthermore, with the rapid development in edge computing techniques, including privacy-aware link prediction[7, 8] and cross-platform service recommendation[9, 10], Internet-of-Things (IoT)

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Manuscript received: 2021-01-25; revised: 2021-03-02; accepted: 2021-03-17

devices can provide hardware support for home-based monitoring. Therefore, an environment-friendly, cost-effective, efficient, and comfortable strategy for insomnia diagnosis is still a great challenge.

Although the mechanism linking insomnia with cardiovascular risk remains unclear, several studies have tested the hypothesis that participants with insomnia would display an increased heart rate, which is representative of their hyperarousal status, when compared to good sleeper controls[11, 12]. Dodds et al.[12] studied recent literature on heart rate with insomnia and discovered that several studies reported significant differences between the participants with insomnia and good sleepers, especially for the middle and elder-age groups. Haynes et al.[13] studied 10 sleep-onset young insomniacs and 11 non-insomniacs who have been identified as good sleepers and observed that the insomniac subjects demonstrated a significantly higher mean heart-rate response than non-insomniacs during the period of before and after the lights off. The increase in the heart rate during sleep was also reported by Bonnet and Arand[14] in a study of 12 young adults with insomnia compared with 12 controls. The above-mentioned evidence illustrates the relevance between heart rate and insomnia. Thus, the heart-rate measurement can be considered as a potential distinctive physiological marker of "hyperarousal" in insomnia. Meanwhile, compared with other physiological signals, such as EEG and oronasal respiration, heart-rate signals can be easily acquired from various wearable devices, such as wristwatches and heart-rate sticks, which are conducive to the acquisition of whole-night data for further analysis and diagnosis.

For the other studies that reported non-significant differences in heart rate between insomniac subjects and good sleeper controls[15], such result might be due to the simple mean value of heart rate for the characterization of the complexity of heart-rate variability (HRV). Numerous metrics and norms in the time-domain, frequency-domain, and nonlinear measurements have been proposed in the past two decades to analyze HRV signals precisely, including long-term and short-term HRV[16]. Entropy is one of the widely used metrics for measuring information of complex signals. Based on the concept of entropy, Costa et al.[17] proposed a multi-scale entropy to analyze the long-range correlation of complex time series and applied this method to the HRV signals of healthy and pathologic groups. Ma et al.[18] introduced the most commonly used nonlinear concepts of fractals and entropy to sleep EEG signal analysis and reviewed the novel findings from their clinical applications.

Given that complex physiological signals may consist of several underlying or physically meaningful sub-components, several signal decomposition approaches (e.g., empirical mode decomposition (EMD)[19, 20] and null space pursuit (NSP)[21, 22]) have been incorporated as pre-processing steps for analyzing the metrics of complex physiological signals. Sun et al.[23] used detrended Mel-Frequency cepstral coefficients (MFCC) as extracted features to automatically classify the excitation location from snoring sounds. Ebrahimi et al.[24] compared EMD and discrete wavelet transform for HRV signals and computed the nonlinear dynamic features of the decomposed sub-component signals to fulfill the automatic sleep staging.

Fractal dimension (FD) is one of the dynamic features that can provide a statistical index of complexity; it measures how detailed a pattern changes on a certain scale. Given that trend and details often represent different scales of physiological signals, the direct computation of the FD of HRV signals will inevitably be affected by the trend component. Therefore, in this paper, we propose a detrended FD (DFD) index for the analysis of heart-rate signals of healthy sleepers and insomniacs. First, we improve the NSP algorithm for adaptive extraction of the trend component from the heart-rate signal of subjects from lights off to falling asleep (i.e., stage N1 of sleep). Then, FD index is calculated from the residual heart-rate signal (i.e., signals after subtraction of the trend component) of the subjects. The experimental results demonstrate significant differences in the DFD index in the independent-sample hypothesis test for good sleepers and insomniacs.

The remainder of this paper is organized as follows. In Section 2, we review several adaptive signal separation approaches and improve the NSP algorithm for trend extraction. Then, in Section 3, we propose a DFD algorithm for the analysis of heart-rate signals. In Section 4, we conduct the independent-sample hypothesis test for healthy and insomnia groups using DFD index. Section 5 provides the conclusion remarks.

2 Adaptive Trend Extraction with the NSP Algorithm

Given that the trend is usually considered as the low frequency component of signals, traditional frequency domain-based filtering algorithms are used for its extraction. However, such algorithms lack flexibility and

adaptability for nonlinear and complex physiological signals. Unlike the frequency or time-frequency-based algorithms, several totally time-domain-based signal separation approaches, which are flexible, adaptive, and data-driven, have been proposed. The EMD is one of these algorithms, and it models a complex signal as the superposition of several intrinsic mode functions (IMFs) with each containing a certain physical meaning[19]. The trend component can be derived by the summation of the last or last several IMFs. Although EMD has a number of merits and is easy to use, it depends substantially on the extremum points of the input signal, which are unstable for real-life physiological signals because of the noise.

The NSP is a time-scale-based signal separation algorithm that uses operators to characterize the property of sub-component signals[21]. When the operator is defined, the sub-component signal in the null space of the operator (i.e., in the solution space of the corresponding differential or integral equation to the operator) can be extracted by the NSP algorithm. Therefore, for different kinds of signals, we can define different kinds of operators to fit them, similar to the integral operator for frequency modulated signals[22] and the complex-valued differential operator for amplitude-modulated and frequency-modulated (AM-FM) signals[25, 26].

In the NSP algorithm[21], given a signal $S(t)$ and a defined operator $\mathcal{P}$, the extracted sub-component $U(t)$ and the residual signal $R(t)$ are determined such that

$$S(t) = U(t) + R(t), \text{ with } (\mathcal{P}U)(t) = 0 \quad (1)$$

where $(\mathcal{P}U)(t) = 0$ means that $U(t)$ is in the null space of operator $\mathcal{P}$. The NSP algorithm uses the following regularization model to obtain $U(t)$:

$$\hat{U} = \arg\min_U \left\{ \|\mathcal{P}U\|^2 + \lambda \left(\|U\|^2 + \gamma \|\mathcal{D}(S-U)\|^2 \right) + \rho f(\mathcal{P}) \right\} \quad (2)$$

where the second term is called the leakage term, parameters λ and γ are used to determine the amount of $U(t)$ to be retained in the null space of $\mathcal{P}$, $\mathcal{D}$ is an operator that regulates the residual signal $R(t)$; the last term is the Lagrange term for the parameters of the operator $\mathcal{P}$, it can be estimated adaptively during the iteration, and ρ is the hyper-parameter for balance the regularization term between the residual signal and the parameters of the operator.

Although Peng and Hwang[21] have proposed an updating formula for the hyperparameters λ and γ, these variables are closely related to each other causing difficulty in finding a suitable stop criterion for a stable solution in certain real-life signals. Here, given that we only consider the trend sub-component which is smooth and slowly varying, we can define an operator $\mathcal{P}$ with a simple form as follows:

$$(\mathcal{P}S)(t) = \frac{\mathrm{d}S^2(t)}{\mathrm{d}t^2} + \varpi(t)S(t), \text{ with } \varpi \leqslant T \quad (3)$$

where T is a small threshold, and ϖ denotes the instantaneous frequency (IF) of the signal $S(t)$. In addition, the regularization of other sub-components and residual signals is unnecessary. Thus, we remove the leakage term and simplify the NSP algorithm to the following model:

$$\hat{U} = \arg\min_U \left\{ \|\mathcal{P}U\|^2 + \lambda \|S-U\|^2 + \rho f(\mathcal{P}) \right\} \quad (4)$$

The regularization term for the operator $\mathcal{P}$ is defined as follows:

$$f(\mathcal{P}) = \int w^2(t)\varpi^2(t)\mathrm{d}t \quad (5)$$

where

$$w(t) = \begin{cases} 1, \text{ if } \varpi(t) > T; \\ 0, \text{ otherwise} \end{cases} \quad (6)$$

In the discrete case, if we used uppercase and bold lowercase letters to denote matrices and vectors, respectively, the operator $\mathcal{P}$ can be represented accordingly as a matrix P and the signal $S(t)$ as vector $\boldsymbol{s}$. In addition, we used a matrix A_x to denote a diagonal matrix, with each elements on a diagonal equal to the vector $\boldsymbol{x}$. Then, the optimization model in Eq. (4) can be rewritten as follows:

$$\hat{\boldsymbol{u}} = \arg\min_{\boldsymbol{u}} \left\{ \|P\boldsymbol{u}\|^2 + \lambda \|\boldsymbol{s}-\boldsymbol{u}\|^2 + \rho \|A_w \boldsymbol{\varpi}\|^2 \right\} \quad (7)$$

where $P = D_2 + A_{\varpi}$, and D_2 is a second order differential matrix. Given that $\boldsymbol{u}$ and $\boldsymbol{\varpi}$ have closed solutions of Eq. (7), they can be estimated by the following forms iteratively. That is, given $\boldsymbol{\varpi}^{(k)}$ and $\boldsymbol{u}^{(k)}$ as the estimation in the k-th iteration, we can derive the $(k+1)$-th estimation of $\boldsymbol{u}$ and $\boldsymbol{\varpi}$ as

$$\hat{\boldsymbol{u}}^{(k+1)} = \left((D_2 + A_{\boldsymbol{\varpi}^{(k)}})^{\mathrm{T}} (D_2 + A_{\boldsymbol{\varpi}^{(k)}}) + \lambda I \right)^{-1} \lambda \boldsymbol{s} \quad (8)$$

and

$$\hat{\boldsymbol{\varpi}}^{(k+1)} = \left(A_{\boldsymbol{u}^{(k)}}^{\mathrm{T}} A_{\boldsymbol{u}^{(k)}} + \rho A_{\boldsymbol{w}^{(k)}}^{\mathrm{T}} A_{\boldsymbol{w}^{(k)}} \right)^{-1} A_{\boldsymbol{u}^{(k)}} D_2 \boldsymbol{u}^{(k)} \quad (9)$$

where I denotes identity matrix. For the hyperparameter λ, we updated it in accordance with the generalized Rayleigh quotient[27] as follows:

$$\lambda^{(k+1)} = \frac{\boldsymbol{u}^{(k)\mathrm{T}} P^{\mathrm{T}} P \boldsymbol{u}^{(k)}}{\left\langle \boldsymbol{s} - \boldsymbol{u}^{(k)}, \boldsymbol{s} - \boldsymbol{u}^{(k)} \right\rangle} \quad (10)$$

Given that the other hyperparameter ρ is used to regularize the value of $\boldsymbol{\varpi}$ less than the threshold T,

we set it to be a fixed large number, that is 10^6, in our experiments.

Therefore, from Eq. (8) to Eq. (10), we can summarize our NSP-based trend extraction algorithm (NSP-Tr) in Algorithm 1. Figure 1 shows two input signals (heart rate of a healthy and an insomnia subject, in blue solid lines) and the corresponding extracted trend components (red solid lines) by our proposed NSP-Tr Algorithm.

3 DFD Analysis (DFDA)

Usually, the heart-rate signal of good sleepers presents a decreasing trend at the beginning of sleep, whereas that of insomniacs exhibits a different trend because of their failure to fall asleep. Thus, if we use FD to analyze the complexity of heart-rate signals, which may partly reflect the cardiac function, for healthy and insomniacs, the influence of the trend in the signal can be removed. That is, given a heart-rate signal $\boldsymbol{s}$, we use our proposed NSP-Tr algorithm (as described in Algorithm 1) to extract its trend component $\boldsymbol{u}$. Then, the residual signal $\boldsymbol{r} = \boldsymbol{s} - \boldsymbol{u}$ is used for the following analysis.

Algorithm 1 NSP-Tr

1: Input signal $\boldsymbol{s}$ and set $\boldsymbol{u}^{(0)} = 0$, $\boldsymbol{\varpi}^{(0)} = 0$, $\boldsymbol{w} = 1$, $\rho = 10^6$, $k = 0$;
2: **repeat**
3: Estimate $\boldsymbol{\varpi}^{(k+1)}$ as in Eq. (9) with $\boldsymbol{u}^{(k)}$ and $\boldsymbol{w}^{(k)}$;
4: Update $\boldsymbol{w}^{(k+1)}$ as in Eq. (6) with $\boldsymbol{\varpi}^{(k+1)}$;
5: Estimate $\boldsymbol{u}^{(k+1)}$ as in Eq. (8) with $\boldsymbol{\varpi}^{(k+1)}$;
6: Update λ as in Eq. (10) with $\boldsymbol{u}^{(k+1)}$, $\boldsymbol{\varpi}^{(k+1)}$, and set $k \leftarrow k + 1$;
7: **until** $\|\boldsymbol{u}^{(k)} - \boldsymbol{u}^{(k-1)}\|^2 < \epsilon$;
8: **return** $\boldsymbol{u}^{(k)}$ as the trend of the signal $\boldsymbol{s}$.

Note: Parameter ϵ is used as stop criterion of the algorithm. However, for different real-life signals, setting a universal value for ϵ is difficult. Thus, in the implementation, we set ϵ to be the mean of the previous five results of $\|\boldsymbol{u}^{(k)} - \boldsymbol{u}^{(k-1)}\|^2$.

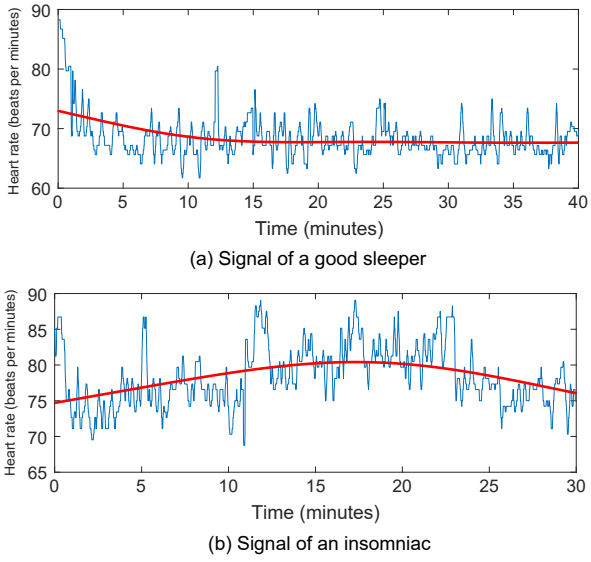

Fig. 1 (a) Heart-rate signal (blue solid line) and its trend component (red solid line) of a good sleeper with its FD (0.5441) and DFD (0.5360), respectively; (b) heart-rate signal (blue solid line) and its trend component (red solid line) of an insomniac person with its FD of 0.5414 and DFD of 0.4838, respectively.

Based on the aforementioned review literature, the heart rate changes in accordance with the advancement of sleep[2, 3]. For healthy people, the heart rate becomes ordered in reduction while falling asleep, whereas the heart rate of insomniac people is supposed to have little or even no changes. This indicates that the FD may be used to distinguish between good sleepers and insomniacs. In our approach, we computed the number of heart-beats in minutes from the ECG signals. Then, we subjected the heart-rate signal to future analysis. Other than the RR-interval signal, such kind of heart-rate signal was used, because it can be easily acquired by a broad range of IoT devices regardless of ECG sticker, remote photoplethysmography (rPPG) monitor, or other similar devices.

Fractal analysis, defined by the Hölder exponent, provides local and global descriptions of the singularities of a signal. However, the precise calculation or estimation at each point of the pointwise Hölder exponent of a function is often impossible (because the realization of a stochastic process is impossible). However, FDs, as indicators of the irregularity of function graphs, became a reckoned measurement tool for signals in the last two decades. Since there are many ways for calculating a dimension that might not be a necessary equivalent, we use Fraclab[28], a MatLab toolbox for numerical computations of FDs. In Fraclab, the box and regularization dimension have been provided, and we use the former one here.

Box dimension or box counting method is one of the numerical implementations for measuring fractal structure. Given a signal $\boldsymbol{s}$, its box dimension can be calculated using the following limitation:

$$dim_B(\boldsymbol{s}) = \lim_{\delta \to 0} \frac{\log(N(\delta))}{-\log \delta} \tag{11}$$

where $N(\epsilon)$ is the smallest number of "boxes" of size at most ϵ which can cover $\boldsymbol{s}$. When the limit does not exist, one uses the lower or upper box dimensions as below:

$$\underline{dim}_B(\boldsymbol{s}) = \lim \inf_{\delta \to 0} \frac{\log(N(\delta))}{-\log \delta} \tag{12}$$

and

$$\overline{dim}_B(\boldsymbol{s}) = \limsup_{\delta \to 0} \frac{\log(N(\delta))}{-\log \delta} \tag{13}$$

Then, we summarized our DFDA algorithm in Algorithm 2. Figure 1 shows two examples of FD and DFD of the real heart-rate signals.

4 Experimental Result

In this section, we evaluated the proposed DFDA, including the dataset description and results analysis, for the heart-rate signal of healthy and insomniac people.

4.1 Dataset description

The dataset used here is a subset of participants enrolled in the multi-center Sleep Heart Health Study (SHHS)[29]. SHHS is a prospective cohort study designed to determine whether sleep disorder (insomnia, obstructive sleep apnea, and other sleep-disordered breathing) is a risk factor for CVD and cerebrovascular disease in the general population. From 1995 to 1998, the baseline cohort of SHHS was collected from nine existing epidemiological studies ("parent study") of cardiovascular and respiratory diseases. The characteristic of the research object is that the montage PSG was used to analyze the characteristics of sleep-disordered breathing. The participants in the "parents" studies were considered eligible if they were 40 years or older and have not received positive airway pressure, oxygen, nor tracheotomy as the treatment for the sleep disorder disease. Finally, 6441 men and women were selected to form the final cohort. Informed consent was obtained from all participants, and the study protocol was approved by the institutional review board of each participating institution. A detailed description of its design and objectives can be found in Ref. [29].

Here, we used a subset of the SHHS cohort for the current analysis, which primarily concerns the HRV of good sleepers and insomniacs. The subset consists of 400 subjects, including 306 (76.5%) healthy people (without sleep disorder breathing or insomnia) and 94 (23.5%) insomniac subjects. All the participants were over 40 years old, and the ratio of men and women was close to 1 : 1 (including 206 males and 194 females).

Algorithm 2 DFDA

1: Input signal $\boldsymbol{s}$;
2: Extract the trend component $\boldsymbol{u}$ from $\boldsymbol{s}$ by NSP-Tr algorithm;
3: Compute the residual component $\boldsymbol{r} = \boldsymbol{s} - \boldsymbol{u}$;
4: Compute the box dimension of the residual $dim_B(\boldsymbol{r})$;
5: **return** Detrended box dimension of the signal $\boldsymbol{s}$.

The heart-rate signals used for exploring the difference between healthy and insomniac people were collected from lights off to the first sleep frame (stage N1 or stage N2). The total time duration collected for healthy and insomniac people was 105 and 43.6 hours, respectively. Thus, the average time duration of each subject in these two was about 20 (healthy subjects), and 28 (insomnia people) min. And we sampled the heart-rate signal once per second in all the following experiments.

4.2 Experimental results

We evaluated the difference in the mean box-dimension from the original and detrended heart-rate signals between healthy and insomniac people by performing a two-side independent sample test. SPSS 25.0 and MatLab R2018b were used for statistical analysis. FracLab toolbox[28] with default parameters was used for box dimension calculation. The DFDA algorithm (Algorithm 2) with default parameters of NSP-Tr was used for computing the detrended box dimension of heart-rate signals.

Table 1 provides the statistical results (including mean and standard deviation) of the box dimension and detrended box dimension for healthy and insomniac groups. The mean and standard deviation of FD of healthy and insomnia subjects' heart-rate signals were ($\mu = 0.51, \sigma = 0.069$) and ($\mu = 0.50, \sigma = 0.071$), respectively. The corresponding values for the DFD of these groups were ($\mu = 0.50, \sigma = 0.063$) for the healthy subjects and ($\mu = 0.45, \sigma = 0.079$) for insomniac subjects. As shown in Table 1, the difference in the mean of FD between healthy and insomniac groups increased after the trend component of heart-rate signals was removed. To further accurately analyze these statistical results, we conducted significance testing (with $p < 0.05$ considered statistically significant) on the statistical data of detrended and non-detrended heart-rate signals.

Table 2 shows the statistic hypothesis testing results. For the FD of the original heart-rate signal, the significance for $H_0 : \sigma_1 = \sigma_2$ (i.e., assuming the standard deviation of FD of heart-rate of healthy and insomnia groups are equal) is 0.03 (< 0.05), which

Table 1 Group statistics of healthy and insomniac participants.

Group (number)	FD		DFD	
	Mean (μ)	Std. (σ)	Mean (μ)	Std. (σ)
Healthy (306)	0.5142	0.0688	0.4987	0.0633
Insomnia (94)	0.5032	0.0712	0.4453	0.0791

Table 2 Hypothesis testing of FD and DFD of two groups.

Data	Hypothesis	Sig. (σ)	Sig. (μ)	t-value
FD	$\sigma_1 = \sigma_2$	0.03	0.006	2.779
	$\sigma_1 \neq \sigma_2$	–	0.112	1.597
DFD	$\sigma_1 = \sigma_2$	0.019	0.004	2.871
	$\sigma_1 \neq \sigma_2$	–	0.007	2.759

means that the original hypothesis H_0 is not true, and $H_1: \sigma_1 \neq \sigma_2$ is accepted. Then, we further tested whether the means of FD of heart-rate of healthy and insomnia groups are equal, i.e., $H_0: \mu_1 = \mu_2$, with $\sigma_1 \neq \sigma_2$. As shown in the third row and forth column of Table 2, the significance for the mean of the two groups is 0.112 (> 0.05), which means that H_0 cannot be rejected. Thus, we cannot assume that the mean of FD of the heart-rate signal of the healthy group is higher than that of the insomnia group.

Similarly, we tested the DFD of the heart-rate signal of these groups. For $H_0: \sigma_1 = \sigma_2$ of the DFD, its significance was 0.019 (< 0.05), which means that $H_1: \sigma_1 \neq \sigma_2$ can be accepted. Then, under this assumption, the significance of hypothesis $H_0: \mu_1 = \mu_2$ of DFD is 0.007 (< 0.05) (as shown in the fifth row and fourth column), which means $H_1: \mu_1 \neq \mu_2$ can be accepted. Thus, under the statistic hypothesis testing, the mean of DFD of the heart-rate of the insomnia group was significantly lower than that of healthy group. Given that FD is always considered to be an index for measuring the complexity of dynamic systems, this conclusion also indicates that the complexity of the heart rate of insomniacs may be lower than that of good sleepers.

Finally, we randomly selected 40 subjects from healthy and insomniac groups, and plotted the FD and DFD values of their heart-rate signal in Fig. 2. The difference in the values between the FD and DFD of the heart-rate signals of healthy people (i.e., the difference between the blue solid circle and red solid triangle) was relatively small. In addition, the DFD value of several healthy subjects was higher than their FD value, which implies that the complexity of their detrended heart rate signals did not decrease. However, a significant decrease in the values between the FD and DFD of heart-rate signals of insomniac people (i.e., the difference between the hollow blue circle and hollow red triangle) was found in Fig. 2. This finding reflects a decrease in the complexity of heart-rate signals of insomniacs after being detrended.

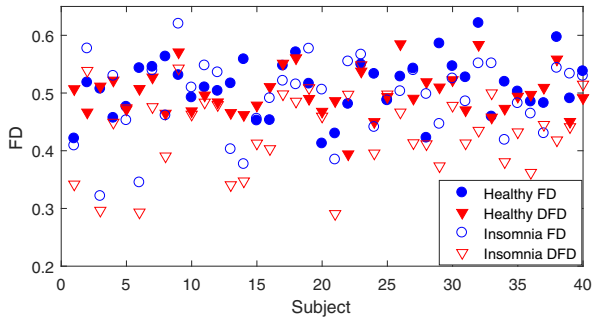

Fig. 2 FD of original and detrended heart-rate signals of randomly selected subjects from healthy and insomniac groups.

5 Conclusion and Discussion

The use of home-based monitoring for insomnia assessment, diagnosis, prognosis, and management is a future trend. We proposed herein a novel index, called the DFD index, based on an adaptive trend extraction algorithm and computed the FD of detrended signals to evaluate the heart-rate signals of the subjects. The experimental results showed a significant difference in the proposed index between the healthy and insomniac groups.

Although other detrended-based time-series analysis approaches exist, most of them use a simple average mean strategy to extract the trend component which is non-adaptive and may be unsuitable for complex physiological signal analysis. The low computational complexity of the proposed DFD index accompanied by the easy acquisition of heart-rate data indicates its potential application in home-based monitoring and assessment environment. However, given that the accuracy of computing FDs is closely related to the signal length, the analysis of signals with a short duration will be a limitation of the proposed index. In the future, we will attempt to use the DFDA on other physiological signals, such as EEG, respiration, and so on, for the detection and analysis of other sleep-related problems.

Acknowledgment

This work was partly supported by the startup research funds of Nanjing University of Science and Technology. We also wish to express our gratitude to the anonymous reviewers for their insightful comments.

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