Physica A 458 (2016) 140–145

Contents lists available at ScienceDirect

Physica A

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

Visibility graph analysis of very short-term heart rate variability during sleep

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ARTICLE INFO

Article history:
Received 18 June 2015
Received in revised form 5 March 2016
Available online 20 April 2016

Keywords:
Visibility graph
Sleep staging
Heart rate variability

ABSTRACT

Based on a visibility-graph algorithm, complex networks were constructed from very short-term heart rate variability (HRV) during different sleep stages. Network measurements progressively changed from rapid eye movement (REM) sleep to light sleep and then deep sleep, exhibiting promising ability for sleep assessment. Abnormal activation of the cardiovascular controls with enhanced 'small-world' couplings and altered fractal organization during REM sleep indicates that REM could be a potential risk factor for adverse cardiovascular event, especially in males, older individuals, and people who are overweight. Additionally, an apparent influence of gender, aging, and obesity on sleep was demonstrated in healthy adults, which may be helpful for establishing expected sleep-HRV patterns in different populations.

1. Introduction

Sleep is a complex physiological process that affects circulation and respiration [1,2]. Generally, nighttime sleep comprises four to six sleep cycles, which normally begin with light sleep (LS), continue to deep sleep (DS), and end in rapid eye movement (REM) sleep [3].

The gold standard known to date for sleep assessment in humans is the analysis of brainwave patterns, achieved through polysomnographic (PSG) monitoring in a sleep lab. This is not only expensive but also time-consuming. Moreover, the numerous electrodes often disturb subjects. Because electrocardiogram (ECG) recording systems are inexpensive, mobile, and convenient, the analysis of heart rate variability (HRV), which is derived from the inter-beat intervals (termed RR intervals) recorded by the ECG, has been recommended as a potential tool for assessing sleep and screening of patients who need a referral to a sleep lab when more detailed assessment is needed [4–10].

For PSG, sleep architecture is usually determined in 30 s epochs. Assessing sleep accurately by using 30 s HRV is somewhat difficult due to the lack of applicable analysis methods. For HRV analysis, evidence suggests that good results can be obtained by combining linear and nonlinear feature extraction methods [6], however, indices derived from nonlinear dynamics are usually calculated over longer periods (300–8000 beats) [11]. Thus, finding a method for robust nonlinear analysis of very short-term HRV [12] is important to assess sleep-related HRV regulation more comprehensively.

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http://dx.doi.org/10.1016/j.physa.2016.03.086
0378-4371/

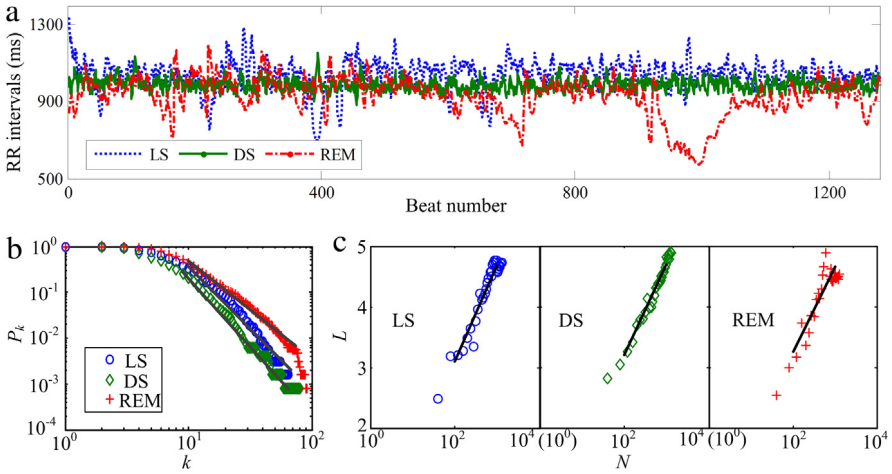

Fig. 1. (Color online) (a) Illustration of RR-interval time series during light sleep (LS), deep sleep (DS), and REM sleep. (b) Log–Log plot of the cumulative degree distribution P_k of the series of RR intervals with 1280 data points. P_k follows a power-law topology when k is greater than 6 and less than 71; thus the degree distribution is $p(k) \sim k^{-\alpha}$ with $\alpha = 4.054 \pm 0.137$ for LS, $\alpha = 4.000 \pm 0.076$ for DS, and $\alpha = 3.293 \pm 0.069$ for REM. (c) Plot of the characteristic path length L of a VG network as a function of the network size N. VG networks are constructed from segments of different lengths derived from the time series in (a). In all cases, the best fitting provides a logarithmic scaling, i.e., $L(N) = -0.05 + 0.68\log(N)$ for LS, $L(N) = 0.22 + 0.64\log(N)$ for DS, and $L(N) = 0.46 + 0.60\log(N)$ for REM, indicating the small-world effect of the networks.

Table 1
Demographic information, number of records, and number of RR segments (data length: 30) during each stage for each group.

Group	Gender	Age	BMI	Records	LS	DS	REM	BS	AS
MALE	Male	37.2 ± 6.6	27.0 ± 3.5	13	4327	1595	1585	411	375
FMLE	Female	37.0 ± 6.3	24.7 ± 3.9	13	4564	1493	931	759	311
OLD	Male	49.6 ± 3.3	28.1 ± 1.9	7	2388	794	1012	297	183
YNG	Male	20.9 ± 3.4	24.7 ± 5.8	7	2403	1441	595	246	242
Overweight	Male	37.2 ± 10.6	31.8 ± 1.9	8	2776	1428	1168	263	232
Normal	Male	33.9 ± 9.7	22.9 ± 1.7	7	2577	1035	730	264	227

Recently, synchronization measures and complex network theory has been introduced to reveal information embedded in physiological data [13–23]. Evidence suggests that a beneficial way for exploring HRV dynamics is to transform it into a complex network whose nodes represent the dynamic units, and edges the interactions between nodes [14,16–18]. Lacasa et al. proposed the visibility-graph (VG) algorithm as a fast computational method for this transformation [24], which can hold the inherent properties of the time series by modeling periodic series, random series, and fractal series to regular graphs, random graphs, and scale-free graphs, respectively [24].

In Fig. 1, we have plotted the behavior of several RR time series derived from a healthy male during different sleep stages, the cumulative degree distribution P_k of the respective visibility graphs [25], and the characteristic path length L as a function of the series length N [26]. All series have visibility graphs with power-law degree distributions and 'small-world' topology, showing that the RR-interval time series are fractal and non-stationary during sleep [24]. Furthermore, both the power α in Fig. 1(b) and the fitting line in Fig. 1(c) are shown to differ across sleep stages. For this reason, in this paper we investigated the application of the VG algorithm for assessing sleep-related heart rate.

2. Material and methods

2.1. Subjects

HRV records are obtained from the Sleep Heart Rate and Stroke Volume Data Bank [10,27]. There are two kinds of record provided in the databank, RR original or RR normal sinus rhythm. The later version is used in the present work. Furthermore, only stationary segments specified by hypnogram codes [27] in each record are considered. The records are classified into six groups: age- and body mass index (BMI)-matched MALE and FMLE groups, BMI-matched OLD and YNG groups, and age-matched Overweight and Normal groups, although they do overlap partially. For each record, according to the hypnogram codes [27], we select all the RR segments which have successive 30 data points (approximately 30 s in time) belonging to a same wake/sleep stage. If there are inadequate successive data points (less than 30), all these points are simply abandoned. Table 1 lists the demographic information, the number of records, and the number of RR segments during each stage for each group. In addition to the sleep stages, two states of wakefulness were considered: wakefulness before sleep (BS) and after nighttime sleep (AS), according to hypnogram codes [27] too.