Evaluation of Wellness in Sleep by Detrended Fluctuation Analysis of the Heartbeats

Toru Yazawa, Ikuo Asai, Yukio Shimoda, and Tomoo Katsuyama

Abstract—**We used detrended fluctuation analysis (DFA), which was originally developed by Peng et al. (1995) to check power-law characteristics, to study the heartbeats of sleeping subjects. Our purpose was to determine whether DFA is a useful method for evaluation of a subject's wellness of both during being awake and sleeping. This is a new challenge to measure sleep without complex machine such as an electro encephalogram. We simply used electro cardiogram (EKG) for the measurements of sleep, although we needed to make a baseline-stable EKG amplifier to perform the measurements. Here, we show a case study that DFA is a new, useful numerical method for quantifying sleep.**

Index Terms—**DFA, Heartbeat, Fluctuation analysis, Sleep.**

I. Introduction

The interval of heartbeats, thereby the heart rate, is determined by the rate of a generation of myocardial contractions (or more precisely muscle action potentials) in terms of physiology. The heart generates contractions periodically, automatically, and regularly to pump blood. This muscle pumping looks simple, but is not an independent variable. The interval is created by the interaction among factors such as the composition of chemicals in the blood and the frequency of discharge of autonomic nerves governing the heart. Therefore, the determination of the heart rate, i.e., interval, is complex and is changed beat by beat, and intervals fluctuate as a result. Since the heartbeat reflects activity of autonomic nerves, it would be possible that heartbeat analysis, in other words, analysis of fluctuation or irregularity of heartbeats, can evaluate the subject's wellness during being awake and sleep.

In Chinese medicine, physicians feel the pulse of patients in diagnosing patients and find out which organ is not functioning well. This fact indicates that pulses or heartbeats carry hidden information about the wellness or sickness of the patient. However, man-made machines have not been able to mimic this practice of physicians, even though it has been more than one hundred years since the industrial revolution developed.

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Despite the historical challenges, we hoped to design a machine that could be used to detect irregularities in heartbeat intervals. For this purpose, we first tested the Fourier power spectral analysis on heartbeat data recorded from physiological experiments. We selected the Fourier method because we trusted that the effectiveness of the Fourier method was to our satisfaction, since the Fourier method is a well known method for studying a periodic phenomenon like rhythmic heartbeat. As for the specimens used in the experiments, we selected crustacean hearts instead of human hearts, because we are familiar with the structure and function of the heart and nervous system of crustaceans. One of the main reasons for using invertebrates was that all animals have a common genetic code (DNA information) for body systems such as the cardiovascular system [1, 2]. All animals fundamentally have a pump (the heart) and a controller (the brain).

The result of our Fourier analysis was less than expected and quite disappointing [3]. However, during the course of the test, we found that the detrended fluctuation analysis (DFA) was more suitable for detecting irregularities in the heartbeat [3]. DFA distinguished the differences between the heartbeat of an isolated heart and an intact heart, even though both of the hearts beat regularly [3]. Using DAF, we calculated that healthy hearts exhibit a scaling exponent of 1.0, which was similar to the results originally reported by Peng et al. in 1995 [4]. The scaling exponent of 1.0 is comparable to 1/f fluctuation, which was reported by Kobayashi and Musha in human hearts [5]. Next, we tested human hearts and found out that premature ventricular contractions (PVCs), a typical extra-systole arrhythmia, lowers the scaling exponent [6] and the alternans, which is an abnormal heart rhythm called "harbinger of death," also lowers the scaling exponent of heartbeat fluctuation dynamics [7]. Moreover, we found that the hearts of heart-transplanted subjects exhibit a scaling exponent as high as 1.2 [8] and the hearts of subjects who have suffered an ischemic heart disease exhibit a scaling exponent of 1.2–1.4 [9, 10]. Therefore, we trusted that this method helps to better diagnose the sleep, because sleep disorders are afflicted with disorders of the brain functions that directly influence the cardiovascular system through the autonomic nervous system.

In this article, we provide an empirical proof for the practical usefulness of DFA. We explain how we can evaluate the wellness of subjects using heartbeat recordings. Our purpose was to evaluate sleep of a normal healthy subject using the DFA.

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II. Materials and Methods

A. Sleep Documented by a Sleep Monitor

Sleep experiments were performed at the laboratory of R & D of Maruhachi Corp. at Hamamatsu, Japan. We used a sleep monitor system (Chiyoda-ku, Tokyo, Japan), which produced a sleep diagram. The monitor system was made to reflect complex physiological factors of being awake and sleep processes, including the brain waves, respiration and the heartbeat. Since the system can distinguish two typical conditions, being awake and deep sleep state, we consider that the system is useful to distinguish the being awake state from the deep sleep state, which is non-rapid eye movements (NREM) sleep.

B. Electrocardiogram and Muscle Movements

During sleep, we always monitored the electro-cardiogram (EKG) and body movements. For EKG, commercial EKG electrodes (Nihonkoden, Japan) were used. The electrodes are composed by AgAgCl electrodes and carbon fiber connection wires. Body movements were detected by a piezo electro-mechanical sensor attached to a finger (AD Instruments, Australia). This sensor responds to pressure of blood flow and movements of fingers, arms, and body. If there are no body movements, the sensor sends only blood flow signals. This piezo recording is thereby efficient to know whether the subjects are stationary, which means that the subjects are in a state of NREM sleep. Another piezo sensor was attached to the face of the subjects. It was attached on the lateral side surface of the face under a frame of a pair of glasses. This can monitor movements of the face including eye movement. EKG signals, finger signals, and face signals are recorded by a Power Lab system (AD Instruments, Australia).

C. A stable Recoding of EKG

We cannot use a common electrocardiogram, because inevitable body movements during sleep disturb a perfect recording of the heartbeat, which means a recording without any missing beat. Body movements during sleep produce a shift of base line of EKG-trace. Body movements furthermore produce many spiking noises in the recordings (see Fig. 1). Therefore, we invented a special EKG amplifier [11]. This enabled us to obtain stable EKG recordings for hours without missing heartbeats (Figs 2 and 3).

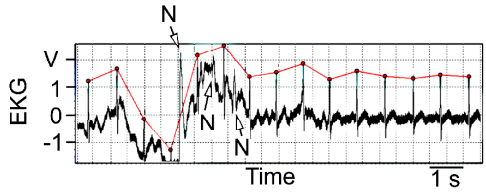

Fig. 1. Bad example of EKG. Contaminated with undesirable noises in recording due to body movements. A complex shift of baseline and spikes indicated by three N. Regardless of this “noises” we can identify all heartbeats by eye-observation on the PC screen as shown in this figure, only if the base line does not scale out from the screen. However, we still needed to remove this “noise”. A perfect detection of the heartbeat was a necessary condition for performing the detrended fluctuation analysis (DFA).

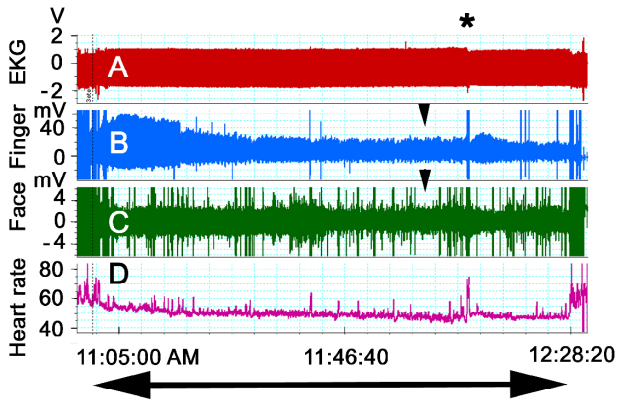

Fig. 2. Stable and perfect EKG recordings during sleep. Period of sleep is shown between arrows. A: Stable EKG was established by our own EKG amplifier. B: Recordings from a finger, a pointer. Movements can be seen as spikes, a large vertical swing. C: Recordings from the face lateral surface. Vertical swings correspond to various movements. D: Automatic calculation of heart rates by a PC program (AD Instrument) from the trace A, a stable EKG trace. *(Asterisk) shows that the subject became awake at this point of time. He said that he was thinking whether it is time to get up or not. But he decided to go to sleep again since he was allowed to sleep for 3 hrs. His heart rate immediately increased when he woke up, but the heart rate returned to a lower value again as soon as he fell into a deep sleep. Less face movements as well as finger movements appeared during the deep sleep (see arrowheads).

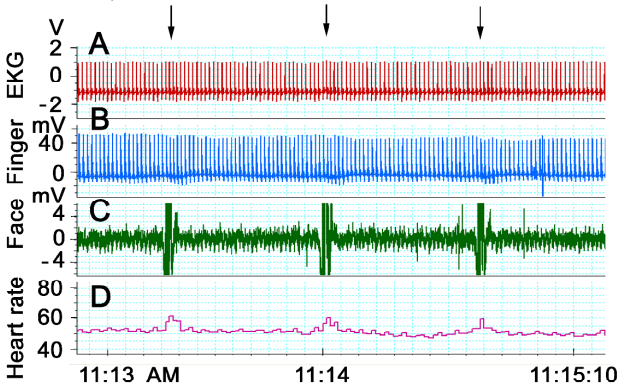

Fig. 3. The same set of recordings as shown in Fig. 2 but shown in different time scales. The timing of individual heartbeats are well recorded in both A and B. The base line of the EKG trace is stable (A). The face muscle moved at the time of three arrows (C). At this moment the heart rate increased (A and D) and blood flow increased (B).

D. DFA: Background

DFA is based on the concepts of “scaling” and “self-similarity” [12]. It has been known as a method that identifies “critical” phenomena because systems near critical points exhibit fluctuations with self-similar properties [12, 13, 14]. The fluctuation is referred to as "self-similar" when recorded signals and their magnified/contracted copies are statistically similar. More strictly, self-similarity is defined as follows: in general, statistical quantities, such as "average" and "variance," of a fluctuating signal can be calculated by taking the average of the signal through a certain section. Here, the average is not necessarily a simple average; in this work,

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we took an average of data squared. The statistical quantity calculated would depend on the section size. The signal is self-similar when the statistical quantity becomes λ^{α} times for the section size magnified by λ. Here, the value α, called the "scaling exponent," characterizes the self-similar property.

Stanley and colleagues have considered that the scaling property could be found in biological data because most biological systems are strongly nonlinear and resemble the systems in nature that exhibit critical phenomena. They applied DFA to DNA arrangement and electrocardiogram (EKG) data in the late 80's to early 90's and found the scaling property in them [13, 14]. They emphasized DFA's potential utility in life science [14]. Technologically, while it has not matured, nonlinear technology is now accepted and increasingly advancing.

E. DFA: Technique

DFA-computation methods have already been explained elsewhere [15]. Here, we describe it for biological scientists who have no background of physics.

(i) The heartbeat is recorded for about 30 to 50 minutes at a single testing because about 1000 beats are required for determination of the scaling exponent. We recorded heartbeats using an EKG or finger pressure pulses.

(ii) Pulse-peak time series $\{t_i\}$ (i = 1, 2,..., N + 1) are captured from the record using an algorithm based on the peak detection method. To avoid false detection, we identified all peaks with eye-observation on the PC screen although it was a time consuming task. Experience in neurobiology and cardiac animal physiology is sometimes necessary when determining whether a pulse-peak is a cardiac signal or a noise.

(iii) The heartbeat-interval time series $\{I_i\}$, such as the R-R intervals of an EKG, are calculated, which is defined as:

$$\{I_i\} = \{t_{i+1} - t_i\}\ , i = 1, 2, ..., N \qquad (1)$$

(iv) The series $\{B_i\}$, upon which we conduct DFA, is calculated as follows:

$$\{B_k\} = \{\Sigma_{j=1}^{k}[I_j - <I>]\}, \qquad (2)$$

where $< I >$ is the mean interval defined as:

$$< I >= \frac{\sum_{i=1}^{N} I_i}{N} \qquad (3)$$

(v) The series $\{B_k\}$ is divided into smaller sections, which include j beats each. The section size j can range from 1 to N. For the efficient and reliable calculation of the scaling exponent in our program, we confirmed by test analysis that the number N is hopefully greater than 1,000.

(vi) In each section, the series $\{B_k\}$ is approximated to a linear function. To find the function, we applied the least square method. This function expresses "trend," the slow fluctuation such as B_k increases/decreases throughout the section size. Then, a "detrended" series $\{B'_k\}_j$ is obtained by the subtraction of $\{B_k\}$ from the linear function.

(vii) We calculate the variance, which is defined as:

$$F^2(j) = <\{B'^{2}_{k}\}_j> \qquad (4)$$

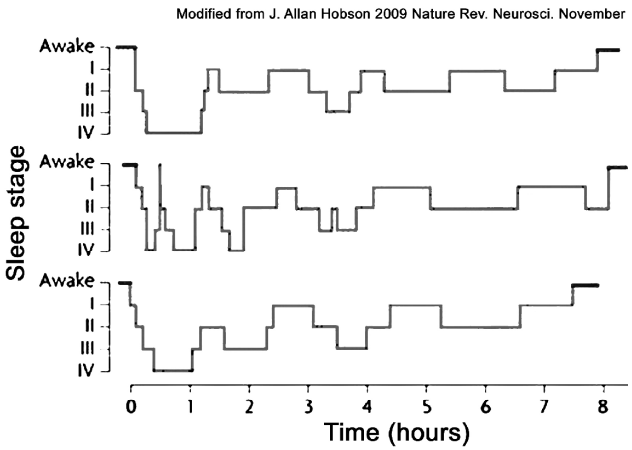

Fig. 4. Representative patterns of sleep. Three different subjects. We made this figure by modification of the original report to show typical sleep patterns. All example recordings show that a deep sleep stage (stage IV, NREM sleep) occurs within one hour.

(viii) The procedure (v) to (vii) is repeated for changing j from 1 to N. Finally, we plotted a variance against the section size j. Then, the scaling exponent is obtained by

$$F^2(j) \quad j^{\alpha} \qquad (5)$$

Most of computations mentioned above, which are necessary to obtain the scaling exponent, are automated. The automatic program gives us a scaling exponent relatively quickly. The scaling exponent exhibits a value near 1.0 for a normal/healthy heart and exhibits a higher or lower value for a sick heart. Although we cannot have a critical discussion regarding whether or not the exponent is precisely 1.0 or not, our automatic program is helpful and reliable to distinguish a normal state of heart from a sick state. Hence, in this report, we mention 3 categories in differentiation: normal, high, and low.

III. Results

A. Sleep and EKG

We do not have a sophisticated electro encephalogram. However, we could record a pattern of sleep using a sleep monitor, such as a stage of being awake and NREM sleep. A deep sleep started as soon as the subjects fell asleep. It was of no importance during which time, day or night, the patient fell asleep. NREM sleep occurred within one hour, if subjects were healthy and sleepy. However, some subjects can never sleep well in a laboratory bed, even if they were deprived of their sleep for a certain period of time prior to the experiment. Since this initial deep sleep process is common to healthy people, we focused on this initial deep sleep in the present investigation. To obtain a good sleep or a good nap, subjects were advised to cut their regular sleeping time shorter.

Our research interest was a possible correlation between EKG and sleep. For that reason we used DFA for heartbeat analysis, since the DFA reflects the functioning of autonomic nerves. We first observed how sleep starts and continues during an EKG recording. Before that, we had to confirm what is a representative sleep pattern, which is well known in

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publications [16]. From Fig. 4, one can see that a deep sleep occurs in the first one hour. Our sleep records also confirmed the same pattern, even if the experiments started at day time (Fig. 5). This subject exhibited a common pattern, where NREM sleep occurred in the first one hour after starting the experiment. Fig. 6 shows a sleep pattern which we analyzed in the present study. Fig. 7 shows heart rate time series corresponding to this sleep patterns shown in Fig. 6. One can see that the heart rate gradually decreased and became more steady during sleep. However, the heart rate changed dynamically during the period of being awake.

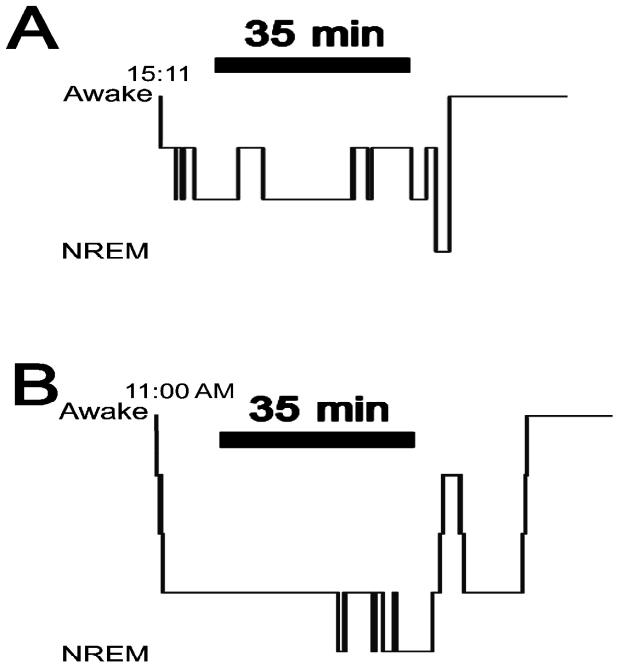

Fig. 5. Two sleep records from the same person in our laboratory. A male subject, 59 years old, took a nap in the laboratory facility. He was advised to sleep less hours the night before these tests. A state of being awake and a state of NREM sleep can be identified, although the software for monitoring sleep is different between A and B. Recorded in February (A) and in May (B) 2010, from the same subject at the same laboratory facility.

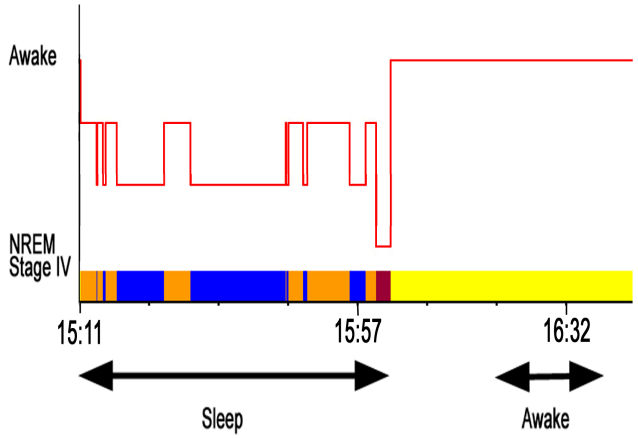

Fig. 6. Entire sleep record shown in Fig. 5A. We recorded the heartbeat during sleep and also during the period shown as "Awake", as described in the Methods section.

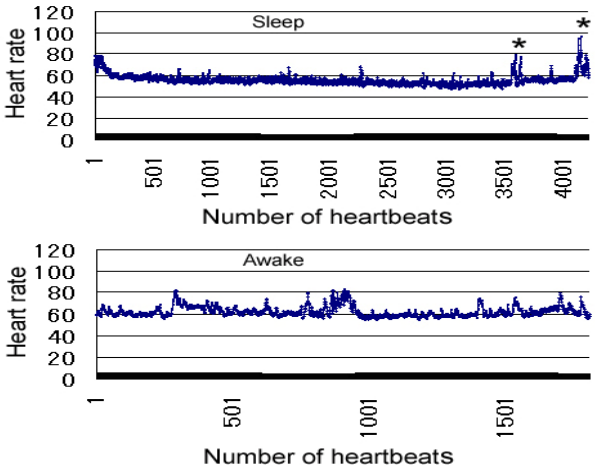

Fig. 7. Time series of the heart rates, calculated from the EKG, recorded during the period of "Sleep" and "Awake" in the sleep diagram of Fig. 6. * Two asterisks: Subject declared he was conscious during this short period of time. This period of being awake was not precisely detected by a sleep diagram, shown in Fig. 6. Therefore, it seems that a sleep diagram does not always perfectly express the brain functioning. Our understanding of sleep in terms of neuroscience is not so advanced as we thought, as mentioned in a reference [17].

B. DFA of Heartbeats

Fig. 7 shows the results of DFA on both data during "Sleep" and "Awake". The scaling exponents during sleep decreased, which was 0.82 (Fig. 7A) although the scaling exponent of the "Awake" state showed a perfect measure of 0.99, almost 1.0 (Fig. 7B). This indicates that this subject is healthy in terms of DFA as has been shown in our previous research [6, 7, 9, 10]. However, we discovered that a deep sleep state is not an ideal state of brain functions in terms of DFA tests. We would suggest that sleeping could be a dangerous condition for living animals. In the animal world, all creatures have to find a safe place for resting at night without being attacked by predators.

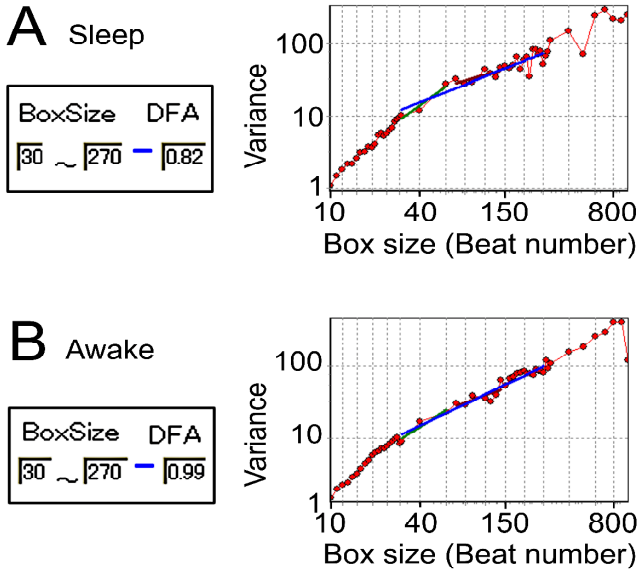

Fig. 8. DFA results of heartbeat patterns during the states of "Sleep" and "Awake", shown in Figs 6 and 7. The scaling exponents are 0.82 and 0.99, respectively.

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IV. Discussion

Time series of the heart rates showed that the heart rates during deep sleep were steady, compared to being awake (Fig. 6). This steadiness can be quantified by DFA and calculated as a lower scaling exponent. This discovery of a low scaling exponent during deep sleep is interesting, since we have already reported that the heart without control of the brain exhibits a low scaling exponent [3]. It is known that the healthy heart under the brain control shows a normal scaling exponent of 1.0 as mentioned above [9]. Even in the phase of deep sleep, if a subject is awake, the heart rates return to a normal rate (see * in Fig. 6). Therefore, the heart in deep sleep is pumping in a state of "minimum control" from the brain. We did not record the brain waves. However, the sleep monitor we used is believed to reflect brain functions, like the autonomic nervous system function. Therefore, it seems that a sleep pattern diagram does not always reflect details of the brain activities. Our understanding of sleep in terms of neuroscience is not so advanced as we thought, as mentioned in a reference [17]. Understanding the brain function regarding to sleep is still in an alpha stage. Or, the understanding of brain waves themselves is not perfect: for example, among millions of neurons, individual neuron function is still under investigation in neuroscience.

It is known that a healthy heart exhibits 1/f rhythm [5]. DFA can reveal that healthy hearts exhibit the scaling exponent of 1.0 [see 6, 7, 9, 10]. This was observable during the awake period. The fact that a deep sleep shows a low scaling exponent suggests that deep sleep functions are not ideal states of brain activities, because the brain process is less involved. In the animal world, all creatures have to find a safe place for resting without being attacked by predators. Sleeping is a dangerous condition for living animals. The low scaling exponent means that the brain itself is taking a rest during deep sleep. A deep sleep state might be a period that the brain works by not controlling the body with full power, but consolidating memories for example. This opinion might be still controversial.

Sleep related problems, such as the association between sleep apnea and the risk of traffic accidents, are a negligible medical concern. If a sleep state can be quantified by a simple method like DFA of the heartbeats, it might be helpful to diagnose sleeping problems. EKG and DFA might be potential solutions in solving the sleep problems.

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