札幌医科大学　医療人育成センター紀要　第 14 号　1 ～ 6（2023）　報告

# Ultra-low and very-low frequency components of power spectral density relative to heart rate variability during marathon running

# マラソン時における心拍変動のパワー・スペクトル密度の極低周波成分および超低周波成分

Toru Sakuta [1,2], Ayako Sumi [3], Keiji Mise [4], Nobumichi Kobayashi [1]

[1] Department of Hygiene, Sapporo Medical University School of Medicine, Sapporo, Hokkaido, Japan

[2] ASICS JAPAN Co., Ltd., Koto-ku, Tokyo, Japan

[3] Division of Physics, Department of Liberal Arts and Sciences, Center for Medical Education, Sapporo Medical University, Sapporo, Hokkaido, Japan

[4] Department of Admissions and High School Liasion, Center for Medical Education, Sapporo Medical University, Hokkaido, Japan

Aerobic exercise is an excellent way to maintain good health, and marathons are a popular form of aerobic exercise. Studies that using spectral analysis of heart rate variability (HRV) to evaluate autonomic nervous activity have established HRV as an indicator of exercise intensity. HRV is analyzed in terms of four distinct frequency bands of spectral power: ultra-low (ULF), very-low (VLF), low (LF), and high (HF) frequencies. This study evaluated two male pacesetter marathon runners wearing Electrocardiogram leads monitored during a 30-km marathon in Japan. Time series data of the runners’R-R intervals over 90 min showed that the spectral power values in ULF and VLF bands exceeded those in LF and HF bands. Others have reported that ULF and VLF power values decrease as cardiovascular disease severity increases. Accordingly, these values all have clinical prognostic potential for the evaluation of individuals’ capacity for exercise.

Keywords: Heart rate variability; Spectral analysis; Ultra-low frequency; Very-low frequency; Running

## INTRODUCTION

The importance of physical exercise to maintain/promote good health as well as prevent lifestyle-related diseases is being recognized. Indeed, for enhancing physical strength, aerobic exercise—walking, running, swimming, bicycling—has attracted the most attention. To perform aerobic exercise safely and efficiently, however, it is necessary to set the exercise intensity that is suitable for each individual planning to engage in an exercise regimen. Recently, evaluation of autonomic nervous activity using spectral analysis of heart rate variability (HRV) has been accepted as an indicator of exercise intensity [1-5].

HRV analysis has been described for four distinct frequency bands of spectral power [6,7]: ultra-low frequency (ULF, <0.003 Hz), very-low frequency (VLF, 0.003–0.04 Hz), low frequency (LF, 0.04–0.15 Hz), and high frequency (HF, 0.15–0.4 Hz). There is considerable evidence that (1) the power in the HF band is a function of parasympathetic activity; (2) sympathetic activity contributes to the LF band [8]; and (3) the LF/HF ratio can be used as a measure of sympathovagal balance [9,10] (i.e., the relative contributions of sympathetic and parasympathetic activity). However, there is no consensus on the origin of HRV in the VLF and ULF bands [8]. This lack of consensus could be a major concern as most of the spectral power is contained in these lowest-frequency bands [11], and clinical interpretations rely heavily on changes in low-frequency power [12].

It was recently reported that ULF and VLF bands play a crucial role in HRV during treadmill running with a refined method of the periodogram [1]. The periodogram,

DOI: 10.15114/jcme.14.1

however, reconstructs a time series from a sum of its Fourier components based on a prior knowledge of the fundamental period of the original time series data. However, such knowledge is rarely obtained in practice. Therefore, periodogram is available only for extremely restrict case, i.e. harmonic time-series, in which theoretically exact solutions are given.

We have already proposed a newly devised method of time series analysis, which overcomes the disadvantage of conventional time series analysis including the periodogram [13,14]. A series of analyses in the present study is composed of spectral analysis based on the maximum entropy method (MEM) in the frequency domain and nonlinear least squares method (LSM) in the time domain. Hence, the current study investigated whether large contributions of the ULF and VLF bands are responsible for HRV during marathon running using our method of time series analysis.

## METHOD

### Subjects

Two healthy male subjects volunteered for this study. The physical characteristics of subject-1 and -2 were ages 39 and 48 years, heights 175 and 172 cm, and weights 57 and 55 kg, respectively. The previous summer the two men had participated in a 30-km marathon in Sapporo, Japan, running as pacesetters at the fixed speeds of 255 s/km and 300 s/km (average temperature 25.3° C, relative humidity 68%, wind velocity 2.0 m/s).

Prior to the race, they had undergone placement of standard three leads from a Holter electrocardiograph to obtain time series data of R-R intervals. Their cardiac activity was recorded on AC100 type, active tracer (GMS Co. Ltd., Japan), with the A/D converted data (sampling frequency of 1 kHz) then transferred to a personal computer.

### MEM spectral analysis

MEM power spectral density (MEM-PSD) $P(f)$ (where $f$ represents frequency) for the time series of R-R intervals with equal sampling interval $\Delta t$ can be expressed by

$$P(f) = \frac{P_m \Delta t}{\left| 1 + \sum_{k=-m}^{m} \gamma_{m.k} \exp\left[-i2\pi fk\Delta t\right] \right|^2}, \qquad (1)$$

where the value of $P_m$ is the output power of a prediction-error filter of order $m$ and $\gamma_{m,k}$ is the corresponding filter order. The value of the MEM-estimated period of the $n$th peak component $T_n$ (=1/$f_n$; where $f_n$ is the frequency of the $n$th peak component) can be determined by the positions of the peaks in the MEM-PSD.

### Ethics Approval and consent to participate

This research was performed in accordance with the Declaration of Helsinki. The study was reviewed and approved by the Ethics Committee of Sapporo Medical University School of Medicine on 25 March 2016. All participants provided written, informed consent.

## RESULTS

### R-R intervals

Figure 1 shows time series data of R-R intervals during a 90-min period for one subject while running. The data (Fig. 1a) show a long-term trend, with a large difference between the beginning and end of the data. To remove this

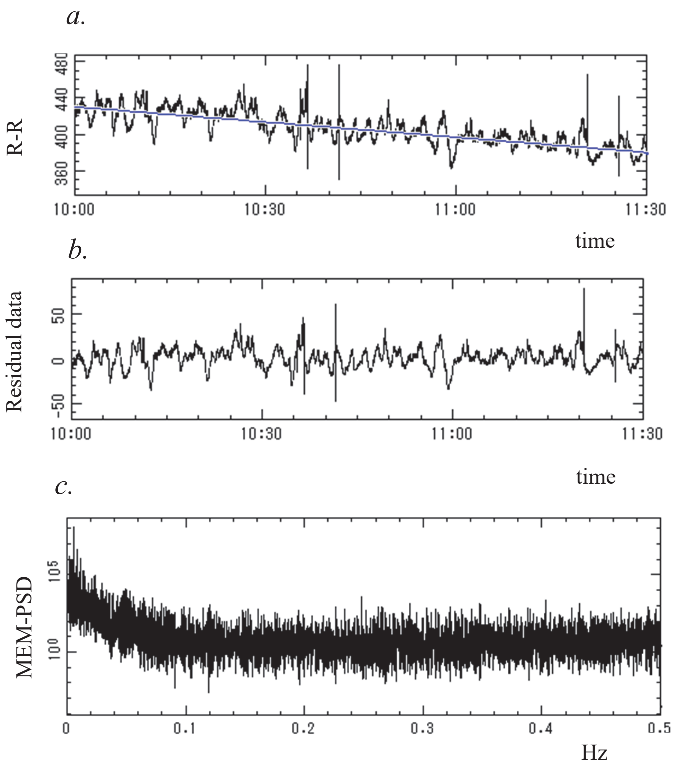


Fig. 1 R-R time series data for a subject during running. (a) Time series data and together the linear regression line (blue). (b) Residual data obtained by subtracting the linear regression line from the original data. (c) Maximum entropy method–power spectral density (MEM-PSD) of the residual data.

long-term trend from the data, a first-order regression line (blue line, Fig. 1a) was removed from the original data, thereby obtaining the residual data (Fig. 1b). The value of the slope of the linear regression line was - 801.2.

## Spectral analysis

Further analysis of the residual data for the R-R intervals was conducted with MEM spectra analysis to obtain the power spectral density (PSD) (Fig. 1c). The integrated PSD was separated into the four frequency-defined components ULF, VLF, LF, and HF. The formulation of MEM-PSD is described in the Appendix.

Figure 2 shows the ratios of the spectral power for specific frequency bands/total power of PSDs (e.g., Fig. 1c) under running and sleeping conditions for two subjects. For the running condition (Fig. 2a), the spectral power values of the PSDs were larger in the ULF and VLF bands than in the LF and HF bands for both subjects. For the sleeping condition (Fig. 2b), the spectral power values of PSDs in the ULF and VLF bands were at almost same level as those in the LF and HF bands.

## Segment time series analysis

To investigate temporal variations in periodic structures of R-R intervals in detail, segment time series analyses were performed for time series data of the heart rate (HR) in beats/min, which were obtained from for the subjects in both running and sleeping conditions. The segment analysis shows that all the time series data (e.g., Fig. 1b) were divided into a subseries of 75, with each segment having a time range of 15 min and the beginning of the range delayed 1 min. The PSD was then calculated for each segment. The 95 PSDs thus obtained were arranged in the order of time sequences to construct a

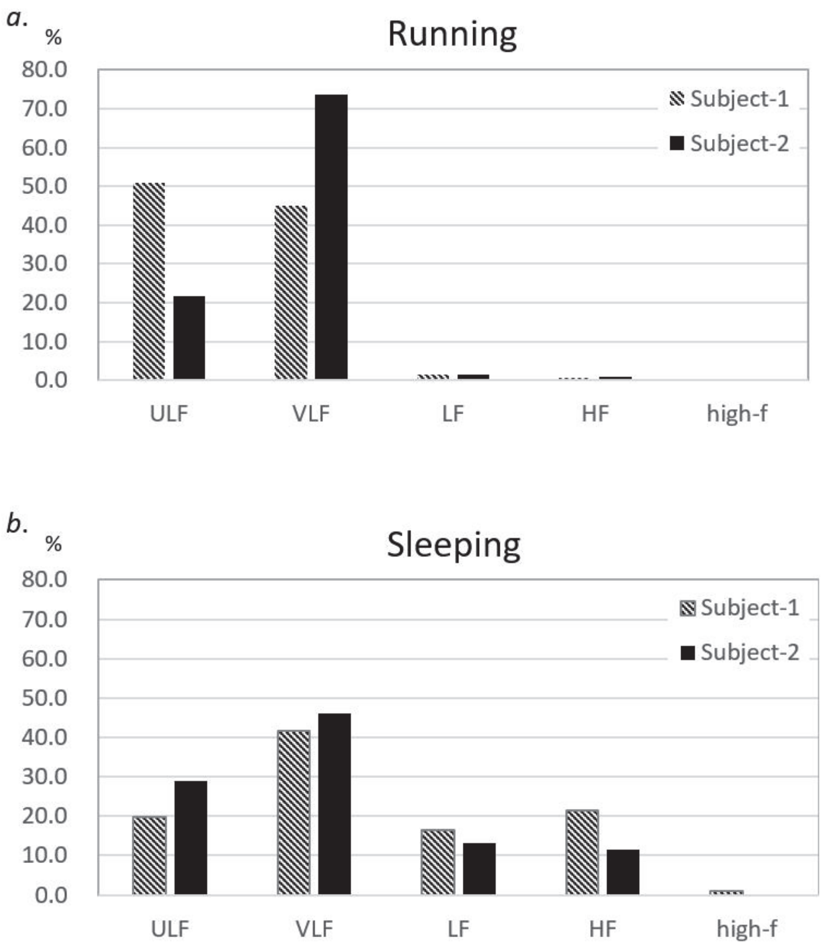


Fig. 2 Changes in spectral power of the R-R time series in specific frequency bands for two subjects. (a) Running condition. (b) Sleeping condition. ULF, ultra-low frequency; VLF, very-low frequency; LF, low frequency; HF, high frequency.

three-dimensional (3D) spectral array, as shown in Figure 3 for subject-1 in the running and sleeping conditions.

For the running condition (Fig. 3a), dominant spectral lines at f = approximately 0.005 Hz (300 s), which is close to the fixed pace of running (255 s), are clearly observed as a fine array over the entire time range. The dominant spectral lines are not observed for the sleeping condition (Fig. 3b). These behaviors of the 3D spectral arrays for running and sleeping conditions were observed for subject-2 as well.

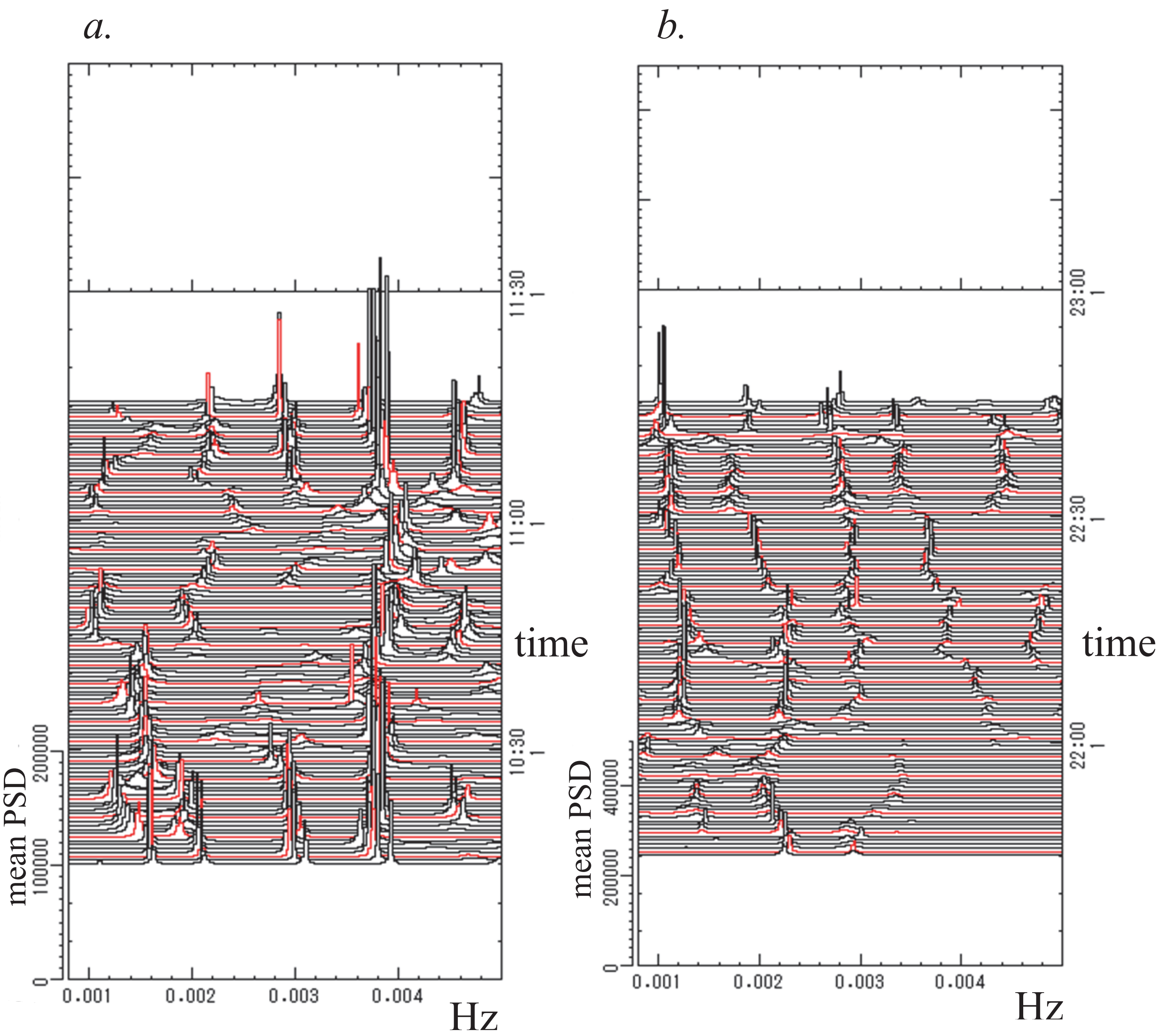


Fig. 3 Segment analysis for time series data of the heart rate shown in Figure 1. (a) Three-dimensional (3D) spectral array under the condition of running. (b) 3D spectral array under the condition of sleeping.

## DISCUSSION AND COUCLUSION

The important result obtained in this study is that the spectral power values of the time series data of R-R intervals in the ULF and VLF bands during marathon running are larger than those in the LF and HF bands (Fig. 2). This finding is supported by Serrador, Finlayson, & Hughson [15], who reported that the spectral power values of the ULF and VLF regions for R-R intervals during walking are larger than those of the LF and HF regions. Otsuka [16] reported that the power values of the ULF and VLF regions decrease as the severity of the cardiovascular disease increases. Thus, from the clinical point of view, analysis of not only the LF and HF regions but also the ULF and VLF regions is an important prognostic indicator of survival [16]. The increasing power values in the ULF and VLF regions may be related to hormonal (angiotensin) regulation [17] and/or thermoregulation [18,19]. Obviously, our understanding of the mechanism involved is still limited [8].

In the 3D spectral array of the time series data for the heart rate in the running condition (Fig. 3a), we confirmed that a distinct spectral array at a frequency around 0.005 Hz, corresponding to 300 s, is close to the fixed pace of running (255 s/km) and does not reflect a control signal, such as a treadmill speed command. The mechanism of the heart rate cycle of about 300 s may be related to the dominant power in the ULF and VLF regions of R-R intervals (Fig. 2). Another study is required for its clarification.

By linking our method of time series analysis with a running watch, runners will be able to utilize the results of this analysis in real time. Construction of this system is a future task.

## LIMITATIONS

The study should be replicated using a larger sample size to ensure that the spectral power values for the RR interval in the ULF and VLF bands are larger than those in the LF and HF bands during the running condition. In addition, we need to change the pace, distance, and duration of running and observe temporal changes in ULF and VLF regions in more detail if we aim to establish a new exercise intensity index for running. Further work is needed to investigate any differences in results between male and female runners. Having this knowledge could make it possible to plan an appropriate amount of training in line with the purpose of the individual' s training, thereby preventing overtraining and allowing to last for a long time. Thus, establishing a new exercise intensity index related to running could be useful not only to athletes aiming to improve their competition skills, but to people who exercise simply to maintain and improve their health.

## ACKINOWLEDGEMENTS

We thank Nancy Schatken, BS, MT(ASCP), from Edanz Group (www.edanzediting.com/ac), for editing a draft of this manuscript.

## FINANCIAL SUPPORT

This study was supported in part by JSPS KAKENHI (grant nos. JP16K09061 and JP19K10666) for the design of the study and writing the manuscript and the Descente and Ishimoto Memorial Foundation for the Promotion of Sport Science for the collection, analysis and interpretation of data.

## CONFLICTS OF INTEREST

None.

## REFERENCES

1) Hunt, KJ., & Saengsuwan, J. Changes in heart rate variability with respect to exercise intensity and time during treadmill running. Biomed Eng. 2018; 17, 128-39.

2) Pichon, AP., Bisschop, CD., Roulaud, M., Denjean, A., Oaoelier, Y. Spectral analysis of heart rate variability during exercise in trained subjects. Med Sci Sports Exerc. 2004; 36, 1702-8.

3) Aubert, AE., Steps, B., Beckers, F. Heart rate variability in athletes. Sports Med. 2003; 33, 889-919.

4) Shin, K., Minamitani, H., Onishi, S., Yamazaki, H., Lee, M. The power spectral analysis of heart rate variability in athletes during dynamic exercise-Part I. Clin Cardiol. 1995; 18, 583-6.

5) Shin, K., Minamitani, H., Onishi, S., Yamazaki, H., Lee, M. The power spectral analysis of heart rate variability in athletes during dynamic exercise-Part II. Clin Cardiol 1995; 18, 664-668.

6) Malik, M., Bigger, JT., Camm, AJ., Kleiger, RE., Malliani, A., Moss, AJ., et al. Heart rate

variability. Standards of measurement, physiological interpretation, and clinical use. Eur Heart J. 1996; 17, 354–81.

7) Sassi, R., Cerutti, S., Lombardi, F., Malik, M., Huikuri, HV., Peng, CK., et al. Advances in heart rate variability signal analysis: joint position statement by the e-Cardiology ESC Working Group and the European Heart Rhythm Association co-endorsed by the Asia Pacific Heart Rhythm Society. EP. 2015; 17, 1341–53.

8) Berntson, GG., Bigger, JT., Eckberg, DL., Grossman, P., Kaufmann, PG., Malik, M., et al. Heart rate variability: origins, methods, and interpretive caveats. Psychophysiology 1997; 34, 623–48.

9) Pagani, M., Lombardi, F., Guzzetti, S., Sandrone, G., Rimoldi, O., Malfatto, G., et al. Power spectral density of heart rate variability as an index of sympatho–vagal interaction in normal and hypertensive subjects. J Hypertens Suppl. 1984; 2, 383–5.

10) Pagani, M., Lombardi, F., Guzzetti, S., Rimoldi, O., Furlan, R., Pizzinelli, P., et al. Power spectral analysis of heart rate and arterial pressure variabilities as a marker of sympatho-vagal interaction in man and conscious dog. Circ Res. 1986; 59, 178–93.

11) Bigger, JT., Fleiss, JL., Steinman, RC., Rolnitzky, LM., Kleiger, RE., Rottman, JN. Frequency domain measures of heart period variability and mortality after myocardial infarction. Circulation 1992; 85, 164-171.

12) Bigger, JT., Fleiss, JL., Steinman, RC., Rolnitzky, LM., Schneider, WJ., Stein, PK. RR variability in healthy, middle-aged persons compared with patients with chronic coronary heart disease or recent acute myocardial infarction. Circulation 1995; 91, 1936-43.

13) Saito, K., Koyama, A., Yoneyama, K., Sawada, Y., Ohtomo, N. (Eds.). A recent advance in time series analysis by maximum entropy method – Applications to medical and biological sciences–. Sapporo: Hokkaido University Press. 1994.

14) Sumi, A., Kobayashi, N. Time-series analysis of geographically specific monthly number of newly registered cases of active tuberculosis in Japan. PLoS ONE 2019; 14, e0213856.

15) Serrador, JM., Finlayson, HC., Hughson, RL. Physical activity is a major contributor to the ultra low frequency components of heart rate variability. Heart 1999; 82, 1-6.

16) Otuka, K. Chronome & Janus-Medicine: heart rate variability and BP variability from a viewpoint of chronobiology and ecology. Tokyo: Medical View Co., Ltd. 1998. [in Japanese]

17) Taylor JA., Carr DL., Myers CW., Eckberg, DL. Mechanisms underlying very-low-frequency RR-interval oscillations in humans. Circulation 1998; 98, 547-55.

18) Fleisher, LA., Frank, SM., Sessler, DI., Cheng, C., Matsukawa, T. Thermoregulation and heart rate variability. Clin Sci. 1996; 90, 97-103.

19) Thayer, JF., Nabors-Oberg, R., Sollers, JJ, 3rd. Thermoregulation and cardiac variability: a time-frequency analysis. Biomed Sci Instrum.1997; 34, 252-6.