A New Proposal For Calculating A Power Spectrum For Heart Rate Variability

Jae Mok Ahn, Jeom Keun Kim

Abstract: Hear rate variability (HRV) is a noninvasive measure for evaluating a physiological response that takes place in the body, which is regulated by the autonomic nervous system (ANS) for a short-term HRV recording, mostly 5 min of data length. Among HRV parameters, frequency components obtained by Fourier transform (FT) have been widely used in clinical applications. However, discrete FT that can classify the strength of frequency components is limited due to discretizing the frequency, resulting in a technically spectral leakage and missing values of the in-between frequency. In this study, a new method for calculating a power spectrum using the overlapping segment is proposed to create a smooth spectrum between frequency boundaries, which divides three frequency components: very low frequency, low frequency, and high frequency. A power spectrum on average calculated from six overlapping segments generated by shifting the 2 min 30 s segment forward every 30 s for the 5-minute dataset showed the best smooth curve of a power spectrum than other segments. A compensation factor was found to minimize the difference between power spectra obtained by 5 min and six 2 min 30 s overlapping segments. The results suggest that a newly proposed method based on overlapping segments would be very useful in calculating a power spectrum to minimize an abrupt change at the frequency boundaries.

Index Terms: heart rate variability, autonomic nervous system, Fourier transform, spectral leakage, power spectrum, overlapping segment

1. INTRODUCTION

Heart rate variability (HRV) reflects the physiological phenomenon of variation in the time interval between normal-to-normal (NN) heartbeats [1, 2, 3]. HRV is used as a noninvasive index of the autonomic nervous system (ANS)'s regulation of the heart, and for instance, rapid fluctuation of HRV can reflect changes of sympathetic and parasympathetic activity [4]. For many meaningful findings, heart rate variability analysis has rapidly expanded from initial cardiovascular to pathological research, including medicine, and is increasingly being used in a number of clinical specialties [5, 6]. HRV analysis was shown to monitor autonomic neuropathy in diabetic patients before the onset of symptoms [7]. A decrease in HRV, which represents low fluctuation of variation in NN intervals, was significantly related to a higher risk of death due to postmyocardial infarction [8]. Therefore, a power spectral density analysis has been used in most studies to quantitatively evaluate parasympathetic and sympathetic control of the heart, and thus quantify autonomic balance. Fourier transform (FT) for calculating a power spectral density has become the prevailing method for obtaining information on frequency components. HRV, which are discrete time signals for the time domain, are transformed into the number of frequency components by applying discrete FT for the frequency domain. A discrete FT inevitably leads to the existence of frequency spacing due to discrete time signals for the time domain, and consequently, a loss of values for the in-between frequencies are produced, which is known as the picket fence effect. Due to such problems with FT technology, values integrated between frequency bands can approach an incorrect conclusion in evaluating ANS activity: very low frequency (VLF), low frequency (LF), and high frequency (HF). The HF bands reflect the rapid changes in the NN heartbeat variability that are due to parasympathetic stimulation, whereas the VLF bands are thought to reflect mostly sympathetic stimulation [9]. The LF bands reflect a combination of both sympathetic and parasympathetic stimulation of the heart [10]. Discrimination of the VLF, LF, and HF bands for a power spectrum plays a critical role in diagnosing the ANS imbalance from frequency domain parameters. Therefore, in this study, a new method, the overlapping segment method, was proposed to address the discrete FT problems and to improve the performance of the HRV analyzer used in many clinical fields. Conventionally, one 5-minute timeframe for a power spectrum is analyzed at a time to obtain the magnitude of frequency components, but the new method we proposed here obtains HRV parameters on average by shifting a predetermined timeframe, a much shorter segment than 5-minute segment, forward by every 30 s or 60 s interval, resulting in producing many overlapping segments between the previous and next segments. A predetermined timeframe for the HRV dataset that includes 1 min, 2 min, and 2 min 30 s data segments was tested. The results demonstrated that the new method achieves a smoother power spectrum than conventional methods for minimizing the value of the difference between adjacent frequency bins, which can divide frequency components. It is concluded that the overlapping segment method can be very useful in increasing the accuracy of HRV parameters.

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2 POWER SPECTRUMS

Power spectral analysis for the HRV dataset was analyzed by fast FT, which is relatively simple and requires little computational power. FT estimates HRV parameters in the frequency domain by analyzing a power spectrum of the short-term HRV dataset. Discrete FT was used to perform Fourier analysis of discrete time signals. Discrete time signal x[n] is defined as

$$X[m] = \sum_{n=0}^{N-1} x[n]e^{-j\omega n}. \quad (1)$$

Since ω=2πf/Fs and f=mFs/N, we have

$$X[m] = \sum_{n=0}^{N-1} x[n]\, e^{-\frac{j2\pi mn}{N}}. \quad (2)$$

Here, N is the number of sampled points, m is the discrete frequency number for the frequency domain, ranging from 0 to N-1, and Fs is the sampling frequency. Using Euler's relation,

$$e^{jx} = \cos(x) + j\sin(x) \quad (3)$$

Discrete FT can be expressed as

$$X[m] = \sum_{n=0}^{N-1} x[n] \cos\left(\frac{2\pi mn}{N}\right) - j\sum_{n=0}^{N-1} x[n]\sin(\frac{2\pi mn}{N}). \quad (4)$$

Discrete FT consists of a real part and an imaginary part for every frequency number m. The magnitude and phase spectra can be expressed as

$$|X[m]| = \sqrt{Re(X[m])^2 + Im(X[m])^2} \quad (5)$$
$$\theta(m) = arctan\frac{Im(X[m])}{Re(X[m])} \quad (6)$$

Where

$$Re(X[m]) = \sum_{n=0}^{N-1} x[n]\cos(\frac{2\pi mn}{N}) \quad (7)$$
$$Im(X[m]) = \sum_{n=0}^{N-1} x[n]\sin(\frac{2\pi mn}{N}). \quad (8)$$

The Hanning window was applied to input discrete time signals, x[n]. The new windowed signal for every point n for input signals was x[n] = x[n]*w[n]. The Hanning window was selected as it has several advantages, such as the fastest roll-off, a smooth transition to zero at window endpoints, and a high maximum side-robe level. The Hanning window is defined as

$$w[n] = 0.5\left[1 - cos\left(2\pi\frac{n}{N-1}\right)\right],\ 0 \le n \le N-1. \quad (9)$$

The frequency domain parameters (Ln HF, Ln LF, Ln VLF) were calculated in real time by using the following equations:

$$\text{Ln HF} = ln\int_a^b |X(m)^2|dm \quad (10)$$
$$\text{Ln LF} = ln\int_c^d |X(m)^2|dm \quad (11)$$
$$\text{Ln VLF} = ln\int_e^f |X(m)^2|dm \quad (12)$$

where high frequency power (Ln HF) represents the frequency activity between a=0.15 and b=0.4 Hz, low frequency power (Ln LF) represents the frequency activity between c=0.04 and d=0.15 Hz, and a very low frequency (Ln VLF) represents the frequency activity between e=0.0033 and f=0.04 Hz. The power spectrum, $X(m)$, was calculated as the squared magnitude of the fast FT of the HRV dataset.

3 PROCESSING SCHEME

The 5-minute HRV recording using a commercial pulse analyzer with a finger-type sensor of a photoplethysmogram (PPG), TAS9VIEW (CANOPY9 RSA, IEMBIO Co. Ltd., Chuncheon-si, South Korea) was obtained. In TAS9VIEW's research mode, three HRV parameters were analyzed by shifting a predetermined data segment called a window (1 min, 2 min, and 2 min 30 s) forward by every 30 s or 60 s during the entire 5-minute HRV dataset. A window refers to the moving window used for subsequent analyses of the HRV data points as shown in Figure 1. Figure 1 shows the processing scheme for calculating overlapping segments for one 5-minute HRV dataset. The analyzed results were automatically stored in an Excel file and used for the investigation. All segments had 1024 data points after a linear interpolation, and PPG signals were sampled at 1000 samples s^{-1}. It was not important in this study to check the participant's health status because the purpose of the study was to investigate the frequency domain HRV parameters using the overlapping segment method.

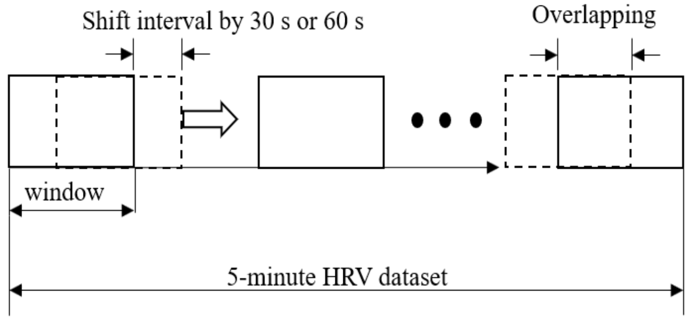


Fig. 1*. The processing scheme for a power spectrum using the overlapping segment method in TAS9VIEW's research mode.*

4 RESULTS

A power spectrum of the 5 min HRV segment and three predetermined HRV segments (1 min, 2 min, and 2 min 30 s), which were moved forward by shift intervals of 30 s and 60 s, is displayed in Figure 2. The averaged power spectrum obtained using shift intervals achieved a smoother power spectrum than the conventional periodogram, which uses one complete cycle for the entire 5-minute HRV dataset. By shift intervals, a shorter interval of 30 s achieved a smoother power spectrum on average than a longer interval of 60 s, despite a higher peak over the entire spectral bins by a shorter interval. The highest spectral value over all frequency bins was 413.04 ms^2 in the 1 min segment by a 30 s interval, followed by 340.42 ms^2 in the 2 min segment by a 60 s interval, 258.91 ms^2 in the 2 min segment by a 30 s interval, 238.82 ms^2 in the 2 min segment by a 60 s interval, and 184.92 ms^2 and 181.16 ms^2 in the 2 min 30 s segment by 30 s and 60 s intervals, respectively as shown in Table 1. The difference value between the maximal power spectra by 30 s and 60 s intervals narrowed in a longer HRV segment than in a shorter one, e.g., 3.76 ms^2 in the 2 min 30 s, 20.09 ms^2 in the 2 min, 72.62 ms^2 in the 1 min segment. All power spectral densities (PSD) for the 1 min, 2 min, and 2 min 30 s HRV segments were compensated by a product of a compensation factor and each power spectral bin, where a compensation factor was calculated by a time length called duration divided by the duration of 5 min HRV segment in Table 1. Following compensation, there were no significant differences between the maximal power spectra in the 5 min, 2 min, and 2 min 30 s HRV segments. The rate of the difference relative to a maximal power spectrum obtained by the 5 min HRV segment was -2.4% and -4.4% in the 2 min 30 s, and 9.5% and 1.0% in 2 min by shift intervals of 30 s and 60 s, respectively, and -12.4% and -27.8% in the 1 min. An averaged power spectrum (n=6) for overlapping segments from 2 min 30 s by a shift interval of 30 s achieved the smoothest spectrum. Table 2 shows the standard deviation of the Ln LF and Ln HF calculated by moving three different segments forward by every 30 s or 60 s shift interval. The lowest standard deviation was 0.45 and 0.06 in the Ln LF and Ln HF for 2 min 30 s by a 30 s shift interval, respectively. A Youden plot that explains a relationship with a rectangle representing 3 SD on both the x-axis and y-axis between the Ln LF on the x-axis and Ln HF on the y-axis is displayed in Figures 3 and 4. In Figure 3 (top), nine values of the Ln LF and Ln HF, which were calculated by moving a predetermined 1 min segment by every 30 s for the entire 5 min dataset were marked with a tracking pathway drawing from a start point to an end point in calculation order, including a mean value of nine Ln LFs and Ln HFs, while five values by a shift interval every 60 s in Figure 4 (top). An area of 3 SD rectangles decreased in a lengthier segment than in a short segment. The values of the SD, mean, min, and max for all the Ln LF and Ln HFs from 3 to 9 in the number of segments are listed in Table 2.

***Table 1**. A comparison of a power spectral density (PSD) between 1 min, 2 min, and 2 min 30 s segments in reference to the PSD value of the 5 min HRV dataset after compensation.*

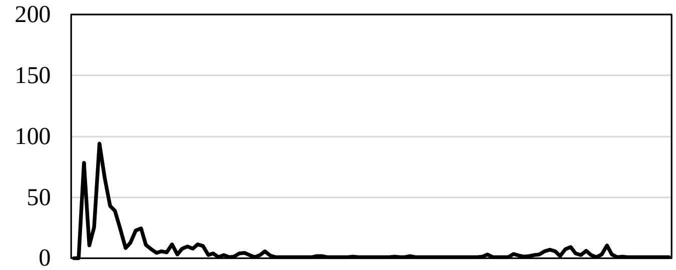
Segments	1 min		2 min		2 min 30 s		5 min
Duration (D)	59970		119559		149177		300429(A)
Comp. factor (C=D/A)	0.1996		0.3979		0.4965		1
Shift interval	by 30 s	by 60 s	by 30 s	by 60 s	by 30 s	by 60 s	-
Max. PSD (B)	413.04	340.42	258.91	238.82	184.92	181.16	94.08
Comp. max. PSD (B*C)	82.45	67.95	103.03	95.04	91.82	89.95	94.08

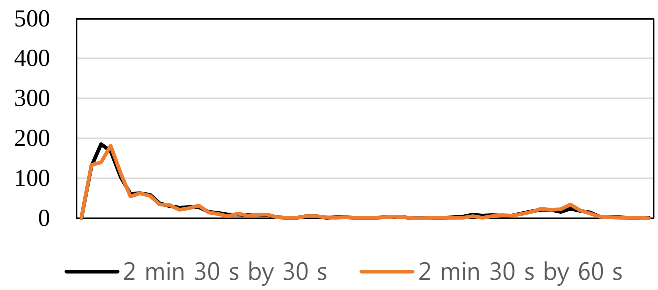
***Table 2**. The standard deviation of Ln LF and Ln HF for 1 min, 2 min, and 2 min 30 s segments divided by 30 s and 60 s shift intervals in the entire 5-minute HRV dataset.*

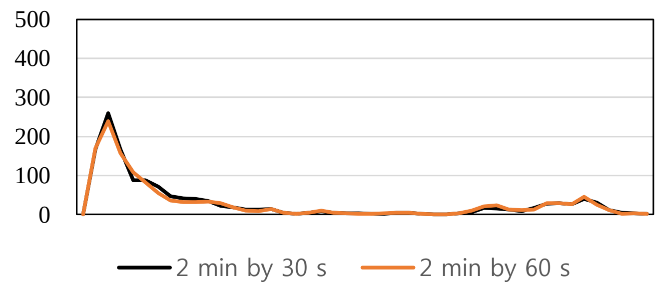
Segment		By 30 s			By 60 s		
		Ln LF	Ln HF	n	Ln LF	Ln HF	n
1 min	SD	0.74	0.17	9	0.6	0.2	5
	Mean	4.34	4.92		4.57	4.85	
	Min	3.01	4.62		3.85	4.62	
	Max	5.52	5.12		5.52	5.12	
2 min	SD	0.49	0.11	7	0.45	0.09	4
	Mean	4.75	4.85		4.64	4.91	
	Min	3.98	4.71		3.98	4.77	
	Max	5.37	4.97		4.94	4.97	
2 min 30 s	SD	0.45	0.06	6	0.61	0.03	3
	Mean	4.85	4.83		4.77	4.84	
	Min	4.08	4.75		4.08	4.82	
	Max	5.21	4.92		5.21	4.87	

***Table 3.** The mean of major HRV parameters for three segments by time shift intervals and a 5 min segment.*

Mean	1 min		2 min		2 min 30 s		5 min
	30 s (n=9)	60 s (n=5)	30 s (n=7)	60 s (n=4)	30 s (n=6)	60 s (n=3)	(n=1)
Mean NN	918	922	910	913	908	911	921
RMSSD	30.66	30.83	30.25	30.43	30.22	30.29	30.77
pNN50	8.03	8.30	7.18	7.84	6.77	6.90	8.28
ApEn	0.4237	0.4184	0.7012	0.7022	0.8148	0.8243	1.1366
SD1	21.83	21.95	21.47	21.60	21.44	21.48	21.79
SD2	41.50	40.39	50.23	50.28	52.30	53.92	58.01
SD2/SD1	1.91	1.85	2.33	2.32	2.43	2.50	2.66
Ln sArea	7.94	7.90	8.12	8.12	8.16	8.19	8.29
SDANN	28.04	32.39	15.62	18.88	11.63	13.95	-
SDNN index	33.17	32.56	38.52	38.66	39.85	41.01	-
Ln TP	5.92	5.96	6.54	6.51	6.71	6.67	6.62
Ln VLF	4.95	4.96	6.05	6.02	6.31	6.27	6.11
Ln LF	4.34	4.57	4.75	4.64	4.85	4.77	5.19
Ln HF	4.92	4.85	4.85	4.91	4.83	4.84	4.77







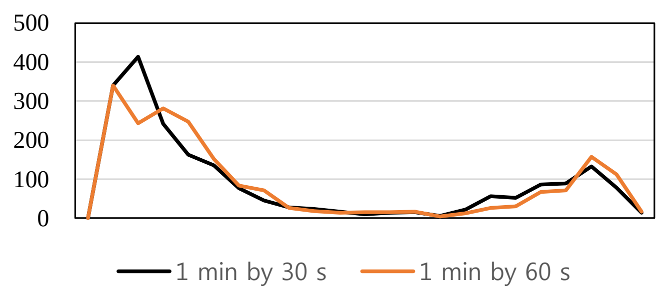


***Fig. 2.** A power spectral density (PSD) for all segments in terms of shift intervals of 30 s and 60 s: predetermined segments (1 min, 2 min, and 2 min 30 s).*

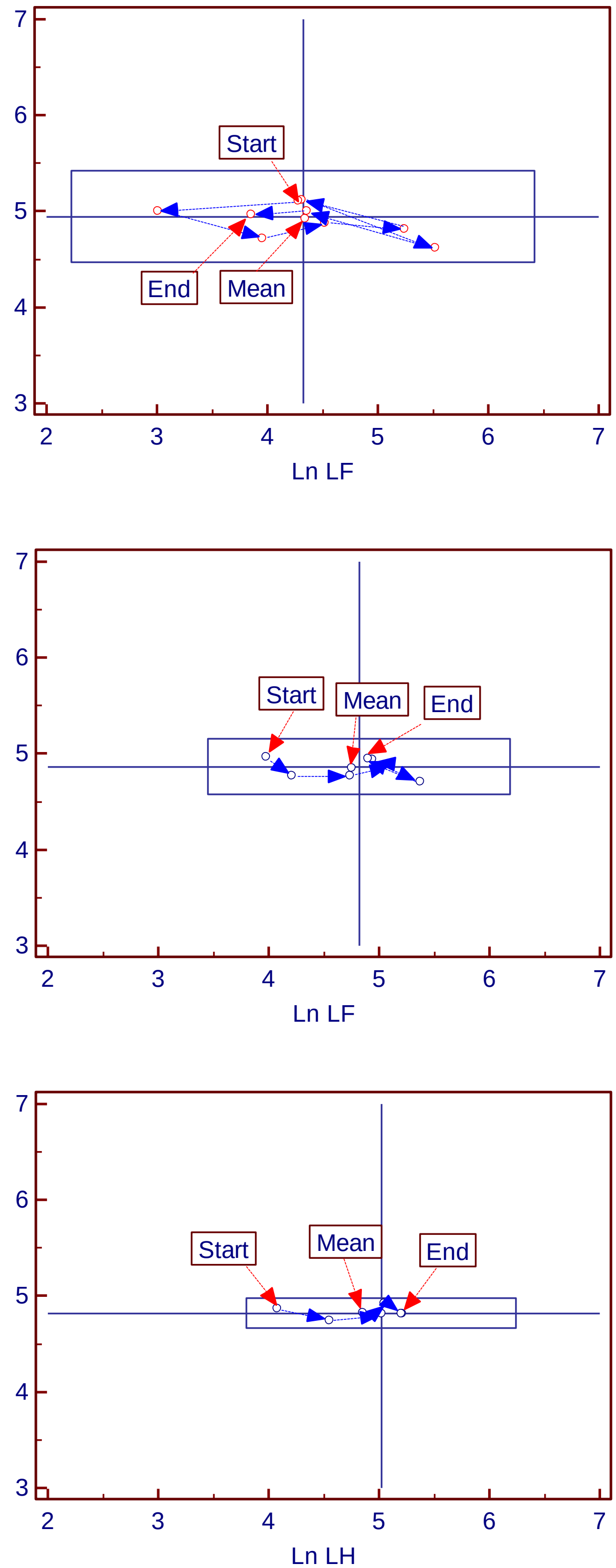


***Fig. 3.** A plot of Ln LF and Ln HF analyzed by shifting 1 min, 2 min, and 2 min 30 s segments forward by 30 s intervals, including a mean value.*

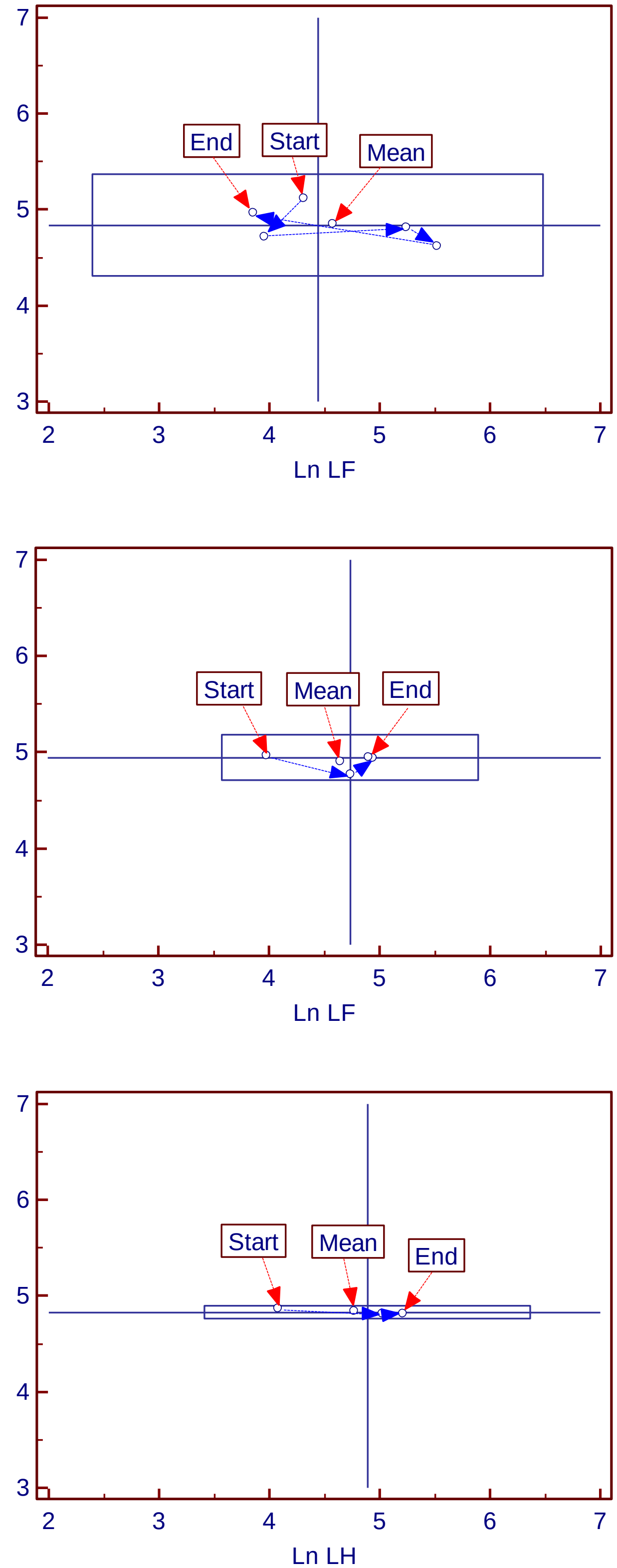


***Fig. 4**. A plot of Ln LF and Ln HF analyzed by shifting 1 min, 2 min, and 2 min 30 s segments forward by 60 s intervals, including a mean value.*

5 CONCLUSION

We proposed an improved method for calculating a power spectrum for the entire 5 min HRV dataset. To find a new method for calculating a power spectrum, the first step in this study was to divide one HRV dataset into three predetermined segments according to a data duration: 1 min, 2 min, and 2 min 30 s. The second step was to shift each segment forward by every interval of 30 s or 60 s to use the overlapped segments between the previous and next data segments. The results demonstrated that the calculation of a power spectrum using the overlapping segment could make a smoother power spectrum than the conventional method using no overlap. Specifically, the best smooth curve of a power spectrum occurred when the HRV parameters in the data segment of 2 min 30 s with a 30 s shift interval were calculated. A tracking pathway was found to reflect changes in ANS activity by drawing an intersection point between the Ln LF on the x-axis and Ln HF on the y-axis. Information on various tracking pathways could not be provided by a conventional method that analyzes the 5 min HRV dataset at a time as in one complete cycle for Fourier transform, but the proposed method could provide potentially meaningful information behind the tracking pathway, such as reflecting mental and physical changes in body condition regulated by the ANS activity. The results showed that our newly proposed method that requires several overlapping segments over the 5 min HRV data length could be very useful in calculating a power spectrum. In further study, the accuracy and repeatability of HRV frequency components such as the Ln VLF, Ln LF, and Ln HF, related to cardiovascular disease will be proven through various attempts, such as shift intervals that are shorter than 30 s.

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