Exploring the Potential of a Wrist-Worn Optical Sensor for Measuring Daily Life Activities

Tomoko Funayama
Dept. of Occupational Therapy
Teikyo University of Science
Yamanashi, Japan
e-mail: funayama@ntu.ac.jp

Yasutaka Uchida
Dept. of Life Science
Teikyo University of Science
Tokyo, Japan
e-mail: uchida@ntu.ac.jp

Eiichi Ohkubo
Dept. of Life Science
Teikyo University of Science
Tokyo, Japan
e-mail: ohkubo@ntu.ac.jp

Yoshiaki Kogure
Professor Emeritus
Teikyo University of Science
Tokyo, Japan
e-mail: kogure@ntu.ac.jp

***Abstract*— In recent years, wearable sensor devices that can be worn in daily life have rapidly gained popularity. The ability to monitor daily life, through a prolonged assessment, enables the detection of subtle changes in health status. Evaluating individuals in their usual daily settings provides an assessment that cannot be obtained within a hospital environment. However, there are not many research data on how activities specifically and objectively affect health. Therefore, in this study, we utilized an optical sensor device worn on the wrist to measure daily activities during individuals' daily routines. We studied heart rate and Fourier analysis and examined the relationship between condition and activity. As a result, the following aspects were deemed necessary to consider during measurement: 1) Analyze the data, taking into account not only the unstable period until the device stabilizes but also the time when subjects are operating the device. Consider the excluded data time and set the measurement time accordingly. 2) In addition to frequencies of 1Hz, 0.3Hz, 0.1Hz, also include analysis of the low-frequency ranges, such as 0.01Hz. 3) In case of significant variations in optical sensor data caused by arm movements, during abrupt and rapid changes (such as when the measured values from the accelerometer sensor exceed a certain threshold), data is excluded from the analysis of the light sensor. 4) Divide and analyze the data based on units, such as 10 seconds, 1 minute, 10 minutes, and investigate the changes in a time series. 5) Compare changes during activities and rest periods, and within the subject's activities. Examine the variations in the time required for cool-down and recovery. 6) Consider external factors, such as the influence of natural light, fluorescent lights, and vibrations from cars or trains. This study suggests that tailored measurement and analysis for various activities and environments are crucial in order to utilize optical sensor for health promotion and rehabilitation in daily life activities.**

Keywords- Optical Sensor; Activities of Daily Living; Spectrum Analysis; Self-Therapy.

I. INTRODUCTION

To enhance the quality of life of individuals with health-related issues, it is crucial to examine the reciprocal relationship between health conditions and activities of daily living and to make necessary adjustments in their daily lives. Circadian rhythms also affect health, and activities such as sleeping, eating, and outdoor activities affect circadian rhythms [1]–[3]. Effective self-management of activities and maintenance of health conditions are essential for self-therapy and improving the overall quality of life. However, grasping the relationship between health condition and daily activities is not a straightforward task. Life activities are not simply judged as inherently good or bad for one’s health. They are influenced by various factors, such as the individual's health condition, intensity of activities, habituation, personal adaptation, and environment, and depend largely on the balance of these factors. There are situations similar to those of workaholics, in which individuals may become engrossed in their activities and find it difficult to pay attention to their health. Compared to objective conditions, such as fever and coughing, it is more difficult to accurately assess subjective conditions, such as pain and fatigue. The ability to objectively perceive fluctuations in health conditions during their daily lives and comprehend the activities that affect their mind and physical well-being holds significant potential for enhancing health management among individuals facing health challenges [4]–[8]. Moreover, it is valuable for rehabilitation in daily living [9]–[12]. Recently, several monitoring and support devices and systems using wearable sensors have been researched, developed, and commercialized for older adults and individuals with health issues [13]–[16]. Wearable devices that employ sensors, such as acceleration, temperature, and pressure sensors are becoming increasingly popular [17].

We have studied methods for assessing body changes during activities. In addition, the relationship between daily

 ISBN: 978-1-68558-112-1

activities and heart rate has been examined using an optical sensor device [18]–[21]. Therefore, in this study, we conducted an exploratory investigation using a wrist-worn wearable device equipped with optical sensors in the context of individuals' daily routines. Activities and health conditions were recorded using a cloud-based service, whereas simultaneous measurements were conducted using a wearable device. We studied the heart rate and Fourier analysis and examined the relationship between the condition and activity. We suggest certain aspects of the measurement methodology for use during daily activities.

This study was approved by the Ethics Committee on Research with Humans as Subjects of the Teikyo University of Science. Section II describes the experimental method, Section III describes the results, Section IV presents the discussion, and Section V presents the conclusions and future work.

II. EXPERIMENTAL METHOD

A. Devices

The device used for the measurement was a Maxim Integrated MAXREFDES103, which was worn on the wrist as a wristwatch. The measurements can be obtained using a PC and an Android device. Three LEDs (green, red, and infrared) were used as optical lights. The green LED uses two diodes and outputs the green and green2 data. It incorporates an Arm Cortex-M4F embedded processor and supports Bluetooth connectivity for data transfer. The Sampling frequency was set to 25 Hz. This device outputs four types of optical light data (green, green2, red, and infrared) in CSV format, three-axis accelerometer data (x, y, and z), heart rate, transcutaneous arterial oxygen saturation (SpO_2), and timestamp information. The heart rate was calculated and provided as a value using MAXREFDES103. In this study, we used the green light sensor data, heart rate, and timestamps obtained from the CSV output.

Figure 1. Device used (MAXREFDES103).

B. Measurement

The measurements were conducted during the participants' daily life activities, as determined by his judgment, using a MAXREFDES103 device. The corresponding situations were simultaneously recorded. The subject was a single man in his 60s, and the data obtained from this individual were used for the analysis. Information on health conditions, stress levels, activity details, activity duration, and activity location from Google Form records were used in the analysis. Health conditions and stress levels were recorded on a scale of 1 to 10, with 1 representing the best state and 10 representing the worst perceived state. A free-text field was also included.

C. Analysis Method

The analysis excluded the initial two minutes of data obtained from the device, comprising 3000 data points, and the final 1000 data points. This exclusion was made to account for the time required for the data to stabilize and the time spent by the subject to operate the device. Thus, a fixed duration of time at the start and end of the measurement period, which included the time spent by the subject operating the clock, was excluded from the analysis. The Fourier analysis was performed using the fft function from the NumPy library in Python, specifically numpy.fft.fft.

III. RESULTS

A. Optical data used in the analysis

We examined the data outputted in four CSV files based on three types of light: green, infrared, and red. The green LED utilizes two different diodes and outputs data for green and green 2. Although the intensity of the stronger light differed from one implementation to another, green light was used because it was often relatively strong in spectral intensity. Figure 2 shows a graph of the output data obtained using optical light. Infrared (hereafter referred to as IR) refers to the near-infrared light. Figure 3 shows an example graph of the green output data, limiting the number of data points to 500.

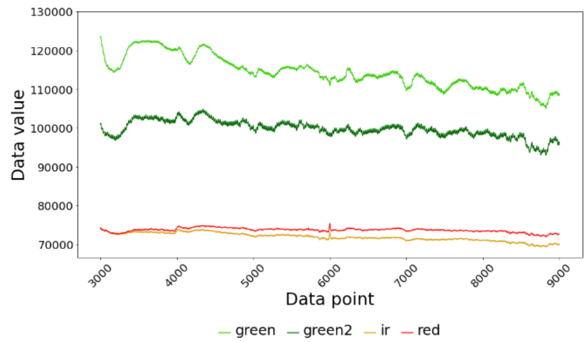

Figure 2. An example of output data by optical light type.

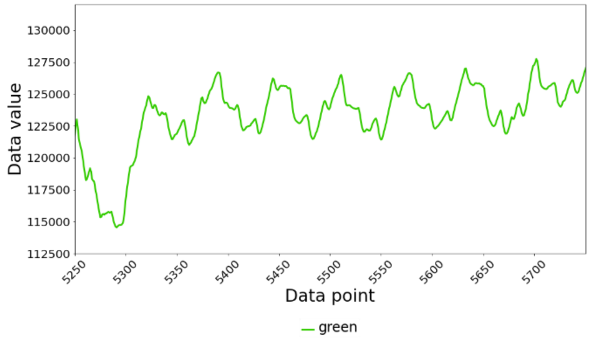

Figure 3. Green output data only 500.

There were periods of rapid changes in the output data within short durations, as well as periods with minimal variations.

B. Data Interval Used for Analysis

Measurements during daily activities are often performed over long periods. This results in a large amount of data. The obtained long-duration data were divided, and the frequencies that were deemed to be influenced by heart rate were identified through Fourier analysis and compared with the heart rates calculated from the device. The frequency with the highest spectral intensity in the range of 0.9 Hz to 2.5 Hz by Fourier analysis was considered to be the frequency that was influenced by the heart rate. The division was performed based on the number of data points after the start of the measurement, specifically at intervals of 250, 500, 1000, 2000, 4000, 6000, 8000, 10000, 15000, 20000 and 30000 data points. Each interval of 250 data points corresponded to approximately 10 seconds. An example of this is shown in Figure 4.

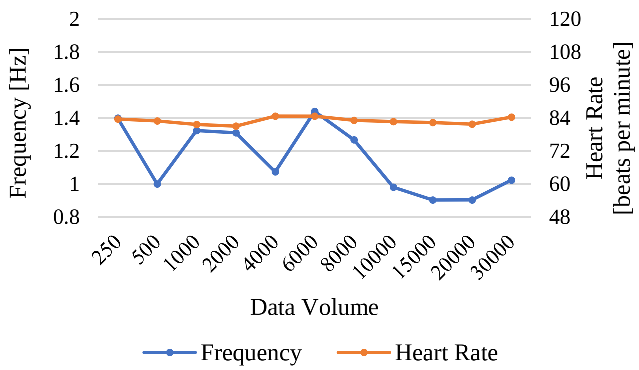

Figure 4. 0.9-2.5 Hz Frequency at maximum spectral and heart rate.

As the number of data points increased, the difference between the heart rates calculated from the device and the actual heart rates increased. With 250 data points, the heart rates closely matched, and this was often the case for up to 1000 data points. Although there were instances where the heart rates matched, even with a larger number of data points, inconsistencies became more frequent when the number of data points exceeded 2000. This may be attributed to factors, other than the heart rate mixing in at 0.9-2.5 Hz, such as increased measurement time, an increase in the number of different heart rates (i.e., more variation in heart rate values) and the impact of Fourier analysis, among other considerations.

C. Characteristic Frequency Bands

The number of data points was set to 1000, 2000, 4000, 6000, 8000, 10000, 15000, and 20000 or more, each of which was Fourier-analyzed to examine the spectral intensity and frequency band characteristics. Peaks were observed near 1.5 Hz, 0.3 Hz, 0.1 Hz, and occasionally below 0.1 Hz with increments of 0.01 Hz, with an occasional peak around 0.01 Hz below 0.1 Hz. Figure 5 and 6 show sample diagrams of the relationship between the spectral intensity and frequency based on Fourier analysis for 1000 and 15,000 data points, respectively. Figure 7 shows an example of the low-frequency region down to 0.20 Hz for 15000 data points.

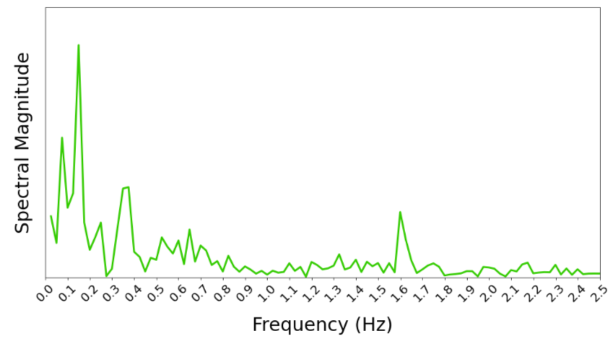

Figure 5. An example with 1000 Data Points.

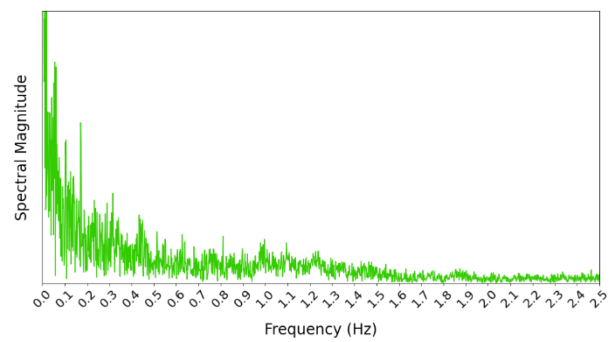

Figure 6. An example with 15000 Data Points.

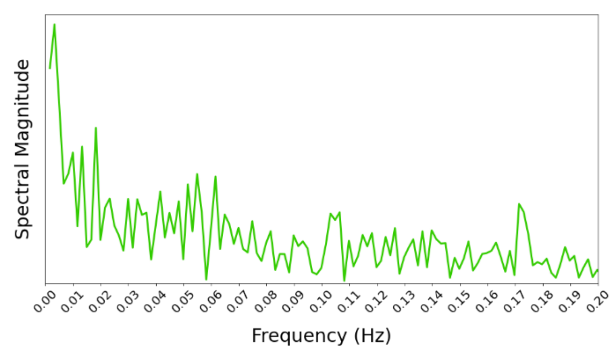

Figure 7. An example with the Low-Frequency Section with 15000 Data Points.

D. Frequency Characteristics due to Health Condition and Stress

The recorded measurements on a 10-point scale for health condition and stress levels were compared in terms of heart rate between states 8 and 9, indicating poor health and high stress, and between states 4 and 5, representing normal conditions. Because there were no recorded measurements for the states rated 3 or below, relatively good states 4 and 5 were

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used for comparison. Figure 8 shows the relationships between perceived health conditions, stress, and heart rate.

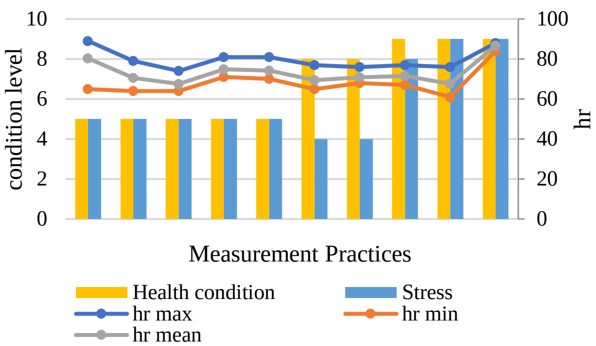

Figure 8. Heart rate related to health condition and stress.

There have been times when both self-perceived health condition and stress level were nine, and during those times, we noticed that the maximum, minimum, and mean heart rates were all high. However, a distinct correlation between the heart rate and these factors could not be established. Even when the patient's health was relatively good, the maximum heart rate remained high.

We examined self-perceived health conditions, stress, and the results of the Fourier analysis (see Figure 9). We extracted the frequencies at the peak spectral intensity within the ranges of 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz. The numbers on the X-axis of the graph represent the stress levels on the right side of the graph, ranging from 1 to 10, and the health conditions on the left side of the graph, ranging from 1 to 10. No obvious features were observed over the entire frequency range.

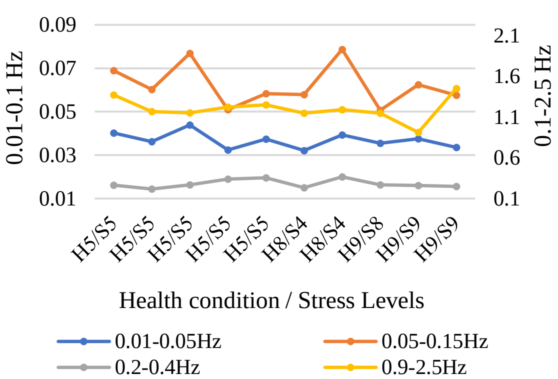

Figure 9. Fourier analysis data related to health condition and stress.

We compared the spectrum intensity and frequency plots from the Fourier analysis. Figures 10 and 11 represent poor and good health, respectively. Figures 10 and 11 show approximately 5000 data points.

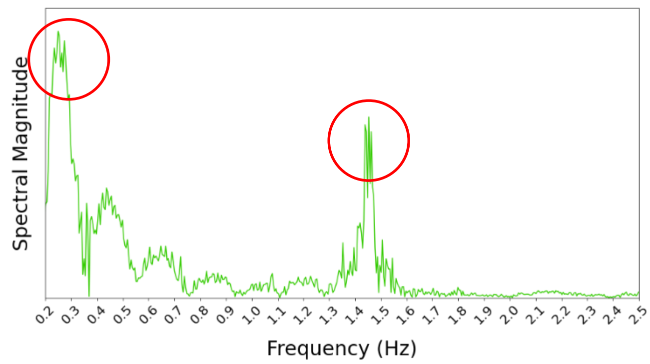

Figure 10. Fourier analysis results for poor health.

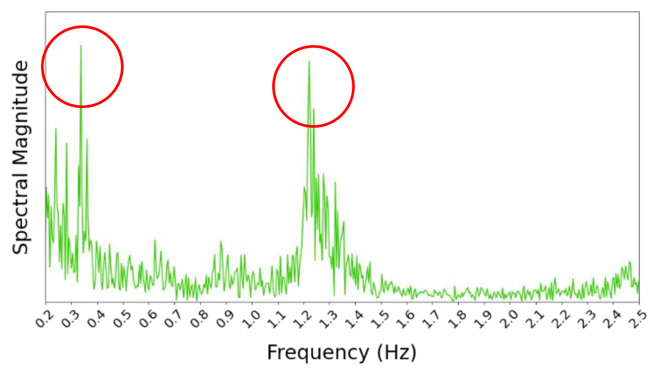

Figure 11. Fourier analysis results for good health.

Although there were no common characteristics across all instances, during periods of poor health, the peaks in the frequency range associated with heart rate and respiration appeared jagged and fluctuating, rather than well defined. However, during times of good health, there were also instances where sharp peaks were observed during periods.

E. Frequency Characteristics due to Bathing

The effects of bathing on each frequency band were also examined. The Fourier results before and after bathing, analyzed at 6000 number of data points, are shown in Figures 12 and 13.

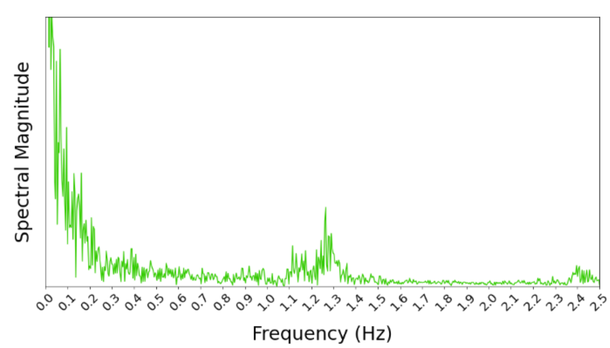

Figure 12. Fourier analysis before bathing.

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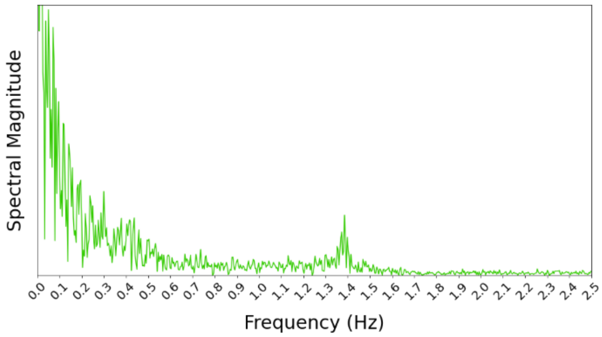

Figure 13. Fourier analysis after bathing.

After extracting the frequencies at maximum spectrum in the frequency bands 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz, it was observed that the frequencies after bathing were higher in all frequency bands. This is illustrated in Figure 14. Owing to the potential differences in the Fourier analysis results between long durations with a large number of data points and short durations with a small number of data points, we extracted and examined the frequencies at the peaks of the maximum spectral intensity when analyzing the data with 250 and 1000 data points. The results are summarized in Table 1.

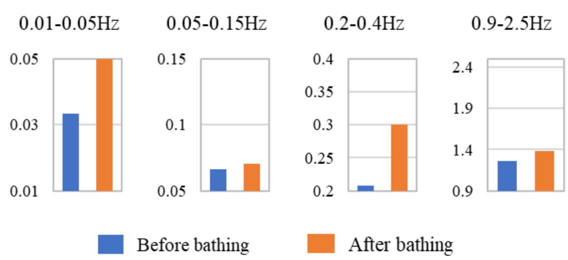

Figure 14. Frequency of the strongest of the spectrum in each frequency band before and after bathing.

TABLE I. FREQUENCY DIFFERENCES BASED ON DATA POINTS.

	250 data	1000 data	6000 data
0.2-0.4Hz Before Bathing	0.20	0.37	0.21
0.2-0.4Hz After Bathing	0.20	0.30	0.30
0.9-2.5Hz Before Bathing	1.20	1.27	1.27
0.9-2.5Hz After Bathing	1.30	1.02	1.39

In the case of 250 data points, for the frequency range of 0.2-0.4 Hz, the frequencies were 0.20 Hz before bathing and 0.20 Hz after bathing, and for the frequency range of 0.9-2.5 Hz, the frequencies were 1.20 Hz before bathing and 1.30 Hz after bathing. In the case of 1000 data points, for the frequency range of 0.2-0.4 Hz, the frequencies were 0.37 Hz before bathing and 0.30 Hz after bathing, and for the frequency range of 0.9-2.5 Hz, the frequencies were 1.27 Hz before bathing and 1.02 Hz after bathing. The frequency varied depending on the data segmentation method used.

F. *Frequency Characteristics due to driving a car*

The raw data obtained during car driving are shown in Figure 15, and the Fourier analysis is shown in Figure 16. During car driving, the wrist wearing the device moves frequently because of steering wheel manipulation.

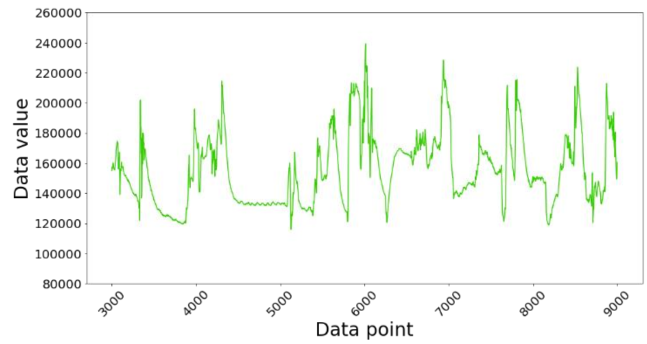

Figure 15. The raw data during car driving.

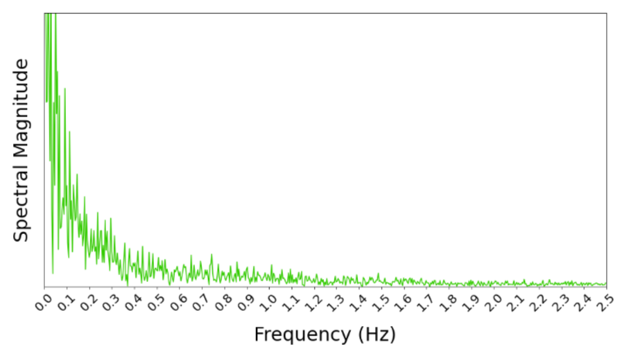

Figure 16. Fourier analysis data during car driving.

Figure 16 shows repeated significant fluctuations. The effect of each frequency band was also examined. No clear peaks were found in all frequency ranges, including 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz.

IV. DISCUSSION

In this study, it was observed that as the number of data points increased, there was a tendency for a larger difference between the calculated heart rate from the device and the frequency at the maximum spectral intensity. Several factors are considered to contribute to this phenomenon. First, as the measurement duration increases, the device may move, resulting in unstable data acquisition. Second, factors other than the pulse rate can interfere with the frequency range of 0.9-2.5 Hz. Additionally, an increased variety of pulse rates and a higher occurrence of different pulse rate values can occur, leading to variations in pulse rate measurements. Finally, the characteristics of the Fourier analysis, such as the

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influence of rapid changes within short time intervals on the entire spectrum, can also play a role.

The spectral intensity and frequency band characteristics were examined using a Fourier analysis with different numbers of data points (1000, 2000, 4000, 6000, 8000, 10000, 15000, and 20000 or more). When using a dataset of 1000 data points, discernible peaks were observed at approximately 1.5 Hz, 0.3 Hz, and 0.1 Hz. One thousand data points were equivalent to 40 s. When using a larger number of data points, such as 15000, it was occasionally observed that peaks near 0.01 Hz were present. It is considered that frequencies around 1.5 Hz are influenced by the pulse rate, whereas frequencies around 0.3 Hz are influenced by respiration. The peak near 0.1 Hz could potentially be associated with Myer wave-related sinus arrhythmia (MWSA) derived from blood pressure. The frequency range of 0.15-0.45 Hz represented high-frequency (HF) components influenced by parasympathetic nervous control, the range of 0.04-0.15 Hz represented low-frequency (LF) components influenced by sympathetic nervous control, and frequencies below 0.1 Hz might be related to myogenic and neurohumoral factors [22]–[24]. However, it should be noted that measurements taken during daily activities are influenced by various factors and do not necessarily accurately represent specific biological information. Hayano cautioned that applying the association between short-term heart rate variability measured under strictly controlled conditions and autonomic function to long-term heart rate variability recorded during free activity often leads to erroneous interpretations [25].

With the widespread adoption of wearable devices, measuring daily activities and physiological signals has become easier. Therefore, in addition to correlating physiological information, it is important to consider activities, perceived health conditions, or stress levels during daily life to enhance rehabilitation and lifestyle interventions. In post-exercise rehabilitation, cool-down is important, and in cardiovascular rehabilitation, it is typically set 5 to 10 min [26]. The cool-down duration may increase with higher levels of fatigue. Cool-down is the process of returning a fatigued body and mind to their original state and promoting recovery. Rest is crucial in daily life, and there are instances in which the body unconsciously rests, even during activity. When measuring the extent of activity and the necessary cool-down, a segmentation method based on 10-minute intervals may be potentially. Ten minutes is 15000 data points, and the fact that a peak around 0.01 Hz was sometimes seen may be one guide to the division method of 15000 data according to 10-min intervals.

In terms of health condition and stress, sharp peaks that were not observed during periods of poor health were observed during periods of good health. It is possible that during poor health conditions, the heart rate is not stable and the heart rate variation increases, whereas during good health conditions, there are times when the heart rate is stable at a certain level. In this study, no clear relationship was found between the Fourier analysis results and health conditions. Nonetheless, physical conditions are related to biological information. It is well known that there is a correlation between stress and biological information, as observed in white-coat hypertension. However, the manifestation of this relationship varies between individuals. As there was no change in biological information, does not mean there was no change in health conditions. The awareness of health conditions also varies among individuals. Factors such as individual differences in manifestation, the relationship between subjective awareness of health conditions and stress, a low correlation between biological information and manifestation, challenges in measurement methods, and devices not picking up information may contribute to these observations.

In the investigation before and after bathing, with 6000 data points, the frequency at the peak spectrum was higher in all frequency ranges of 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz compared to before bathing. However, with 1000 data points, it was lower in the frequency ranges of 0.2-0.4 Hz and 0.9-2.5 Hz. The frequency ranges of 0.01-0.05 Hz and 0.05-0.15 Hz were excluded from the analysis due to the limited number of data points. It can be inferred that the frequency is higher after bathing; however, depending on the extracted data to be analyzed, such as when movement is involved, the results may not match.

No distinctive results were observed while driving. This may be due to external factors other than the individual, such as the repeated movement of the upper limbs while wearing the device during steering wheel operation and the vibration of the vehicle. Considering that driving always occurs outdoors, natural light may also have an impact. However, the fact that a device is affected also implies that it affects a person. Considering the external factors that can influence a person, it is important to conduct further investigation. Additionally, by dividing and analyzing the data in short intervals, such as 10 s, instead of long durations, it may be possible to obtain distinctive data when the upper limbs wearing the device are in a stationary state.

V. Conclusion and Future work

Measurements during activity cannot be directly extrapolated from results obtained during rest. However, long-term measurements are beneficial for rehabilitation in daily life. It is important to consider what kind of activity, perceived health condition, and stress the individual is undergoing, and how they respond to them. In doing so, the following points will be important to keep in mind. In addition to frequencies of 1 Hz, 0.3 Hz, and 0.1 Hz, the analysis should include low-frequency ranges, such as 0.01 Hz. For long-term measurements, data points should be excluded from the analysis if there are significant device movements or rapid changes This implies that there are changes that exceeding a certain threshold within a specific time frame. If accelerometer data is also collected, any time data in which the accelerometer readings surpass a certain threshold will be excluded from the analysis. The data will be divided and analyzed at different time intervals: 10 s, 1 min, and 10 min. It is important to compare changes due to activity and rest as well as changes during the subject's activity, examine the changes in the time required for recovery, including cool-down, and consider the influence of factors such as natural light, fluorescent lighting, and external stimuli, such as vibrations from cars or trains should be considered. These are our suggestions. Human behavior is diverse and the impact of activities on the body is influenced by individual preferences, personalities, and characteristics. Therefore, it was not possible to categorize them mechanically. However, with the advent of big data utilization, it is possible to make objective judgments from the flexible data of activities. We intend to continue investigating the relationship between activities and health conditions to contribute to our understanding of lifestyle pathology and health promotion.

Acknowledgment

This study was supported by JSPS KAKENHI, Grant Number JP23K11207.

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