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A Method for Estimating Physician Stress Using Wearable Sensor Devices

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The idea of Society 5.0 initiative has been proposed to solve various social problems by connecting virtual cyberspace and real physical space through information technology. When applying the idea to improve the work-life balance of physicians in the medical field, we must consider the increased stress owing to their long continuous working hours. Estimating the stress of physicians in their daily lives by the questionnaires is insufficient, because of the difficulty of accurate their activity recalling. By using bio-metric information such as heart rate, physical activity, and sleeping information, it was expected that the daily stress state of physicians with high accuracy. In this paper, we propose a method for estimating physician stress by analyzing bio-metric information acquired by wearing a wearable sensor device. The proposed method estimates the state of stress during daily activities by acquiring data on heart rate variability (HRV) during wakefulness as well as sleep depth during rapid eye movement (REM) and non-REM sleep. Up to seven physicians wore the wearable sensor device for the maximum of eight weeks and the sleep depth and low-/high-frequency (LF/HF) components of HRV were obtained. Our observation showed that physicians' root mean square of successive differences (rMSSDs) were constantly high in their healthy state. Therefore, the decreasing of this index can be used as an indicator of fatigue and stress. In addition, by combining LF/HF components to the rMSSDs, we may estimate the stress state of physicians and find personal stressors.

1. Introduction

Recently, stress among physicians in the medical field has been increasing owing to longer working hours, making it difficult for physicians to maintain a work-life balance in their daily

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lives. According to the 2017 Basic Survey on Employment Status by the Ministry of Internal Affairs and Communications of Japan, the average percentage of employees who worked 60 hours or more per week was 11.8% for all occupations, whereas for physicians, it was 37.5%.[1] When physicians work long hours, they can lose concentration, resulting in medical accidents. Therefore, to prevent a decline in the quality of medical care, it is necessary to establish a system that can detect physicians who need rest at an early stage by sequentially evaluating changes in physician stress.

In Japan, it is important to solve various social problems by applying the Society 5.0 initiative to connect virtual cyberspace and real physical space through information technology.[2] When applying Society 5.0 to improve the work-life balance of physicians, we need to consider the risk of medical accidents occurring because physicians work long, continuous hours, causing their ability to concentrate to decrease. Therefore, we must establish a system to prevent deterioration in the quality of medical care through the early detection of physicians who need to rest by estimating changes in their stress.

The work-life balance scale (SWING-J) is a method for assessing the level of stress in daily life.[3] SWING-J allows subjects to check their work-life balance through a four-point subjective evaluation of work, family, positive aspects, and negative aspects using a questionnaire. However, this questionnaire cannot detect changes in physical conditions that the subject is not aware of. Therefore, SWING-J cannot accurately estimate changes in stress. In addition, since the working style of physicians differs greatly from that of general office workers, the causes of physician stress cannot be estimated from the SWING-J responses alone.

Estimating the magnitude of stress in daily life through biometric data analysis, including heart rate variability (HRV), has been widely studied. Stress affects the autonomic nervous system, which controls the functioning of internal organs and blood vessels. To estimate the state of stress, it is necessary to obtain biological information of the parasympathetic and sympathetic nerves, which constitute the autonomic nervous system, for all activities of daily life. Acquiring this biometric information through a wearable device on the body is advantageous.

In this paper, we propose a method to estimate the stress state of physicians by analyzing biometric data using a wearable sensor device. The proposed method can estimate the stress state with high accuracy by acquiring HRV data during wakefulness and sleep depth data during sleep states, such as rapid eye movement (REM) and non-REM.

The contribution of our paper is to propose a method for optimizing the work-life balance of physicians. In addition, using the biometric data of up to seven physicians wearing three types of wearable sensor devices over a long period of time, we estimate the potential causes of stress among physicians, which cannot be determined by daily questionnaires alone.

The remainder of our paper is organized as follows. We discuss the relevance and effects of stress and heartbeat in Sect. 2. In Sect. 3, we explain the mechanism of sleep. In Sect. 4, we explain our proposed method in detail, and we explain related works in Sect. 5. We evaluate and discuss the performance of our proposed method in Sects. 6 and 7. Finally, we conclude in Sect. 8.

2. Stress and Heartbeat

2.1 Stress

Stress is a state of tension caused by external psychological, emotional, environmental, and physical stimuli. Stress is affected by the autonomic nervous system, which controls the functioning of internal organs and blood vessels. The autonomic nervous system is composed of two opposing parts: the sympathetic nervous system and the parasympathetic nervous system. The sympathetic nervous system is greatly affected by increased stress during periods of wakefulness and tension. On the other hand, the parasympathetic nervous system is activated when stress decreases during periods of sleep and rest. Therefore, we can infer that a person with an active sympathetic nervous system is tense and a person with an active parasympathetic nervous system is relaxed.

2.2 Heartbeat

The heartbeat is generated when the sinoatrial node located near the right atrium of the heart generates an electrical signal to contract the heart muscle. There are two methods of measuring heart rate: the electrocardiogram (ECG) method and the photoelectric volumetric plethysmography (PPG) method. The ECG method uses an ECG to acquire and record weak electrical signals generated by electrode pads worn on the chest. The heartbeat interval is the R–R interval (RRI), which is the interval between upward R waves in the ECG waveform. Although the ECG method can measure the heart rate with high accuracy, it places a heavy burden on the user because of the need to wear an electrode sensor on the chest.

The PPG method measures the pulse by shining near-IR light on the skin surface and receiving the reflected light with a photodiode. The PPG method utilizes the light-absorbing property of hemoglobin in arterial blood vessels and has been adopted in wristwatch-type wearable devices. The PPG method measures the interbeat interval (IBI), which is the interval between adjacent beats, and the heart rate based on changes in blood flow. Although the accuracy of the PPG method is lower than that of the ECG method, the PPG method is less demanding on the user because it can be used on all parts of the skin.

2.3 HRV and autonomic activity

The heart rate interval is not always constant and fluctuates periodically. This cyclic variation is called HRV. Among the stimulus signals of HRV, two types of blood pressure fluctuation cycles are strongly related to autonomic nerve activity: the respiratory cycle of the stretch receptor of about 3–4 s, which senses lung expansion and contraction due to breathing, and the cycle of the arterial baroreceptor of approximately 10 s, which senses blood pressure fluctuations in the arteries. Respiratory variability is reflected in HRV using only the parasympathetic nervous system. On the other hand, blood pressure variability is reflected in HRV using both sympathetic and parasympathetic nerves.

The low-frequency (LF) component is in the frequency range of 0.04 to 0.15 Hz and is an index of sympathetic and parasympathetic nerves. The high-frequency (HF) component is in the frequency range of 0.15 to 0.40 Hz and is an index of the parasympathetic nervous system. Their ratio, LF/HF, is used as an index of sympathetic nerve activity. In autonomic balance based on the parasympathetic and sympathetic states, when the HF component is small and the LF component is large, we can conclude that the sympathetic nervous system becomes active and tense. On the other hand, when the HF component is large and the LF component is small, we can conclude that the parasympathetic nervous system is active and relaxed.

2.4 Analysis method of HRV

HRV, which is a periodic fluctuation of the heartbeat, is widely used to analyze the function of the autonomic nervous system. There are two types of methods for analyzing HRV: time domain analysis and frequency domain analysis.

Time domain analysis calculates the standard deviation of normal-to-normal intervals (SDNN) consisting of the root mean square of successive differences (rMSSD), the number of heartbeat interval differences exceeding 50 ms (NN50), and the fraction of heartbeats for which NN50 occurs (pNN50). SDNN has a strong correlation with the overall HRV. rMSSD, NN50, and pNN50 correlate with parasympathetic nerve activity. In this paper, we use rMSSD, which can estimate the parasympathetic state during sleep, as an index for stress estimation. Next, frequency domain analysis is used to determine LF and HF by calculating the power spectrum of the HRV time series using the discrete Fourier transform. In this paper, we use LF/HF as a measure of stress.

3. Sleep

3.1 Sleep stages

Sleep is classified into REM and non-REM sleep according to the depth of sleep. REM sleep increases sympathetic activity while decreasing muscle activity. Adults spend an average of 20 to 25% of their total sleep time in REM sleep. This ratio varies depending on stress and living conditions. When REM sleep is extremely long, the depth of sleep can be judged as shallow. On the other hand, non-REM sleep decreases the heart rate, respiratory rate, and blood pressure by suppressing brain activity and sympathetic nervous system activity. As the ratio of non-REM sleep time increases, the secretion of growth hormone increases and fatigue is recovered. Non-REM sleep is classified as shallow or deep sleep, and fatigue can be alleviated by increasing the duration of deep sleep. Generally, shallow sleep alternates with deep sleep at the onset of the sleep state. Deep sleep is concentrated in the first half of the sleep state. As waking approaches, the duration of REM sleep increases and the transition from the sleep state to the waking state occurs.

3.2 Sleep and autonomic nervous system activity

The autonomic nervous system acts not only during periods of wakefulness but also during sleep, and the relationship between sleep and autonomic activity has been shown.[4–7] In non-REM sleep, the predominance of parasympathetic nerves reduces circulatory system activity in the heart and lowers the heart rate. In REM sleep, the parasympathetic nerve is basically dominant, but the parasympathetic tone decreases owing to the transient increase in sympathetic nerve activity synchronized with REM. Therefore, we can estimate the autonomic activity by analyzing the transition between sleep stages. The proposed method estimates the magnitude of fatigue and stress by analyzing the percentage of deep sleep.

4. Proposed Method

4.1 Summary

We propose a stress estimation method for physicians that uses a wearable sensor device. Our proposed method estimates the magnitude of physician stress by measuring and continuously monitoring the deep sleep rate and rMSSD during sleep as well as LF/HF during the day for physicians wearing the sensor device. We also estimate the potential stress of physicians and find physician-specific stressors by combining the proposed method with a conventional questionnaire-based assessment.

The stress state according to the value of each parameter used in the proposed method is shown in Table 1. rMSSD is an index of parasympathetic nervous system activity; the lower the rMSSD value, the more tense the body becomes. Since deep sleep plays a role in recovering from fatigue, a high percentage of deep sleep indicates a high load during the day. The proposed method uses LF/HF as a sympathetic nerve activity index along with the deep sleep ratio and can estimate the stress state with high accuracy when the deep sleep ratio is high and LF/HF during the day is high.

4.2 System model

Figure 1 shows the structure of the proposed method. Physicians wear three types of wearable sensor devices to measure biometric data during the day. In addition, the physicians input questionnaire-based data on their daily life. These data are uploaded to a server. The evaluator retrieves and analyzes the data, and then feeds back the analysis results to the physicians.

Table 1
Stress state according to value of each parameter.

	Low value	High value
rMSSD	Nervous	Relaxed
Percentage of deep sleep	Relaxed	Nervous
LF/HF	Relaxed	Nervous

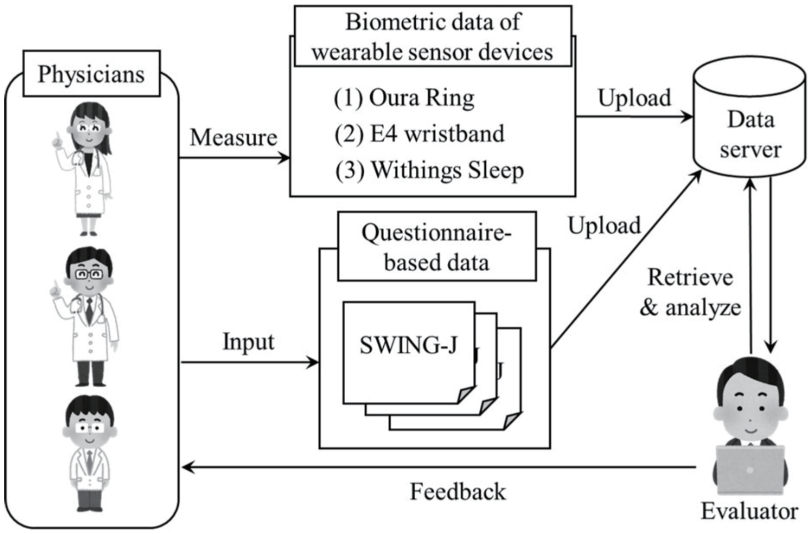

Fig. 1. Structure of proposed method.

4.3 Wearable sensor devices

4.3.1 Oura Ring

We use a ring-shaped sensor device called Oura Ring.(8) Oura Ring mainly acquires data during sleep. The rMSSD value obtained by Oura Ring is the square root of the mean of the squares of the differences between successive adjacent IBIs. We use rMSSD as an index of parasympathetic activity, where the higher the rMSSD value, the more active the parasympathetic nervous system is likely to be. In this paper, we analyze the data acquired by Oura Ring during sleep.

4.3.2 E4 wristband

We use a wristwatch-type sensor device called the E4 wristband.(9) The E4 wristband uses the PPG method to acquire HRV during the day. Although the PPG method has a lower data acquisition accuracy than the ECG method, the E4 wristband is easy to wear and places little burden on the user. The E4 wristband can acquire data on acceleration, the volumetric pulse wave, skin potential, heart rate, IBI, and skin temperature. In this paper, we calculate LF/HF by analyzing the IBI based on the volumetric pulse wave in the frequency domain.

4.3.3 Withings Sleep

We use a mattress-type sensor device called Withings Sleep.(10) Withings Sleep acquires biometric information during sleep similarly to Oura Ring. Unlike Oura Ring and the E4 wristband, Withings Sleep is a stationary device that is placed between the bed frame and the mattress. Withings Sleep can acquire data on sleep duration, sleep stages, minimum heart rate, average heart rate, and the number of sleep interruptions. In addition, unlike Oura Ring, Withings Sleep can detect snoring during sleep.

4.3.4 Criteria for selecting wearable devices

The proposed method estimates physician stress by monitoring the deep sleep rate and rMSSD during sleep and LF/HF during the day. To reduce the burden on physicians, we selected three types of wearable devices as described in Sects. 4.3.1–4.3.3.

The wearable heart rate sensor that monitors LF/HF during the day other than the E4 wristband is myBeat WHS-1.(11) myBeat WHS-1 requires the subject to affix the electrode pad directly to his/her chest. However, physicians performing CT and MRI examinations cannot wear the electrode pad at all times. Therefore, we selected the E4 wristband, which is a removable wristwatch-type sensor device.

To obtain the deep sleep rate and rMSSD during sleep, subjects need a device they can always wear during sleep. To reduce the burden on subjects and to measure changes in stress while wearing the device, we selected Oura Ring, a ring-type sensor with the lowest stress when wearing the device.

Finally, to investigate the relationship with the deep sleep rate, we need to acquire snoring during sleep, which cannot be measured by Oura Ring. Therefore, we selected Withings Sleep, a mattress-type sensor device.

5. Related Works

Mozos *et al.* proposed a machine learning approach for the automatic detection of stress in people in a social situation by combining two sensor systems that capture physiological and social responses.(12) Their experimental results show that, by combining the measurements from both sensor systems, they could accurately discriminate between stressful and neutral situations during a controlled Trier social stress test (TSST).

Kodama *et al.* proposed a context recognition method using information obtained from the nostrils.(13) They developed a system to acquire nostril temperature using small temperature sensors connected to glasses. Their experimental results show that the proposed system can detect breathing correctly, workload with an accuracy of 96.4%, six behaviors with an accuracy of 54%, and eight behaviors in daily life with an accuracy of 86%.

Sakai and Yokoyama designed an interactive system to estimate mental load, such as fatigue and concentration on work, from seat pressure fluctuations.(14) The evaluation results confirmed that their system can estimate work efficiency based on surface pressure using the random forest method.

Shao *et al.* studied operators' mental workload by using the HRV signal while operating a dual-arm robot.(15) By using the HRV signal of five subjects for training and that of one subject for testing with the gentle boost (GB) method, they obtained the highest average classification accuracy (80.56%).

Umetani *et al.* proposed a method for continuously detecting changes during sleep, such as the movements of the person and the bedding, from the acceleration, temperature, and the humidity of the comforter.(16) Through the measurement of several types of ambient conditions, their proposed method constructed a system that improves sleep quality and prevents accidents, such as falling off the bed.

Coutts *et al.* acquire HRV with a wearable device worn on the wrist and estimate mental health states such as depressed, positive, and anxious moods, which are binarized into two groups, namely, high and low.(17) The results of deep learning-based estimation showed that they could classify with high accuracy. However, this experiment was conducted on students only and cannot estimate the stress of physicians assumed in this study.

Umair *et al.* introduced a mixed-methods approach to compare the data quality and user acceptance of the six most common wearable heart rate monitoring biosensors.(18) Authors performed quantitative analysis consisting of correlation and agreement analysis on the HRV data and thematic analysis on qualitative data obtained from interviews. However, this approach analyzed the data in terms of aesthetics, wearability, and comfort, and did not cover the stress analysis of physicians assumed in this study.

Our proposed method estimates the magnitude of physician stress by analyzing a combination of biometric data from wearable sensor devices and questionnaire-based data.

6. Evaluation

First, as an initial evaluation, we measured various types of data with seven physicians wearing Oura Ring and the E4 wristband. Next, we analyzed the characteristics of the parameters to estimate the stress of the physicians.

All physicians reviewed the explanatory documents and provided informed consent. This study was conducted with the approval of the Osaka University Research Ethics Committee, Okayama University Ethics Review Committee (No. 2009-019), and Kyoto Prefectural University of Medicine Medical Ethics Review Committee (No. ERB-C-1880).

6.1 Initial evaluation of Oura Ring

Daily activity can be calculated from the calories burned while the body is fully relaxed, and the minimum threshold for activity is 1.5 METs (metabolic equivalents).(19) Therefore, we classified a day with activity above this minimum threshold as an active day and a day with activity below it as an inactive day, and then we analyzed the subjects' data acquired with Oura Ring.

6.1.1 Fatigue and sleep stages

Table 2 shows the percentage of each sleep stage based on daytime activity. The sleep stages are categorized as REM sleep, shallow sleep, and deep sleep. The percentage of deep sleep was determined to be 22% for a low-activity day and 30% for a high-activity day. When the body

Table 2
Percentage of each sleep stage based on daytime activity.

	Low activity	High activity
REM sleep (%)	24	21
Shallow sleep (%)	54	49
Deep sleep (%)	22	30

becomes fatigued owing to increased activity during the day, the duration of deep sleep increases as the body recovers from the fatigued state.

6.1.2 Fatigue and rMSSD values

Table 3 shows the minimum, maximum, and average values of rMSSD according to the level of activity during the day. When physical fatigue accumulated due to high daytime activity, we determined that the maximum value is about 130 − 80 = 58 (ms) lower and the average value is about 72 − 31 = 41 (ms) lower than low daytime activity.

Next, we compared the distributions of sleep stages according to the level of activity during the day. The distributions of rMSSD values for six days, three inactive days and three active days, are shown in Figs. 2 and 3, respectively. The vertical axis shows rMSSD and "hypnogram" on the horizontal axis indicates the stage of sleep; 4 indicates wakefulness, 3 indicates REM sleep, 2 indicates shallow sleep, and 1 indicates deep sleep.

As shown in Figs. 2 and 3, rMSSD values on active days were markedly lower than those on inactive days. We confirmed that the parasympathetic nervous system function decreased on active days owing to the increased load on the body caused by the increased activity.

6.1.3 Sleep stages and rMSSD values

The minimum, maximum, and average rMSSD values for each sleep stage according to daily activity are shown in Table 4 for inactive days and Table 5 for active days. For inactive days, the mean values of REM sleep, shallow sleep, and deep sleep are 59, 78, and 73, respectively. Therefore, we confirmed that the rMSSD values for REM sleep were significantly lower than those for shallow sleep and deep sleep. On the other hand, as shown in Table 5, the rMSSD values on active days were lower in all sleep stages on active days, with little difference between the rMSSD values in each sleep stage.

6.2 Initial evaluation for E4 wristband

As described in Sect. 4, we evaluated the degree of fatigue according to the LF/HF values measured by the E4 wristband according to the daily activity. Figure 4 shows the power spectra calculated from the time series of HRV on active and inactive days. The horizontal axis is the frequency and the vertical axis is the power spectrum density. Figure 4 shows that the LF component of active days is much higher than that of inactive days. The LF/HF values were about 5.14 for active days and about 1.37 for inactive days. Therefore, the sympathetic nervous system is activated when the physician is stressed.

Table 3
rMSSD values according to level of activity.

	rMSSD (ms)	
	Low activity	High activity
Minimum value	17	12
Maximum value	138	80
Average value	72	31

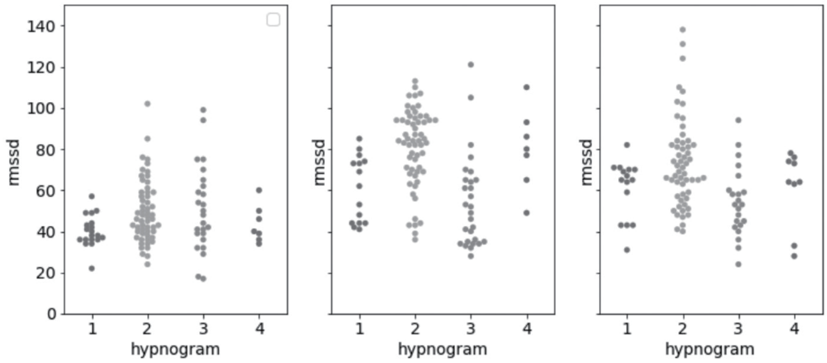

Fig. 2. Distribution of rMSSD values on three inactive days.

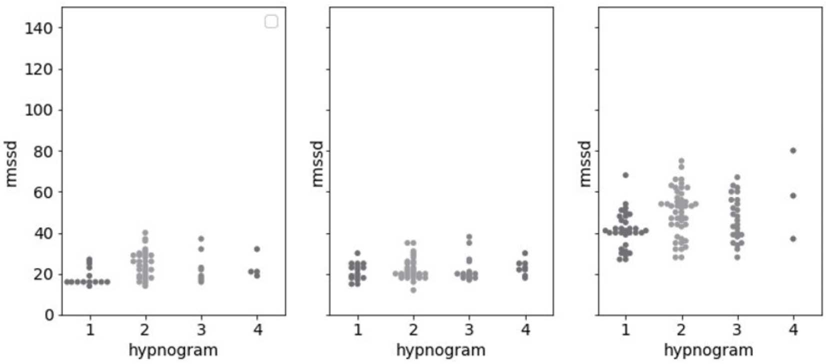

Fig. 3. Distribution of rMSSD values on three active days.

Table 4
Sleep stages and rMSSD values on inactive days.

	REM sleep (ms)	Shallow sleep (ms)	Deep sleep (ms)
Maximum	17	24	22
Minimum	125	138	127
Average	59	78	73

Table 5
Sleep stages and rMSSD values on active days.

	REM sleep (ms)	Shallow sleep (ms)	Deep sleep (ms)
Maximum	13	12	14
Minimum	67	75	68
Average	33	33	29

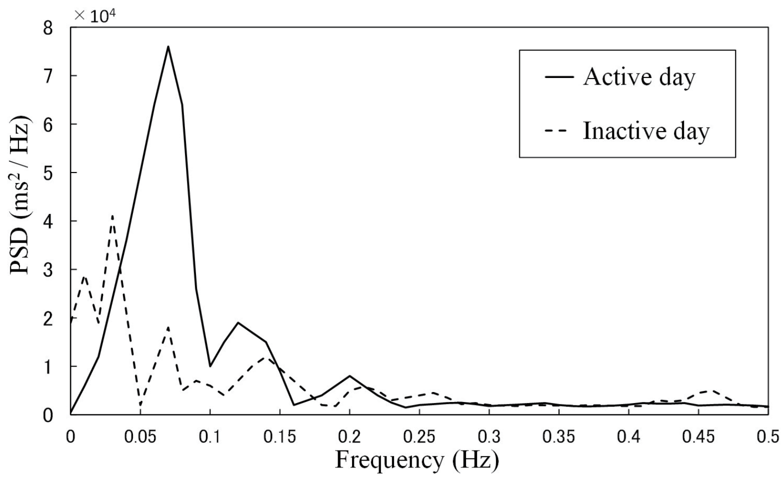

Fig. 4. Frequencies and power spectral densities on active and inactive days.

6.3 Evaluation of stress estimation for physicians

We evaluated the proposed method for estimating the stress of physicians by analyzing the biometric data acquired by multiple wearable sensor devices. The subjects were seven physicians who wore up to three different wearable sensor devices: Oura Ring, the E4 wristband, and Withings Sleep. These devices measured biometric data for the subjects during the day and at night for eight weeks. In the subjective evaluation of the questionnaire, the subjects answered questions based on SWING-J every day.

Oura Ring was used by seven physicians, the E4 wristband was used by two physicians, and Withings Sleep was used by one physician. We evaluated the devices in two different semesters: a 4-week period from October 19, 2020 to November 15, 2020 (first semester) and a 4-week period from November 16, 2020 to December 13, 2020 (second semester).

6.3.1 Oura Ring evaluation results

The average sleeping data for the first semester for the seven subjects (01 to 07) is shown in Table 6. Sleep stages were categorized as shallow sleep, deep sleep, and REM sleep. We calculated the duration of each stage as a percentage of total sleep. Next, the ratio of sleeping time to bed time was calculated by measuring the time spent in bed asleep and the time spent awake. Furthermore, we calculated rMSSD and the number of breaths per minute during sleep.

As shown in Table 6, subject 02 tended to have a much higher rMSSD value than the other six subjects. On the other hand, in the questionnaire about stress, subject 02 answered that they felt little stress during the day. Therefore, when rMSSD is constantly high, we judge that the stress of the physician is low.

Subject 03 with the lowest percentage of deep sleep answered in the questionnaire that they felt a high level of stress in daily life. Therefore, if the ratio of deep sleep for a physician is permanently low, the body of the physician will not be able to fully recover through sleeping.

Table 6
Average sleep data for subjects 01 to 07 in first semester.

	Subject						
	01	02	03	04	05	06	07
REM sleep (%)	18	10	32	24	26	22	19
Shallow sleep (%)	45	55	54	54	36	58	63
Deep sleep	37	35	14	22	38	20	18
Bed (s)	20578	26000	29702	24650	22453	26907	27060
Sleep (s)	16840	19218	27174	21256	20262	20007	23282
Awake (s)	3738	6782	2528	3394	2191	6900	3778
Sleep/bed (%)	82	74	91	86	90	74	86
rMSSD (ms)	38	58	34	35	25	36	27
Number of breaths per min	15.1	13.2	16.7	15.6	18.4	13.1	15.3

Next, the averages of the sleeping data in the second semester for the six subjects (02 to 07) are shown in Table 7. There were no characteristic differences between subjects 02, 03, and 06. For subject 04, shallow sleep changed from 54% in the first semester to 49% in the second semester, deep sleep changed from 22 to 26%, and rMSSD changed from 35 to 49 ms. In addition, the average of the 5-point scale for mental fatigue increased from 2.46 to 3.25, indicating that the increase in the percentage of deep sleep for subject 04 was due to fatigue. Next, in the evaluation of subject 05, the percentage of shallow sleep changed from 37 to 31% and the percentage of deep sleep changed from 38 to 42%. Similarly, for subject 07, REM sleep changed from 19 to 22% and deep sleep from 18 to 14%. However, subjective evaluation using the questionnaires showed no clear difference between subjects 05 and 07.

For subject 05 in the first semester, the duration of each sleep stage as a percentage of the total sleep time and the waking and sleeping times as percentages of the total bed time are shown in Figs. 5 and 6, respectively. No measurements could be made on day 26. Figures 5 and 6 show that the deep sleep on days 17 and 18 was more than 50%, which is a significant increase from the average of 38%. On the other hand, subjective evaluation showed that subject 05 was not aware of the increase in deep sleep. Therefore, if the percentage of deep sleep increases continuously without the awareness of the subject, it is likely that the subject is fatigued. This result indicates that the proposed scheme is effective in detecting potential stress.

Next, for subject 05 in the first semester, the duration of each sleep stage as a percentage of the total sleep time and the durations of waking and sleeping times as percentages of the total bed time are shown in Figs. 7 and 8, respectively. No measurements could be made on days 3, 19, and 20. According to Figs. 7 and 8, the deep sleep on day 8 for subject 05 was very high at 66%. On the eighth day, subject 05 was on holiday but received an emergency call at night to perform an operation at the hospital. We believe that the percentage of deep sleep of subject 05 increased to recover from the accumulated fatigue. On the other hand, on day 17, the percentage of deep sleep was 17% and that of sleeping time was 63%, which were both the lowest values during the semester. In this case, we believe that the fatigue of subject 05 on day 17 was low.

In the questionnaire after using Oura Ring, the subjects did not report any problems with wearing the device. On the other hand, they did report concerns about wearing Oura Ring all the

Table 7
Average sleep data for subjects 02 to 07 in second semester.

	Subject					
	02	03	04	05	06	07
REM sleep (%)	10	33	25	27	24	22
Shallow sleep (%)	55	53	49	31	57	64
Deep sleep (%)	35	14	26	43	19	14
Bed (s)	27182	30759	25663	22145	27095	27478
Sleep (s)	20604	27320	22473	19481	20514	24383
Awake (s)	6578	3439	3190	2664	6580	3095
Sleep/Bed (%)	70	89	88	89	76	89
rMSSD (ms)	60	35	49	27	33	24
Number of breaths per min	13.3	16.8	15.5	18.3	12.8	15.0

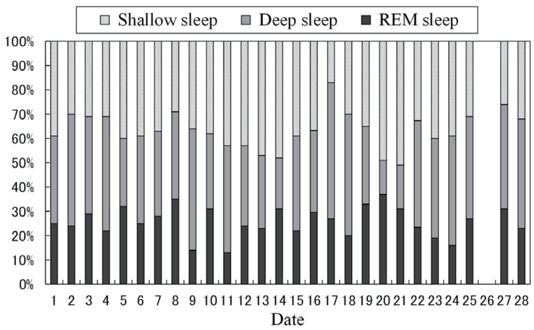

Fig. 5. Duration of each sleep stage as a percentage of total sleep time for subject 05 in first semester.

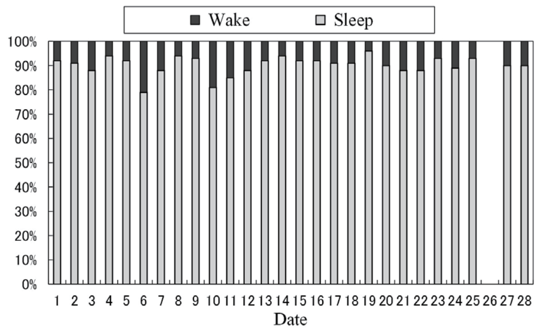

Fig. 6. Waking and sleeping times as percentages of total bed time for subject 05 in first semester.

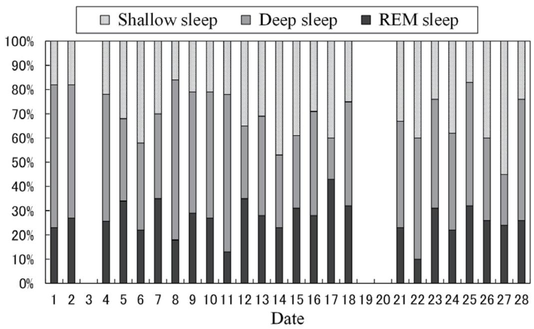

Fig. 7. Duration of each sleep stage as percentage of total sleep time for subject 05 in second semester.

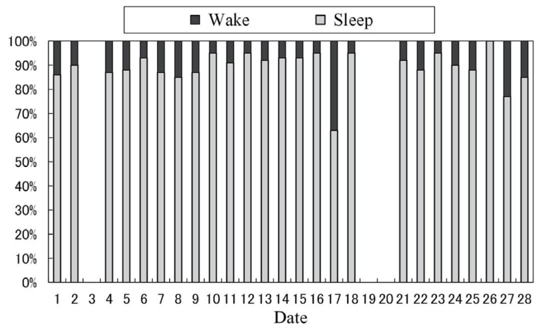

Fig. 8. Waking and sleeping times as percentages of total bed time for subject 05 in second semester.

time in terms of the risk of losing it and preventing infections such as COVID-19 in the hospital. Oura Ring is completely waterproof and can be worn while bathing. However, in a hospital where infection control is important, it is necessary to assume a situation where the physician cannot wear the device.

6.3.2 E4 wristband evaluation results

Biometric data were collected from subjects 02 and 06 with the E4 wristband during the second semester. First, to standardize the sampling interval, we resampled the 120 s IBI time series data at rest every second using linear completion. Next, for the linearly interpolated IBI time series data, we computed the power spectrum by a discrete Fourier transform using a Hamming window function of 120 s length. From the power spectrum, we calculated the LF, HF, and LF/HF components. As described in Sect. 4, the higher the LF/HF value, the higher the load on the body. In this paper, we analyzed the combination of the deep sleep ratio and LF/HF obtained from Oura Ring.

LF/HF and the deep sleep percentage for subject 02 in the second semester are shown in Table 8. The percentage of deep sleep was 51% and LF/HF was 2.23 on day 10, both of which were maximum. On the other hand, the correlation coefficient was 0.53 and we could not confirm a strong correlation.

LF/HF and the deep sleep percentage for subject 06 in the second semester are shown in Table 9. LF/HF exceeded the average on days 6, 9, and 10, when the ratio of deep sleep was high and the burden on the body was estimated to be high in Oura Ring measurement. LF/HF on day 6 was 2.49, which was maximum in the period. The increase in LF/HF indicates sympathetic activation, i.e., increased tension and stress. On other measurement days, LF/HF changed according to the rate of deep sleep. The correlation coefficient between LF/HF and the rate of deep sleep was 0.80.

Next, subject 06 showed a strong correlation between LF/HF and the percentage of deep sleep, whereas the correlation for subject 02 was weak. In this case, it appears that stress increases on days when both LF/HF and the percentage of deep sleep are high.

6.3.3 Withings Sleep evaluation results

We obtained the biometric data of Withings Sleep from subject 05. Table 10 shows the biometric data of Withings Sleep for subject 05 in the first semester. No measurements could be

Table 8
LF/HF and deep sleep ratio for subject 02 in second semester.

Date	LF/HF	Deep sleep ratio (%)
5	1.96	37
10	2.23	51
11	1.45	44
12	0.90	21
13	0.79	34
17	1.84	42
18	1.44	37
20	0.72	46
22	0.62	36
26	0.63	32
Average	1.26	38

Table 9
LF/HF and deep sleep ratio for subject 06 in second semester.

Date	LF/HF	Deep sleep ratio (%)
6	2.49	26
8	0.92	20
9	1.68	27
10	1.40	27
12	0.28	19
14	0.64	12
16	0.31	11
24	1.56	23
25	0.97	18
28	1.84	24
Average	1.21	21

made on days 4, 13, 14, 15, and 21. As observed from the results measured by Oura Ring and Withings Sleep for subject 05, there were differences in sleep duration and sleep stage. This is due to the difference between a contact device and a stationary device.

In the subjective evaluation, subject 05 was not aware of waking up during sleep. On the other hand, subject 05 snored continuously over the semester, indicating that their physical condition was changing. When a subject wakes up repeatedly during sleep, external factors that interfere with sleep, such as the sleep environment, and internal factors, such as the subject's own health condition, affect sleep. Analyzing the subject's physical condition during sleep by monitoring mid-sleep waking and snoring over a long period of time is effective in detecting potential stress that occurs without the subject being aware of it.

Table 10
Withings Sleep data for subject 05 in first semester.

Date	Sleep time (s)	REM sleep (%)	Shallow sleep (%)	Deep sleep (%)	Number of awakenings	Snoring (s)
1	21480	22	52	26	2	180
2	21540	13	37	50	1	360
3	19680	23	31	46	0	180
4	Unmeasurable		Unmeasurable		Unmeasurable	
5	39360	36	19	45	1	540
6	16560	22	54	24	0	0
7	23820	29	27	44	3	0
8	29760	25	40	35	2	1440
9	26220	23	32	45	1	660
10	27780	27	50	23	1	300
11	14880	13	58	29	0	0
12	23460	28	49	23	1	0
13	Unmeasurable		Unmeasurable		Unmeasurable	
14	Unmeasurable		Unmeasurable		Unmeasurable	
15	Unmeasurable		Unmeasurable		Unmeasurable	
16	22800	27	28	45	0	0
17	14700	25	25	50	0	0
18	26400	35	23	42	0	0
19	24360	29	29	42	0	0
20	25860	22	40	38	0	0
21	Unmeasurable		Unmeasurable		Unmeasurable	
22	20220	27	22	51	1	0
23	18600	19	24	57	0	0
24	17940	27	25	48	0	1380
25	23100	25	23	52	0	0
26	20460	23	18	59	1	1620
27	23340	31	23	46	1	0
28	16860	25	33	42	0	0

7. Discussion

7.1 Hygienic environment of wearable devices

Subjects answered a questionnaire about the wearing comfort of the wearable device after using Oura Ring for four weeks. We confirmed that most subjects wore the wearable device without any discomfort. On the other hand, subjects pointed out the hygienic environment of the wearable device. Oura Ring is completely waterproof, and subjects can wear it while bathing. However, the physician in charge of the subjects pointed out the need for adequate infection control measures in the medical field and the stress of wearing the ring-shaped sensor all the time. Therefore, we need to pay sufficient attention to the hygienic environment for infectious diseases such as COVID-19.

7.2 Accuracy of biometric data acquisition

In this study, we obtained biometric data when subjects wore three types of sensors. However, we could not acquire biometric data on some days owing to poor contact with the human body caused by the loosening of the device when the subject was wearing it and owing to the effect of forgetting to wear the wearable sensor device. To improve the accuracy of biometric data acquisition, we need to support subjects to wear the wearable sensor device correctly every day by adequately explaining the experimental method to them in advance.

8. Conclusion

In this paper, we proposed a stress estimation method based on the analysis of biometric data acquired by a multi-sensor device. The proposed method used the deep sleep rate, rMSSD, and LF/HF as indices for stress estimation. By analyzing the biometric data of seven physicians, we confirmed that rMSSD can be used as an index of fatigue and stress in the long term and we can conclude that physicians whose rMSSD is constantly high are in a healthy state. In addition, the deep sleep ratio can be used to estimate the magnitude of fatigue and stress in the short term and long term, and on days when the deep sleep ratio rises significantly, physicians can be judged to have a high workload. Finally, by combining LF/HF calculated from the IBI time series acquired during the day and the deep sleep ratio, we confirmed that the proposed method estimated the potential stress of physicians and found physician-specific stressors.

In the future, we will acquire and evaluate biometric data from wearable sensor devices considering the hygienic environment and the accuracy of data acquisition. In addition, we will consider stress estimation methods considering the knowledge of human physiology and behavior study.

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