Sleep Stage Estimation Comparing Own Past Heartrate or Others’ Heartrate

Yusuke Tajima*, Fumito Uwano*, Akinori Murata*, Tomohiro Harada**, and Keiki Takadama*

Abstract: To increase the accuracy of real-time sleep stage estimation when only a small number of sleep data can be obtained such as after going to bed, the information for the subject’s own sleep and other’s past sleep can be used. However, the types of other sleep data such as the subject’s own sleep data or other’s sleep data, which can contribute to the increase of the sleep stage estimation accuracy, are unknown. Therefore, this paper focuses on these two types of sleep data (i.e., the subject’s own sleep data and other’s sleep data) and aims to investigate the usefulness of these data for increasing the sleep stage estimation accuracy. Using human subject experiments, the following conclusions have been revealed: (1) the accuracy of the sleep stage estimation is improved using the similarity of either the subject’s own past sleep or others’ sleep and (2) the accuracy of the estimation method using the sleep data of six other people is higher than those obtained using the data for none, one, or two people.

Key Words: sleep stage, estimation method, heartrate, health care.

1. Introduction

Humans spend some time on daily activities, such as resting, eating, and sleeping, which are essential for human health. A large amount of time is spent on daily activities such as working, eating, and resting, while approximately a third of the day is devoted to sleep. Daily activities and sleep are related to each other; for example, it is empirically known that exercise or work induces better sleep. However, many other relations of this type have not been revealed yet. For example, the relation between sleeping patterns observed on different days has not been revealed yet. For example, it is not determined whether one can sleep the next day despite of not sleeping enough the previous day. Therefore, this paper seeks to elucidate the relation between current sleep and the subject’s own past sleep or others’ sleep using the sleep stage as an index. The Rechtschaffen and Kales (R&K) estimation sleep stage method [1] is currently considered to be the highest quality method and is widely employed in polysomnograms. The polysomnogram is an example of the techniques such as the electroencephalogram (EEG), the electromyogram (EMG), and the electrooculogram (EOG) that are used for the examination of several sleep problems. This technique also determines the sleep stage according to the characteristics of the essential data that are obtained by this method. The R&K method is useful for providing sleep stage data; however, it requires not only a connection of highly constrained devices to the human body but also the involvement of medical experts to determine the sleep stage from the obtained data. This method uses many devices to determine the sleep stage; therefore, it is difficult to determine the daily sleep stage from the data obtained during sleep using this method. In addition, the sleep stage cannot be identified immediately without the assistance of medical experts. To address this problem, Watanabe developed an air mattress biosensor, which can acquire vital data such as the heartrate, body movement, and respiration, without connecting any devices to the human body, and proposed a sleep estimation method that can roughly estimate the sleep stage using the vital data obtained by the air mattress biosensor without the involvement of medical experts [2]. The sleep stage is mainly estimated in detail according to the middle frequency range of the obtained heartrate data. (We note that body movement data are also used to estimate the sleep stage. For example, the sleep stage wherein the body movements occur frequently in a short time is identified as shallow sleep.) Since this method uses the same heartrate frequency scale to estimate the sleep stage of all the subjects, the sleep stage obtained using this method is not sufficiently accurate. To increase the accuracy of the sleep stage identification, Takadama proposed a sleep stage method which can adjust the identification of the stage for each individual subject by estimating the appropriate middle frequency range of the heartrate data for each individual [3]. Compared to the Watanabe’s method, this method could determine the sleep stage with higher accuracy. Then, motivated by the inability of these methods to estimate the sleep stage in real time, Harada proposed a method for real-time sleep stage determination using the trigonometric function approximation [4]. While the above three methods are very useful for sleep stage estimation without connecting any devices to human body nor involving medical experts, it must be noted that the accuracy of these three methods is not as high as that of the global standard R&K method. To address this problem, this work focuses on the improvement of Harada’s sleep stage estimation method by comparing either the current sleep data to the subject’s past sleep or the sleep of other persons and using this information for sleep stage identification. The rest of this paper is organized as follows. First, the previous work related to
The sleep stage estimation is introduced in Section 2. Section 3 describes the proposed method that employs the approximate heartrate calculated from the subject’s own past sleep. Section 4 describes the experiments conducted on the subjects and presents the obtained results. Section 5 describes the proposed method that employs the approximate heartrate calculated from others’ sleep. Section 6 describes the conducted experiments on the subjects and the obtained results. Finally, the conclusions of this paper are presented in the final section.

2. Sleep Stage Estimation Method

Sleep stages are classified into six categories based on the differences in electroencephalogram information during sleep. As shown in Fig. 1, the sleep stages are classified into the following six types: (i) awake (W) is the shallowest sleep; (ii) rapid eye movement (REM) sleep (R) is deeper sleep than awake and generally occurs during the sleep period rhythm changes. During REM sleep, the body is recovering from fatigue, but the brain and the eyes are active. For this reason, humans experience dreams and sleep paralysis in this state; (iii) Non-REM sleep 1~4 (NR1~4) are deep sleep stages (note that the sleep depth increases from NR1 to NR4). As described in Section 1, the sleep stage estimation methods are classified into the following categories: (i) the sleep stage is determined according to vital data obtained from the electroencephalogram, eye movement, and electromyogram through a connection of devices to human body (e.g., the R&K method); (ii) the sleep stage is estimated according to the vital data of heartrate, body movement, and respiration measured by a mattress biosensor without connecting any devices to the human body (e.g., Watanabe’s method, and Harada’s method). All three methods are explained in the following subsections.

2.1 Rechtsaffen and Kales Method

The Rechtsaffen and Kales method, or the R&K method, is the gold standard method for the determination of the sleep stage [1] and is generally used in the treatment of sleep disorders. As shown in Fig. 2, medical experts determine the sleep stage without the involvement of medical experts as shown in Fig. 3. Since several reports suggested that the heartrate is strongly related to the sleep stage [5],[6], Watanabe’s method estimates the sleep stage by using the heartrate obtained from the air mattress sensor. Specifically, Watanabe’s method divides the heartrate into the low frequency region (lower than 1/135 min), the high frequency region (shorter than half of the average time of the peak heartrate), and the middle frequency region (between the low and high frequency regions), and then estimates the sleep stage according to the model of low, high, and middle frequency heartrate regions. Additionally, body movement data is also used to estimate the sleep stage as described in Section 1. Since the Watanabe’s method does not require any devices to be connected to the human body, it has great potential for application for the estimation of the sleep stage for the elderly and for possible use for the estimation of the sleep stage in the daily health care regimen. However, the low, high, and middle frequency regions of the heartrate in this method were determined based on the data obtained from a small number of young and healthy subjects. This gives rise to the following problems: (1) the accuracy of the estimated sleep stage may not be high for people unlike those who participated in Watanabe’s study and in particular the elderly; and (2) the accuracy of the sleep stage may not be robust for subjects in poor physical condition.

2.2 Watanabe’s Method

To address the above-described problem of the R&K method, Watanabe developed an air mattress biosensor that can acquire the vital data (such as heartrate, body movement, and respiration) without connecting any devices to the human body and proposed the sleep estimation method that can roughly estimate the sleep stage without the involvement of medical experts as shown in Fig. 3. Since several reports suggested that the heartrate is strongly related to the sleep stage [5],[6], Watanabe’s method estimates the sleep stage by using the heartrate obtained from the air mattress sensor. Specifically, Watanabe’s method divides the heartrate into the low frequency region (lower than 1/135 min), the high frequency region (shorter than half of the average time of the peak heartrate), and the middle frequency region (between the low and high frequency regions), and then estimates the sleep stage according to the model of low, high, and middle frequency heartrate regions. Additionally, body movement data is also used to estimate the sleep stage as described in Section 1. Since the Watanabe’s method does not require any devices to be connected to the human body, it has great potential for application for the estimation of the sleep stage for the elderly and for possible use for the estimation of the sleep stage in the daily health care regimen. However, the low, high, and middle frequency regions of the heartrate in this method were determined based on the data obtained from a small number of young and healthy subjects. This gives rise to the following problems: (1) the accuracy of the estimated sleep stage may not be high for people unlike those who participated in Watanabe’s study and in particular the elderly; and (2) the accuracy of the sleep stage may not be robust for subjects in poor physical condition.

2.3 Harada’s Method

To estimate the sleep stage from the heartrate in real time, Harada proposed the trigonometric function approximation method. Figure 4 shows the flowchart of the Harada’s method. The heartrate is first approximated as a sum of trigonometric functions and the sleep stage is estimated from the intermediate frequency range of the approximate heartrate. The approximate heartrate is modeled by

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where \( h(t, \phi) \) is the estimated heart rate at time \( t \) with the model parameter \( \phi \), \( L \) is the maximum period of the intermediate frequency component and is equal to 214 s, \( N \) is the number of the component trigonometric functions and is equal to 13, and \( \phi \) is the model parameter \( \phi = \{a_n, b_n, c\}, n \in \{1, 2, ..., N\} \). The model parameters \( \phi = \{a_n, b_n, c\} \) are calculated by the maximum likelihood estimation method that minimizes the likelihood function given by

\[
J(t) = \frac{1}{T} \sum_{t=1}^{T} [(HR(t) - h(t))^2] + \frac{1}{N} \sum_{n=1}^{N} (a_n^2 + b_n^2). \quad (2)
\]

In this equation where \( T \) is the time elapsed after falling asleep, \( HR(t) \) denotes the obtained actual heart rate at time \( t \), \( a_n \) is the coefficient of the \( n \)th cosine wave, and \( b_n \) is the coefficient of \( n \)th sine wave. We note that the second term in this equation is the regularization term, which contributes to avoiding the large parameters which only fit the “current” actual heart rate as specialized parameters. Following the calculation of parameters \( \phi \), the sleep stage is estimated by discretizing the approximate heart rate \( h(t, \phi) \) according to

\[
s(t) = \begin{cases} 
5, & \left[ \frac{f(0) - \text{ave}}{\text{stdev}} \right] > 5, \\
0, & \left[ \frac{f(0) - \text{ave}}{\text{stdev}} \right] < 0, \\
\text{otherwise}, & \end{cases} \quad (3)
\]

where \( s(t) \) is the sleep stage at time \( t \), and \( \text{ave} \) and \( \text{stdev} \) are the average and the standard deviation of the approximate heart rate \( h(t, \phi) \), \([x]\) is the ceiling function that returns the smallest integer value equal to or larger than \( x \), and the values from 5 to 0 correspond to W, R, NR1, NR2, NR3 and NR4, respectively. This discretization formula is based on the results of previous research [2],[3]. However, the heart rate model used in Harada’s method overfits the current heart rate. Since the function is tightly fit to the heart rate data obtained during a short time period, overfitting often occurs when the number of data points available just after going to bed is small, due to the minimization of the difference between actual and approximated heart rate during a short time period as shown in Fig. 5. In this case, the approximate heart rate using the small number of the heart rates data may have deleterious effects on the estimation of the future approximate heart rate as shown in the upper line in this figure. To address this problem, Harada’s method uses other subjects’ sleep as an approximate reference obtained in advance of the sleep measurement. For example, if it is possible to obtained in advance at the sleep measurement as shown by the under dotted line in this figure, it is possible to appropriately approximate the heart rate. However, the properties of sleep do not only vary among different people but also vary with different physical conditions for a single person, making it difficult to determine the appropriate criteria. In addition to the overfitting problems, it is difficult for Harada’s method to take into account a sleep specific ultradian rhythm in a short time.

Figure 6 shows an ultradian rhythm of a human where the solid line and dashed line indicate the sleep stage and the ultradian rhythm respectively. The ultradian rhythm has the periodicity of 90 min - 120 min. Since sleeping time is generally around 7 hours, ultradian rhythms appear about 4 or 5 times within one sleep as shown in Fig. 6. This rhythm shows differences in the periodicity between different individuals, e.g., for some people an ultradian rhythm has the periodicity of 90 min, while for others the periodicity of 120 min is observed. We note that even for the same person this rhythm changes, not only from day to day but also during sleep. Figure 6 shows the data obtained from one subject during sleep, and it can be seen that the fourth ultradian rhythm shows shorter periodicity than the first one. Generally, the differences between individuals and the periodicity changes during sleep cannot be known before going to bed because such individual differences and periodicity changes are affected by the subject’s health condition, sleep conditions of the previous night, daytime activities, weekly variation, seasonal effects, and other factors.

3. Proposed Method 1: Estimation Based on Own Sleep

As described in Section 1, this work focuses on improving the accuracy of the sleep stage estimation of Harada’s method. While Harada’s method is based on the approximate heart rate calculated based on data obtained from a particular person, in this work the approximate heart rate is calculated using the subject’s own past sleep data. Since there may be similarity in the sleep of the same person, the proposed method initially compares the approximate heart rate and the subject’s own past heart rate. Figure 7 shows the comparison of the data for the subject’s sleep during the past 3 days to the currently obtained heart rate. The proposed method employs the model parameter \( \phi \) of the subject’s own past heart rate that shows the highest similarity. In this figure, since the heart rate of March 28 is the most similar to the current heart rate among the three data sets, the model parameters of March 28 are employed to approximate the current heart rate. Since this approach approximates the heart rate using another sleep profile, it prevents overfitting.
and improves the accuracy of sleep stage estimation. To provide a better understanding, a detailed illustration of the proposed method is shown in Fig. 8. The method compares the actual heartrate with the subject’s own heartrate in the past days to calculate their similarity. The similarity is calculated according to

\[
\text{similarity} = \frac{\sum_{t=1}^{T} | f(n) - g(n) |}{T},
\]

where \(f\) is the estimated heartrate, \(t\) is the estimated time, and \(g\) is the subject’s own heartrate during past sleep periods. Since the estimation is done every minute in the Harada’s method [4], the similarity is calculated every minute in our method as well. Therefore, the similarity value is not constant but rather changes according to the real-time estimation of heartrate and sleep stage. The similarity is calculated as the average of the absolute value of the deviation from the actual heartrate, because this value shows the deviation between the estimated heartrate and the heartrate of the subject’s past sleep, with the similarity increasing for smaller deviations. In Fig. 8, the similarity of Day 1 is higher than Day 2, and therefore the heartrate model parameters of Day 1 are selected to approximate the current heartrate. This comparison is performed at every data acquisition time. Using this operation, it is possible to use the standard for appropriate estimation all the time.

4. Experiment 1

4.1 Setup

To investigate the effectiveness of the proposed method, we conducted human subject experiments. Table 1 shows the details of the three healthy subjects with no sleeping disorders. Since we investigate the sleep during an ordinary day, we do not impose any restriction on the subjects, so that they can go to bed and wake up at any time as usual. This provides highly diverse sleep data, allowing us to demonstrate the potential of our proposed method for such diverse sleep data that roughly represent the sleep data of many other people. AlicePDx and Emfit biometric sensors were used to obtain the sleep data. Figure 9 shows AlicePDx which is a kind of the electroencephalograph, while Fig. 10 shows Emfit which is a non-contact biosensor used to measure the subject’s heartrate, body movement, and respiration by lying on a bed mattress. In this paper, all heartrate data (i.e., the current heartrate data, the subject’s past heartrate data, other subject’s heartrate data) in our experiments were obtained using Emfit installed in the subject’s bed. The data obtained using the AlicePDx is used to calculate the sleep stage by the R&K method, whereas the data obtained using Emfit is used to estimate the sleep stage according to the proposed method and Harada’s method. The parameters used for the estimation of the sleep stage in Harada’s method are listed in Table 2.

4.2 Evaluation Criteria

The sleep stage estimated by the proposed method is compared to the sleep stage estimated by the R&K method. Because the R&K method is the gold standard method all over the world, the sleep stage estimated by this method is assumed to be correct. The sleep stage derived by the proposed method is compared to the correct sleep stage. In the comparison, the Non-REM sleep 1 and the Non-REM sleep 2 stages, and the Non-REM sleep 3 and the Non-REM sleep 4 stages are combined; in other words, this experiment uses 4 stage categories instead of 6. Then, the purpose of this study is to increase the correct rate of the sleep stage estimation when the sleep data set is small as during bedtime after sleeping. This is because the estimation of sleep stage is difficult for a small sleep dataset. Therefore, we focus on precision for times between 0 min and 120 min after going to bed for the first cycle.

4.3 Results

Figure 11 shows the results for three days for each subject, where the vertical axis indicates the accuracy (in percent) of the sleep stage while the horizontal axis indicates the sleep time (i.e., 0 min - 30 min, 30 min - 60 min, 60 min - 90 min, 90 min - 120 min and all times are represented by bars filled with dots, vertical lines, horizontal lines, stripes, and by black bars, respectively). The estimation result for the first (Day 1), second (Day 2), third days (Day 3) are shown in the top, middle, and bottom panels, respectively. The three figures on the
Fig. 11 Result of Experiment 1. Left: Subject A, middle: Subject B, right: Subject C. Top: Day 1, middle: Day 2, bottom: Day 3.

left-hand side in the areas labeled Without $\phi$ show the results obtained without utilizing any other heartrate data during sleep, while the three figures on the right-hand side in areas labeled With $\phi$ (Own) show the result obtained by utilizing the subject’s own past heartrate data during sleep for the sleep stage estimation. Examination of Fig. 11 shows that for Day 3 of Subject B, the accuracy of our proposed method with $\phi$ (Own) is slightly higher than that of the method without $\phi$ (which corresponds to the conventional Harada’s method [4]). For Day 1 and Day 2, the accuracy of with $\phi$ (Own) improves by more than 50% compared to that obtained for the without $\phi$ method. For Subjects A and C, no significant improvement in accuracy was observed, and the accuracy was the same as that obtained using the conventional method. These results imply that the proposed method can provide a higher estimation accuracy than the previous method. However, it should be noted here that our proposed method cannot be employed in the case where the subject’s previous heartrate data during sleep is unavailable.

5. Proposed Method 2: Estimation Based on Others’ Sleep

For estimation of the sleep stage without using the subject’s own sleep data, we proposed to use the estimation method that applies the similarity test to the data obtained from the sleep of people other than the subject. We note that this method does not use the sleep profiles that are highly similar to the subject’s sleep profile. This is because unlike in the case of the subject’s own sleep, the sleep of other people will be generally very different from the sleep of the subject. In this case, the estimation criterion is determined by using the weighted average based on the degree of similarity with others’ sleep data. Figure 12 shows an illustration of this method. In this figure, for estimation of the subject’s sleep stage, three different subjects are compared. The similarities values $W_A$, $W_C$ and $W_B$ increase in the order of A, C, and B. The criteria are determined by difference comparison with each heartrate. The estimated subject’s $\phi$ is calculated by the following equation:

$$\phi_{\text{estimated}} = \sum_{n=1}^{M} W_{\text{subject}(n)} \phi_{\text{subject}(n)}.$$  \hspace{1cm} (5)

Our proposed method calculates $\phi_{\text{estimated}}$ by employing all subject data as shown in this formula where $M$ is the number of available subjects. We note that the subject ($n$) indicates the $n$th subject (e.g., subject (1) is Subject A, subject (2) is Subject B, and subject (3) is Subject C). For better understanding, Fig. 13 provides a detailed illustration of this method. Similar to our proposed method based on the similarity to the subject’s own sleep, this method compares the actual measured heartrate with the others’ heartrate to calculate their similarity. It calculates the average of the absolute value of the deviation from the actual heartrate as $\text{Coeff}$, which is given by

$$\text{Coeff}_{\text{subject}} = \frac{1}{\sum_{k=1}^{N} \text{similarity}_k} \sum_{k=1}^{N} \text{Coeff}_k.$$  \hspace{1cm} (6)

In this figure, since the similarity is higher for Subject B than for Subject A, the parameter of the heartrate of Subject B is strongly affected compared to that of Subject A. This procedure
shown in Fig. 13 is repeated every time the data are obtained.

6. Experiment 2

In this experiment, we investigate how others’ heartrate data contribute to increasing the sleep stage identification accuracy of $\phi$(Others) through a comparison with the two cases without $\phi$ and with $\phi$(Own) conducted in Experiment 1. Six days of others’ heartrate data are used in the model.

6.1 Results

Figure 14 shows the results for three days for each subject, where the vertical axis indicates the accuracy (in percent) of the sleep stage identification while the horizontal axis indicates the sleep time (i.e., 0 min - 30 min, 30 min - 60 min, 60 min - 90 min, 90 min - 120 min and all times are represented by the bars filled with dots, vertical lines, horizontal lines, stripes, and by black bars, respectively). The estimation results for the first (Day 1), second (Day 2), and third days (Day3) are shown in the top, middle, and bottom panels, respectively. The three figures on the left-hand side in the area labeled Without $\phi$ show the results of not utilizing any other data of heartrate during sleep, the middle three figures in the area labeled With $\phi$(Own) show the results of utilizing data for own past heartrate during sleep, and the three figures on the right-hand side in the area labeled With $\phi$(Others) show the results of utilizing the data for others’ heartrate during sleep, respectively. For Days 1 and 3 of Subject B, the accuracy of our proposed method with $\phi$(Others) is higher or slightly higher than that of the method without $\phi$ and with $\phi$(Own). However, for Day 2 of Subject B, the accuracy of our proposed method with $\phi$(Others) is lower than that of our method with $\phi$(Own). This is because the heartrate of no other subject was similar to the actual heartrate of Subject B. Thus, the opposite result will change to the similar results obtained for Days 1 and 3 when the number of sleep data of others increases. For Subject A, the results are shown in Fig. 14 where the vertical and horizontal axes, all bars, and the three figures in the left, middle, and right areas have the same meaning as in the previous figure. This figure shows that the accuracy of our proposed method with $\phi$(Others) is higher than that of the method without $\phi$ and our method with $\phi$(Own) for all three days. In particular, the estimation accuracy of our method with $\phi$(Others) for Day 3 is approximately 30% higher than those for the other methods. The estimation accuracy of our method with $\phi$(Others) for Day 2 is lower than that of the other methods until 60 min (i.e., just after bedtime) but it becomes higher than those of the other methods as the sleep time increases. We note that the accuracy of our method with $\phi$(Others) for Subject C showed the same tendency as the result for Subject A. For Subject C, no significant improvement in accuracy was observed, but no significant decrease in the accuracy was observed either, with results the same as those obtained by the conventional method. The previous results showed that the estimation method using others’ heartrate during sleep can estimate the sleep stage with a higher accuracy than the previous method. Figure 15 shows how many day’s data of others’ heartrate during sleep are needed. This figure shows the estimations of the sleep stage for three days in Subjects A, B and C, respectively. The left, middle left, middle right, and right plots indicate the results of utilizing the data for 0, 1, 2, and 6 days of others’ heartrate during sleep (0 days corresponds to the case of not utilizing others’ sleep data). The results for Subject A show that the accuracy does not depend on the number of days used for obtaining the others’ data. By contrast, the accuracy of Subjects B and C become higher with greater number of days of others’ heartrate used. As an interesting point, the accuracy for Subjects A and C do not improve even if we use others’ heartrates for more than two days.

6.2 Discussion

Generally, the sleep stage is estimated by medical specialists, and it is generally difficult even for medical specialists to perfectly (accuracy of 100%) estimate the sleep stage. Actually, the sleep stage is determined by a majority vote of three or more medical specialists and the accuracy is around 76%. Therefore, this work does not focus on the accuracy rate itself but focuses on how it can be increased by utilizing own past or others’ heartrate through a comparison with the case of the stage estimation without utilizing any other heartrate data, and then consider a big factor that leads to good estimation by finding coefficients using more sleep data of others. Since the sleep
The influence of the number of sleep data on accuracy. Left: Subject A, middle: Subject B, right: Subject C. Top: Day 1, middle: Day 2, bottom: Day 3.

data of others is less similar than their own sleep data, and the possibility of applying it is low, it is considered that it is caused by not being adapted to the estimator when only one sleep data of others is used. Conversely, when many data are used, it is considered that the characteristic part of another person disappears due to the use of the weighted average formula, and it is possible to derive the subject’s own sleep data. Therefore, highly accurate estimation can be made for other people without similarity in their sleep data.

7. Conclusion

This paper focused on the sleep stage estimation method based on the approximate heartrate calculated from the subject’s own past sleep data or the data for the sleep of other persons, and improved its estimation accuracy by employing the approximate heartrate calculated using these data. More specifically, the proposed approximate heartrate is the weighted sum of the approximate heartrate data calculated from the subject’s own past sleep or the sleep of other people. Using the human subject experiments, the following conclusions have been revealed: (1) the accuracy of the sleep stage estimation method based on the approximate heartrate calculated from the subject’s own past sleep is higher than that of the previous method based on the approximate heartrate data calculated from the sleep of other people; and (2) the accuracy of the sleep stage estimation increases as with increasing the number of the heartrate data of other people used for calculating the approximate heartrate. It should be noted here that the results have been obtained from only three subjects, which means that further careful qualifications and justifications, such as an increase of the number of subjects, are necessary to generalize our results. In addition to this important direction, the following issues must be addressed in the near future: (1) since sleep is affected by internal and external factors such as the subject’s health condition, previous night’s sleep conditions, daytime activities, weekly variation, and seasonal effects, these should be addressed in the next stage of this research; (2) since the accuracy of our proposed method differs with the estimation time from 50% to 90%, we should improve our method for more stable and accurate sleep stage estimation by addressing (2-1) the re-estimation at a time when a sleep rhythm changes, e.g., the re-estimation at every ultradian rhythm when the periodic rhythm changes from 90 min to 120 min; and (2-2) the use of the body movement and respiration data for the estimation of the sleep stage.

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Yusuke Tajima

He received his B.S. and M.S. degrees from The University of Electro Communications, Japan, in 2013 and 2017 respectively. He is currently a Ph.D. student at The University of Electro-Communications. His research interests include evolutionary calculation and health care.

Fumito Uwano

He received her B.S. and M.S. degrees from The University of Electro-Communications, Japan, in 2015 and 2017, respectively. He is currently a Ph.D. student at The University of Electro-Communications. His research interests include multi-agent system and reinforcement learning.

Akinori Murata

He received her B.S. and M.S. degrees from The University of Electro-Communications, Japan, in 2015 and 2017, respectively. He is currently a Ph.D. student at The University of Electro-Communications. His research interests include multi-objective optimization.

Tomohiro Harada

He received his M.E. and Doctor of Engineering degrees from The University of Electro-Communications, Japan, in 2012 and 2015. He is currently an assistant professor from 2017. His research interests include evolutionary calculation reinforcement learning.

Keiki Takadama (Member)

He received Doctor of Engineering degree from The University of Tokyo, Japan, in 1998. He joined Advanced Telecommunications Research Institute (ATR) from 1998 to 2002 as a visiting researcher and worked at Tokyo Institute of Technology from 2002 to 2006 as a lecturer. He moved to The University of Electro-Communications as associate professor in 2006 and is currently a professor from 2011. His research interests include multi-agent system, reinforcement learning, and evolutionary computing.