# Sleep Stage Estimation Using Heart rate variability divided by sleep cycle with Relative Evaluation

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## Abstract

This paper aims to estimate sleep stage with high accuracy. We improves the existing estimation method which analyses heart rate variability features obtained from the pressure sensor by the trigonometric function regression model for achieve it. Specifficaly, we focused on huge heart rate variability in order to take into account the tendency of the sleep cycle repeated in sleep, and to estimate sleep stage with each sleep cycle. The purpose of this improvement is to calculate sleep rhythms obtained by the intermediate frequency components of heart rate more accurately. To prove the effectiveness, we conducted the subject experiment for the two subjects and evaluated sleep by the 4 stages classification, REM, N1, N2, N3. The results showed the accuracy was 61.1 % which was higher 6.5 points than the existing method. This result suggests that estimating the sleep stage in each sleep cycle, in this case two divided part(the beginning and the latter sleep,) was effective to improve the estimate accuracy of sleep stage.

## Introduction

Sleep quality is one of the most significant factors on well-being. Because it relates to human body and activities. For example, sleep quality contributes to the physical and mental systems and influences our health directly. Dementia is one example of that sleep disturbance increases the risk (Shi et al., 2018). Moreover, the number of people who suffers from sleep disorders has been increasing year by year (Ministry of Health, Labor and Welfare, 2015). These trends increase the needs of sleep measurement and imply that sleep measurement is essential not only to treat the patient for sleep disorders but also to observe humans health conditions.

For measuring sleep condition, the professional people determine sleep condition as the evaluation of its depth. They have patients to get the examination called polysomnography (PSG) and analyze the obtained data such as brain activities, eye movement and muscles activity, then sleep depth is indicated. The analysis for measuring sleep depth must be conducted by several professional people, which takes deals of time. In addition, PSG gives huge burden to subjects, because subjects have to be attached some electrodes, which is unusual condition for them. Therefore, it is difficult in that way to measure sleep stage in the long term and to adapt it to several people such as children.

To overcome these shortages, sleep stage estimations have been researched using the non-contact ways which are able to obtain some biological data in place of brain wave and so on. For example, one of the sleep stage estimations employs the visual processing method and apply the obtained biological data from image data (PROCHZKA et al., 2016). As the above example, lots of way exists to obtain some biological data which could be utilized to observe sleep activity. These sleep stage estimations are categorized by these sensing ways, moreover, these can be also categorized as two groups based on the approaching way. One is machine learning method such as Random Forest (Komine et al., 2016). The feature of machine leaning is that it is difficult for us to extract the rules to classify the input data to sleep stage for human understanding. The aim to apply machine learning is to get the high accuracy, therefore they do not tend to consider the rules and the waveform of sleep stage related with the time. The other is statistical approach such as regression analysis. Some of researches apply the regression analysis with the biological knowledge that sleep activity is related with the intermediate frequency components of heart rate, and estimate sleep stage based on it (Watanabe and Watanabe, 2002) (Harada et al., 2017). However, these approaches also have the problem. One is the accuracy in sleep stage estimation is depended on the accuracy of the regression model. The other is a limitation in the relationship between heart rate and sleep stage.

To solve these problems in some regression models of statistical analysis, we employ the existing sleep stage estimation applying another biological knowledge in addition to the relationship between the intermediate frequency component of heart rate based on the sleep cycle. Then, we attempt to improve this existing method and achieve the higher accuracy with the regression model. In the proposed method, we focus on the difference in a cycle of sleep stage. Sleep stage has the cycle repeated from the light sleep to deep sleep several time in sleep. Each cycle occurred during sleeping has different features in the value of the amplitude and the acrophase. To determine these features of each sleep cycle, we build the hypothesis that the heart rate variability changes with huge range when the sleep cycle switches. Based on it, we divide sleep into two parts and estimate in each part. By dividing as described above, the regression model fits the heart rate in comparison with the existing sleep stage method

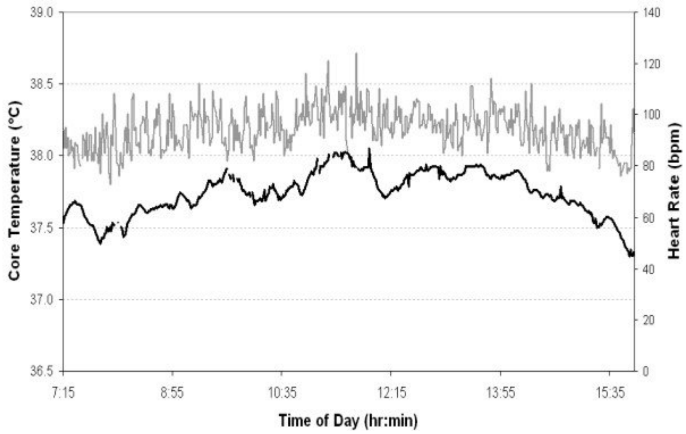


Figure 1: Relationship between heart rate and body core temperature(Stewart and Hunt ,2011)

we employed, and the achieve to improve the accuracy of sleep stage estimation.

The rests of this paper are organized as follows. In the section of Sleep Mechanism, we explain sleep stage and the biological rhythms involved it. Next, some statistic approaches are introduced in section Related work, then we move on the our proposed method inspired by the related works. After that, we indicate experiment and their results, and analyze these in the section of Discussion. Finally, we conclude this paper.

# Sleep Mechanism

## Sleep Stage

According to the AASM, Sleep is divided into five stages, Wake, Rapid Eye movement (REM) stage, N1, N2, N3 from light to deep sleep(Berry et al., 2012]). To estimate sleep stage, some biological data such as brain wave, eye movement and muscle activity are essential while the standard rule is based on the relation with these data. In addition, sleep stage has the relationship with heart rate variability especially in REM and Non-REM sleep stage.

## The biological rhythms involved with sleep activity

The human body has many biological rhythms which involved in the physical activities. Sleep activities are affected by two kinds of biological cycles called an ultradian rhythm and a circadian rhythm. An ultradian rhythm is approximate 90 minutes cycles which composes sleep activities. Human repeat the cycle of deep and light sleep in sleep based on this rhythm. It can be calculated with heart rate variability in specific frequencies range A circadian rhythm is approximate 24 hours cycle, which involved with the physiological activities in a day, including sleeping and waking. It is acquired by a core body temperature. Moreover, several researchers showed the body core temperature is similar movement to that of heart rate, Therefore, it is possible to observe body core temperature by heart rate data as Figure1 shows (Stewart et al., 2011).

# Related works

Watanabe proposed non-contact method for estimating sleep stage based on the researches, that idea indicates the heart rate relates sleep stage strongly (Watanabe and Watanabe, 2002). Based on it, they employed a mattress sensor as a non-contact device to obtain the heart rate, and suggest the intermediate frequency component of heart rate is specifically concerned with the sleep stage in the paper. Following this research, some of researchers attempts to employ Watanabe's idea and to improve the estimate accuracy.

## Real-time Sleep Stage Estimation(RSSE)

Real-time Sleep Stage Estimation (RSSE) can estimate sleep stage with a non-contact device in real time (Harada et al., 2017). RSSE is inspired by the sleep stage estimation proposed by Watanabe. Based on Watanabes research, RSSE analyzes an intermediate frequency component of heart rate obtained by pressure sensor with the regression model as following sequence. First, RSSE approximates an intermediate frequency component of heart rate by the trigonometric regression function model as follows,

$$h(t,\phi) = c + \sum_{n=1}^{N} a_n \cos(\frac{2\pi t}{L/n}) + b_n \sin(\frac{2\pi t}{L/n}) \qquad (1)$$

$h$ denotes the heart rate estimated at time $t$ with the model parameter, which composes three kinds of parameters: (1) $L$ denotes the maximum period in the intermediate frequency component of heart rate, (2) $N$ denotes the number of the trigonometric functions composed of the prospective intermediate frequency, and (3) a set of parameters $phi = a1, b1, ..., an, bn$ denotes the most approximated coefficients to adapt the raw heart rate, which are provided as the following likelihood function is minimized;

$$J(\phi) = \frac{1}{T} \sum_{t=1}^{T} (HR(t) - h(t,\phi))^2 + \frac{\lambda}{N} \sum_{n=1}^{N} (a_n^2 + b_n^2) \qquad (2)$$

where $T$ denotes the time elapsed after a subject starts to sleep, $HR$ denotes the obtained heart rate at time $t$. Next, the sleep stage is estimated by the discretization of the predictive heart rate $h$ based on the equation:

$$s(t) = \begin{cases} 5 & \lceil \frac{(h(t,\phi)-ave.)}{stdev.} + 2 \rceil > 5, \\ 0 & \lceil \frac{(h(t,\phi)-ave.)}{stdev.} + 2 \rceil < 0, \\ \lceil \frac{(h(t,\phi)-ave.)}{stdev.} + 2 \rceil & \text{otherwise.} \end{cases} \qquad (3)$$

$$ave. = \frac{1}{\max(T,L)} \sum_{t=1} \max(T,L) h(t,\phi) \qquad (4)$$

$$stdev. = \sqrt{\frac{1}{\max(T,L)-1} \sum_{t=1} \max(T,L)(ave. - h(t,\phi))^2} \qquad (5)$$

where $s(t)$ denotes the sleep stage at time $t$. This discretization formula is derived according to the previous research (Takadama et al., 2010).

Finally, RSSE independently classifies Wake and REM stage. Wake detection focuses on the huge body movement (BM) during sleeping, which is calculated by the standard deviation of body movement in every minute and the average of body movement until current sleep according to the following function.

$$\frac{BM_{std}}{BM_{ave}} > 1.0 \quad (6)$$

For REM classification, RSSE focuses on the increasing ratio of heart rate during recent minutes, and detects the start sleep and the end of sleep to estimate the term for REM stage. To detect start of REM stage, RSSE compares the median heart rate within recent $x$ minutes with the median one from recent $2x$ minutes to $x$ minutes in every minute. In detail, when the increasing ratio exceeds a certain threshold, RSSE decides that the REM stage starts. With continuing to observe the increasing ratio, then RSSE decides the end of REM stage when the ratio starts to increase after the ratio gets zero. Additionally, to reduce misclassification between REM stage and Wake stage, RSSE cancels the REM detection in the start point if huge body movement occurs during $2x$ minutes before, because of the features that Wake stage occurs when heart rate increases rapidly.

$$\frac{(HR_{med}^{recent} - HR_{med}^{prev})}{HR_{med}^{prev}} > 0.04 \quad (7)$$

## Real-time Sleep Stage Estimation Based on Circadian Rhythm(RSSECR)

Real-time Sleep Stage Estimation (RSSE) obtains biological data (heart rate and body movement) from biological pressure sensor, and estimates sleep stage utilizing them (Tobaru et al., 2018). Specifically, the shape of sleep stage is estimated from an intermediate frequency component of heart rate, and Wake/REM are estimated from heart rate variability and body movement in several minutes. However, RSSE has the problem that estimation accuracy becomes low in the middle of sleep. One of the reasons for this is that RSSE did not take into consideration the biological rhythms of human. Humans have circadian rhythm with a 24 hours cycle and ultradian rhythm with a 90 minutes cycle. Considering these when estimating sleep stage has the potential that improves that problem and more accurate sleep stage estimation.

Therefore, in this paper, RSSE based on Circadian Rhythm (RSSECR) is an improving method of RSSE to estimate sleep stage, which focuses on circadian rhythm to take into account time elapse. Specifically, the following estimation methods are added to RSSE; (1) extraction of low frequency components of heart rate, (2) change of distribution in standardization for sleep stage and (3) revision by comparing of intermediate frequency component and low frequency component of heart rate.

**(1) Extraction of low frequency components of heart rate** The low frequency component of heart rate as circadian rhythm, while circadian rhythm is generally obtained by measuring core body temperature (Goel et al., 2011). Because core body temperature is related with heart rate (Vandewalle et al., 2007) and the low frequency with a period of twenty-four hours which is one of synthetic wave in heart rate is adequate to replace circadian rhythm also having a period of twenty-four hours. Based on this idea, RSSECR supposes a circadian rhythm is extracted by a low frequency components of heart rate. Especially, in this paper, the low frequency component of heart rate is eighteen hours circle as circadian rhythm. Since RSSE uses FFT, RSSECE focuses on $2^{16} = 65536sec = 18.2hour$, which is the number of data close to the period of twenty-four hours in the data number of powers of two.

**(2) Change of distribution in standardization for sleep stage** The distribution of sleep stage has deviation, one of them is the proportion of N2. N2 is the most frequent stage during sleep. Thus, RSSECR changes the distribution in standardization for increasing the proportion of N2 as following equation.

**(3) Revision by comparing of intermediate frequency component and low frequency component of heart rate** To consider a circadian rhythm, RSSECR executes the weighting deal to the adjusted intermediate frequency. In formula(8), the subtraction indicates the calculation for the adjusted intermediate frequency in order to reflect the circadian rhythm to sleep cycle, and $f(t)$ denotes the adjustment by parameter which attenuates amplitude of the adjusted intermediate frequency.

$$f(t) = \beta\{h(t, \phi_{MF}) - h(t, \phi_{LF})\} \quad (8)$$

$h(t)$ denotes the heart rate at time $t$, $MF$ denotes the intermediate frequency component of the heart rate, and $LF$ denotes the low frequency component of the heart rate. is set between 0.1 and 1.0, and is indicated the degree of influence of the circadian rhythm.

RSSECR achieves to improve the accuracy of sleep stage estimation in comparison with RSSE, however, the sleep stage waveforms are not enough to observe sleep situation. Because the effects of correction in (3) are too strong and counteract the details movements in sleep stage waveform. Although, the correction in (3) works as an adjustment for a gap of the intermediate frequency components of heart rate compared with heart rate, the accuracy of the adjustment frequency tends to be depended on the accuracy of the intermediate frequency. Therefore, the high accuracy intermediate frequency components of heart rate is essential to maintain sleep stage waveforms with high accuracy of sleep stage estimation.

# Proposed method

For the problem in RSSECR, we propose the improving method to estimate the intermediate frequency with more fitted waveform to the raw heart rate. The improvement in the proposed method is to divide whole sleep data into two parts depended on each sleep cycle. This improvement is effective when the heart rate variability is huge during sleep. Because, the synthetic wave for the ultradian rhythm is calculated to minimize the gap between the raw heart rate and the intermediate frequency components of heart rate in the regression model, which is difficult to capture each sleep cycle. To solve it, we estimate the intermediate frequency components of heart rate on the suitable durations by dividing sleep data. The proposed method employs the estimation process of RSSECR excluding the correction in (3), and the step is added before estimating the intermediate frequency components of heart rate. In order to estimate sleep cycle as the added step, we focus on the detection for REM stage in RSSE to estimate sleep cycle. Each sleep cycle gradually gets deep stage and become light stage, and whose aggregation composes of sleep. Therefore, the REM detection is utilized to distinguish when the cycle changes from the deep stage to light stage. Based on it, sleep is divided as a one cycle when the REM detection works first after 30 minutes from falling asleep. According to the above statement, the following sequence shows how to estimate sleep stage in the proposed method; (step 1) to obtain the heart rate from the biological sensor, (step 2) to divide sleep into two parts by the REM detection, (step 3) to estimate the intermediate frequency and the low frequency components of the prospective heart rate, (step 4) to calculated the difference between the intermediate frequency and the low frequency, (step 5) to standardize the difference and (step 6) to estimate sleep stage by the discretization of $z$ values. In this paper, we propose two ways to estimate the adjusted frequency components of heart rate in the step 5 as following; Case1: to calculate the average and standard deviation with whole sleep data. Case2: to calculate the average and the standard deviation in each sleep cycle. Both cases attempt to improve the estimation of the intermediate frequency components of heart rate, however the aim is different. Case1 considers the relationship with the whole sleep data, on the other hands, the aim in Case2 is to focus on each sleep cycle only excluding the consideration of the variation in whole sleep.

## Experiment

To verify the effectiveness of the proposed method subject experiments are conducted. In this experiment, one day's worth of sleep was measured for each of two healthy subjects, and that data was used. At that time, in order to get used to the measuring equipment like PSG, the subjects put on the equipment for two days and go to bed in advance. Those data were not used in the experimental results. Each subject wore the PSG of measuring sensor and slept with laying the biological sensor under the bed so as to measure their heart rate at the same time. This experiment used EMFit sensor as to measure the biological sensor. EMFit sensor developed by the VTT Technical Research Center of Finland as a non-contact biological sensor, which can measure heart rate as pressure signal every one second. On the day before the sleep measurement day, the subjects were not let activities that disrupted the living rhythm such as all night, and excessive exercise and drinking on the day.

Table 1: The accuracy of each subjects in all cases

| | Subject1 | Subject2 | Average |
|---|---|---|---|
| RSSECR | 56.6 | 52.6 | 54.6 |
| Case1 | 69.3 | 53.0 | 61.1 |
| Case2 | 67.7 | 53.4 | 60.2 |

The proposed method is compared the accuracy and the sleep stage between RSSECR and the following two cases;(1) The first part was estimated with the sleep data from falling asleep to have a REM flag, (2) the first part was estimated with the overall sleep data. The accuracy is evaluated sleep stage in four stages excluding Wake(REM, NREM1-3) by the comparison in the sleep stage estimation with PSG as the correct answer. Because Wake is a sudden occurrence, it can not be estimated by the biological rhythm that the proposed method focuses on. And NREM4 tends to appear more often in younger people, the sleep of these subjects did not appear 4.

## Results

Table1 shows the result. In each method, the proposed methods, Case1 and Case2, showed higher accuracy than RSSECR. In particular, the result of subject 1 was improved a high accuracy.

Figure2 shows the sleep stage with PSG in the Subject2 and the result of the REM detection. The blue line represents the sleep stage estimated using PSG, and the orange line represents the Rem detection. The horizontal axis is the sleep time, and the vertical axis for the blue line represents the sleep stage and for orange the presence or absence of detection. The REM stage by estimating using PSG was separated overall of the sleep stage into four parts. And three of them were estimated correctly by the REM detection excluding in the last part. The reason why the first REM detection was incorrect is that heart rate and body movement are unstable after bedtime, so different estimation methods are needed. However, in order to know the disturbance of the rhythm, there is no problem since REM sleep can be accurately estimated by this estimation method.

Based on these results of REM detection, sleep cycles were divided into two parts, which contributed to estimate heart rate variability more correctly with the trigonometric regression function model. Figure3 shows the results of the estimated heart rate. The top graph shows the relation between estimated heart rate with whole sleep data and raw heart rate which was obtained by the biological sensor. The bottom graph shows the result which distinguished sleep cycles to two parts compared with raw heart rate. The wave of the proposed method was more fitted than the wave of RSSECR. The top graph in Figure4 shows the heart rate and its low and middle frequency components, and the bottom graph shows the z value used in the proposed method. Figure 5 shows the results of estimating the sleep stage using these. Figure5 shows the results of sleep stage in each case compared with PSG. The point in these results was the sleep stage estimations in the first part and the last part. The first

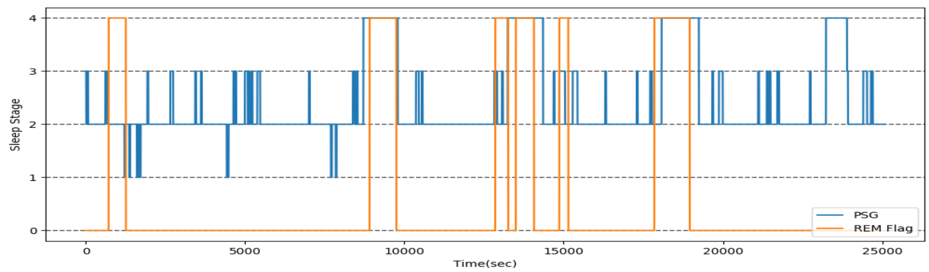


Figure 2: The comparisons in each sleep stage estimations

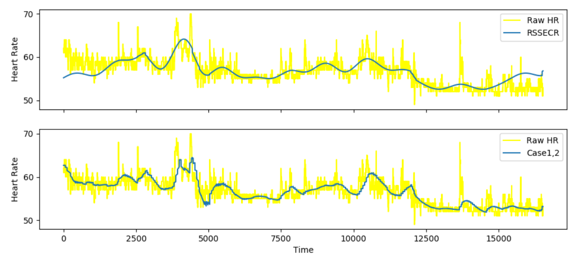


Figure 3: Heart Rate Estimated by RSSECR, Case1,2 compared with RawHR

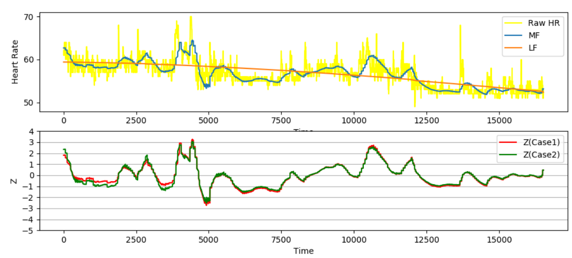


Figure 4: The results of standardization in Case1 and Case2

part as getting sleep was not estimated in RSSECR, however Case1 and Case2 distinguished more accurately. Moreover, the last part as getting awake was also estimated with high accuracies in comparison of RSSECR.

## Discussion

As Figure2 shows, the REM stage was estimated by PSG in the four parts, and the proposed REM detection estimated three of them correctly excluding in the first and last part. The estimation was not exactly correct for example the time of starting REM. Because, the REM detection was employed in order to recognize the sleep cycles, and the aim of it was not estimate REM stage in this experiment. However, the current REM detection excluded some results occurred within 60 minutes from getting sleep to avoid distinguishing in the wrong part. We need to verify the more appropriate threshold, while this threshold was set as 60 minutes based on the general length in an ultradian rhythm.

Focused on the raw heart rate variability, the overall average was 56.6. When considering the heart rate variability in the both 90 minutes from the beginning and end of sleep, the average was 59.1 in the beginning sleep, and it was 53.7 in the end of sleep. The average in the beginning was lower than the average in whole sleep, on the other hands, the average in the end was higher, which was one of the reasons that the estimation in the beginning and the end of sleep was difficult as the top figure shows in the Figure3. As the bottom graph shows, the heart rate variability estimated by the proposed method was more adapted the raw heart rate wave in comparison with the RSSECR, which verified the effectiveness of the sleep cycles.

This paper aims to increase the accuracy in sleep stage estimation based on the periodic regression analysis with heart rate variability which obtained by a pressure sensor. The proposed estimation attributes to find the appropriate parameter to approximate the low frequency so as to reflect the tendency over sleep, and to take into account the sleep cycle by dividing the sleep data. According to the subject experiment to indicate the effectiveness, the average of accuracy was 58.5 % and the following imprecations was revealed; (1) The low frequency should be approximated excluding short waves because it could perform as a noise; and (2) sleep stage must assess in the view of overall trend and the current trend with time while it contributes to concern the tendency with time.

## Conclusion

This paper proposed two improvements of the current version of the RSSE method, which is proposed in our previous research. In particular, we proposed the use of the personal sleep feature to construct the model in the RSSE method in order to compensate for a biological information shortage, and the real-time Wake and REM sleep stage classifications depends on obtained heart rate and body movement. To investigate the effectiveness of the proposed method, we conducted the subject experiment. Two subjects participate this experiment, and two data of sleeping is obtained for each subject. The experimental result reveals that the proposed improvements increase the estimation accuracy of the RSSECR, and more than 50% of the estimation accuracy is

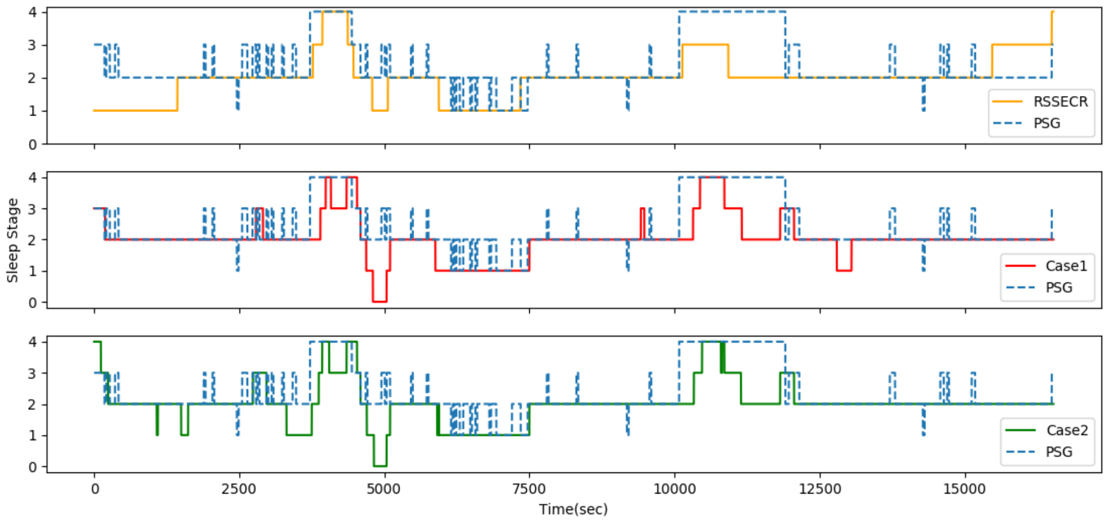


Figure 5: The comparisons in each sleep stage estimations

achieved for all subjects and all experiment days by the integrated method of the RSSE method with the proposed personal sleep feature and the Wake and REM classifications. What should be noted here is that since this result is achieved only from two subjects, a verification with more human subjects is necessary. And some parameters in the Wake and REM classifications, e.g., the threshold of the body movement, are device dependent values, which should be automatically calibrated depending on the trend of the obtained biological data. These have to be pursued in the near future in addition to the following tasks: (1) Adequate and automatic selection or generation of the personal sleep feature for robustness of sleep estimation; and (2) an implementation of the WAKE and REM classifications to reduce misclassification.

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