What Is a Correct Output by Generative AI From the Viewpoint of Well-being? - Perspective From Sleep Stage Estimation -

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Abstract

This paper explores an answer to the question of "what is a correct output by generative AI from the viewpoint of well-being?" and discusses an effectiveness of taking account of a biological rhythm for this issue. Concretely, this paper focuses on an estimation of the REM sleep stage as one of sleep stages, and compared its estimations based on random forest as one of the machine learning methods and the ultradian rhythm as one of the biological rhythms. From the human subject experiment, the following implications have been revealed: (1) the REM sleep stage is wrongly estimated in many areas by random forest; and (2) the integration of the REM sleep stage estimation based on the biological rhythm with that based on random forest improves the F-score of the estimated REM sleep stage.

Introduction

Recently, the generative AI such as ChatGPT (Wei et al. 2022) has attracted much attention by showing its high potential of generated contests. However, the generative AI may derive wrong/not-required/not-intentional contents. When focusing on the sentence generated by ChatGPT, for example, the wrong/not-required/not-intentional contents are partially embedded in the whole sentence. From this viewpoint, what is the correct sentence derived by the generative AI? One of the simple answers is the perfect sentence which does not have any wrong/not-required/not-intentional contents. However, not only ChatGPT but also human-being cannot guarantee to provides such perfect sentence. Considering this fact, what is the correct sentence which allows to partially include wrong/not-required/not-intentional contents? It is difficult to perfectly answer this question. One possible answer may be the sentence which follows a "context" of the given question.

What should be noted here is that "well-being" meets the same problem, i.e., it is quite difficult to derive the correct output on well-being by not only the generative AI but also the recent machine learning technologies (e.g., deep learning), even though such AI has a potential of providing useful suggestions for good health by considering health condition. Examples of suggests include exercise (e.g., walking, fitness, sport), healthy meal (e.g., organic food, fresh salad), relaxation (e.g., aroma, yoga), and recreation. However, it goes without saying that such suggestions cannot always derive good health condition "every day", meaning that they are not useful in a certain day. This is similar to the sentence generated by ChatGPT which partially includes wrong/not-required/not-intentional contents. Since it is not enough to derive the good health condition only one day but is important to maintain it as many days as possible, this derives the very similar question related to the previous question above: what is the correct suggestion of a weak/month care which is not useful in a certain day? For this issue, very bad health condition should be avoided by the suggestion. This is not an ideal suggestion of a weak/month care but contributes to keeping health condition. To avoid very bad health condition, what should we do? One of possible answers is to take account of a "biological rhythm" (like a "context" in the sentence) because our health condition is affected by the biological rhythm.

Since the biological rhythm is composed of a lot of rhythms, *e.g.*, a month rhythm as a circalunar rhythm, a weak rhythm as a circaseptan rhythm, 24 hours rhythm as a circadian rhythm, and 90 minutes rhythm as an ultradian rhythm), it is quite difficult to select appropriate rhythms to avoid very bad health condition. For this issue, this paper focuses on an "ultradian rhythm" because health condition becomes bad when an ultradian rhythm becomes unstable and its rhythm can be roughly estimated by detecting the "REM sleep stage" as one of sleep stages. Concretely, the REM sleep stage follows an ultradian rhythm, *i.e.*, the REM sleep stage appears around the 90 minutes cycle. However, it is difficult to perfectly estimate the REM sleep stage based on the biological vibration data (i.e., a composition of a vibration of heartbeats, respirations and body movements) acquired from mattress sensor or smart-watch. This means that the wrong estimations by machine learning are partially included (like the sentence generated by ChatGPT). To reduce the wrong estimations, this paper discusses an effectiveness of an integration of the REM sleep stage estimation based on machine learning and biological rhythm.

This paper is organized as follows. The next section explains the sleep stage and the problem of the REM sleep stage estimation by machine learning, and Section 3 introduces our approach that estimate the REM sleep stage from the viewpoint of both on machine learning and biological rhythm, and shows our human subject experiments. Finally, the conclusion is given in Section 4.

Sleep Stage and REM Sleep Stage Estimation

Sleep Stage and Its Monitoring System

Our previous research (Takadama et al. 2014) developed the sleep monitoring system that can estimate the sleep stage without connecting any devices to human's body as shown in Figure 1. The upper part of Fig. 1 shows the estimated sleep stage displayed in a potable devise such as a smart phone, tablet PC, or pad. In detail, the horizontal axis indicates the sleep time in a bed, while the vertical axis indicates the sleep stage divided into five stages, *i.e.*, the wake stage, REM sleep stage, and Non-REM sleep stages 1, 2, and 3 represented by W, R, 1, 2, and 3, respectively. Note that the stage 3, in particular, has the deepest sleep, while the wake stage has the lightest sleep. The lower part of Fig.1, on the other hand, shows the mattress sensor set under the bed to measure the heartrate of a person lying down on the bed, and transmits its data to a potable devise via WiFi (or the Ethernet cable) to estimate their sleep stage from the heartrate data. In this monitoring system, the sleep stage is estimated according to a biological rhythm or machine learning method, each of which is explained in the next subsection.

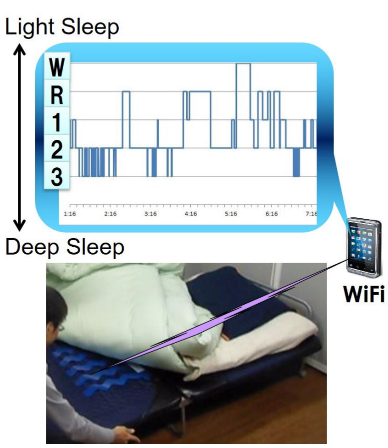

Figure 1: Sleep stage and its monitoring system

Sleep Stage Estimation Based on a Biological Rhythm

As an approach based on a biological rhythm, the real-time sleep stage estimation (RSSE) method (Harada et al. 2016) was proposed to estimate the sleep stage based on the medium frequency component of a heartrate. This is based on the several reports that a heartrate has the strong relation to the sleep stage (Harper, et al. 1987; Otsuka, et al. 1991; Shimohira et al. 1998). The RSSE method is executed as follows: (1) a model of the medium frequency component of a heartrate during a sleep is constructed by the regression of the trigonometric function; (2) a prospective heartrate is predicted from the model; and (3) the sleep stage is estimated in real-time from a prospective heartrate. Concretely, the medium frequency component of the heart rate is modeled as shown in the following equation:

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

where $h(t, \varphi)$ denotes the predicted heartrate at time t with the model parameter $\varphi = \{c, a_1, \cdots, a_N, b_1, \cdots, b_N\}$, L denotes the maximum period of the medium frequency component, N denotes the number of the composed trigonometric functions. The model parameters φ are calculated by the maximum likelihood estimation method from the following likelihood formula:

$$J(\phi) = \frac{1}{T} \sum_{t=1}^{T} \left(HR(t) - h(t,\phi)\right)^2 + \lambda P(\phi),$$

where T denotes the elapsed time after falling asleep, $HR(t)$ denotes the obtained heartrate at time t. In this equation, the first term calculates the mean square error between the predicted and the obtained heartrate each time, while the second term, $P(\varphi)$, denotes the penalty function for the model parameter. λ has a function for a balance between the mean square error and the penalty function. As the penalty function $P(\varphi)$, the following equation is employed:

$$P(\phi) = \frac{1}{N} \sum_{n=1}^{N} \left(a_n^2 + b_n^2\right),$$

which is the normalized term that penalizes the large model parameter values to avoid over-fitting to training data.

After calculating the parameters φ, the sleep stage is estimated by discretizing the predicted heartrate $h(t, \varphi)$ according to the following formula:

$$s(t) = \begin{cases} 5 & f(x) > 5 \\ 1 & f(x) < 1 \\ \left\lceil \dfrac{f(t) - average}{stdev} + 2 \right\rceil & otherwise \end{cases}$$

where $s(t)$ denotes the sleep stage at time t, while *average* and *stdev* denote the average and the standard deviation of the predicted heartrate $h(t, \varphi)$, respectively. $\lceil x \rceil$ denotes the ceiling function that returns the minimum integer value equal to or greater than x. After discretization, the value from 5 to 1 is assigned to the sleep stages of WAKE, REM, Non-REM 1, 2, and 3, respectively.

However, the Wake stage and REM sleep stage estimated by the RSSE method are hard to be correctly estimated due to their rapid changes in the sleep stage. Such a problem occurs because the RSSE method estimates an approximate change of the sleep stage. To tackle this issue, the following correction was conducted (Harada et al. 2017).

- **Wake stage correction:** The sleep stage estimated by the RSSE method is corrected as the Wake stage when BM_{std} / BM_{ave} > 1, where BM_{std} and BM_{ave} are respectively the standard deviation and average of body movement calculated every minute.
- **REM sleep stage correction:** The sleep stage estimated by the RSSE method is corrected as the REM sleep stage from its detected start point to its detected end point. Considering the tendency that a heartrate temporally increases when the REM sleep stage starts, a median of a heartrate obtained during the recent x minutes (represented as HR_{med}^{recent}) is compared with that of a heartrate obtained during the x minutes to the $2x$ minutes before (represented as HR_{med}^{prev}) every minutes (x=5 [min] is employed in this paper), and the start point of the REM sleep stage is determined when $\Delta HR_{med} = (HR_{med}^{recent} - HR_{med}^{prev})/HR_{med}^{prev} >$ a certain threshold (*i.e.*, 0.04 (4%) in this paper). After determining the REM start point, ΔHR_{med} is continuously calculated and the end point of the REM sleep stage is determined when "the previous $\Delta HR_{med} < 0$" and "the current $\Delta HR_{med} >$ the previous ΔHR_{med}".

Sleep Stage Estimation Based on a Machine Learning

As an approach based on a machine learning (ML), this paper employs Random Forest (RF) (Breiman, 2001) which is an ensemble learning method composed of the multiple decision trees as a weak classifier and determines the output (i.e., the classification result) by the majority vote of the classification results of the decision trees. Note that any kind of machine learning method can be employed other than RF in the sleep stage estimation.

RF is executed as follows to learn the model of estimating sleep stage: (1) the training datasets (*i.e.*, a set of a biological vibration data acquired from a mattress sensor during one epoch (*i.e.*, 30 seconds) and the correct sleep stage in one epoch) are generated by randomly sampling from the whole training dataset; (2) the decision trees are constructed according to their own training datasets; and (3) the output is determined by the majority classification results of the decision trees. In this research, Gini impurity (Timofeev, 2004) is employed to determine the condition in the nodes of the decision trees. The value of Gini impurity decreases when the ratio of the same label in the sampled data in the node increases.

Problems of REM Sleep Stage Estimation

The upper part of Figure 2 shows (1) the correct sleep stage by calculated by the R&K method (Rechtschaffen and Kales, 1968) through the polysomnography (PSG) test (represented by blue line); (2) the estimated sleep stage based on the biological rhythm calculated by the RSSE method (represented by the green line); and (3) the estimated REM sleep stage calculated by RF as one of MLs (represented by the orange line). Note the that the correct sleep stage is calculated from the biological data of electroencephalography (EEG), electrooculogram (EOG), and electromyogram (EMG), and the estimated REM sleep stage by RF shows either REM sleep stage (represented by the vertical line) or not (represented by no vertical line). The lower part of Figure 2 shows the enlarged figure of the upper part in the dashed square. The blue and orange lines in the lower part of figure have the same meaning of the upper part of figure.

From this figure, the estimated sleep stage by the RSSE method shows the biological rhythm (*i.e.*, the ultradian rhythm), but it is not perfectly correct (*i.e.*, the first and third arrows of the green line is located in the correct REM sleep stage (represented by "○") while the second arrow is slightly earlier than the correct REM sleep stage (represented by "×")). More importantly, the range of the estimated REM sleep stage is not correct. On the other hand, the estimated REM sleep stage by RF does not show the biological rhythm, meaning that the sleep stage is REM (or is not REM) when the output of RF is REM (or is not REM) like the flag is set on/off. This causes a serious problem because RF may estimate the REM sleep stage as the light sleep even in the range of the deep sleep as shown in (a) of the lower part, even though it can mostly estimate the REM sleep stage in the range of the correct REM sleep stage as shown in (c) of the lower part. However, the output of RF

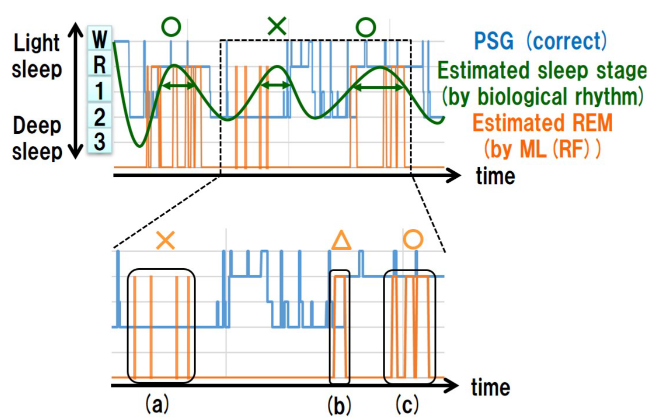

Figure 2: REM sleep stage estimation

has a potential of estimating the start/end point of the REM sleep stage as shown in (b) of the lower part.

Proposed Method: Integration of RSSE With RF

To overcome the REM sleep stage estimation of the RSSE method and RF described in the previous section, this paper proposes the simple method that integrates both methods. The point of the proposed method is summarized as follows: (1) the range of the REM sleep stage estimation by RF are set to cover all estimated ones which are located within two minutes as shown Figure 3 (i) and (ii). This is because the REM sleep stage generally continues five minutes and more. Note that two minutes are set from the preliminary experiment; and (2) the estimation of the RSSE method is prioritized over the estimation of RF. As shown in Figure 3 (i), the output of the proposed method covers the only range of the REM sleep stage estimation by the RSSE method when the ranges of the REM sleep stage estimation by the RSSE method and RF are not overlapped. As shown in Figure 3 (ii), the output of the proposed method covers the ranges of the REM sleep stage estimation by the RSSE method and RF (*i.e.*, OR condition of the estimated ranges of the RSSE method and RF) when both the ranges are overlapped.

Figure 4 shows the correct REM sleep stage by PSG (represented by the blue line) and the estimated ones by the proposed method (represented by the red line), the RSSE method (represented by the green line), and RF (represented by the orange line). This figure shows that the range of estimated REM sleep stage by the proposed method is mostly the same as the correct one, while the ranges by the RSSE method and RF are different form the correct one.

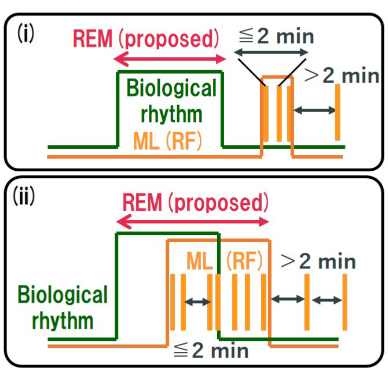

Figure 3: Proposed REM sleep stage estimation

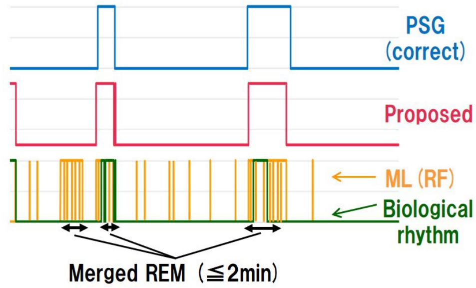

Figure 4: Estimated REM by proposed method

Human Subject Experiment

To investigate the effectiveness of the proposed method, human subject experiment was conducted. Concretely, 20 nights data of healthy human subjects were obtained, where their ages are ranged from 20's to 60's including both genders.

Figure 5 shows the F-score of the estimated REM sleep stages of the three methods, RF, the RSSE method, and proposed method, which are represented by the orange, green, and red boxes, respectively. In this figure, the vertical and horizontal axes indicate the F-score and 9 nights of 3 human subjects (selected from 20 nights). Note that the ages of M, H, and K are 20's, 40's, and 60's. As an evaluation criterion, the F-score is employed because it takes account of both precision (i.e., the number of true positive results divided by the number of all samples predicted to be positive) and recall (*i.e.*, the number of true positive results divided by the number of all samples that should have been identified as positive). The F-score is calculated by the harmonic mean of the precision and recall. From this figure, the F-score of the proposed method are higher than that of RF in all nine nights and are higher than that of the RSSE method in eight nights. This indicates that an integration of the RSSE method and RF (*i.e.*, the sleep stage estimation based on both biological rhythm and machine learning) contributes to increasing the F-score of the REM sleep stage.

Figure 5: F-score of estimated REM sleep stage

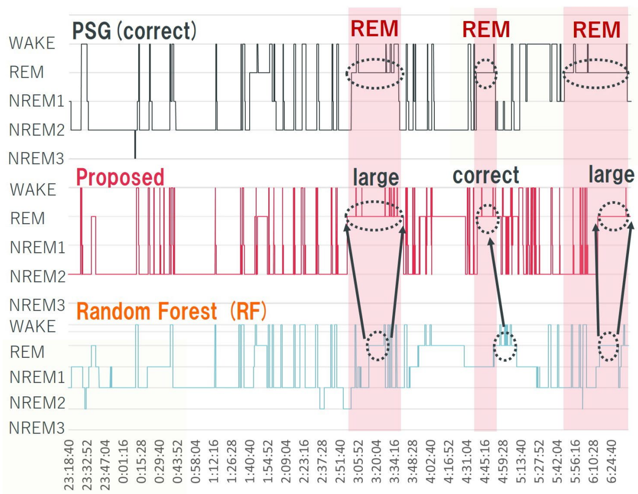

Figure 6: Correct and estimated sleep stages

Figure 6 shows the sleep stage of one human subjects. In detail, this figure shows the correct sleep stage by PSG and the estimated sleep stage by the proposed method and RF, which are represented in the upper, middle, and lower parts. In this figure, the vertical and horizontal axes indicate the sleep stage and a time during sleep. When focusing on the three areas of the REM sleep stage in the pink background color, the first and third ranges of the estimated REM sleep stage by the proposed method is larger than those by RF, and the ranges by the proposed method are mostly the same as or within the those of PSG. The second range of the estimated REM sleep stage by the proposed method is corrected by shifting earlier than the that by RF. This result also suggests that an integration of the RSSE method and RF (*i.e.*, the sleep stage estimation based on both biological rhythm and machine learning) contributes to precisely estimate the REM sleep stage.

Conclusion

This paper focused on generative AI and investigated what are the good suggestions by generative AI from the viewpoint of well-being. For this issue, this paper focused on the REM sleep stage on as one of sleep stages, and compared its estimation based on the machine learning with that based on a biological rhythm. Since random forest (RF) as one of machine learning wrongly estimates the REM sleep stage in many areas, this paper proposed to take account of a biological rhythm into RF. Concretely, the RSSE method based on a biological rhythm is integrated with RF. From the human subject experiment, the following implications have been revealed: (1) the REM sleep stage is wrongly estimated in many area by random forest, meaning that the REM sleep stage as the light sleep stage may be estimated even in the deep sleep stage; and (2) the integration of the REM sleep stage estimation based on the biological rhythm with that based on random forest improves the F-score of the estimated REM sleep stage in comparison with RF and the RSSE method. In particular, the estimated REM sleep stage by the proposed method is larger than those by the RSSE method and is corrected by shifting earlier than the that by the RSSE method.

What should be noticed here is that the implications have only been obtained by 20 nights data, therefore an increase of the number of nights and human subjects are needed to generalize the obtained implications. Such important directions must be pursued in the near future in addition to (1) an investigation of other sleep stages; and (2) an exploration of appropriate biological rhythms other than an ultradian rhythm to improve the F-score of machine learning.

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