Estimation of sleep onset and awaking time using a deep neural network with physiological data during sleep

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Abstract: A deep Neural Network (DNN) is used to estimate the sleep onset and awaking time of a subject with physiological data during sleep, in order to control the sleeping environment based on sleep phase. The results of the estimation from 40 minutes before the actual sleeping time show approximately 2.8 minutes mean error. Regarding awaking time, the results of the estimation from 120 minutes before show approximately 9.9 minutes mean error. Furthermore, the results of estimation in case of the range from 60 to 20 minutes before the actual awakening time show approximately 7.5 minutes mean error. The proposed DNN estimation is found to be effective for control of a comfortable awaking environment.

Key Words: big data analysis, deep neural network, sleep quality, environmental and vital data sensing

1. Introduction

It is widely thought that the quality of sleep has been deteriorating in recent times. Many people feel a low satisfaction with sleep when they awake. A control system for the sleeping environment is needed to improve the quality of sleep.

Temperature, humidity, and light are listed as examples for controllable sleep environment factors. It is reported that temperature and humidity influence sleep satisfaction [1]. For instance, smart mattresses and mattress pads, which adjust temperature automatically have been commercialized [2]. In case of lighting, it is also reported that the balance of the autonomic nervous system and melatonin secretion, which controls the biological clock, are influenced by lighting [3, 4]. For instance, Balluga® is a bed where people can adjust the functions of the mattress to make it match people individually. Lights under the bed turn on automatically when someone gets up from it [5].

Control systems for the sleeping environmental factors exist in this wise. However individual physiological data is more important for tailor-made sleep support system than environmental factors. The polysomnography, one of the previous methods to diagnose sleep disorders, records individual physiological data such as respiration, electrocardiogram, and motions of legs etc. However polysomnography...
needs large-scale and constrained equipment. It is trend to measure physiological data during sleep with unconstrained or non-invasive device recently [6]. Although there is an example of sleep or wake identification using wrist actigraph [7], this constrained device disturbs sleep. Considered this problem, a result has been reported on estimation of awaking time with physiological data obtained from unconstrained and non-invasive sensors [8].

Therefore, in this study, in order to provide a comfortable sleep by control of the sleeping environment, we aim to estimate not only individual awaking but also individual sleep onset time with physiological data obtained from non-invasive and unconstrained sensors.

Procedures of the sleep experiment, sensors used, data obtained and the deep neural network used will be explained in section 2. Results on estimation of time for awaking and sleep onset, and discussion will be in section 3. In section 4 this paper will be concluded.

2. Experiment and analysis

2.1 Experiment

A healthy male in his thirties participated in this sleep experiment. One subject is preliminary chosen to ascertain that proposed DNN is sufficient to estimate sleep onset and awaking time. He was allowed to sleep without any limitations regarding sleep starting time. Therefore the length of sleep was not constant. The subject slept in his own room. Data was taken for 106 days including 4 seasons. Sensors used were accelerometers, a microwave sensor and pressure sensors (Nemuri Scan NN-C110; Paramount Bed Co., LTD., Tokyo, Japan). Accelerometers and Nemuri Scan are installed under the pillow and mattress, respectively. A microwave sensor, attached to the ceiling, was directed at the bed and used to obtain heart rate and respiratory frequency. Nemuri Scan was used to record sleep onset and awaking times. Figure 1 shows sensors used and data obtained. Acceleration data was sent to server via micro-computer. Microwave sensor data was saved on PC and Nemuri Scan data was saved on SD card.

The method of getting heart rate and respiratory frequency is as follows: frequency analysis was performed on the heartbeat wave, respiration and movement with Matlab R2014b. Sampling frequency was 64 Hz, window function was Hamming window, window interval was 60 sec. and overlap...
was 10 sec. Heart rate and respiratory frequency were defined as maximum Power Spectrum Density between 0.5–4.0 Hz and 0.1–2.0 Hz, respectively. This procedure is shown in Fig. 2. Acceleration was measured every 10 seconds during sleep.

The experiment was done after getting approval by the ethics review committee of Yamagata University.

2.2 Analysis

A 6-layered deep neural network (hereinafter referred to as DNN) was used as the estimation system. The DNN procedure is shown in Fig. 3. This model was the best among tried 10 kinds of models. The input layer, intermediate layers, output layer, initialization, learning, and optimization of the DNN and verification of test data will be explained.

Input data were 300 data sets composed of 10 minutes of data which consisted of 5 kinds of information: 3-axis directional acceleration, frequency of heart rate and respiratory frequency as shown in Eq. (1).

$$5 \text{ infos. @ 10 sec. } \times \frac{6 \text{ sets}}{1 \text{ min}} \times 10 \text{ min} = 300 \text{ data sets}$$  

Multiple Regression Analysis (hereinafter referred to as MRA) is performed before trying DNN to determine kinds and numbers of parameters. It is found that 5 parameters can be the most effective among results using 1, 2, 3, 4, and 5 parameters to MRA. These 5 parameters will be used hereinafter. Using a 6-layered DNN 300 nodes were refined to 1 output data as mentioned later.

The first, second, third, fourth and fifth layer had 300, 200, 200, 100 and 50 of nodes in the layer, respectively. Rectified Linear Units (hereinafter referred to as ReLUs) were used at the 2nd, 3rd and 4th layers. A hyperbolic tangent, tanh, was used at the 5th layer. When ReLU functions are used, the output is 0 when the input is smaller than 0 and an output is same as the input when the input is larger than 0. Figure 4 (a) shows a ReLU function. Using the tanh function, the output comes closer to 1 when the input becomes larger. The output comes closer to -1 when the input becomes smaller. Figure 4 (b) shows tanh function. A real number is output from the 6th layer using the identity function, \(a(x) = x\).

Figure 5 shows an example of output from the Nemuri Scan software produced by Paramount Bed Co., LTD., and the analysis method. It shows each sleep onset and awakening time. The transition time between asleep and awake was used to teach the DNN. Then the time to sleep onset and awakening was estimated as an output by counting back from the actual sleeping and awakening time. Time to sleeping and awakening time was estimated by using the DNN shifting every 10 sec initially from certain periods before actual sleeping and awakening time. The output data was this estimated time.
In terms of initialization bias $b = 0$, then following procedures were used for weight, $w$: He initialization [9] was used for ReLUs, and Xavier initialization [10] was used for the other activation functions. Then error function, square error in this case, was minimized with a back-propagation algorithm. Learning was done using the stochastic gradient decent, in which the size of mini batches were 128, with the Adam optimizer [11], and using the dropout [12] of rate 0.5 for all the layers except the output layer.

There were 3,497 and 51,369 data points suitable for analysis in the obtained data for sleep onset and awaking time, respectively. The number of data points for sleep onset were less because a time length before sleeping was shorter than that of awaking. 85% of whole data were used for training, and 15% of them were used for testing. The former data were 2,939 and 43,495 then the latter data were 558 and 7,874 for sleep onset and awaking time, respectively.

3. Result and discussion

The Mean absolute error (hereinafter referred to as MAE), shown in Eq. (2), was used for evaluation of estimation
Fig. 5. An example from Nemuri Scan viewer software and method of analysis. The figure is cut from approximately 00:00–06:00. Vertical axis doesn’t have units. Horizontal axis is time. Yellow and blue shading shows awakening and sleeping time, respectively. Black bars show magnitude of movement. Time between sleep and awakening is used to train DNN. Input data was vital signs i.e. heart rate, respiratory frequency and movement for 10 min. Time to sleeping and awakening time was estimated by using the DNN shifting every 10 sec. initially from certain periods before actual sleeping and awakening time.

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|
\]  

where \( N \), \( y_i \), and \( \hat{y}_i \) are the number of the testing data for estimation, actual value and estimated value, respectively. The MAE in case of MRA which was performed as comparison with DNN was 23.4 mins.

The results of DNN estimation for awakening time is shown in Fig. 6. When estimation started 120 minutes before actual awakening time, the total estimated mean error was approximately 9.9 minutes. The error was shortened to approximately 7.5 minutes when the estimation time was limited to the range 60 to 20 minutes before actual awakening time. Those MAE were less than half of MRA’s.

Incidentally, the averaged value of training data was approximately 46.5 mins. In Fig. 6, plot points among 30–60 mins are especially concentrated around red line which shows accurate estimation. It means that learning with DNN focuses estimation around 46.5 mins, the averaged value of training data. Although it is the fact that there is over estimation for short range, it is possible to say that this tendency was brought from facts mentioned above. It is needed to further optimize of DNN structure including kinds and numbers of parameters. The obtained accuracy of estimation is sufficient for providing comfortable sleep by controlling environment based on sleeping rhythm considered that the MAE is exceedingly small compared to time interval of Rapid Eye Movement (REM) and non-REM sleep, widely known that 90–120 minutes.

Next sleep onset time is estimated. Since it was thought that basic concept for distinction of state transition using physiological data was common between sleeping and awakening, the same model as awakening was used. This result is shown in Fig. 7. The total estimated mean error was approximately 2.8 minutes when estimation started 40 minutes before actual sleeping time. High accuracy is obtained in spite of using same model.

These results show novelty that proposed 6 layered DNN is capable to estimate sleeping and awakening time with simple 5 kinds of physiological data only obtained from non-invasive and unconstrained sensors. Future work includes: to control environment based on not only estimated time of sleep onset and awakening but also when the subject wants to wake up and to increase the number of subject since the necessity of this is highly recognized.
Fig. 6. The results of estimation 120 minutes before awakening time using 6-layered DNN. Estimated error is 9.9 min. The estimated error is shortened to 7.5 min when the estimation time was limited to the range from 60 to 20 minutes before the actual awakening time, shown with the blue square. The maximum number of horizontal axis is 110 since estimation started 120 minutes before awakening time and length of data set is 10 minutes.

Fig. 7. The results of estimation 120 minutes before awakening time using 6-layered DNN. Estimated error is 2.8 min. The maximum number of horizontal axis is 40 since subject went to sleep within 40 minutes.

4. Conclusions
Sleep onset and awakening time was estimated using a 6-layered DNN based on 300 physiological data sets which consisted of 3-axis directional acceleration, frequency of heart rate and respiratory frequency. When estimation for sleep onset started 40 minutes before actual sleeping time, the total estimated mean error was approximately 2.8 minutes. When estimation for awakening time was started from 120 minutes before actual awakening time, whole mean error was within approximately 9.9 minutes. Furthermore, the error was shortened to approximately 7.5 minutes when the estimation time was narrowed to the range 60 to 20 minutes before actual awakening time. The estimation using DNN was compatible with proposal to provide a comfortable sleep environment depending on estimated times.

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