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DROWSINESS DETECTION BASED ON EEG AND BLINK INFORMATION MEASURED WITH A SINGLE ELECTRODE

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Abstract. *In this study, we construct a system that promotes arousal by sounding an alarm according to a score, which is based on the estimated electroencephalogram (EEG) and blink components of a waveform obtained from a single electrode attached to the scalp. In this system, the arousal score is defined by the first principal component after calculating the magnitude of frequency components of the EEG and blinks from the measured waveform. The score is used to evaluate the degree of arousal, and a warning sound is generated when the score falls below the set threshold. To evaluate the performance of this system, we used two indices to determine the accuracy of drowsiness detection: comparing the timing of the warning with a video inspection and the score obtained from a questionnaire given to the subjects after the experiment. As a result, although there were variations among individuals, for 10 subjects, the average video inspection-based accuracy was 79.5% and the average questionnaire result was 4 on a 5-point scale. In addition, the subject's alertness increased immediately after the warning and the arousal score increased, showing the effectiveness of this method.*
Keywords: Electroencephalogram (EEG), Blink, Drowsiness detection, Warning system

1. **Introduction.** The state of drowsiness is a fluctuating intermediate state between wakefulness and sleep that delays reaction and reduces attention and performance in human behavior. In the case of drowsy driving, for example, banners and rumble strips are used for prevention, but they cannot reliably awaken a driver in a drowsy state. Therefore, in recent years, a doze detection or warning system based on images acquired by an in-vehicle camera during driving has been developed and commercialized. These detections are based on the appearance of drivers such as head movements in addition to blinks and face recognition. However, to more accurately determine the degree of human alertness, it is essential to use biological signals based on brain activity, which reflect the internal (e.g., mental) state of a person. Among these signals, electroencephalography (EEG) is widely used because it can acquire brain activity using a relatively inexpensive and compact device. It has long been known that the power in the alpha band decreases and the power in the delta and theta bands increases with sleep onset, and these have been considered useful for estimating sleepiness [1, 2]. For example, Sauvet et al. used power in the alpha, beta, and theta frequency bands [3]. In recent years, many methods for detecting drowsiness using EEG have been reported, and an increasing number of these methods use deep learning based on a large number of EEG data to improve the accuracy of drowsiness detection [4, 5]. Hwang et al. reported that sleepiness can be discriminated using the power in the delta, theta, alpha, beta, and gamma frequency bands as input to

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a deep neural network [5]. However, it is difficult to know the exact basis of a decision obtained by deep learning, and thus interpretation is not easy. Other approaches have also been tried. Chen et al. analyzed a functional brain network considering the connection strength between two EEG sensors and classified the alert and drowsy states of a driver [6]. Generally, components other than the EEG signal such as eye movements are present in the EEG waveform. Therefore, those components are usually removed as artifacts in drowsiness detection [7, 8]. However, various biological signals are thought to contain many components related to drowsiness. Therefore, methods that improve performance using other components along with EEG have been reported. In particular, blinks have been used to detect drowsiness in drivers, and in combination with EEG, should improve detection performance. Picot et al. measured EEG using a single electrode, whereas eye movements were measured with a different electrode and blink features were extracted from the measured waveforms. The three states of awake, drowsy, and very drowsy were then detected. Compared to detection of eye movements alone, it was reported that the false alert rate was reduced to 5% without decreasing the rate of true positives [9]. Arnin et al. used a numerical value derived from the appearance of the theta, alpha, and beta waves in the EEG signal to develop a sound and light warning system. Here, they used an electrooculogram (EOG) to detect eye blinks and movements by classifying artifacts and eye behavior based on the largest signal peak. The alarm system is based on EEG and EOG information [10]. As well as research on improvements in detection accuracy, there has been increasing research on developing portable systems. Ogino and Mitsukura detected drowsiness with EEG measured by a portable and inexpensive device. They extracted power spectral density features using step-wise linear discriminant analysis from a waveform on a single electrode placed in the frontal region, and classified the features into two classes (alert or drowsy) using a support vector machine [11]. Similarly, Patrick et al. extracted many features from EEG data obtained with a single electrode wearable system, including the maximum and minimum values, center frequency, and relative power in various EEG bands such as the delta, theta, and alpha bands. They then classified these data into awake and drowsy states [12].

Previous reports have focused primarily on classifying awake and drowsy states, but have been unable to determine the degree of drowsiness. Deep learning and the use of a large number of features do not provide a clear basis for this judgment, and it is difficult to evaluate the validity of the results. Therefore, we attempt to develop a system that quantifies and detects drowsiness in real time using a small number of explainable features measured with a small number of electrodes. In this study, by placing one electrode for EEG measurement on the frontal area, we obtain both brain activity and blink information by extracting the two components reflecting the EEG and blinks from the measured waveform. This method is based on the fact that blink information is found in the EEG signal obtained from the frontal region. In drowsiness detection, because the arousal score is defined as an index based on medical knowledge, the relationship between the EEG and blink signals is easy to determine. A warning sound is generated to alert the user when the score becomes lower than a set threshold. This method is different from the approach of searching for features by deep learning from a large number of data, and has the advantage that it enables learning with a small number of data for each individual. This paper is organized as follows. Section 2 describes the EEG recordings and presents the proposed approach for drowsiness detection. Section 3 reports the experimental results. Section 4 discusses the performance of the system based on the results. Finally, the conclusions and the extensions of the current work are presented in Section 5.

2. Methods.

2.1. EEG measurement.

In this study, an electroencephalograph (g.MOBIlab, g.tec) was used to measure potentials on the scalp at a sampling frequency of 256 Hz from an active electrode placed at the right frontal pole (Fp_2 in the international 10-20 system) for 10 male subjects (23.0 ± 1.34 years old). In parallel with the EEG measurement, a video was taken to observe the subject's condition. They participated in the experiment after informed consent. This study was approved by the Ethics Committee of the Faculty of Engineering, Yamagata University (approval number: 1121-2).

2.2. EEG analysis.

The EEG and blink components are estimated from the waveform obtained from a single electrode. Our aim is to quantify the degree of arousal from these two components. For this purpose, we introduce an approach that evaluates the degree of arousal according to the deviation from the distribution of the two components in the arousal state. Therefore, it is necessary to know the distribution in the awake state before using the system. Because there are individual differences, it is necessary to obtain the data for each individual for calibration. Here, these data are used to train the system to estimate the degree of arousal. In this study, we acquired training data for 5 mins in order to set the threshold to detect drowsiness for each individual. Since the training data will be used as the standard for evaluating the arousal state, it is desirable to acquire these data under a constant state. In an event-related potential measurement in clinical examination, the measurement time is about 5 mins. We hence set the measurement time to 5 mins because it allows the subject to remain in a stable state without causing drowsiness or fatigue. From these data, we quantified the degree of wakefulness by plotting the amplitude of the EEG and blink signals in the awake state as a distribution and defining an arousal score as the degree of deviation from that distribution. When the arousal score falls below a certain threshold, the state is determined to be the drowsy state. In the experiments, the system was used for 10 mins, and if the score fell below the threshold, the subject was alerted by a warning sound to urge them to wake up. Since the purpose of this test was to detect drowsiness, the test duration was set to 10 mins to consider the burden on the subject, but there is no need to impose any particular time limit. The flowchart of the evaluation, from measurement for calibration to the evaluation of the system operation, is shown in Figure 1. In this study, the parameter values are fixed because they affect the evaluation of the system, but the specification allows parameter settings based on the situation conditions, such as user and processor capabilities. For example, the current analysis window is 10 s, but if this is increased, the system will be robust enough to reliably capture localized blinks. By contrast, decreasing the window reduces the amount of computation, thus improving real-time performance and making it possible to use the system even when processor capacity is low. As for the drowsiness threshold, the detection sensitivity can be increased by lowering the threshold, such as when driving, and decreased by raising the threshold, such as when only extreme drowsiness needs to be detected. The threshold is defined on the basis of probabilities, so that individual comparisons can be made. The details of each process are described in the subsequent sections.

2.3. Measurement for calibration.

This section describes how the arousal score is calculated and how the threshold for alertness is determined. First, a fast Fourier transform (FFT) of 4096 points is performed with an analysis window of 10 s. Because the number of sample points in the analysis window is smaller than the number of points required for the FFT, the FFT to obtain the magnitude of the spectrum is performed after zero padding. The average amplitudes of the EEG and blink components are then

Measurement at an arousal state for calibration and video acquisition (Measurement time: 5 minutes)

↓

Acquisition of the amplitude of the EEG and blink components using the FFT of a 10-s analysis window

↓

Generation of two-dimensional maps of the amplitude of EEG and blink components

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Threshold setting for drowsiness detection

↓

Use of warning system (Real-time processing and alertness by warning sound) (Measurement time: 10 minutes)

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Evaluation by video inspection and a questionnaire given to the subjects after the mesurement

FIGURE 1. Flowchart of the evaluation

calculated. Here, the passband of the EEG component was set to 5-20 Hz, which includes a part of the alpha to beta bands. The passband of the blink component was set to 1-3 Hz. The frequency bands were determined by visually confirming that the waveforms were separated by the filter in a large number of actual subject data. Figure 2 shows two cases of signal separation into EEG and blink components by applying a filter. In Figure 2(a1), the amplitude of the EEG is smaller than that of the blink, and in Figure 2(a2), the amplitude of the EEG is almost the same as that of the blink. The respective spectra are shown in Figures 2(b1) and 2(b2). Here, the hatched regions are the blink and EEG passbands, and the amplitude is normalized (0 dB) by the maximum amplitude in each frequency range. The blink signals after filtering are shown in Figures 2(c1) and 2(c2), and the filtered EEG signals are shown in Figures 2(d1) and 2(d2). Although a small amount of the blink component remains in the EEG component in Figure 2(d1), the blink artifacts are not as noticeable in Figure 2(d2). In both cases, the waveform of each component is unknown, so the separation accuracy cannot be evaluated correctly. However, it can be confirmed by visual inspection that they are almost separated. The mean amplitude was calculated repeatedly by FFT while sliding the 10-s analysis window in the temporal direction in steps of 1 s. Then, the obtained mean amplitudes were plotted in two-dimensional space, where the horizontal axis represents the mean amplitude of the EEG and the vertical axis represents the average amplitude of the blink (Figure 3). Thus, the number of points in the plot corresponds to the number of times the FFT was used. Because this distribution is elliptical, we applied principal component analysis. Note that we confirmed by statistical test that each principal component follows a normal distribution. In this study, we define a measure of drowsiness based on empirical evidence. Because both the EEG and blink components decrease when sleepiness increases, the points should move to the lower left as the power of both components decreases. Therefore, the degree of drowsiness is given by the distance from the center (which is the average obtained during wakefulness) of the two-dimensional map of EEGs and blinks along the primary principal axis with a positive slope. In this way, this study differs from other studies in that it defines drowsiness based on features that can be reasonably explained. Here, we defined the arousal score (Z_s) as the value obtained by normalizing the first principal component z_1 by the standard deviation σ or the square root of maximum

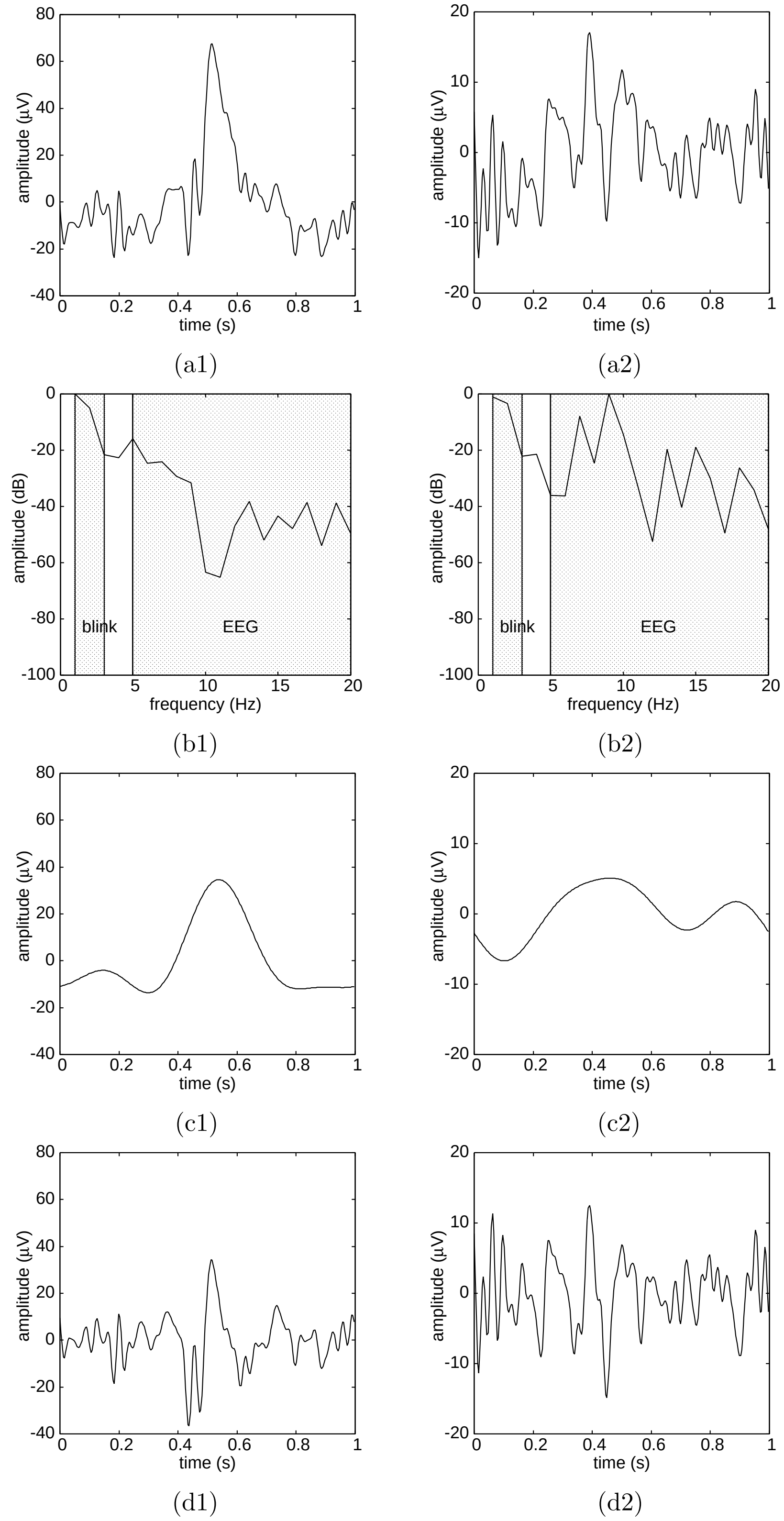


Figure 2. Separation of measured waveform into EEG and blink components (left: a case where the amplitude of the blink component is much larger than that of the EEG component ((a1)-(d1)); right: a case where the amplitudes of the blink and EEG components are close ((a2)-(d2)); top to bottom rows: measured waveforms ((a1), (a2)), amplitudes of the EEG and blink components ((b1), (b2)), extracted blink component ((c1), (c2)), and extracted EEG component ((d1), (d2)))

eigenvalue λ_1 $\left(Z_s = z_1/\sigma = z_1/\sqrt{\lambda_1}\right)$. Because the first principal component follows a normal distribution indicated by the red line, we set the threshold Z_{th} at -1.44, with the probability density of about 7.5% from the left of distribution as the boundary between the awake and drowsy states. A warning sound was generated when the value fell below that level, which is indicated by the hatched region.

2.4. **Use of warning system and evaluation of the system performance.** The warning system was used for 10 mins by 10 subjects, and the performance of the system was evaluated using two evaluations. One is evaluation by inspection using video taken during the measurement. The system was said to detect drowsiness correctly when the difference between its time of detection and the time of detection determined by video inspection was within 3 s. The other is evaluation via a questionnaire given to the subjects after the experiment. In this questionnaire, the subjects were asked to rate the results according to five levels. Five was the highest rating for perfect warnings, four indicated the system was correct in most situations, three was neither good nor bad, two indicated the system was wrong in many situations, and one was the lowest rating, indicating the system was unusable. This measurement was not performed during the calibration session.

3. **Results.** When the arousal score fell below the threshold, the subject was considered to be in a drowsy state and was alerted with a warning sound to wake up. In this study, we focused on the frequency component, as shown in Figure 2. We separate the blink from the EEG by taking advantage of the fact that a blink contains a large number of low frequency components. Therefore, although the rough outline of the blink waveform is captured (2(c1), 2(c2)), the parts that change abruptly are extracted as EEG (2(d1), 2(d2)). Normally, blinking does not occur continuously for long periods of time, so its effect on the distribution of the plots in Figure 3 is small. Even if the subject constantly blinks frequently, the distribution of the plots is elliptical and does not affect the detection of drowsiness. Examples of drowsiness detection during this measurement are shown in Figure 4. Figure 4(a) presents case in which the warning sound occurred frequently and Figure 4(b) presents a case in which the warning sound rarely occurred. The red line shows the threshold value, and it can be seen that the score rises immediately after it has fallen below the threshold. This indicates that the system works correctly. In the figure, the

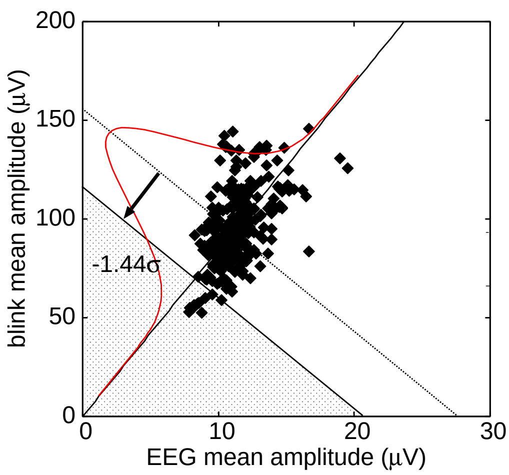
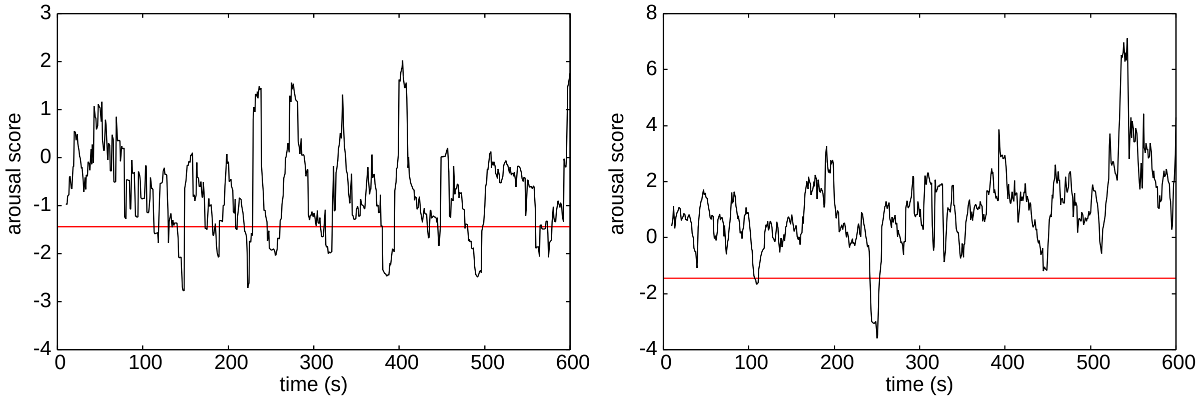


FIGURE 3. (color online) Relationship between the EEG mean amplitude and blink mean amplitude



(a) (b)

FIGURE 4. (color online) Examples of temporal changes in the arousal score of the system (left: a case where warning sounds occur multiple times, right: a case where warning sound occurs a few times, red line: threshold for drowsiness detection)

mean of the training data during wakefulness corresponds to 0. Figure 4(a) indicates that the subject was sleepy during the test data measurement because the arousal score was negative overall. Thus, the score was often below the threshold, and many warning sounds were generated. In contrast, in Figure 4(b), the scores were positive for the majority of the cases, suggesting that the subjects were in a state of arousal that was equal to or higher than when they were awake. Therefore, the number of times the score fell below the threshold was small, and warning sounds were generated a small number of times.

Table 1 shows the results of the questionnaire for all 10 subjects. The evaluation of this system reveals that the system has an accuracy of $79.5 \pm 23.3(\%)$ based on inspection of the subject's state by video, and a questionnaire score of 4.00 ± 0.894 on a 5-point scale.

TABLE 1. Results for video inspections and questionnaire scores

Subject	Accuracy by video inspection (%)	A questionnaire score
A	100	5
B	40	4
C	100	4
D	100	4
E	100	4
F	50	4
G	50	2
H	75	3
I	100	5
J	80	5
Average	79.5 ± 23.3	4.00 ± 0.894

4. **Discussion.** The temporal change in Figure 4(a) shows that the subject's arousal level was low and the score was below the threshold indicated by the red line several times. In addition, the arousal score rose and returned to the awake state just after a warning sound was generated and the subject was awakened. This confirms that the system works properly. Next, we evaluated the performance of the system. In the evaluation by video

for 10 subjects, the warning sound was generated correctly 100% of the time for half of the subjects, and the average was 79.5%. However, there was a large variation among the subjects. The drowsiness detection depends on the state of the subject during the measurement for calibration. As shown in Figure 4(b), the score remained high as a whole and rarely fell below the threshold. Therefore, almost no warning sound was generated. Because this method uses the measurement data at the time of calibration as the standard of arousal, it may be affected by the degree of arousal at the time of calibration. We used 5 min of awake data for calibration, but we believe that increasing the number of training data will improve the performance by learning fluctuations in the subject's awake state. In the questionnaire evaluation, 8 out of 10 subjects gave the system a score of 4 or higher, indicating their satisfaction. However, subjects who gave scores of 2 or 3 were not very drowsy during the measurement, which may have led to a low evaluation because drowsiness was not often detected. Although 10 subjects were used to obtain the results of this study, a larger number of subjects is desirable. However, this study is not particularly small when compared with similar research reports. In EEG analysis research, a review paper by Yosrita et al. noted that most EEG-based imagine speech brain-computer interface studies use five subjects [13]. To construct a general-purpose system in the future, it will be necessary to evaluate it with many subjects.

Drowsiness detection methods have been proposed by other researchers. Li and Chuang surveyed the literature on EEG-based driver drowsiness detection and reported that 71% of the literature used FFT-based features [14]. Frequency information is the most important feature in EEG analysis, and it is also used in this paper. There are many reports on drowsiness estimation based on the power in a certain frequency band or the ratio of powers using two or more bands. Stancin et al. introduced an index described by the power in the delta and alpha bands [15], and Flumeri et al. introduced an index calculated from the global field power calculated in the alpha band [16]. The EEG changes from moment to moment, and the power fluctuates widely over time. When ratios are used, there is also the instability of large fluctuations in values due to changes in the power of the denominator signal. In recent years, deep learning has been used to detect drowsiness, but it is difficult to analyze the processing in the network clearly. Therefore, the mechanism of drowsiness detection has not been fully elucidated, and it is hence difficult to evaluate its validity [4, 5]. Similarly, classification in high dimensionality with a large number of features and indices derived from multivariate explanatory variables is also difficult to interpret. Gangadharan and Vinod used a wavelet thresholding algorithm to remove blinks and then acquired 19 features including the sample entropy to classify alert and drowsy states [17]. Arefnezhad et al. performed dimensional shrinkage on various frequency powers and extracted 50 features for use [18]. A method using eye movement information mixed with EEG that is suitable for detecting drowsiness was also proposed. Tarafder et al. classified alert and drowsy states by extracting features that reflect eye movements, such as duration and maximum peak, from EEG mixed with ocular artifacts [19]. In contrast to the above studies, our method uses two components, EEG and blinks, from a single time-series dataset, which enables stable detection. Moreover, because both components can easily explain the relationship with drowsiness based on previous findings, interpretation of the results is also easy.

In our results, an accuracy of 100% was obtained for five out of the 10 subjects, but when drowsiness detection is used in driving, the accuracy must be close to 100% for all subjects. Therefore, it will be necessary to check each error individually to determine under what circumstances it occurs and to set the parameters adaptively. For example, for subjects with a low detection accuracy, it may be necessary to lower the threshold and increase sensitivity. Because this method evaluates drowsiness using the deviation from the mean of the awake state, training data should be acquired in various states, and the number of points in the two-dimensional distribution of EEG and blink data should be increased to obtain accurate distributions (mean and standard deviation) for individuals.

Finally, in this study, the strengths of the EEG and blink components were determined using the mean amplitudes in the frequency bands, but the two components actually overlap, and hence it is difficult to completely separate them. Although many separation methods have been proposed, they are computationally expensive and are not suitable for cases where a real-time warning system is required and delays are not tolerated. We prefer to consider improving the separation method by taking account of the balance between computational cost and accuracy.

5. **Conclusions.** In this study, we defined an arousal score that quantifies the degree of drowsiness based on the magnitudes of the spectra of EEG and blink components acquired during a calibration measurement. Using the frequency of these components, our system alerts the user with a warning sound when the frequency falls below a set threshold. The actual measurement confirmed that the subjects were stimulated to wake up after the warning sound, and that the arousal score increased immediately, indicating the effectiveness of this method. The performance of the system was evaluated by confirming a subject's state using video and by a post-experiment questionnaire. Although there was some variation among individuals, the average score for the former was 79.5%, and the average score for the latter was 4 out of 5 points. In future, we would like to improve performance by increasing the number of training data.

REFERENCES

[1] M. Matousek and I. Petersén, A method for assessing alertness fluctuations from EEG spectra, *Electroencephalography and Clinical Neurophysiology*, vol.55, no.1, pp.108-113, 1983.

[2] T. Hori, Spatiotemporal changes of EEG activity during waking-sleeping transition period, *Int. J. Neurosci.*, vol.27, nos.1-2, pp.101-114, 1985.

[3] F. Sauvet, C. Bougard, M. Coroenne, L. Lely, P. Van Beers, M. Elbaz, M. Guillard, D. Léger and M. Chennaoui, In-flight automatic detection of vigilance states using a single EEG channel, *IEEE Trans. Biomedical Engineering*, vol.61, no.12, pp.2840-2847, 2014.

[4] J.-H. Jeong, B.-W. Yu, D.-H. Lee and S.-W. Lee, Classification of drowsiness levels based on a deep spatio-temporal convolutional bidirectional LSTM network using electroencephalography signals, *Brain Sci.*, vol.9, no.12, 348, DOI: 10.3390/brainsci9120348, 2019.

[5] J.-H. Hwang, S.-W. Ahn, J.-Y. Kim and J.-H. Chi, Drowsy driving prevention service using EEG, *International Journal of Grid and Distributed Computing*, vol.11, no.10, pp.1-10, 2018.

[6] J. Chen, H. Wang, C. Hua, Q. Wang and C. Liu, Graph analysis of functional brain network topology using minimum spanning tree in driver drowsiness, *Cogn. Neurodyn.*, vol.12, no.6, pp.569-581, 2018.

[7] S. M. R. Noori and M. Mikaeili, Driving drowsiness detection using fusion of electroencephalography, electrooculography, and driving quality signals, *J. Med. Signals Sens.*, vol.6, no.1, pp.39-46, 2016.

[8] A. R. Sparrow, C. M. LaJambe, H. P. A. Van Dongen, Drowsiness measures for commercial motor vehicle operations, *Accid. Anal. Prev.*, vol.126, pp.146-159, 2019.

[9] A. Picot, S. Charbonnier and A. Caplier, On-line detection of drowsiness using brain and visual information, *IEEE Trans. Systems, Man, and Cybernetics – Part A: Systems and Humans*, vol.42, no.3, pp.764-775, 2012.

[10] J. Arnin et al., Wireless-based portable EEG-EOG monitoring for real time drowsiness detection, *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp.4977-4980, 2013.

[11] M. Ogino and Y. Mitsukura, Portable drowsiness detection through use of a prefrontal single-channel electroencephalogram, *Sensors (Basel)*, vol.18, no.12, 4477, DOI: 10.3390/s18124477, 2018.

[12] K. C. Patrick, S. A. Imtiaz, S. Bowyer and E. Rodriguez-Villegas, An algorithm for automatic detection of drowsiness for use in wearable EEG systems, *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp.3523-3526, 2016.

[13] E. Yosrita, Y. Heryadi, L. A. Wulandhari and W. Budiharto, Acquisition design and objectives of imagined speech research based on EEG: Review paper, *ICIC Express Letters*, vol.15, no.7, pp.711-717, 2021.

[14] G. Li and W.-Y. Chung, Electroencephalogram-based approaches for driver drowsiness detection and management: A review, *Sensors (Basel)*, vol.22, no.3, 1100, DOI: 10.3390/s22031100, 2022.

[15] I. Stancin, N. Frid, M. Cifrek and A. Jovic, EEG signal multichannel frequency-domain ratio indices for drowsiness detection based on multicriteria optimization, *Sensors (Basel)*, vol.21, no.20, 6932, DOI: 10.3390/s21206932, 2021.

[16] G. Di Flumeri, V. Ronca, A. Giorgi, A. Vozzi, P. Aricò, N. Sciaraffa, H. Zeng, G. Dai, W. Kong, F. Babiloni and G. Borghini, EEG-based index for timely detecting user's drowsiness occurrence in automotive applications, *Front. Hum. Neurosci.*, vol.16, 866118, DOI: 10.3389/fnhum.2022.866118, 2022.

[17] K. S. Gangadharan and A. P. Vinod, Drowsiness detection using portable wireless EEG, *Comput. Methods Programs Biomed.*, vol.214, 106535, DOI: 10.1016/j.cmpb.2021.106535, 2022.

[18] S. Arefnezhad, J. Hamet, A. Eichberger, M. Frühwirth, A. Ischebeck, I. V. Koglbauer, M. Moser and A. Yousefi, Driver drowsiness estimation using EEG signals with a dynamical encoder-decoder modeling framework, *Sci. Rep.*, vol.12, no.1, 2650, DOI: 10.1038/s41598-022-05810-x, 2022.

[19] S. Tarafder, N. Badruddin, N. Yahya and A. H. Nasution, Drowsiness detection using ocular indices from EEG signal, *Sensors (Basel)*, vol.22, no.13, 4764, DOI: 10.3390/s22134764, 2022.

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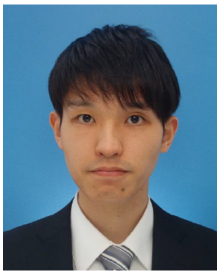

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