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Detecting the Early Drop of Attention using EEG Signal

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***Abstract*—The capability to detect the drop of attention as early as possible has many practical applications including for the development of the early warning system for those who involve in high-risk works that require a constant level of concentration. This study intends to develop such the capability on the basis of the data of the brain waves: delta, theta, alpha, beta, and gamma. For the purpose, a number of participants are asked to participate in the study where their brain waves are recorded by using a low-cost Neurosky Mindwave EEG sensor. In the process, the participants are performing a continuous performance test from which their attention levels are directly measured in the form of the response time in conjunction to those waves. When the response time is much longer than a normal one, the participant attention is assumed to be dropped. A simple k-NN classification method is used with the $k = 3$. The results are the following. The best detection of the attention drop is achieved when the attention features are extracted from the earliest stage of the brain wave signals. The brain wave signal should be recorded longer than 1 s since the time the stimulus is presented as a short signal leads to a poor categorization. A significant drop in the level of response time is required to provide the brain signal that better predicts the change of the attention.**

I. Introduction

Many lines of works require a high level of attention in order to be able to perform the works safely, efficiently, and effectively. Those works include doctors, drivers, machine operators, students, and much more. For the reason, developing a methodology from which the level of attention can be accurately monitored has been the central issue of the study of many researchers.

Those research works have explored the use of various biological signals and have studied their relation to the level of attention. The first work on measuring the attention level was detected in 1979 [1]. Since the time, the attention level had been correlated to various measurable biological signals such as brain waves, blood pressure, eye movement, facial expression, and heart beat [2], [3]. For examples, Ref. [4] utilized the information from facial expressions and Ref. [5] used those from the change of the body temperature. Reference [6] used functional imaging techniques to relate the brain signal to the execution of cognitive functions. Reference [7] used Electrocardiograph (ECG) as a fundamental physiological signal, to analyze and predict the presence or lack of cognitive attention during a task execution. Reference [8] demonstrated that the level of attention could be predicted at 83% accuracy by using visual attention recognition (VAR). Reference [9] used the brain waves and reported an accuracy of 77%.

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According to [9], the establishments of the relationship of the brain electrical activity signals in the form of electroencephalogram (EEG) signal to the level of attention is relatively recent. Reference [10] classified the level of driving attention using EEG signal. Reference [11] used EEG signal for brain computer interface. The EEG signal is widely considered consisted of five sub-signals, namely, delta, theta, alpha, beta, and gamma waves. Those sub-signals are defined on the basis of their frequency ranges. The delta waves are the components of the EEG signal within the range of 0.5–3 Hz. The theta, alpha, beta, and gamma waves are respectively within the range of 4–7 Hz, 8–13 Hz, 14–30 Hz, and 31–50 Hz.

In this approach, a device that is called brain-computer interface is used to record the brain waves. Then, the waves data in the time domain are transformed into the frequency domain in which the sub-signal components are extracted. In this work, the EEG signal is used to detect the early onset of the attention drop. The temporal change of attention is controlled by means of the continuous performance test (CPT). The test also allows us to measure the participant response time, another measurable quantity that is strongly related to the attention level. By using this approach, the early drop of attention can be detected and its relation to the EEG signal can be established.

II. Research Method

In order to relate the brain wave signals and the change of attention, the following procedures were performed; see Fig. 1. Firstly, fifteen participants were asked to join the experiment where their attentions are controlled by means of

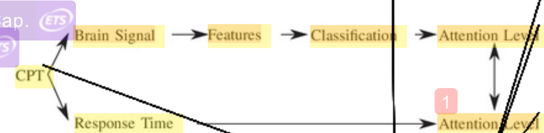

Fig. 1. The research procedure.

the continuous performance test (CPT) advised by [12]. During the test, their brain wave signals were recorded by Neurosky Mindwave EEG sensor. In addition, as a part of the CPT, the respondents' response time are also measured and recorded. The respondents' attentions are assumed to be drop when their response time is much longer than the average.

A. The Continuous Performance Test

Fifteen participants of 20–30 years old were asked to participate in CPT. Figure 2 illustrates the test. The results of the test are the data of the EEG signals and the response time of the respondents. A CPT session takes 5 minutes duration. For every 2 s interval, a random character is presented to the respondents for a short duration of 0.25 s. The respondents is expected to hit the Space key as quickly as possible when any character but 'X' appears. The time required to hit the key is defined as the response time.

The EEG signal was recorded using Neurosky Mindwave EEG sensor. The device samples the brain signals at the rate of 512 Hz. The raw data of the brain signal are the signed integer data type within the range of $-32\,768$ and $+32\,768$. The data were transformed into the frequency domain by applying the Fourier transform:

$$X(\omega) = \int_{-\infty}^{+\infty} x(t)\, e^{-\jmath\omega t} dt, \tag{1}$$

where ω denotes the circular frequency, $x(t)$ is the brain signal in the time domain, and $X(\omega)$ is the signal in the Fourier domain. Subsequently, the spectrum $X(\omega)$ is used to computed the signal power spectral density (PSD) by the equation:

$$\mathrm{PSD} = |X(\omega)|^2, \tag{2}$$

where $|X(\omega)|$ is the modulus.

Finally, the PSD is used to provide the energy of delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) waves. Those waves are differentiated with respect to their frequency contents. The delta waves are within the frequency range of 0.5–3.0 Hz, theta in 4.0–7.0 Hz, alpha in 8.0–13.0 Hz, beta in 14.0–30.0 Hz, and 31.0-50.0 Hz. The energy of each component is simply a summation of all spectra within its defined range. The energy of those five wave types are selected as the features of the brain signal.

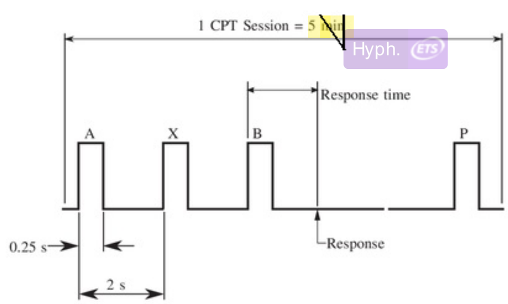

Fig. 2. The illustration of the continuous performance test. One CPT session takes 5 min. A random letter is shown for every 2 s interval for a duration of 0.25 s. When any character but 'X' appears, the test participant is expected to hit the SPACE key as quickly as possible. The response time is defined as the duration the participant required to hit the key, and is the indicator of the attention level.

In addition to the brain EEG signal, the test also provides the data of the respondent response time. This time is related to the level of respondent attention. The response time is usually in the order of a few hundred milli-second.

B. EEG Recording Instrument

The brain waves are recorded by using Neurosky Mindwave EEG sensor. The device has the following specifications (see Table I). The device records the brain wave signal at a sampling frequency of 512 Hz. The raw data of the brain signal have the data type of signed integer with their values are within the range of $-32\,768$ and $+32\,767$.

C. k-NN Classfication Method

The level of attention is simply divided into two levels: strong and weak attention. For the ground truth of the data, the participant attention is considered weak if the participant requires a statistically significant large response time in the CPT. The determining features are the energies of the five types of the brain waves discussed above. As for the classification method, we utilized a very simple pattern classification method that is the k-nearest neighbors algorithm or k-NN. In

TABLE I
THE SPECIFICATIONS OF NEUROSKY MINDWAVE EEG SENSOR.

No	Description
	Features
1	Uses the TGAM1 module
2	Autmatic wireless pairing
3	Single AAA battery
4	8-hour battery run time
5	Bluetooth v2.1 class 2 (10 meters range)
6	Static headset ID (headsets have a unique ID for pairing purposes)
7	iOS and Android support
	Measures
1	Raw-brainwaves
2	Processing and output of EEG power spectrums
3	Processing and output of NeuroSky proprietary eSense meter for attention, meditation, and other future meters
4	EEG/ECG signal quality analysis (cane be used to detect poor contact and whether the device is off the head)
	Physical
1	Weight: 90g
2	Sensor arm up: height: 225mm × width: 155 mm × depth: 92 mm
3	Sensor arm down: height: 225 mm 155 mm 165 mm
	Bluetooth
1	BT version: 2.1
2	BT output power: class 2
3	BT minimum voltage: 1.0V
4	BT range: 10 m range
5	BT power onsumption: 80 mA *(when connected and transmitting)
6	Low bettery indicator 1.1 V
7	UART (serial): VCC, GNC, TX, RX
8	UART baudrate: 57,600 Baud

the method, an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors.

Regarding the classification methods, k-NN and Support Vector Machine (SVM) have been utilized for the case of EEG signal [9], [10], [13]. Reference [9] reported a classification accuracy of 77% by using SVM. Reference [13] compared the two methods and concluded that k-NN provided a higher classfication accuracy.

D. Performance Indicator

The performance of the classification is simply measured in the sense of the classification accuracy, which is defined by

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{3}$$

where TP denotes true positive, TN is true negative, FP is false positive, and FN is false negative.

III. Results and Discussion

This section presents the research results, arranged in the following order. Firstly, in Subsection III-A, we discuss the raw data of the measured response time and their statistical distribution. Secondly, in Subsection III-B, we discuss how the threshold time, a time instance that separates the time associated with the strong attention state and that of the weak attention state, affects the classification accuracy. Thirdly, in Subsection III-C, we discuss the effects of the length of the measured EEG signal to the classification accuracy. Finally, in Subsection III-D, we discuss how the location of the data segment on the temporal dimension affects the classification accuracy.

A. Response Time Data and Their Statistical Distribution

Firstly, we present the data of the response time, which is defined as the time difference between the time when a stimulus is presented and the time of the participant's response. This time is usually very short, in order of ms. The shorter response time is associated with the higher level of the attention state.

The distribution of the response time data in the form of the histogram is shown in Fig. 3. The figure shows that the distribution is rather similar to the log-normal distribution.

The fitness of the data to the log-normal distribution is evaluated numerically by using the χ^2 statistic and graphically by using the quantile-quantile plot. The results are presented in Fig. 4.

The fitness study concludes the following. The test results of the χ^2 statistic is 39.7548 with the associated p-value of 1.201E-08. These results suggest that the assumption of the log-normal distribution is rejected. However, the quantile-quantile plot reveals that the deviation from the assumption of the log-normal distribution mainly occurs when the magnitude of the response time is relatively large. The boxplot, see the figure on the right panel of Fig. 4, shows that the response time is considered an outlier when its value is larger than about 550 ms. The boxplot shows many data are outlier. However,

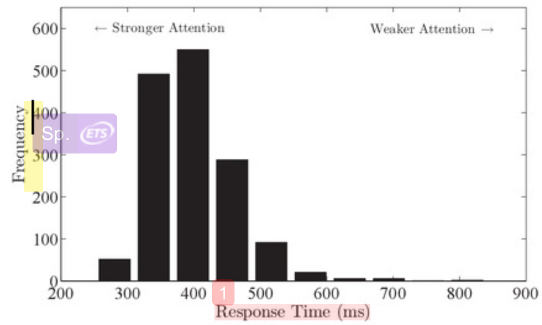

Fig. 3. The distribution of the response time data. The data are fitted with the log-normal distribution with a mean value of 5.98027 (equivalent with the time of 400.0 ms) and a standard deviation value of 0.152886 (equivalent with the time of 61.5 ms). The shorter response time represents the stronger attention state and vice versa.

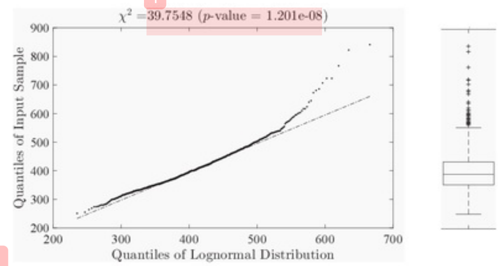

Fig. 4. The quantile-quantile plot of the response time. The data are assumed to follow a log-normal distribution with a mean value of 5.98027 and a standard deviation value of 0.152886. On the right panel, a boxplot is provided and it shows: many data are outliers, marked with '+'

for the small value of the response time, the assumption of the log-normal distribution seems to hold reasonably well.

Subsequently, we eliminate the outlier data, and reevaluate the fitness of the response time data and the log-normal distribution. The results are presented in Fig. 5 where the distribution of the response time data are compared with the distribution of the theoretical log-normal data. The two distributions fit reasonably well.

The response time data are also used to provide a ground truth for the attention level. When the response time is significantly longer than the normal, the attention is considered low. The statistical significance is represented by the quantity of the significance level and is denoted by α. Figure 6 shows the definition of the significance level and its relation to the threshold time.

In Table II, we provide the relation between the significance level α to the value of the response time. Those times are considered to be the critical response time. When a response time value is higher than the critical value, the attention level has dropped from the normal condition.

The measured response time, as reproduced in Fig. 7, show that the quantity is rather random. On various occasions, we witness that the time increased to a very high value.

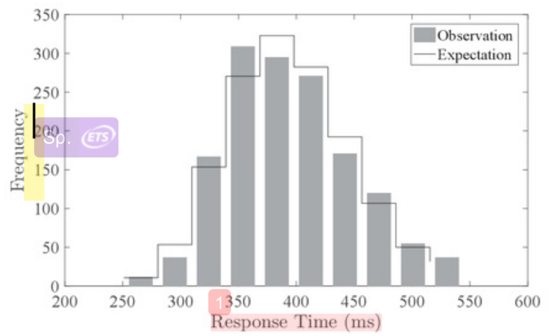

Fig. 5. A comparison of the distribution of the response time data and the log-normal distributed data.

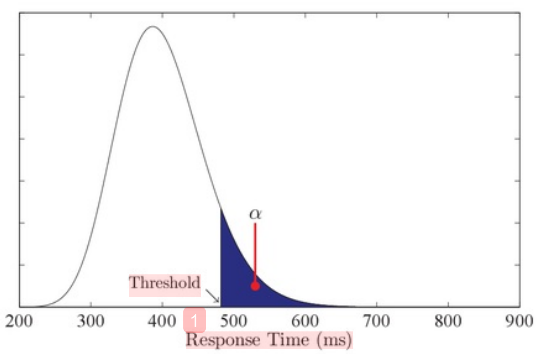

Fig. 6. The definition of the significance level α for defining the condition of weak attention. The significance level is the probability that the response time is longer than the specified threshold. The significance level is set at 5%, 10%, 15%, and 20%.

TABLE II
THE THRESHOLD TIME AND THE PROBABILITIES THAT THE ATTENTION TIME TAKES A VALUE HIGHER THAN THE THRESHOLD TIMES.

Threshold time (ms)	507	483	467	455
Significance level α	0.05	0.10	0.15	0.20

B. Threshold Time and Its Effect on Classification Accuracy

Many previous studies suggest that the response time could be an indicator of attention. Those with a high level of attention could provide response to the visual excitation within a short duration. Those with a low level of attention might require more time. The previous results show that the variation of the response time data, as an aggregate, is rather a smooth function, not an abrupt change.

In this study, we set an onset of time from which the strong attention condition is differentiated from the weaker attention condition. Table II shows a number of the threshold times and the level of significance. The definition of the significance level is defined in Fig. 6. It is essentially defining the probability of occurrence that the response time is higher than the threshold time.

We study for four setting of the threshold time, namely, 507 ms, 483 ms, 467 ms, and 455 ms. They are related to the significance levels of 0.05, 0.10, 0.15, and 0.20. We study whether the threshold is able to differentiate the strong conditions from those of weaker attention. The study is performed indirectly by accessing the accuracy of the classification. Theoretically, a clear discrepancy between features of attention and those weak attention should lead to a high level of classification accuracy. In the other words, the low classification accuracy may be attributed to the features that they are not uniquely associated to the conditions under consideration.

The results are presented in Fig. 8. It shows that the accuracy is higher with lower significance level α or higher the threshold time. Indirectly, these results suggest that the features of strong attention and less attention are much more different.

C. The Effects of the Length of the Measured EEG signal

In the present study, the two measured quantities are the response time and the EEG signal. Both are measured since the time the stimulus letter is presented. In this section, we discuss the duration of the measurement of the EEG signal and how it affects the classification accuracy.

We evaluate the accuracy for four duration of measurements: 500, 1000, 1500, and 2000 ms. As the interval between two successive letters is 2000 ms, the measurement duration of 2000 ms means that the measurement is performed continuously along the 5-minute CPT session.

The effects of the EEG signal duration to the classification accuracy are depicted in Fig. 9. The figure suggests the following. For the EEG signal duration of 500 ms, the accuracy of predicting the attention level is very low at around 50%. However, the accuracy increases quickly with increasing the signal duration. At the signal length of 1000 ms, the accuracy is about 58% on the median sense. From the point forward, the improvement of the accuracy with the increasing signal duration is relatively small. The accuracy using the signal duraction of 1500 ms and 2000 ms is about the same.

D. The Effects of Segment Data Position on the Temporal Dimension

The term temporal dimension denotes the time along the 5-minute CPT session.

Naturally, we may expect that on the average, the attention of the respondents are high at the beginning of the CPT session and drops with time due to fatigue. At their best, the participants may show the capability of maintaining their level of attention through the time. We do not expect that the attention level to be increasing monotonically or on the average with the time.

On the basis of the above description, in the section, we study how the attention level changes across the temporal dimension in a CPT session. We only consider three segments: the initial, middle, and final segments. The initial segment means that the high attention level features are extracted

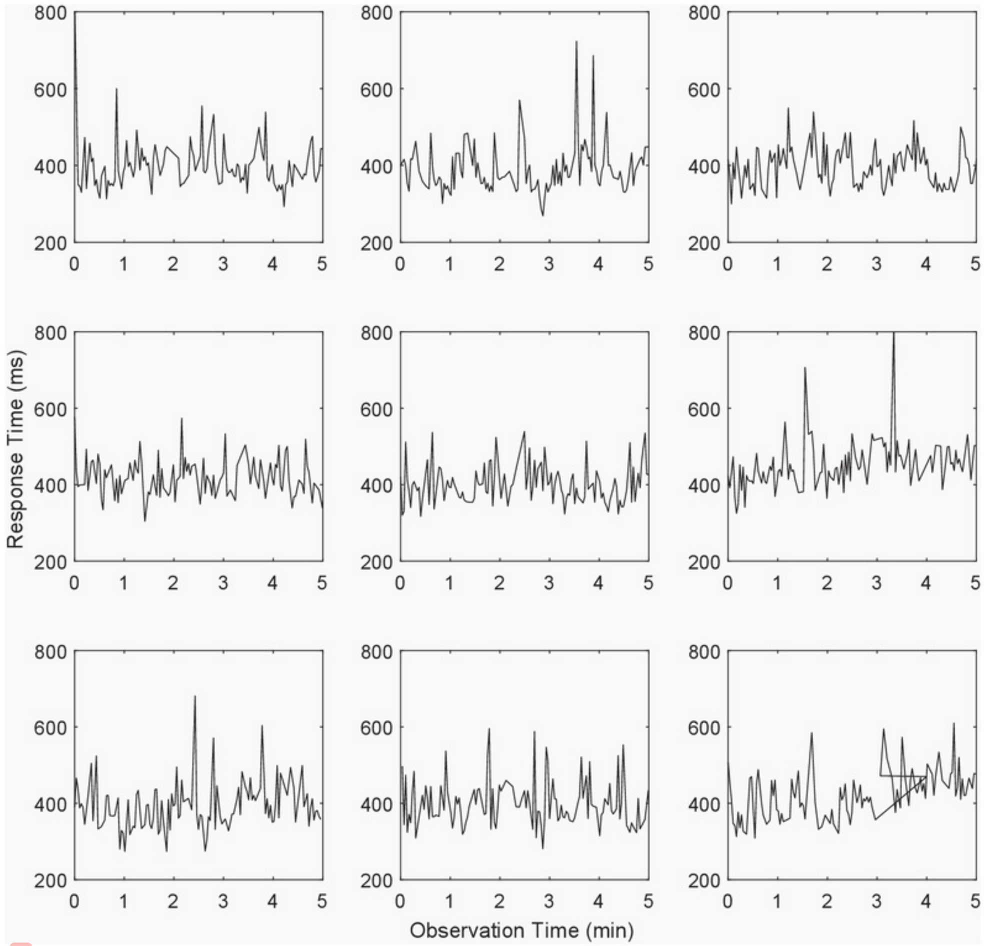

Fig. 7. The change of the response time during the observation time. Only the results of nine respondents are shown in the figure.

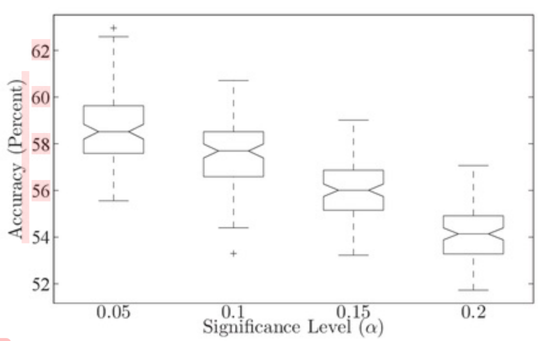

Fig. 8. The effects of the response time threshold to the classification accuracy.

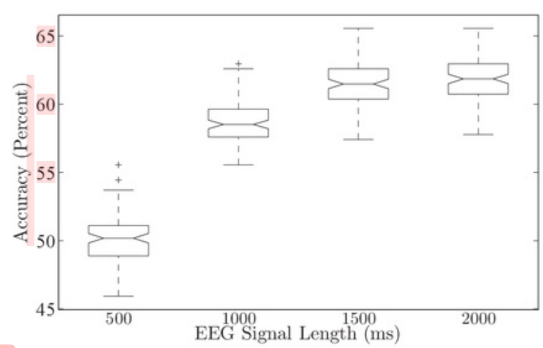

Fig. 9. The Effects of the Duration of the Measured EEG Signal to the Classification accuracy.

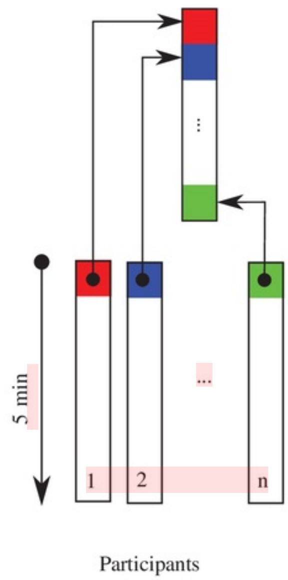

Fig. 10. The illustration of the use of the initial segments of the data of the CPT session as the attention data set.

We use the features associated with the attention condition on the three segments and compare them to the weak attention condition. In addition, we also take the attention data randomly across the CPT session. This scenario is illustrated in Fig. 10. The figure illustrates the case where the attention data are taken from the initial segment of the CPT session. From each respondent, we take the initial attention data and arrange them to construct a data set of the attentive condition.

The results of this study are shown in Fig. 11. The classification of the strong and weak attentions is much better when the attention data are taken from the initial segment of the CPT session. Using this data set, the classification of the strong and weak attentions can be achieved at an average of about 70%. The same level of accuracy is also achieved when the attention data set is taken from the middle segment of the CPT session. The worst accuracy is given by the data set taken randomly and from the final part of the CPT session.

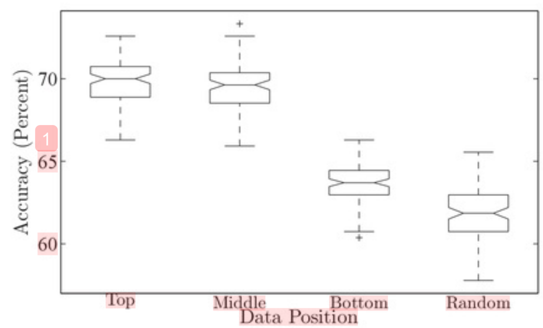

Fig. 11. The effects of the segment of data on the classification accuracy. The segment of data on the initial measurement time provides the highest classification accuracy.

IV. Conclusions

This research intends to evaluate to which extend the early drop of attention can be detected from the EEG signals. The research uses EEG data taken from the participants of the continuous performance test where the attention level is accurately monitored from the response time the participants when a stimulus is provided. The following aspects were noted from the data and analysis. The use of EEG features taken from the initial segment of the test when the attention level is assumed to be the highest leads to the highest classification accuracy. The EEG signal that measured after the stimulus is displayed should be measured for a duration longer than 1 s. The change of attention is much more pronounce on the response time data than in the EEG signal.

References

[1] J. N. Bassili, "Emotion recognition: the role of facial movement and the relative importance of upper and lower areas of the face." vol. 37, no. 11. American Psychological Association, 1979, p. 2049.

[2] S. Marouane, S. Najlaa, T. Abderrahim, and E. K. Eddine, "Towards measuring learners concentration in e-learning systems," *International Journal of Computer Techniques*, vol. 2, no. 5, pp. 27–29, 2015.

[3] H. Hindarto and S. Sumarmo, "Feature extraction of electroencephalography signals using fast fourier transform," *CommIT (Communication & Information Technology) Journal*, vol. 10, no. 1, pp. 49–52, 2016.

[4] C. Busso, Z. Deng, S. Yildirim, M. Bulut, C. M. Lee, A. Kazemzadeh, S. Lee, U. Neumann, and S. Narayanan, "Analysis of emotion recognition using facial expressions, speech and multimodal information," in *Proceedings of the 6th international conference on Multimodal interfaces*. ACM, 2004, pp. 205–211.

[5] S. Nomura, M. Hasegawa-Ohira, Y. Kurosawa, Y. Hanasaka, K. Yajima, and Y. Fukumura, "Skin tempereture as a possible indicator of student's involvement in e-learning sessions," *International Journal of Electronic Commerce Studies*, vol. 3, no. 1, p. 101, 2012.

[6] M. Butti, A. Pastori, A. Merzagora, C. Zucca, A. Bianchi, G. Reni, and S. Cerutti, "Multimodal analysis of a sustained attention protocol: Continuous performance test assessed with near infrared spectroscopy and eeg," in *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE*. IEEE, 2006, pp. 1040–1043.

[7] A. Belle, R. H. Hargraves, and K. Najarian, "An automated optimal engagement and attention detection system using electrocardiogram," *Computational and mathematical methods in medicine*, vol. 2012, 2012.

[8] K. Takahashi and M. Ueno, "Improvement of detection for warning students in e-learning using web cameras," *Procedia Computer Science*, vol. 35, pp. 747–756, 2014.

[9] N.-H. Liu, C.-Y. Chiang, and H.-C. Chu, "Recognizing the degree of human attention using eeg signals from mobile sensors," *Sensors*, vol. 13, no. 8, pp. 10 273–10 286, 2013.

[10] Z. Wan, J. He, and A. Voisine, "An attention level monitoring and alarming system for the driver fatigue in the pervasive environment," in *International Conference on Brain and Health Informatics*. Springer, 2013, pp. 287–296.

[11] H. Hindarto and S. Sumarmo, "Feature extraction of electroencephalography signals using fast fourier transform," *CommIT (Communication & Information Technology) Journal*, vol. 10, no. 1, pp. 49–52, 2016.

[12] H. E. Rosvold, A. F. Mirsky, I. Sarason, E. D. Bransome Jr, and L. H. Beck, "A continuous performance test of brain damage," *Journal of Consulting Psychology*, vol. 20, no. 5, pp. 343–350, 1956.

[13] R. M. Mehmood and H. J. Lee, "Emotion classification of eeg brain signal using svm and knn," in *Multimedia & Expo Workshops (ICMEW), 2015 IEEE International Conference on*. IEEE, 2015, pp. 1–5.

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