Journal of Medical and Biological Engineering (2018) 38:847–856
https://doi.org/10.1007/s40846-017-0344-z

ORIGINAL ARTICLE

EEG-Based Detection Model for Evaluating and Improving Learning Attention

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Received: 10 October 2016 / Accepted: 19 May 2017 / Published online: 18 December 2017

Abstract
People are often tempted by external factors which lead to decreased attention. Failing to concentrate over the long term will gradually cause the inability to focus, which creates obstacles for learning and decreases one's ability to learn. However, using the proper recovery method, attention can be restored, thereby improving learning effectiveness. Thus, how to measure a student's attention level precisely, and how to provide an effective attention recovery method for are topics worth attention in the field of learning. An attention level assessment model based on EEG analysis is developed to measure subjects' attention level precisely during learning exercises. The study also observes the relationship between brain wave changes and varying attention levels during learning, and provides attention recovery methods that can help students restore attention and improve their learning efficiency. The study finds that napping is a good recovery method which can help male and female leaners recover their focus states. Conversely, adopting a recovery method which the participant finds more attractive (e.g., playing mobile games or watching YouTube) leads to increased focus on the more attractive activity, and fails to restore attention to the original task.

Keywords Electroencephalography (EEG) · Attention · Attention recovery · Learning performance · Associative Petri net

1 Introduction

While the rapid development of mobile Internet services has spawned a diversity of applications and ushered in an era of convenience, many negative issues have also resulted, including a perceptible decrease in students' learning attention. During learning activities, students are often tempted to browse webpages, check Facebook, and play online games, all of which lead to decreased attention. Over the long term, however, failure to concentrate will gradually leave students with an inability to focus, a lack of patience and organizational competence, an impaired memory, insufficient intelligence, and a decreased ability to interpret information, stunting their ability to overcome learning obstacles and learn [1]. From the cognitive psychology perspective, attention and learning are thought to be tightly bound together. Attention is positively correlated with learning, memory, and recognition capability. The higher the level of concentration, the more efficient the learning. Proper attention recovery methods can help restore attention during the learning process, thereby improving learning effectiveness [2]. Therefore, how to precisely measure a learner's attention level and provide proper methods for attention recovery are topics worthy of attention in the field of education and learning.

Most past studies related to attention and learning have employed questionnaires, scales and experimental measures, which were unable to directly and rapidly measure the subject's attention level or allow for instant examination and feedback. The electroencephalogram (EEG) takes advantage of the inherent features of brain waves, instantly displaying the subject's attention level and allowing researchers to measure various aspects of attention. It has proven to be a fast, objective tool for evaluating attention levels [2, 3]. However, since EEG signals are relatively weak and subject to interference and noise, they can be hard to recognize. The emitted signals will also differ depending on the individual, the subject's physiological status, and the time zone. For example, fatigue, pain and even closed eyes can distort the measurements [4]. As such, the reduction of brain wave signal errors proves critical to the precise evaluation of

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attention level. Past studies related to brain waves and attention level have pivoted on measurement, with little description of how the features of the brain waves change between learning and various attention levels.

Therefore, by combining singular value decomposition, the Fourier transform, the minimum entropy principle, and an associative Petri net, this study provides a means by which to analyze and process information of personal brain wave features to reduce errors in measurement. An attention level assessment model is developed to precisely measure subjects' learning attention level. Our experiment observes the relationship between changes in brain waves and attention level during learning activities, and we provide methods for attention recovery to help learners restore attention and improve learning efficiency.

2 Literature Review

2.1 Electroencephalogram

Electroencephalography (EEG) is typically a non-invasive method to record the electrical activity of large ensembles of neurons in the brain. Electrodes are placed on the scalp and the computer records the brain's electrical activity as waveforms. Many studies have indicated that different brain activity frequencies in the frontal lobe are highly associated with personality, emotion, attention, rationality and creativity [5–7]. Therefore, EEGs can be used to determine changes in attention state.

According to the International Federation of Societies for Electroencephalography and Clinical Neurophysiology, EEG bands are divided by frequency, ranging from low to high: delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), and beta (14–30 Hz). Alpha waves occur when people are awake, quiet, calm, stable and focused. Beta waves occur when people are actively thinking and engaged in work. Beta waves can also be associated with feelings of nervousness, anxiety, overexcitement, and tension. Theta waves appear during drowsiness and light sleep, and rarely occur in normal adults who are fully conscious. Delta waves are found during sleep and do not appear in normal adults who are awake.

A great deal of research has provided evidence that brainwave frequencies are closely related to attention state. Changes in the amplitude and frequency of alpha, beta, and theta waves can reflect different states of attention. Prinzel et al. [6] discovered that an increase in workload and attention is marked by an increase in alpha waves and a decrease in theta waves. Another study demonstrated that the amplitude of alpha waves diminishes when participants concentrate on doing mental math. Moreover, an increase in theta waves and a decrease in the beta band can greatly improve concentration and memory [5, 8, 9] suggested that theta waves are correlated to sustained attention, message processing, and resource distribution. Furthermore, sensory stimulation, perceptual performance, and cognitive processes can decrease alpha amplitudes. A decrease in alpha amplitudes and an increase in frequency indicate deep concentration [10].

2.2 Attention

Attention is an important mechanism for learning, and is indispensable for life in general. Eysenck and Keane defined attention as the ability to focus on a specific thing [11]. Coull [12] described attention as the allocation of processing resources stimulated by different locations, objects or time. Attention is commonly known to be a complex neural and psychological phenomenon involving many different brain structures and mechanisms [13]. Mayer and Moreno [14] described attention as placing the focus of one's behavioral or cognitive process on one or multiple stimuli.

Scholars have classified attention into several different types [15–17] which are defined as follows. *Selective* attention: maintaining a response set despite distractions. *Divided* attention: responding to more than one task at a time. *Sustained* attention: maintaining a consistent response in the face of continuous, repetitive activity. *Focused* attention: responding to stimuli sequentially presented in a certain modality. *Alternating* attention: switching attention back and forth between activities that require different responses.

Learning involves transferring sensory information such as message, movement and language into short-term memory and, ultimately, into long-term memory. However, short-term memory cannot be transferred into long-term memory without a certain level of attention. Reif [18] suggested that attention plays a key role in learning, affecting the depth of message processing and learning effectiveness. In other words, learning effectiveness is influenced by attention level [19]. For determining the level of attention, EEGs can directly and quickly reflect the attention state, providing more objective and practical insights for attention evaluation.

2.3 Related Work

Most past literature on brainwave-based attention measurement has used EEGs to obtain different waveforms, and then employed methods such as data mining, artificial neural networks, and statistical analysis to automatically determine the level of attention. EEG signals can be analyzed in the time and frequency domains, and the most-discussed features are waveform, band, and band power in the alpha, beta, and theta bands. The features are described in Table 1. For example, Ghassemi et al. [3] used a visual continuous performance test to explore sustained visual attention. They used a 19-channel EEG recording, extracted 58 features by computing the components' amplitude and latency, and then applied linear discriminant analysis (LDA) to discriminate the attention classes. Sauseng et al. [9] examined frontal midline theta activity and discovered that an increase in theta waves reflects focused attention, confirming the close relationship between theta rhythm and attention. Doppelmayr et al. [20] investigated brainwave activity during rifle shooting, and found that frontal midline theta waves increase steadily before the shot. Some researchers have also discovered that when athletes are highly focused, alpha and beta activities increase in the left temporal region, though there is no significant change in the right temporal region [21–23].

Klimesch et al. [24] found that alpha power increases when people are attentive, and decreases during attention shifts, showing that alpha waves change as attention shifts. Huang et al. [25] recorded EEG data as participants underwent driving simulations. They applied independent component analysis (ICA) and time–frequency analysis to study brain dynamics and found that alpha power in the occipital cortex changes in better attention conditions. Li's [26] study used a visual attention task, and the results suggest that while alpha rhythms are stronger in an attention task, there are no significant differences in theta and beta rhythms. Yan et al. [27] used a directed transfer function (DTF) to estimate the direction of propagation of EEG function coupling, and the results indicate that the DTF-diff in alpha and beta declines in the focused attention state. Li et al. [2] analyzed the amplitude, frequency and entropy of EEG measurements by k-Nearest Neighbor (kNN) and Naive Bayes to distinguish concentration behavior. Li et al. [28] designed four experimental scenarios (eyes closed, silent reading, conceptual understanding, and mental math test) to gain differences based on EEG bands. Muangjaroen and Wongsawat [29] conducted a golf putting experiment and calculated the power spectrum of the putts. Their results show that high alpha power and theta power are found when golfers' attention is highly focused.

Ming et al. [30] designed three experimental tasks: attention (playing tennis), inattention (thinking about things other than playing tennis), and rest. They analyzed the EEG data statistically to evaluate attention level. To obtain data for each band of brainwaves, Xu et al. [31] used four activities: relaxation (no attention), viewing computer images (low attention), playing a simple math subtraction game (middle attention) and complex mathematical multiplication and division games (high attention). They then applied the approximate entropy and fuzzy entropy methods to classify attention into four levels. Based on the above studies, brainwaves and other physiological parameters can be used to detect different levels of attention. Accordingly, this study intends to use the power densities in alpha, theta and beta frequencies as the main features by which to measure attention state.

Table 1 Features descriptions

	Features	Description
x_1	Alpha band (α)	Average amplitude of the α band
x_2	Lower alpha band (α_L)	Average amplitude of the α_L band
x_3	High alpha band (α_H)	Average amplitude of the α_H band
x_4	Lower beta band (β_L)	Average amplitude of the β_L band
x_5	Theta band (θ)	Average amplitude of the θ band
x_6	High beta band (β_H)	Average amplitude of the β_H band
x_7	SMR	Sensorimotor rhythm

3 Materials and Methods

This section is a brief description of methods used in this research such as singular value decomposition (SVD), the Fourier transform, the minimize entropy principle approach (MEPA), and an associative Petri net (APN) to process, transform and analyze brainwave features.

3.1 Participants and Materials

Our experimental subjects were ten physically and mentally healthy graduate students: five male and five female. Ages ranged from 24 to 26 (average age = 24.2). We screened participants in order to exclude smokers and anyone who reported psychiatric or neurological disorders, head trauma or a history of drug or alcohol abuse. All participants had normal sight, and all were right handed as assessed by the Edinburgh Handedness Inventory, a measurement scale published by Oldfield in 1971 [32–34]. Participants were required to sleep at least 8 h each day for the two days before the experiment. The EEG signals were recorded using the MindWave Mobile headsets designed by NeuroSky. Electrodes were placed on the participant's frontal lobe and the sampling frequency was set to 512 Hz. The EEG signals were transmitted to computer via Bluetooth and processed using EEGLAB Toolbox running in MATLAB R2012a [35].

Many studies have proven the Sustained Attention to Response Task (SART) to be an effective measure of sustained attention and response [36, 37]. Among SARTs, GO/NOGO tasks have been shown to be particularly useful in evaluating sustained attention [32]. Therefore, our experiment used a GO/NOGO task (i.e., "respond to the digits 1–9 with one exception: do not respond to the digit 3") to measure attention level.

In the experiment, three SART parameters were recorded to evaluate the attention state. (1) NOGO success: properly withholding a response to digit 3. (2) Omission error: missing responses to any digit other than

3. (3) Mean response time: all reaction times of correct responses to any digit other than 3 were included to calculate the mean and standard deviation of response time.

The experiment was divided into two sessions, and each session contained two blocks of SART trials. We used SART to lead the participants into a state of focused attention and recorded the EEG signals under attention/inattention tasks. In our SART, a digit (varying from 1 to 9) was presented on the monitor in one of five randomly selected font sizes. Each digit appeared for a short time only (250 ms), followed by a 900 ms mask. The trial duration of a digit plus the mask was 1.15 s. For each block of trials, each digit appeared 25 times (total 225 times) and each font size appeared 45 times. A block of trials took about 4.3 min to complete. Participants were instructed to press the spacebar in response to all stimuli except for the digit 3, as shown in Fig. 1.

In the first session, five minutes before the experiment started, participants were checked to ensure their MindWave Mobile headsets were properly situated and that any devices (e.g., mobile phone, digital watch) that might disturb EEG signals had been turned off. They were also informed of the research method and experiment procedures. Then, participants undertook 2 blocks of trials (total about 10 min) and were asked to stay focused throughout the trials [38]. Following the SART trials, the participants took a 15-min, eyes-closed rest [39]. The first session lasted about 30 min, after which participants rested for 5 min and prepared to undergo the second session, which took about 25 min. In total, participants performed 4 blocks of SART trials. Their EEG data were recorded to build the research model.

The omission rate and the NOGO success percentage were examined to evaluate participants' attention state. In accordance with past literature, we set a threshold that allowed for a maximum omission rate of 0.05% and a minimum NOGO success rate of 60% [32]. Participants were asked to stay focused during the entire experiment, otherwise they would need to go through the experiment again.

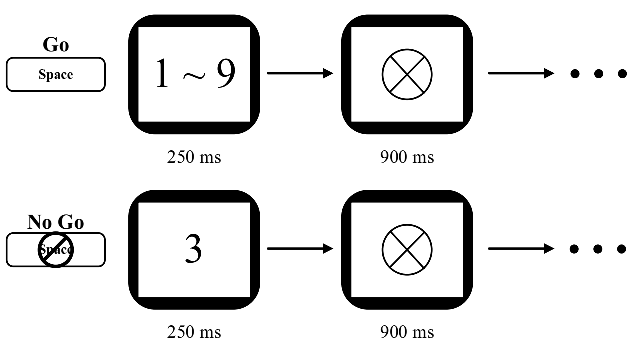


Fig. 1 Sustained attention to response task

3.2 Singular Value Decomposition

The singular value decomposition (SVD) is a technique of decomposing a real or complex matrix and can be used to filter signals. It is widely used in signal processing and statistics fields. Through the rotation and decomposition of matrices, it can decrease the noise of EEG signals. Past research indicated that SVD can not only effectively remove signal noise but also retain important characteristics of signals [40]. SVD is calculated as:

$$S = U \sum V^T \tag{1}$$

where S is an $m \times n$ matrix, U is an $m \times m$ orthogonal matrix, V is an $n \times n$ orthogonal matrix, and is an $m \times n$ diagonal matrix.

3.3 Fast Fourier Transform

The fast Fourier transform (FFT) algorithm computes the discrete Fourier transform (DFT) of a sequence, or its inverse. The Cooley-Tukey FFT is adopted to transform time-domain signals into frequency-domain signals. It divides a DFT of size N into two interleaved DFTs of size $N/2$ with each recursive stage. The DFT is defined by the Eq. (2), where x_n is the original signal and N is the sequence number (which has to be a power of 2).

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j\frac{2\pi}{N}kn}, k = 0, 1, 2, 3, \ldots, N-1. \tag{2}$$

3.4 Minimize Entropy Principle Approach

The minimize entropy principle approach (MEPA) creates the fuzzy membership function by applying information entropy. Through MEPA, data are divided into different segments using the interval partition method. The minimized information entropy method is then used to assess the degree of information entropy within each specific data interval. The interval partition of the minimum information entropy can be determined from this assessment [41].

3.5 Associative Petri Net

Associated Petri net (APN) is a mathematical and graphical modeling tool to describe parallel and concurrent behavior of complex system. It is an advanced Petri Net which incorporates an Apriori algorithm with ordinary Petri nets, to generate associative production rules (APRs) which can express the associative degree between two propositions. APNs have the ability to express knowledge and supporting rule-based reasoning to solve decision making problems. The APN model consists of five APR types, each with its own computing method [42]. Therefore, association knowledge in application systems can infer through APRs and reasoning algorithm. Also, APNs have widespread application in the artificial intelligence and data mining area.

4 Experiment

The process of building a model to diagnose attention can be divided into three steps: (1) data processing, in which EEG signals are classified into one of two states: attention and inattention; signal filtering is also done in this phase; (2) feature extraction, in which a Fourier transform is used to transform time-domain brainwave characteristics into frequency-domain characteristics, and important features are extracted; and (3) diagnosis of attention, for which we adopted MEPA and APN for the transfer function and the classification of attention state [43].

4.1 Data Processing

We obtained experimental data from 20 blocks of attention/inattention states. We excluded data from the first minute and the last minute of each block, and divided the remaining data into 30-s segments. After eliminating data containing missing values, we obtained 810 records (attention: 346 records; inattention: 464 records). Figure 2 shows changes to the brainwave signal waveforms before and after SVD filtering.

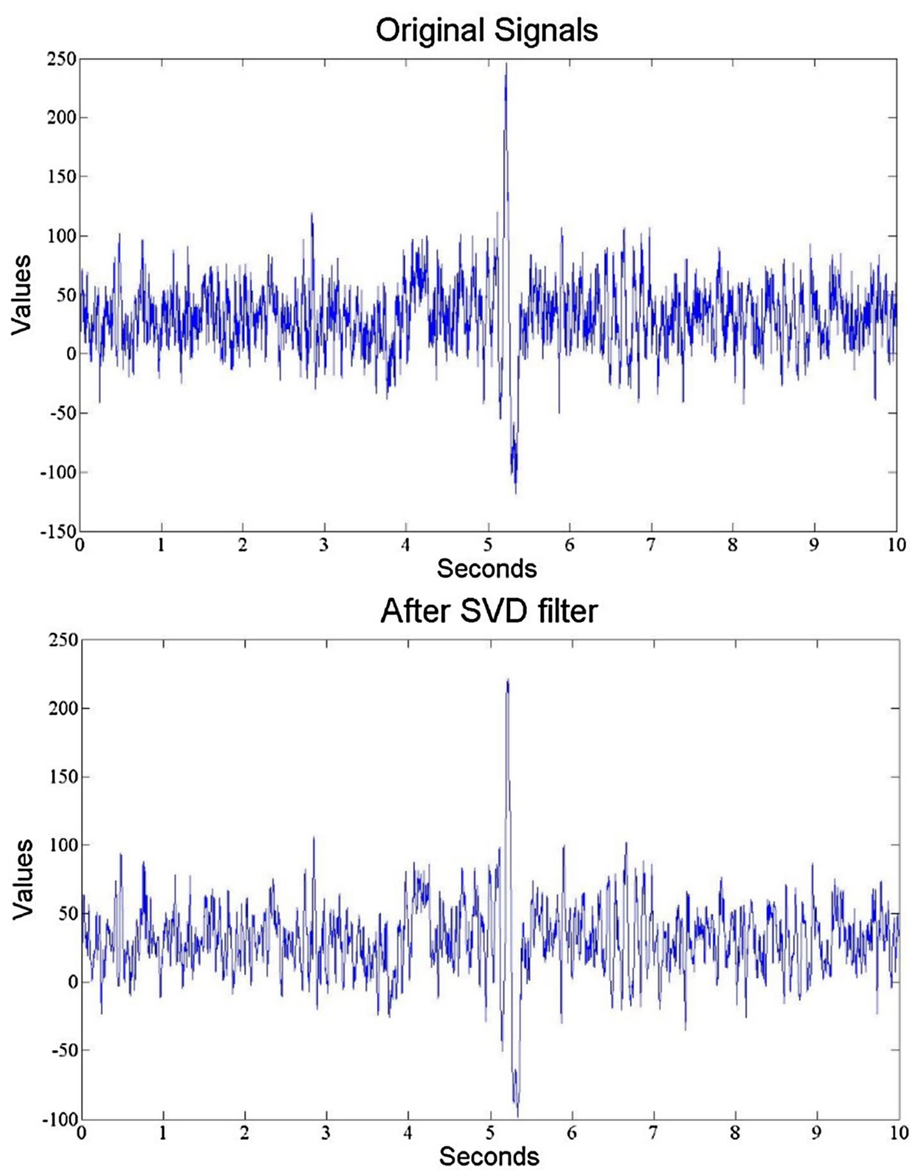


Fig. 2 Comparison of EEG signals before and after filtration

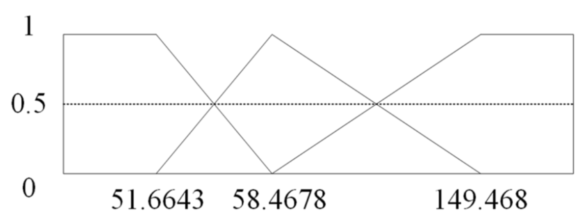
4.2 Feature Extraction

Most past studies on EEG have focused on EEG signals from the frequency domain perspective and extracted certain features for analysis. The present study focuses on the following band features: theta, lower alpha (LA), high alpha (HA), Alpha, lower beta (LB), high beta (HB), and Sensorimotor rhythm (SMR). A fast Fourier transform was performed in MATLAB R2012a to change the raw EEG into frequency-domain data, and power spectral density (PSD) was used to calculate the distributions of the extracted features in the attention and inattention states.

4.3 APN Model Construction

MEPA was adopted to build the fuzzy membership function for each feature. The fuzzy membership functions for theta are shown in Fig. 3. Its corresponding linguistic values and membership degrees were defined based on different characteristics and conditions. The information gain for each feature was then calculated to determine its importance in the diagnosis of attention. A larger information gain implies that the information entropy is smaller and the feature plays a more important role in evaluating attention level.

In our APN model, the linguistic value and membership degree of a feature was mapped to its associated proposition and degree of truth. We then calculated the relationship between each feature and attention. The thresholds of support and confidence degree were set to 0.05. Using these thresholds, we determined whether there was any relationship between the features. The association production rules (APRs) were applied in building the model for diagnosis of attention shown in Fig. 4.



$$\text{Theta} = \begin{cases} Theta_L = \begin{cases} 1 & x < 51.6643 \\ \dfrac{58.4678 - x}{6.8035} & 51.6643 < x \le 58.4678 \end{cases} \\ Theta_M = \begin{cases} \dfrac{x - 51.6643}{6.8035} & 51.6643 < x \le 58.4678 \\ \dfrac{149.468 - x}{91.0002} & 58.4678 < x \le 149.468 \end{cases} \\ Theta_H = \begin{cases} \dfrac{x - 58.4678}{91.0002} & 58.4678 < x \le 149.468 \\ 1 & x > 149.468 \end{cases} \end{cases}$$

Fig. 3 Fuzzy membership function of Theta

4.4 Evaluation of Constructed APN Models

In order to compare our proposed APN model with other approaches to data mining (i.e., Decision Tree, Neural Network, Support Vector Machine (SVM), Naïve Baye (NB) and Bayes Net), the 810 records obtained from the attention experiment were used as training and testing data. In the decision tree model, the minimum split node size was 2, and the pruning threshold was set to 0.25. In multilayer perceptron, one type of artificial neural network, learning was run for 500 iterations with a learning rate of 0.3. The SVM was set to perform with a 3-dimensional polynomial kernel. The cross-validation process was repeated 10 times for each method to test the classification results. As shown in Table 2, our APN model outperformed the other data-mining methods in precision rate, recall rate, F-measure, G-mean, and accuracy. This result was further compared with those of Fathy et al. [39], in which EEG recordings were obtained from three healthy subjects using a 14-channel EEG device with a sampling rate of 128 in order to detect attention state. As shown in Table 3, the comparison result indicates that our APN model can successfully detect attention state.

4.5 Attention Recovery

The present study also conducted experiments to evaluate the effectiveness of attention recovery methods. Four attention recovery methods were added to our SART to evaluate

Fig. 4 An APN model for attention state detection

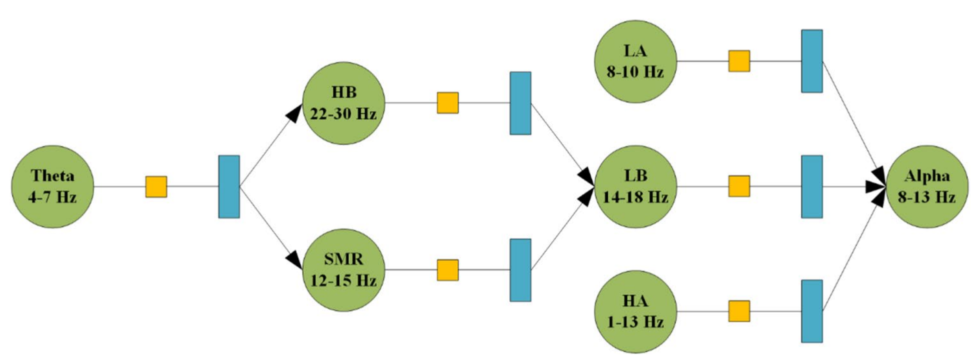


Table 2 Performance measure of different approach

Methods	Precise (%)	Recall (%)	AUC	F-measure	G-mean	Accuracy (%)
C4.5	72.75	72.54	0.811	0.726	0.760	76.7
Neural Network	77.74	73.69	0.865	0.756	0.788	79.8
SVM	47.23	54.33	0.545	0.505	0.545	54.6
Bayes Net	67.8	60.98	0.699	0.642	0.691	71.0
NB	51.7	67.63	0.674	0.586	0.598	59.3
APN	92.12	84.68	0.904	0.882	0.895	90.4

Table 3 Comparison with other research

Dimensionality reduction	Methods	Accuracy (%)	Author
Principal component analysis	LDA	70	Fathy et al. [39]
	NB	69.5	
	SVM	69.6	
	DBN	83	
Information gain	APN	90.4	Our study

their recovery effects. By using convenience sampling, we interviewed 28 graduate students (20 males) to select the 4 most used attention recovery methods. The average age of the interviewees was 24.6. Two participants (one male and one female) took part in the experiments. Participants first undertook SART trials for about 20 min and then applied an attention recovery method for 10 min. Following the 10-min attention recovery activity was a 20-min SART. Brainwave signals and related parameters were recorded during the experiment which lasted about 1 h in total. The experiments were administered over a four-day period, and one recovery method was applied on each day. On the first day participants recovered by closing their eyes and napping with the lights off. On the second day, they watched talk shows about gender and relationships on YouTube. On the third day they played puzzle games on a mobile phone. On the fourth day, they browsed goods online and searched for desired targets (online shopping). In each of the experiments, we tried not to disturb the participants. Lastly, we observed the recovery effects of these four methods.

By observing the power spectral density (PSD) of alpha, we can recognize changes in participants' attention states. Figure 5 shows the alpha activity in the experiment, including the recovery method of napping. The lower power of alpha indicates that the participants are more focused. Alpha power below the red line (75.25) represents participants' increased attention (i.e., the attention state), while alpha power above the blue line represents decreased focus (i.e., the inattention state). Figure 5 shows that participants started to be less focused at about 10 min after the experiment began, and remained in the inattention state before the 10-min break. As shown in Fig. 6, response times also became prolonged around 10 min after the experiment began. The data clearly shows that participants became less focused as time passed.

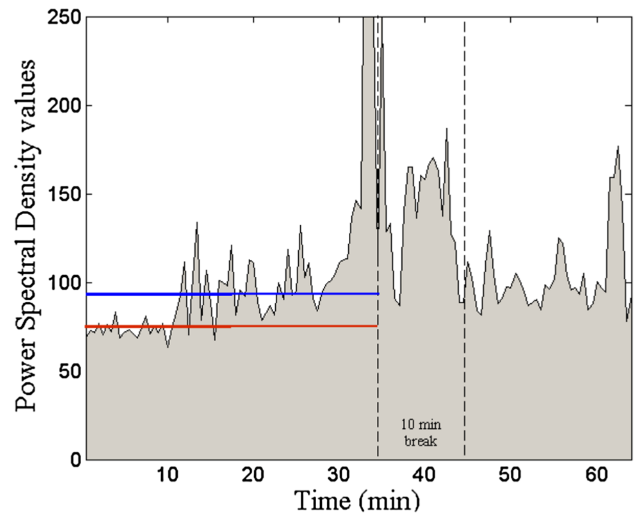


Fig. 5 Power spectral density of alpha

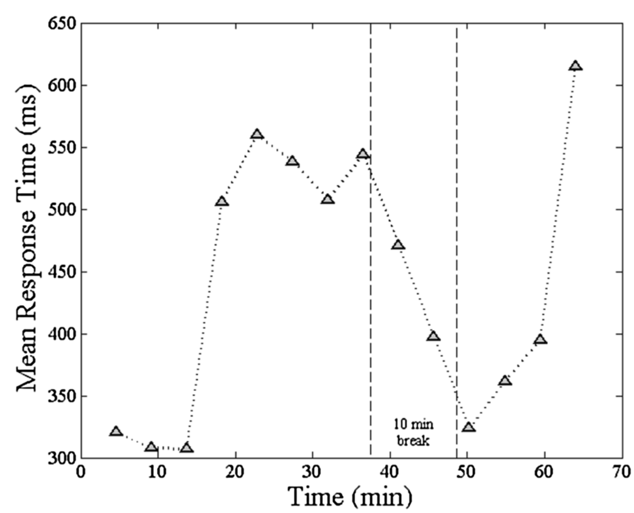


Fig. 6 Mean response time (ms)

We conducted a *pair*-sample *t* test to evaluate the effects of attention recovery methods. The 18-min "low attention phase" in the last part of the first block of SART (38-min) and the 18-min "high attention phase" after the recovery activity were selected as the paired samples (see Fig. 7). EEG data were recorded on each of the four testing days, and the mean value of alpha's PSD was analyzed by gender to determine if there are gender differences in the influence of different attention recovery methods.

4.6 Male Sample

We conducted a *pair*-sample *t* test for male participants, and the study results revealed significant differences in closed-eyed resting (i.e., "napping") ($p = 0.021$), watching YouTube ($p = 0.01$), and online shopping ($p = 0.006$), while no significant difference was found in playing mobile games ($p < 0.729$). By studying the mean value of alpha's PSD in the phases of low attention, recovery and high attention, we discovered that participants' attention level changed in these phases when different recovery methods were applied. As shown in Table 4, when participants applied the recovery method of napping or watching YouTube, the mean value of alpha's PSD was higher in the recovery phase (MeanR) than it was in the low attention phase (MeanL), suggesting that these two methods did help participants relax and rest. The mean value of alpha's PSD decreased in the high attention phase (MeanH) after the recovery activity, and the omission rate and response time were both under the threshold, indicating that participants regained concentration after applying the recovery methods.

In the experiment that included playing mobile games and online shopping, the participants were even more focused in the recovery phase than in the low attention phase. It is possible that the type of attention that participants used in the SART experiment was focused attention. When playing mobile games, participants shifted their attention from the SART to something more attractive. Therefore, the degree of focus was the same or even higher in the recovery phase. Since playing mobile games induced the participants to stay focused for a longer period of time, their attention level declined faster in the high attention phase (the omission rate was substantially higher and the NOGO success percentage decreased).

Regarding the online shopping recovery method, it seems possible that this activity was not highly attractive to male participants. Although it also involved a shift in attention, the type of attention changed from focused to divided attention. Therefore, the mean value of alpha's PSD indicated that participants remained in the attention state. However, the increase in the omission rate and the decrease in the NOGO success percentage indicate that the participants were distracted and could not return to a focused state. In summary, recovery methods such as napping and watching YouTube assisted the recovery of attention, while playing mobile games and online shopping appeared to render the participants unable to recover their attention level.

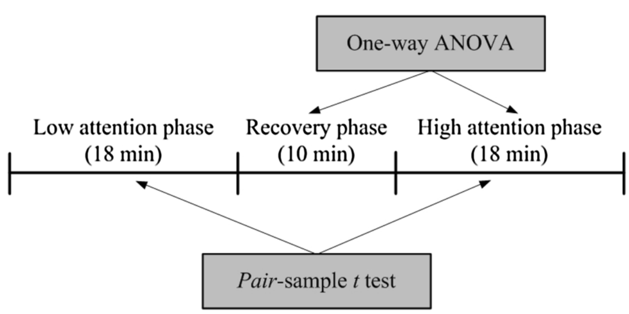


Fig. 7 Different phases of attention recovery

4.7 Female Sample

Besides analyzing the data collected from male participants, we also conducted a *pair*-sample *t* test for female participants. The results in Table 5 show a significant difference ($p < 0.041$) in the recovery method of watching YouTube for females. For the napping recovery method, the data shows that the mean value of alpha's PSD was much higher in the recovery phase (MeanR) than it was in the low attention phase (MeanL). In the high attention phase, the mean value of alpha's PSD diminished slightly, indicating that participants were slowly easing back to the attention state. However, the high omission rate and the low NOGO success percentage in the high attention phase implied that the recovery effect of napping was limited.

For the other three recovery methods (watching YouTube, playing mobile games, and online shopping), the mean value of alpha's PSD was lower in the recovery phase (MeanR)

Table 4 Mean value of alpha's PSD in various phases (male)

Methods	MeanL	SD-L	MeanR	SD-R	MeanH	SD-H	MeanL-H	*t*	*p*
Napping	120.0	46.64	132.4	33.70	100.5	22.95	19.45	2.43	0.021*
Watching YouTube	102.2	33.35	110.6	57.53	87.0	24.26	15.19	2.73	0.010*
Playing a mobile game	129.5	74.91	112.5	46.75	124.8	54.64	4.70	0.34	0.729
Online shopping	118.1	50.39	96.5	30.93	93.7	28.54	24.43	2.90	0.006**

* $p < 0.05$, ** $p < 0.05$; MeanL, MeanH and MeanR are the mean values of alpha's PSD in low, high and recovery phases, respectively

Table 5 Mean value of alpha's PSD in various recovery phases (female)

Methods	MeanL	SD-L	MeanR	SD-R	MeanH	SD-H	MeanL-H	t	p
Napping	115.6	68.73	145.2	46.73	131.8	68.24	− 16.12	− 1.41	0.168
Watching YouTube	131.0	73.70	128.7	37.50	157.1	68.06	− 26.06	− 2.12	0.041*
Playing a mobile game	146.2	86.91	133.9	45.51	163.4	48.06	− 17.24	− 1.19	0.242
Online shopping	150.5	44.67	108.2	15.04	157.5	30.29	− 6.99	− 0.94	0.354

* $p < 0.05$; MeanL, MeanH and MeanR are the mean values of alpha's PSD in low, high and recovery phases, respectively

than it was in the low attention phase (MeanL), and it was higher in the high attention phase (MeanH) than in the previous two phases. A possible explanation for these results may be that female participants were more attracted to activities such as watching YouTube, playing mobile games, and online shopping, so they simply shifted their focused attention to the more attractive stimulus. These three recovery methods allowed participants to stay focused for a longer period of time, consuming more of their energy and attention, thus decreasing their focus in the high attention phase, as shown in Table 5. The increase in the omission rate and the decrease in the NOGO success percentage also indicated that participants could not recover and return to the attention state.

In summary, we found that napping was the only recovery method that had even a slight attention recovery effect for female participants; the other three methods actually increased their focus and kept them from recovering and returning to the attention state.

5 Conclusion

This research integrated singular value decomposition, the Fourier transform, the minimum entropy principle, and an associative Petri net to develop an attention evaluation technique. The level of accuracy achieved by this technique (> 90%) is higher than that of the other techniques to which we compared it. The level of accuracy is also higher than those found by past related studies. Therefore, this technique could be used in teaching and studying to help learners monitor their attention status and improve their learning effectiveness.

The results of our evaluation show differing effects for the four attention recovery methods. The effectiveness with which they aid attention recovery also differs for male and female participants. Moreover, adopting a recovery method which the participant finds more attractive (e.g., playing mobile games [males], or watching YouTube [females]) leads to increased focus on the more attractive activity, and fails to restore attention to the original task. We conclude that napping can help all participants recover their focus, while watching videos can also help males recover effectively. In contrast, uncertainty remains regarding the effectiveness of the other recovery methods for either males or females. Therefore, this study suggests that it is not appropriate to transfer learners' attention to other activities that are more attractive to them, or to focus on other events too long during the learning process. Their attention states will not be restored quickly, and their learning outcomes will be poor.

Hence, future studies can explore and test the effects of other attention recovery methods on different genders. Moreover, our technique can be used in mobile applications to analyze the data from brainwave monitors so that users can accurately monitor their levels of attention and relaxation in real time.

Acknowledgements The author would like to express his sincere appreciation for the financial support from the Ministry of Science and Technology of Taiwan (Grant NSC 102-2410-H-025-024).

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