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Assessing the attention levels of students by using a novel attention aware system based on brainwave signals

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Abstract

Rapid progress in information and communication technologies (ICTs) has fueled the popularity of e-learning. However, an e-learning environment is limited in that online instructors cannot monitor immediately whether students remain focus during online autonomous learning. Therefore, this study tries to develop a novel attention aware system (AAS) capable of recognizing students' attention levels accurately based on electroencephalography (EEG) signals, thus having high potential to be applied in providing timely alert for conveying low-attention level feedback to online instructors in an e-learning environment. To construct AAS, attention responses of students and their corresponding EEG signals are gathered based on a continuous performance test (CPT), ie, an attention assessment test. Next, the AAS is constructed by using training and testing data by the NeuroSky brainwave detector and the support vector machine (SVM), a well-known machine learning model. Additionally, based on the discrete wavelet transform (DWT), the collected EEG signals are decomposed into five primary bands (ie, alpha, beta, gamma, theta, and delta) as well as each primary band contains five statistical parameters (including approximate entropy, total variation, energy, skewness, and standard deviation), thus generating 25 potential brainwave features associated with students' attention level for constructing the AAS. An attempt based on genetic algorithm (GA) is also made to enhance the prediction performance of the proposed AAS in terms of identifying students' attention levels. According to GA, the seven most influential features are selected from 25 considered features; parameters of the proposed AAS are optimized as well. Analytical results indicate that the proposed AAS can accurately recognize individual student's attention state as either a high or low level, and the average accuracy rate reaches as high as 89.52%. Moreover, the proposed AAS is integrated with a video lecture tagging system to examine whether the proposed AAS can accurately detect students' low-attention periods while learning about electrical safety in the workplace via a video lecture. Four experiments are designed to assess the prediction performance of the proposed AAS in terms of identifying the periods of video lecture with high- or low-attention levels during learning processes. Analytical results indicate that the proposed AAS can accurately identify the low-attention periods of video lecture generated by students when engaging in a learning activity with video lecture. Meanwhile, the proposed AAS can also accurately identify the low-attention periods of video lecture generated by students to some degree even when students engage in a learning activity by a video lecture with random disturbances. Furthermore, strong negative correlations are found between the students' learning performance (ie, posttest score and progressive score) and the low-attention periods of video lecture identified by the proposed AAS. Results of this study demonstrate that the proposed AAS is effective, capable of assisting online instructors in evaluating students' attention levels to enhance their online learning performance.

Introduction

In traditional face-to-face instruction, teachers generally observe students' facial expressions to determine whether they are sufficiently attentive. However, this method is excessively subjective and consumes a significant amount of the teacher's energy (Liu, Chiang & Chu, 2013). In addition to face-to-face instruction, e-learning allows students to learn anytime and anywhere. However, students may become easily distracted in e-learning environments, owing to the absence of teacher's face-to-face supervision (Liu *et al*, 2013; Zhang, Zhou, Briggs & Nunamaker, 2006). However, while attention significantly affects learning performance, maintaining a high degree of attention among students on e-learning activities for an extended period is a challenging task (Chen & Huang, 2014). Among the several types of attention affecting learning performance include sustained, selective, spatial, focused, shifting, and divided attention (Driver, 2001; Lezak, Howieson & Loring, 2004; Wager, Jonides & Reading, 2004). According to Hedges *et al* (2013), different classroom activities may be related to different aspects of attention. Their study pointed out that sustained attention may be connected to the learning attentiveness of students to the teacher's instruction throughout a lesson. Smith, Colunga and Yoshida (2010) noted that effective learning depends on sustained attention, and sustained attention plays a major role in aggregating, acquiring and applying knowledge. Moreover, a related study highlighted the importance of sustained attention in cognitive psychology, owing to its strong correlation with learning performance (Steinmayr, Ziegler & Träuble, 2010).

Despite the importance of maintaining sustained attention during a learning activity to ensure successful learning, evaluating whether students maintain their concentration on a learning activity is extremely difficult, owing to the lack of supervised mechanisms to monitor their attention states. Several studies have attempted to elevate learning performance in e-learning environments by developing e-learning systems with an attention aware model to evaluate students' attention states (Chen & Huang, 2014; Hsu, Chen, Su, Huang & Huang, 2012; Liu *et al*, 2013). Although highly promising for use of electroencephalography (EEG) signals in developing attention aware systems (AAS), EEG signals are highly prone to noise interference. As a voltage signal that arises from synchronized neural activity, the human EEG signal is fired by millions of neurons in the brain. Moreover, human EEG signals contain several frequency bands; several studies (Belle, Hargraves & Najarian, 2012; Lutsyuk, Éismont & Pavlenko, 2006) have confirmed that the relative level of activity within each frequency band is associated with attentional processing. Importantly, the human EEG signals must be enhanced by the amplifier because they are generally measured by weak electrical signals of the brain. Therefore, developing an engineering approach that can accurately measure learners' attention levels based on EEG signals still remain an extremely challenging task. Currently, a thinkGear™ eSense algorithm that can identify attention levels accurately to some degree based on human EEG signals has been developed by Neurosky Company (San Jose, CA, USA) (http://www.neurosky.com/). However, this algorithm was never addressed in any academic literature due to patent protection. Fortunately, recently developed noninvasive EEG measurement technologies have become increasingly mature and capable of providing a convenient means of monitoring human brain activity. Thus, this study

Practitioner Notes

What is already known about this topic

- Despite the importance of maintaining sustained attention during an online learning activity to ensure successful learning, evaluating whether students maintain their concentration on an online learning activity is extremely difficult, owing to the lack of supervised mechanisms to monitor their attention states.
- Two attention measures are commonly used to assess a learner's degree of attention. One measure is an attention scale with a set of questions answered by a learner to determine whether the learner concentrates on learning targets. The other measure develops attention aware systems (AAS) to identify a learner's attention level based on human behaviors or physiological signal measurements. However, with advances in the assessment of human physiological signals, e-learning research has increasingly used physiological signals to determine students' attention levels.
- Several studies have attempted to elevate learning performance in e-learning environments by developing e-learning systems with an attention aware model to evaluate students' attention states. However, electroencephalography (EEG) signals are highly prone to noise interference. Therefore, developing an engineering approach that can accurately measure learners' attention levels based on EEG signals still remain an extremely challenging task.

What this paper adds

- An e-learning environment is limited in that online instructors cannot monitor immediately whether students remain focused during online autonomous learning. By using GA-LIBSVM with optimal model selection and feature selection, this study develops a novel AAS based on human EEG signals to identify high- and low-attention levels of students in an autonomous e-learning environment.
- Based on human EEG signals, this study confirmed that the seven most relevant features associated with human attention levels are γ-approximate entropy, γ-total variation, β-approximate entropy, β-total variation, β-skewness, α-total variation and θ-energy.
- Analytical results indicate that the proposed AAS can accurately recognize individual student's attention state as either a high or low level, and the average accuracy rate reaches as high as 89.52%. Meanwhile, the proposed AAS can also accurately identify the low-attention periods of video lecture generated by students to some degree even when students engage in a learning activity by a video lecture with random disturbances.

Implications for practice and/or policy

- The conventional means of capturing EEG signals is based on invasive EEG electrodes with 10–20 channels. This study gathers EEG signals by using a noninvasive EEG sensor with single-channel dry to develop a novel AAS capable of recognizing students' attention levels accurately and providing timely feedback to online instructors. The proposed AAS is characterized by its ease of wear and its high potential in practical applications.
- Significant negative correlations are found between the students' learning performance (ie, posttest score and progressive score) and the low-attention periods of video lecture identified by the proposed AAS. Therefore, reviewing the periods of video lecture with a low attention level identified by the proposed AAS is a highly promising means of supporting remedial learning in an autonomous learning environment.

tries to develop a novel AAS based on raw human EEG signals sensed by Neurosky's MindWave earphone to fill the research gap. Additionally, this study also integrates the proposed AAS with a video lecture tagging system so that the integrated system has high potential to be applied in providing timely alert for conveying low-attention level feedback to online instructors in an e-learning environment.

Literature review

Effects of sustained attention on learning performance in e-learning environments

Attention research has played a major role in psychology for over four decades. James (1983) defined attention as a psychological process comprised of focus and concentration, which enhances cognition speed and accuracy. In particular, attention is closely related to learning performance (Chen & Huang, 2014; Chen & Lin, 2014). Broadbent (1958) indicated that identification, effective learning and memory are impossible when learning without attention. Restated, learning is ineffective when a learner neglects learning content, explaining why instructors should improve learning quality by stressing learner attention and providing effective strategies. Teachers normally observe students' facial expressions to determine whether they are concentrating on learning targets during traditional face-to-face instruction. However, this overly subjective approach expends a significant amount of the teacher's energy (Liu *et al*, 2013). Besides face-to-face instruction, students may use e-learning to perform autonomous learning. Despite their convenience owing to no location or time constraints, e-learning courses lack the informal social interaction and face-to-face contact of traditional classroom training. Assessing students' attention states in e-learning environments is thus more difficult than doing so during face-to-face instruction.

Among the different forms of attention, sustained attention is especially related to e-learning performance (Chen & Huang, 2014). Sustained attention describes a subject's state of readiness to detect rare and unpredictable changes in a stimulus over an extended period (Sarter, Givens & Bruno, 2001). Chen and Huang's (2014) study confirmed the existence of a correlation between the reading comprehension and sustained attention for learners who apply the attention-based self-regulated learning mechanism (ASRLM) for online reading of annotated English texts. Based on their design of a mobile reading experiment with a two-factor experimental design, Chen and Lin (2014) evaluated how selected static, dynamic, and mixed text display types (which were presented in sitting, standing and walking contexts respectively) affect the reading comprehension, sustained attention and cognitive load of learners. According to their results, reading comprehension of learners in the high-reading-comprehension group was significantly and positively correlated with sustained attention. Apparently, the effective sustained attention is the key point that students focus on learning content and improve their performance in e-learning environments.

Attention aware technologies

Two attention measures are commonly used to assess a learner's degree of attention. One measure is an attention scale with a set of questions answered by a learner to determine whether the learner concentrates on learning targets (Das, 1986). The other measure develops AAS to identify a learner's attention level based on human behaviors (Ba & Odobez, 2009, 2011; Stiefelhagen, Yang & Waibel, 2002; Toet, 2006) or physiological signal measurements (Belle *et al*, 2012; Chen & Lin, 2014; Moradi, Buračas & Buxton, 2012). Roda and Thomas (2006) defined AAS as systems capable of supporting human attentional processes. These systems should include three major features: identification of learner's current attentional state, identification and evaluation of possible alternative attentional states, and creation of focus switch or maintenance-related strategies. In contrast to an attention scale assessed after learning, AAS provide insight into students' attention statuses in real time. According to Rapp (2006), AAS may provide benefits of teaching diverse learners, assessing student performance, providing feedback during curriculum development and adding value to computer-assisted teaching methodologies. Importantly, AAS provides a dynamic approach for online instructors to receive feedback on their instructional designs and directs student attention during computer-based instruction. Restated, students must be guided to focus on certain aspects of lessons in order to facilitate their comprehension of material because online learners have considerable freedom to engage in learning activities. The ability of online learning courses to incorporate attention aware functionalities would greatly facilitate learners in completing their learning tasks. AAS should thus be viewed as an additional component of the educators' assessment toolkit (Rapp, 2006).

Many human behaviors, including head pose tracking (Ba & Odobez, 2009, 2011), face tracking (Stiefelhagen *et al*, 2002) and eye gaze tracking, are used in developing AAS (Toet, 2006). However, with advances in the assessment of human physiological signals, e-learning research has increasingly used physiological signals to determine students' attention levels (Chen & Huang, 2014; Hsu *et al*, 2012). Related efforts in recent years have assessed learners' emotions by using human physiological signals, such as heart rate variability (HRV) and EEG (Chen & Sun, 2012; Chen & Wang, 2011) and attention (Chen & Lin, 2014; Rebolledo-Mendez *et al*, 2009). Moreover, EEG signals have also been successfully applied in computer-based assessment (Wolpaw, McFarland, Neat & Forneris, 1991), brain-computer interface (Schalk, McFarland, Hinterberger, Birbaumer & Wolpaw, 2004; Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002), visual-aural attention modeling (Zheng *et al*, 2008), classification of human emotion (Murugappan, Nagarajan & Yaacob, 2010) and assessment of learning performance (Harmony *et al*, 2001). Of previous studies that developed AAS based on physiological signals, Hsu *et al* (2012) developed a reading concentration monitoring system to facilitate reading activity with e-books in order to allow instructors to more thoroughly understand students' reading concentration states. By using three sensors (ie, webcam, heartbeat sensor and blood oxygen sensor) to capture various physiological signals of students, their study evaluated their reading concentration. Analytical results indicated that their reading concentration monitoring system allows instructors to more thoroughly understand the students' reading concentration states in an intelligent classroom learning environment. Chen and Huang (2014) also applied the MindSet earphone developed by NeuroSky that can identify attention levels based on human EEG signals to develop a web-based reading annotation system with an attention-based self-regulated learning mechanism to enhance the sustained attention of learners while reading annotated English texts online, thereby promoting online reading performance. According to their results, sustained attention and reading comprehension of the experimental group with an attention-based self-regulated learning mechanism for web-based collaborative reading are better than those of the control group without an attention-based self-regulated learning mechanism. Moreover, Liu *et al* (2013) identified whether students are attentive or inattentive during instruction by using EEG signals. Based on use of the support vector machine (SVM), their study analyzed features to identify the optimum combination of features that indicates whether students are attentive. The proposed method in their study provides a classification accuracy of up to 76.82%. While attempting to assess the sustained attention of learners and further increase their sustained attention on learning targets in order to improve learning performance in e-learning environments, this study thus develops a novel AAS to assess students' attention levels in real time based on human EEG signals.

Assessing sustained attention

Several tests have been developed for evaluating human attention based on self-reports by human subjects, including the Stroop color-word interference test, Talland letter cancellation test, trail making test, digit symbol substitution test, continuous performance test and Wisconsin card sorting test (Mirsky, Anthony, Duncan, Ahearn & Kellam, 1991). Of the methods to evaluate human attention, the continuous performance test (CPT) (Rosvold, Mirsky, Sarason, Bransome & Beck, 1956) is widely used to evaluate sustained attention and selective attention. Sustained attention involves direct and focus cognitive activity on some continuous activity over a certain period, whereas selective attention focuses on task-relevant cues and ignores background noise or distraction. By using CPT, several studies have identified children with attention-deficit hyperactivity disorder (ADHD) (Li, Gratton, Yao & Knight, 2010; Sohn *et al*, 2010). Moreover, by using CPT, Ghassemi, Moradi, Tehrani-Doost and Abootalebi (2009) defined the level of sustained attention. Their study also used the morphological features of EEG's independent components to serve as input features of the classifier model, ie, linear discriminant analysis (LDA), for identifying the sustained attention level. According to their results, significant correlations exist between the level of sustained attention identified by CPT and certain features of EEG signals.

Based on the reliability of CPT in evaluating human sustained attention, this study develops an AAS based on the supervised machine learning model—SVM. Students' attention responses and their corresponding EEG signals on a CPT are gathered by the NeuroSky MindWave headset. These patterns are then assigned as training and testing data. Next, feature selection is performed using the genetic algorithm (GA) to optimize the considered attention features of EEG signals. Additionally, the proposed AAS is integrated with a video lecture tagging system to examine the ability of the proposed AAS to accurately identify the high- and low-attention levels of learners when they are watching a video lecture for autonomous learning. Importantly, the proposed AAS can assist online instructors in assessing whether learners maintain their focus on a learning activity in an online learning environment.

Research methodology

Gathered training and testing data for constructing AAS

Ten invited volunteers' attention responses and their corresponding EEG signals on the CPT (Cohen & Servan-Schreiber, 1992) were collected as training and testing data to construct the AAS. Figure 1 shows an example of the CPT. During CPT, one must maintain the task instruction of responding only when a specific stimulus ('A') is followed by another specific stimulus ('X'), as well as holding in mind, each stimulus representation until a decision of whether to respond can be made. Namely, the test focuses on identifying the 'AX' pattern from CPT; the other patterns are nontarget patterns. Rosvold *et al* (1956) demonstrated that the CPT as a measure of sustained attention was highly sensitive to brain damage or dysfunction. Riccio, Reynolds, Lowe and Moore (2002) argued that CPT performance can be viewed as symptom specific (attentional disturbance), but it is not disorder specific (eg, ADHD). To gather the EEG signals correctly, ten healthy graduate students were reminded to click the right mouse button when the CPT appears with the target pattern 'AX', and to click the left mouse button for the nontarget patterns. CPT generally lasts for several minutes to assess the maintenance of focused attention (Clark, Kempton, Scarnà, Grasby & Goodwin, 2005). Several functions are critical to successful performance in CPT, which

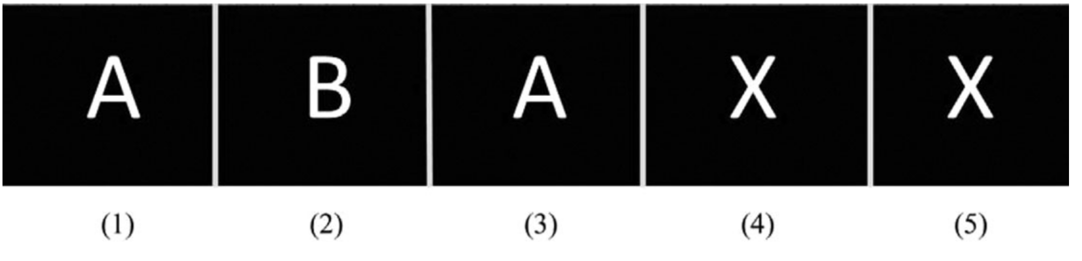

Figure 1: An example of the continuous performance test (CPT)

includes encoding the stimulus (task-relevant information), maintaining task instruction and the stimuli in working memory, and generating an appropriate response while inhibiting inappropriate responses (Lee & Park, 2006). Restated, any difficulty at each step could result in a CPT error.

Additionally, to consider possible EEG signal variations because of gender differences (Limbu, Sinha, Sinha & Paudel, 2015), EEG signals were collected from ten healthy graduate students including five men and five women, who wore MindWave headsets developed by NeuroSky, while performing CPT, in this study. The MindWave headset, which can measure and output the power spectra of EEG signals, is a reliable equipment to assess human brainwaves (NeuroSky, 2015). The MindWave headset consists of a headset and sensor arm. The MindWave headset, which resembles a standard stereoscopic wireless earphone, uses a comfortable noninvasive dry electrode, with which users merely wear an earphone and place the earphone's forearm on their foreheads to measure EEG signals. Sampling rate of the MindWave headset for gathering human EEG signals is 512 Hz and all sampling data can be saved into a computer by a CSV file format. In this study, the time series data of EEG signals were obtained when an examinee completed CPT. The time series data were then divided into separate time slots, based on the clicking time of each CPT trial, to identify the 'AX' pattern. Next, the obtained brainwaves in separate time slots were labeled as the positive class (ie, high-attention level class) if the examinee responded correctly when identifying the 'AX' pattern in CPT; otherwise, they were labeled as the negative class (ie, low-attention level class). Totally, 2787 brainwave data were collected, including 1988 brainwave data with a high-attention level and 799 brainwave data with a low-attention level.

Preprocessing of EEG data and feature selection

After the EEG data were labeled, features associated with high and low attention levels were extracted from the raw EEG signals by using the discrete wavelet transform (DWT). In this study, 2787 data were obtained, in which approximately 3/4 (2100 data) were randomly selected as training data; the remaining 1/4 (687 data) were selected as the testing data. Next, based on a fourth-order DWT, the gathered EEG signals were decomposed to five bands, including α activity, β activity, γ activity, θ activity and δ activity (Gregory & Pettus, 2005; Sanei & Chambers, 2007). Additionally, five statistical parameters (ie, approximate entropy, total variation, energy, skewness and standard deviation) were calculated for each band. Therefore, each EEG's training or testing data include 25 features. Figure 2 shows the architecture of DWT for extracting potential EEG features associated with human attention level. Based on feature selection for the 25 considered features by GA, this study found that most relevant features associated with attention-level classification are γ-approximate entropy, γ-total variation, β-approximate entropy, β-total

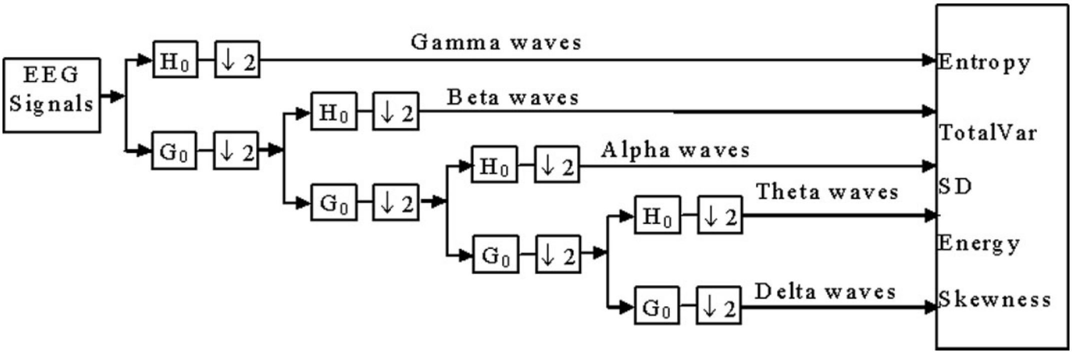

Figure 2: The architecture of discrete wavelet transform (DWT) for extracting potential electroencephalography (EEG) features associated with human attention level

variation, β-skewness, α-total variation and θ-energy. Restated, the highest prediction accuracy of attention level achieved under the above seven features is considered.

The α activity indicates that the brain is in a state of relaxation, detected either by EEG or MEG; the β activity originates mainly from the frontal lobe and is associated with normal waking consciousness and alertness. Also, the γ activity is related to gestalt perception and cognitive functions such as attention, learning, perception, cognition and memory (Kaiser & Lutzenberger, 2003). Some studies have also suggested that γ activity is related to selective attention (Herrmann & Mecklinger, 2001; Lee, Williams, Breakspear & Gordon, 2003); the θ activity occurs mainly in the parietal and temporal regions of the cerebrum. This activity can be observed during drowsy, meditative or sleeping states. Evidence suggests that EEG oscillations in the θ band are a recall of working memory representations and are involved in active maintenance (Lee *et al*, 2003); δ activity is normally associated with the deepest stages of sleep, lacking oxygen, unconscious or anesthetized. Moreover, the parameters of energy, skewness and standard deviation are common statistical characteristic measures. Therefore, this study only briefly explains the less familiar approximate entropy and the total variance. As a measure used to quantify the creation of information in a time series (Pincus, 1991), the approximate entropy is a time domain feature and is also widely considered an important feature in EEG data processing (Chen, Luo, Deng, Wang & Zeng, 2009; Sabeti, 2009; Yuan, 2011; Yun, 2012). In statistics, an approximate entropy is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time-series data (Pincus, Gladstone & Ehrenkranz, 1991). In mathematics, the total variance can be used based on specific circumstance to define and explain. It is widely used in image denoising (Rudin, Osher & Fatemi, 1992) and numerical analysis of differential equations (Zhao, Shi & Xu, 2010). Total variance in the data refers to the sum of the variances of the individual components. A larger value of total variance implies a rapid fluctuation of a selected time interval, and vice versa.

Proposed AAS constructed by GA-LIBSVM

This study developed the AAS based on seven selected EEG features by using a library for support vector machines (LIBSVM) (http://www.csie.ntu.edu.tw/~cjlin/libsvm/) (Chang & Lin, 2011), which is an integrated software for support vector classification. Several kernel functions can map input feature spaces with nonlinear distribution to higher dimensional spaces, allowing for input feature spaces to become a linear distribution while using LIBSVM for classification. The radial basis function (RBF) was selected here as the kernel function for LIBSVM, owing to its appropriateness for most classification problems. Moreover, the two parameters of LIBSVM, including the penalty parameter C and parameter γ of the kernel function of RBF, must be appropriately determined in advance. Selecting the optimal parameters of LIBSVM to construct the AAS is especially important because it enhances the classification performance. Notably, LIBSVM can automatically determine these two parameters using the grid parameter search approach (Chang & Lin, 2011). Therefore, based on the grid parameter search approach, this study attempted to find the near-optimal parameters for the penalty parameter C and the parameter γ of the kernel function of RBF. Moreover, feature selection was performed for the 25 considered features by using the GA to identify the key features associated with attention level for training LIBSVM in order to construct the AAS. This study thus named LIBSVM with GA-based feature selection as GA-LIBSVM. Figure 3 shows the flowchart of the used GA-LIBSVM algorithm for constructing the AAS.

Integrating the proposed AAS with a video lecture tagging system

Figure 4 shows the user interface of integrating the proposed AAS with a video lecture tagging system, which contains a playing panel of a video lecture, a display interface of low-attention periods labeled by learners and a display interface of low-attention periods identified by the

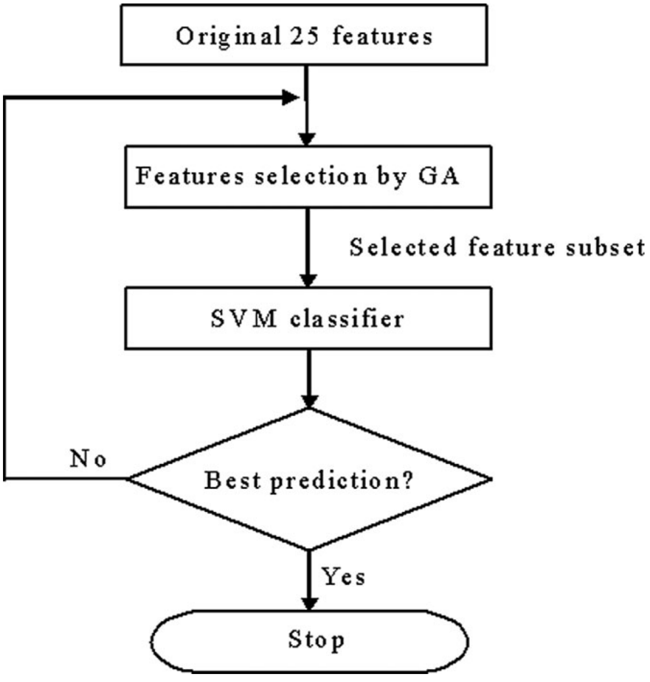

Figure 3: The flowchart of the employed GA-LIBSVM algorithm for constructing the attention aware system (AAS). GA, genetic algorithm; SVM, support vector machine

proposed AAS. A learner can label any periods of the video lecture with low-attention level by clicking the "low-attention" button of the user interface of the integrated system after viewing a video lecture. The integrated system then records the learner's low-attention periods and displays them on the upper left screen (Figure 5). After the learner finishes viewing the video lecture, the integrated system accurately predicts all low-attention periods of the learner based on the EEG signals by the proposed AAS. Meanwhile, the learner can click the "load" button on the lower left portion of the screen to display the low-attention periods predicted by the proposed AAS (Figure 6). Additionally, the integrated system also provides a convenient graphical user interface that can simultaneously display the low-attention periods respectively labeled by the learner and predicted by the proposed AAS (Figure 7). The graphical user interface is very convenient for learners to determine whether the low-attention periods identified by the proposed AAS are consistent with the low-attention periods labeled by the learner. Additionally, the system of integrating the proposed AAS with a video lecture tagging system can identify the periods of video lecture that lead to learners with low-attention level to online instructors based on learners' EEG signals while performing a learning activity by video lecture. Thus, the proposed AAS has high potential to be applied in providing timely alert for conveying low-attention level feedback to online instructors in an e-learning environment.

Experimental design for assessing the prediction performance of the proposed AAS

Based on the integrated system that combines the proposed AAS with a video lecture tagging system, this study also examined the prediction performance of the proposed AAS for learners engaging in a learning activity with video lectures. Several learners were invited to learn about electrical safety in the workplace by the playing the interface of the video lecture in the integrated system. The integrated system can identify the learners' high or low attention periods while learning from the video lecture. Meanwhile, learners can label any period of the video lecture

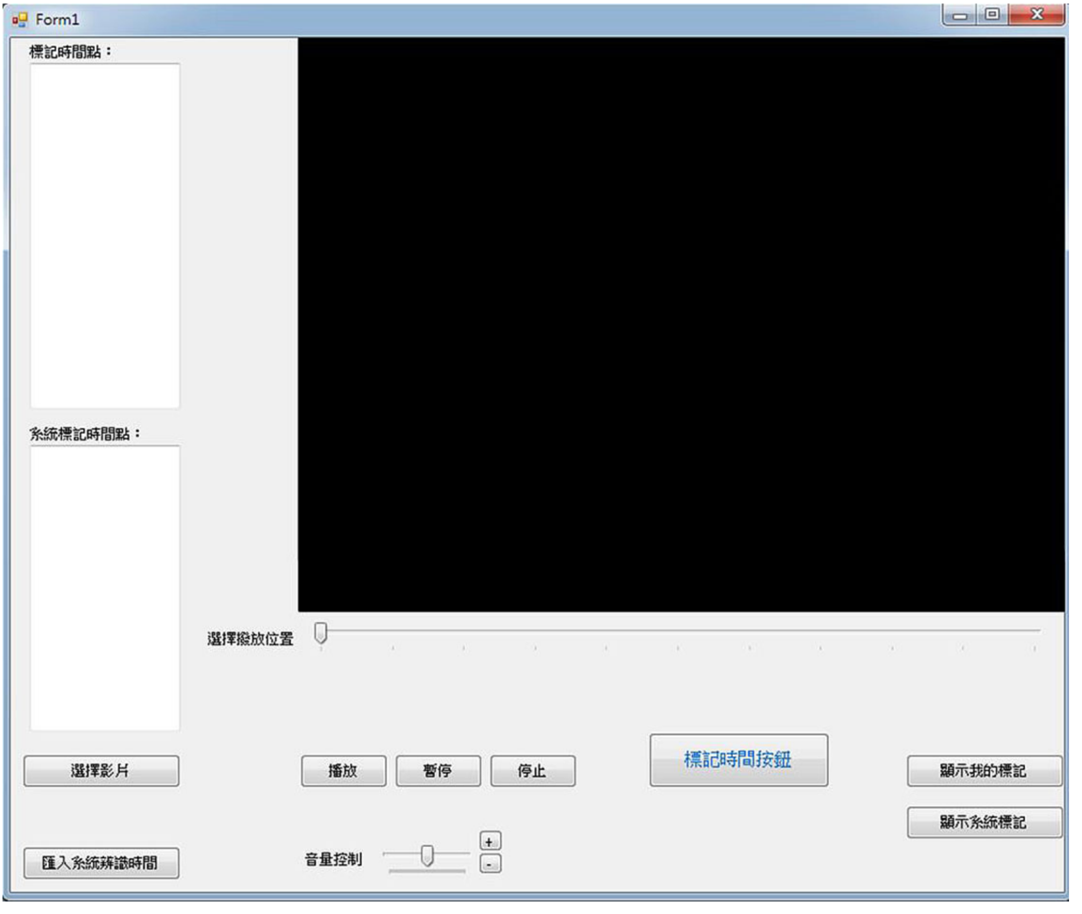

Figure 4: The user interface of integrating the proposed attention aware system (AAS) with a video lecture tagging system

with low-attention level while learning during the video lecture by clicking the "low-attention" button on the integrated system. Following completion of the learning process, the periods of video lecture with low-attention level respectively labeled by the learners and predicted by the proposed AAS are simultaneously displayed on a display interface to allow learners to review the identified periods of the video lecture with low-attention level.

By using precision rate, recall rate and F-measure as the evaluation measures of prediction performance, this study assessed the consistent degree of low-attention periods labeled by learners and predicted by the proposed AAS. The mathematical formulations of the three evaluation measures are expressed as follows:

$$Precision\ Rate = \frac{\#(relevant\ items\ identified)}{\#(identified\ items)} \tag{1}$$

where *#(relevant items identified)* denotes the number of low-attention periods identified by the proposed AAS that are also labeled by the learner, and *#(identified items)* represents the number of low-attention periods identified by the proposed AAS.

$$Recall\ Rate = \frac{\#(relevant\ items\ identified)}{\#(relevant\ items)} \tag{2}$$

Figure 5: The display interface of low-attention periods labeled by a learner

where #*(relevant items identified)* refers to the number of low-attention periods identified by the proposed AAS that are also labeled by learners, and #*(relevant items)* is the number of low-attention periods labeled by learners.

$$F-measure = 2\times\frac{Precision\ Rate\times Recall\ Rate}{Precision\ Rate+Recall\ Rate} \tag{3}$$

where F-measure is a monotonic measure which simultaneously combines the precision and recall rates.

In addition to assessing the prediction performance of the proposed AAS, this study also designed four experiments to confirm whether the proposed AAS can indeed identify the periods of video lecture with a low-attention level generated by the research participants and manually adding disturbances that may disperse the attention of research participants, whether participants' agreement degree on the periods of video lecture with a low-attention level identified by the proposed AAS is high, and whether the low-attention periods of video lecture identified by the proposed AAS significantly correlate with the posttest scores and progressive scores of the participants. The aim is to confirm the effects of the proposed AAS on identifying low-attention level generated by the research participants from four different perspectives. The four experiments are detailed as follows:

1 Experiment 1

Four graduate students aged 22–23 from The Department of Industrial Education of National Taiwan Normal University were invited as research participants to view a 16-minute video

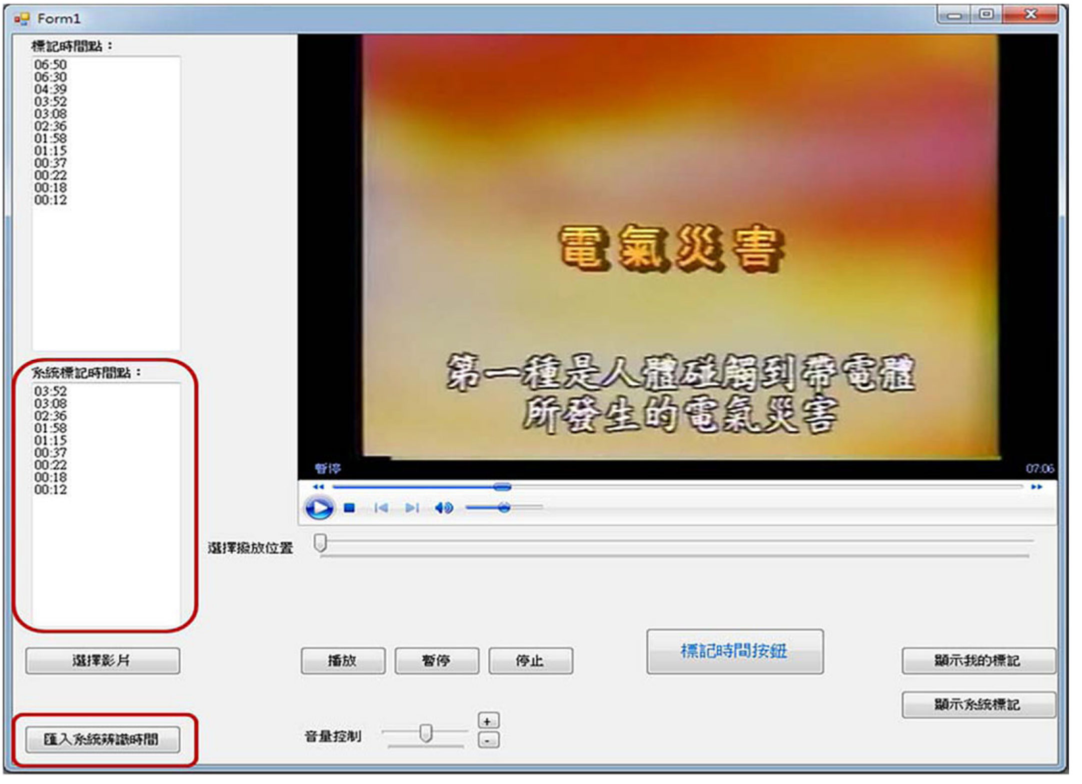

Figure 6: The display interface of low-attention periods of a learner identified by the proposed attention aware system (AAS)

lecture on electrical safety in the workplace. Following the learning activity, the periods of video lecture with a low-attention level labeled by the participants and those predicted by the proposed AAS were compared and evaluated based on the precision rate, recall rate and F-measure.

2 Experiment 2

Four graduate students who are the same with the research participants in the experiment 1 were invited to view a 10-minute video lecture on electrical safety in the workplace in which seven disturbances were made during the lecture. Each disturbance, including sound and small icons, was manually added into the 10-minute video lecture to disperse the attention of participants. The periods of video lecture with disturbances are assumed here to lead to low-attention levels. Following completion of the learning activity, this study confirmed whether the proposed AAS can successfully identify the periods of the video lecture with disturbance as the learning periods with a low-attention level. Experiments 1 and 2 have the same performance evaluation method.

3 Experiment 3

Four graduate students who are the same with the research participants in experiment 1 were invited to view a 10-minute video lecture on electrical safety in the workplace. All participants were then invited to fill in an attention survey questionnaire with a 5-point Likert scale in order to assess their agreement degree on the periods of video lecture with a low-attention level identified by the proposed AAS.

Figure 7: The graphical user interface of the integrated system for simultaneously showing the low-attention periods labeled by learner and identified by the proposed attention aware system (AAS)

4 Experiment 4

Eight graduate students, including the same four research participants in experiment 1 and four additional research participants, were invited to view a 16-minute video lecture on electrical safety in the workplace. The pretest was conducted before the eight participants engaged in the learning activity. All participants then participated in the learning activity with the video lecture. Thereafter, they were guided to review the low-attention periods of video lecture identified by the proposed AAS. Following completion of the learning process, a posttest was performed. Finally, based on Pearson product-moment correlation analysis, this study also assessed whether a significantly negative correlation exists between the low-attention periods of video lecture identified by the proposed AAS and the posttest score as well as whether a significantly negative correlation exists between the low-attention periods of video lecture identified by the proposed AAS and the progressive score. If the significantly negative correlations exist, then this implies that increasing the identified low-attention periods of video lecture will lead to the posttest scores and progressive scores of the learners decreasing as well. That is, the proposed AAS can accurately identify the low-attention periods of video lecture that the learners generated when they engaged in a learning activity with a video lecture.

Analytical results

Assessment of the proposed AAS in terms of prediction accuracy

In this experiment, 2787 EEG data were obtained, in which approximately 3/4 (2100 data) were randomly selected as training data; the remaining 1/4 (687 data) were selected as the testing data. Table 1 shows the prediction accuracy of the proposed AAS on the high- and low-attention levels evaluated by testing data under automatically determined learning parameters, including the penalty parameter C and parameter γ of the kernel function of RBF. Analytical results indicate that the prediction accuracy rates on the high- and low-attention levels are 91.60% and 87.44% under the automatically determined learning parameters by the grid parameter search approach in LIBSVM ($C = 98$ and $\gamma = 0.001217$) respectively. The overall prediction accuracy of the proposed AAS on the high- and low-attention levels is as high as 89.52%. Those results demonstrate that the correct ratio of high-attention level is higher than that of low-attention level. This finding implies that the learner's high-attention level based on EEG signals is more easily identified than the low-attention level, possibly owing to more noise interference in the EEG signals with low-attention level.

Comparison of low-attention periods labeled by the learners and predicted by the proposed AAS

Four graduate students were invited to view a 16-minute video lecture on electrical safety in the workplace. Following completion of the learning activity, the low-attention periods labeled by the learners and predicted by the proposed AAS were compared based on the precision rate, recall rate and F-measure. Table 2 summarizes those results. According to those results, the average precision rate, recall rate and F-measure are 48.32%, 74.75% and 0.5853 respectively. The highest precision rate, recall rate and F-measure are 61.36%, 94.78% and 0.7047 respectively. Those results shown in Table 2 demonstrate that the proposed AAS identify correctly the low-attention periods of learners to some degree when they engage in a learning activity by a video lecture. However, labeling low-attention periods based on learners' memory recall easily generates errors due to the limits of human memory, thus affecting the matching degree between the low-attention periods labeled by the learners and predicted by the proposed AAS.

Table 1: The prediction accuracy of the proposed AAS on the high- and low-attention levels

The identified attention level	*Number of correct prediction*	*Number of Incorrect prediction*	*Prediction accuracy (%)*
High-attention level	447	41	91.60
Low-attention level	174	25	87.44
High- and low-attention levels	621	66	89.52

Table 2: Comparison of the low-attention periods of video lecture labeled by the learners and predicted by the proposed AAS

Learner	*Precision rate (%)*	*Recall rate (%)*	*F-measure*
1	56.09	94.78	0.7047
2	40.00	62.20	0.4869
3	61.36	80.68	0.6971
4	35.84	61.32	0.4524
Average	48.32	74.75	0.5853

AAS, attention aware system.

Assessing the prediction accuracy of the proposed AAS for identifying low-attention periods caused by the video lecture with manually adding disturbances

Four graduate students who are the same with the research participants in the experiment 1 were invited to view a 10-minute video lecture on electrical safety in the workplace, in which seven disturbances were manually added. The study also assessed whether the proposed AAS can successfully identify the low-attention periods of the video lecture caused by manually adding disturbances. Table 3 summarizes those results. According to those results, the average precision rate, recall rate and F-measure are 39.60%, 62.27% and 0.4780 respectively. The highest precision rate, recall rate and F-measure are 46.25%, 77.55% and 0.5441 respectively. The average number of un-recognition units is lower than 2. Above results demonstrate that the proposed AAS can effectively identify the low-attention periods of video lecture, owing to the manually adding of disturbances to some degree. However, the evaluation results are based on the hypothesis that the periods of video lecture with manually adding disturbances will lead to learners' low-attention levels. Although this hypothesis is logical, some exceptions might happen in some research participants.

Learners' survey for assessing the prediction accuracy of the proposed AAS on low-attention periods of a video lecture

Four graduate students who are the same with the research participants in the experiment 1 were invited to view a 10-mimute video lecture on electrical safety in the workplace. Following completion of the learning activity, all learners were requested to fill in a questionnaire with a 5-point Likert scale, ranging from 1 for "strongly disagree" to 5 for "strongly agree," to examine the consistency of the low-attention periods of video lecture predicted by the proposed AAS and recognized by the learners. Table 4 summarizes those results. This table reveals that all survey scores are less than 4 points. The highest score is 3.36 points and the lowest score is 2.09. The average survey score is 2.83 points, which is close to neutral, indicating that the learners agreed

Table 3: The prediction results of the proposed AAS on identifying low-attention periods of video lecture causing by manually adding disturbances

Learner	*Precision rate (%)*	*Recall rate (%)*	*F-measure*	*Number of un-recognition*
1	43.86	51.02	0.4717	2
2	35.40	77.55	0.4861	1
3	46.25	66.07	0.5441	1
4	32.90	54.42	0.4103	3
Average	39.60	62.27	0.4780	1.75

AAS, attention aware system.

Table 4: Survey scores of participants for the low-attention periods predicted by the proposed AAS

Learner	*Number of low-attention periods identified by the proposed AAS*	*Survey score of participants*
1	22	3.36
2	36	3.00
3	23	2.86
4	32	2.09
Average	28	2.83

AAS, attention aware system.

with the prediction results of low-attention periods by the proposed AAS to some degree. Similarly, assessing the consistency of the low-attention periods of video lecture predicted by the proposed AAS and recognized by the learners based on learners' memory recall also easily generates errors due to the limits of human memory, thus affecting the average survey score of the questionnaire.

Correlation between the identified low-attention periods with the posttest score and the progressive score

Eight graduate students, including the same four research participants in the experiments 1 and four additional research participants, were invited to view a 16-minute video on electrical safety in the workplace. In addition to viewing the video lecture, all participants were instructed to review the low-attention periods of the video lecture identified by the proposed AAS after finishing the learning activity. A posttest was performed to assess the participants' learning performance. Table 5 summarizes the descriptive statistics results of the low-attention periods of video lecture identified by the proposed AAS, pretest, posttest and progressive score. According to those results, seven participants have progressive scores except for one participant. Moreover, by further using the Pearson product-moment correlation, this study assessed whether a correlation exists between the low-attention periods of video lecture identified by the proposed AAS and the posttest score and whether a correlation exists between the low-attention periods of video lecture identified by the proposed AAS and the progressive score. Table 6 summarizes those results. Analytical results indicate that the low-attention periods of video lecture identified by the proposed AAS and the posttest scores reached a statistically strong negative correlation ($r = -.806$, $p = .016 < .05$) and the low-attention periods of video lecture identified by the proposed AAS and the progressive scores also reached a statistically strong negative correlation ($r = -.768$, $p = .026 < .05$). This finding implies that the identified low-attention periods of video lecture increase, and the posttest

Table 5: The descriptive statistics results of the low-attention periods of video lecture identified by the proposed AAS, pretest, posttest and progressive score

Learner	*Low-attention periods identified by the proposed AAS (seconds)*	*Pretest score*	*Posttest score*	*Progressive score*
1	87	82.5	90	7.5
2	10	83	97	14
3	34	91.5	95.5	4
4	70	80.5	86.5	6
5	51	81	90	9
6	81	87.5	89.5	2
7	110	92.5	88.5	−4
8	68	87	88.5	1.5

AAS, attention aware system.

Table 6: Correlation among the low-attention periods of video lecture identified by the proposed AAS, the posttest score and the progressive score

Item	*The low-attention periods of video lecture identified by the proposed AAS*	*Two-tailed test of significance*
Pretest score	.269	.519
Posttest score	−.806*	.016
Progressive score	−.768*	.026

*$p < .05$. AAS, attention aware system.

Table 7: The regression analysis results between the learning performance and the low-attention periods of video lecture identified by the proposed AAS

Model summary			*ANOVA*		*Unstandardized coefficients*		
Selected variable	*R*	R^2	*F*	*Sig.*	*β distribution*	*t*	*Sig.*
Using the low-attention periods of video lecture identified by the proposed AAS to forecast the posttest score	.806	.649	11.096	.016	−.093	−3.331	.016
Using the low-attention periods of video lecture identified by the proposed AAS to forecast the progressive score	.768	.590	8.62	.026	−.132	−2.936	.026

AAS, attention aware system.

scores and progressive scores of the learners decrease as well. Above results demonstrate that the proposed AAS can accurately identify the low-attention periods of video lecture that the learners generated when they engaged in a learning activity with a video lecture.

Moreover, regression analysis was performed of the learning performance and the low-attention periods of a video lecture. Table 7 summarizes those results. This table reveals that the low-attention periods of video lecture identified by the proposed AAS can accurately forecast the posttest scores ($R^2 = .649$), and can explain a variance of the posttest scores of up to 64.9%. Meanwhile, the low-attention periods of video lecture can accurately forecast the progressive score ($R^2 = .590$), and can explain the progressive score variance of up to 59%.

Discussion

EEG recordings can be broadly divided as invasive EEG and noninvasive EEG recordings (Ball, Kern, Mutschler, Aertsen & Schulze-Bonhage, 2009; Zumsteg & Wieser, 2000). Invasive EEG recordings are those recordings that are made with electrodes that have been surgically implanted on the surface or within the depth of the brain, whereas noninvasive EEG recordings are those recordings obtained from electrodes attached to the scalp surface (Ball *et al*, 2009). To date there is no single noninvasive EEG test that provides definitive information on which surgery can be based despite continuous improvement and development of promising new noninvasive techniques (Zumsteg & Wieser, 2000). Invasive EEG recordings are frequently used for diagnostics in patients suffering from brain diseases with two or more lesions and an unknown seizure origin where pharmacological treatment is insufficient and the possibility of neurosurgical treatment is evaluated (Nair, Burgess, McIntyre & Luders, 2008). That is, invasive EEG techniques might be indispensable because they still play an essential role in patients undergoing presurgical evaluation (Zumsteg & Wieser, 2000). Although invasive EEG recordings facilitate the observation of all EEG signal changes, its practical implementation is extremely inconvenient (Liu *et al*, 2013). Therefore, this study gathers EEG signals by using a noninvasive EEG sensor with single-channel dry. Compared with invasive EEG recordings gathered by 10–20 electrodes, using a noninvasive EEG sensor with single-channel for sensing EEG signals lowers the accuracy of EEG signals, but this scheme is characterized by its ease of wear and its high potential in practical applications.

The EEG signal is frequently used to recognize human attention levels based on the selected features of α, β, γ, θ and δ waves. According to those results of applying GA for feature selection, the seven most relevant features associated with human attention levels are γ-approximate entropy, γ-total variation, β-approximate entropy, β-total variation, β-skewness, α-total variation and θ-energy. Restated, the highest prediction accuracy of attention level is achieved when considering the above seven features. As expected, no brainwave features associated with δ activity are included in the seven most relevant features on the recognition problem of attention level. The δ activity should normally not appear when an individual is awake. Importantly, analytical results indicate that two features of the γ activity (including γ-approximate entropy and γ-total variation) are strongly correlated with human attention levels. The results are consistent with several studies (Herrmann & Mecklinger, 2001; Kaiser & Lutzenberger, 2003; Lee *et al*, 2003), indicating that γ activity is related to selective attention. Moreover, three features of the β activity (including β-approximate entropy, β-total variation and β-skewness) are also strongly correlated with human attention levels. This correlation is reasonable because β activity is associated with normal waking consciousness, stimulation and alertness. These results are consistent with those of Egner and Gruzelier (2004), indicating that the variation in the β wave in the EEG is strongly correlated with attention. Our results further demonstrated that the θ-energy of the θ activity is correlated with human attention levels. Recent research has suggested that θ oscillations are generated in frontal brain regions and play a major role in memory maintenance (Lee *et al*, 2003). Additionally, α-total variation of the α activity is selected in this study as one of the seven most relevant features with human attention levels. The α activity normally indicates that the brain is in a state of relaxation. Exploring why the θ-energy and α-total variation are correlated with human attention levels is a worthwhile task.

Moreover, based on an SVM that produces excellent two-class results as the classifier, Liu *et al* (2013) attempted to identify whether students are attentive or inattentive during instruction based on human EEG signals. In their study, five features extracted from EEG signals were considered as the key features associated with human attention levels for identifying students' attention states. However, their study did not implement a feature selection scheme. Nevertheless, their study demonstrated that the prediction accuracy of the proposed method reaches 76.82%. Moreover, while conducting EEG examinations using brain power-related tasks, Li *et al* (2011) instructed the subjects to report their attention levels. Based on *k*NN classifier, their study designed a system for measuring human's attention levels immediately. The prediction accuracy of the proposed system was 57.3%. Fortunately, based on GA-LIBSVM, this study develops the AAS and performs a feature selection for identifying the most relevant EEG features associated with human attention levels. According to our results, the overall prediction accuracy of the proposed AAS on the high- and low-attention levels reaches as high as 89.52%. Obviously, the proposed AAS in this study achieves the highest prediction accuracy of identifying human attention levels.

Despite its contributions, this study has certain limitations. First, while this study develops an AAS as a flexible means of assessing students' attention levels, MindWave headsets developed by NeuroSky are used, which is a noninvasive EEG sensor with single-channel dry, to collect EEG signals associated with students' attention levels. Students merely need to wear MindWave headsets on their foreheads while gathering EEG signals. The limitations of a single-channel dry sensor may lower the accuracy of collecting EEG signals associated with students' attention levels. However, according to a study undertaken by Johnstone, Blackman and Bruggemann (2012), the EEG signal collected by the MindWave headsets resembles that of the Biopac system, a wet-electrode equipment widely used in medical and research applications. Moreover, detecting the EEG signals generated in this area of the brain is a highly effective method as the cerebral cortex in the forehead controls human emotions, mental states and levels of attentiveness (Liu *et al*, 2013). Second, because gathering a large number of EEG signals with low- and high-attention levels as training and testing data for constructing the proposed AAS is rather time consuming, this study only invited ten volunteers to gather their attention responses and their corresponding EEG signals on the CPT to construct the AAS. The small sample size may limit efforts to identify representative EEG signals for constructing the AAS. Finally, this study designed four experiments with small sample size to confirm the prediction performance of the proposed AAS on identifying learners' attention levels due to the difficulty of recruiting research participants. This may affect the results of assessing the prediction performance of the proposed AAS in terms of identifying learners' attention levels.

Conclusions and future work

By using GA-LIBSVM with optimal model selection and feature selection, this study tries to develop a novel AAS based on human EEG signals to identify high- and low-attention levels of students in an autonomous e-learning environment. Analytical results indicate that the prediction accuracy rates of the proposed AAS on high- and low-attention levels are 91.60% and 87.44% respectively. The overall prediction accuracy of the proposed AAS reaches as high as 89.52%. Moreover, according to our results, the key features associated with attention level are γ-approximate entropy, γ-total variation, β-approximate entropy, β-total variation, β-skewness, α-total variation and θ-energy. Additionally, most of the seven features correlate well with the theoretical results. Moreover, the proposed AAS is integrated with a video lecture tagging system to further evaluate the prediction accuracy of the proposed AAS in terms of identifying low-attention periods of learners while engaging in a learning activity by watching a video lecture. According to our results, the proposed AAS can accurately identify the low-attention periods of video lecture that learners generated to some degree based on the performance measures of precision rate, recall rate and F-measure. Furthermore, the proposed AAS is robust in terms of identifying low-attention periods of video lecture with disturbances. A questionnaire survey with a 5-point Likert scale also confirms that most of the learners agreed with the prediction results of low-attention periods of video lecture identified by the proposed AAS to some degree. Also, statistically significant negative correlations and predictability exist between the low-attention periods of video lecture identified by the proposed AAS and posttest scores and between the low-attention periods of video lecture identified by the proposed AAS and progressive scores. Results of this study demonstrate that the proposed AAS can accurately identify the low-attention periods of video lecture that the learners generate while performing a learning activity with video lecture.

Several issues warrant further investigation. First, reviewing the periods of video lecture with a low-attention level identified by the proposed AAS is a highly promising means of supporting remedial learning in an autonomous learning environment. Therefore, we recommend that future research designs an instruction experiment to confirm whether reviewing the periods of a video lecture with a low-attention level improves remedial learning performance. Second, by using GA-LIBSVM, this study develops a novel AAS that can identify human attention states as a low- or high-attention level based on EEG signals. Future work should consider developing an AAS that can identify human attention states as continuous values based on machine learning models with a forecasting capability of contiguous states, such as support vector regression (Smola & Lkopf, 2004) or neural networks. Third, the physiological signal adopted in this study for constructing the proposed AAS is the EEG signal. However, future research should consider whether combining the EEG signal with human behavior, such as eye gaze tracking (Toet, 2006), to construct the proposed AAS can achieve a higher prediction accuracy than the current method. Additionally, future research should extend the participant pool to a larger sample size and different age groups for the four deigned experiments to confirm the prediction performance of the proposed AAS in terms of identifying learners' attention levels.

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Statements on open data, ethics and conflict of interest

To open the human EEG data associated with attention states obtained from the study, we consider submitting the gathered training and testing EEG data for constructing attention aware system to UCI machine learning repository (http://archive.ics.uci.edu/ml/), which is a public datasets for machine learning, after the research is published. Moreover, to consider the research ethics of the designed experiment that involves recording attention states of the research subjects, written informed consent was obtained from the research subjects following full explanation of the experiment. The informed consent letter contains the specific nature of the research, including that assessing EEG signals by the MindWave headsets developed by NeuroSky is safe as well as it would not result in any potential risks to human body, the data that collect from them are only for the research, their name will never appear on any data collected and that instead we will provide a unique identification number on their data and that this information will remain secure such that only the principal investigator of this study will have access to it, the collected data that are no longer needed will be destroyed, and how participation will make a contribution to our study's goals. Finally, we certify that there is no conflict of interest in this paper.

References

Ba, S. O. & Odobez, J. M. (2009). Recognizing visual focus of attention from head pose in natural meetings. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *39*, 1, 16–33.

Ba, S. O. & Odobez, J. M. (2011). Multiperson visual focus of attention from head pose and meeting contextual cues. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *33*, 1, 101–116.

Ball, T., Kern, M., Mutschler, I., Aertsen, A. & Schulze-Bonhage, A. (2009). Signal quality of simultaneously recorded invasive and non-invasive EEG. *Neuroimage*, *46*, 3, 708–716.

Belle, A., Hargraves, R. H. & Najarian, K. (2012). An automated optimal engagement and attention detection system using electrocardiogram. *Computational and Mathematical Methods in Medicine*, *2012*, Article ID 528781, 12 pages.

Broadbent, D. E. (1958). *Perception and communication*. London: Pergamon press.

Chang, C. C. & Lin, C. J. (2011). LIBSVM: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, *2*, 27, 1–27.

Chen, C. M. & Huang, S. H. (2014). Web-based reading annotation system with an attention-based self-regulated learning mechanism for promoting reading performance. *British Journal of Educational Technology*, *45*, 5, 959–980.

Chen, C. M. & Lin, Y. J. (2014). Effects of different text display types on reading comprehension, sustained attention and cognitive load in mobile reading contexts. *Interactive Learning Environments*, doi: 10.1080/10494820.2014.891526.

Chen, C. M. & Sun, Y. C. (2012). Assessing the effects of different multimedia materials on emotions and learning performance for visual and verbal style learners. *Computers & Education*, *59*, 4, 1273–1285.

Chen, C. M. & Wang, H. P. (2011). Using emotion recognition technology to assess the effects of different multimedia materials on learning emotion and performance. *Library & Information Science Research*, *33*, 244–255.

Chen, L., Luo, W., Deng, Y., Wang, Z. & Zeng, S. (2009). Characterizing the complexity of spontaneous electrical signals in cultures neuronal networks using approximate entropy. *IEEE Transactions on Information Technology in Biomedicine*, *13*, 3, 405–410.

Clark, L., Kempton, M. J., Scarnà, A., Grasby, P. M. & Goodwin, G. M. (2005). Sustained attention-deficit confirmed in euthymic bipolar disorder but not in first-degree relatives of bipolar patients or euthymic unipolar depression. *Biological Psychiatry*, *57*, 2, 183–187.

Cohen, J. D. & Servan-Schreiber, D. (1992). Context, cortex, and dopamine: a connectionist approach to behavior and biology in schizophrenia. *Psychological Review*, *99*, 1, 45–77.

Das, J. P. (1986). *Attention checklist*. Edmonton, Canada: J. P. Das Developmental Disabilities Center, University of Alberta.

Driver, J. (2001). A selective review of selective attention research from the past century. *British Journal of Psychology*, *92*, 53–78.

Egner, T. & Gruzelier, J. H. (2004). EEG biofeedback of low beta band components: frequency-specific effects on variables of attention and event-related brain potentials. *Clinical Neurophysiology*, *115*, 1, 131–139.

Ghassemi, F., Moradi, M. H., Tehrani-Doost, M. & Abootalebi, V. (2009). Classification of sustained attention level based on morphological features of EEG's independent components. Proceedings of the IEEE/ICME International Conference on Complex Medical Engineering, USA, 1–6.

Gregory, T. K. & Pettus, D. C. (2005). An electroencephalographic processing algorithm specifically intended for analysis of cerebral electrical activity. *Journal of Clinical Monitoring and Computing*, *2*, 3, 190–197.

Harmony, T., Feranndez, T., Antonio, F. B., Juan, S. P., Bosch, J., Lourdes, D. C. *et al* (2001). EEG changes during word and figure categorization. *Clinical Neurophysiology*, *112*, 8, 1486–1498.

Hedges, J. H., Adolph, K. E., Amso, D., Bavelier, D., Fiez, J. A., Krubitzer, L. *et al* (2013). Play, attention, and learning: how do play and timing shape the development of attention and influence classroom learning? *Annals of the New York Academy of Sciences*, *1292*, 1–20.

Herrmann, C. S. & Mecklinger, A. (2001). Gamma activity in human EEG is related to high-speed memory comparisons during object selective attention. *Visual Cognition*, *8*, 3, 593–608.

Hsu, C. C., Chen, H. C., Su, Y. N., Huang, K. K. & Huang, Y. M. (2012). Developing a reading concentration monitoring system by applying an artificial bee colony algorithm to e-books in an intelligent classroom. *Sensors*, *12*, 10, 14158–14178.

James, W. (1983). *The principles of psychology*. New York: Holt.

Johnstone, S. J., Blackman, R. & Bruggemann, J. (2012). EEG from a single-channel dry-sensor recording device. *Clinical EEG and Neuroscience*, *43*, 2, 112–120.

Kaiser, J. & Lutzenberger, W. (2003). Induced gamma-band activity and human brain function. *The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry*, *9*, 6, 475–484.

Lee, J. & Park, S. (2006). The role of stimulus salience in CPT-AX performance of schizophrenia patients. *Schizophrenia Research*, *81*, 2–3, 191–197.

Lee, K. H., Williams, L. M., Breakspear, M. & Gordon, E. (2003). Synchronous gamma activity: a review and contribution to an integrative neuroscience model of schizophrenia. *Brain Research Reviews*, *41*, 1, 57–78.

Lezak, M. D., Howieson, D. B. & Loring, D. W. (2004). *Neuropsychological assessment* (4th ed.). New York: Oxford University Press.

Li, L., Gratton, C., Yao, D. & Knight, R. T. (2010). Role of frontal and parietal cortices in the control of bottom-up and top-down attention in humans. *Brain Research*, *1344*, 173–184.

Li, Y., Li, X., Ratcliffe, M., Liu, L., Qi, Y. & Liu, Q. (2011). A real-time EEG-based BCI system for attention recognition in ubiquitous environment. The International Workshop on Ubiquitous Affective Awareness and Intelligent Interaction, Beijing, China, 17–21 September 2011, pp. 33–40.

Limbu, N., Sinha, R., Sinha, M. & Paudel, B. H. (2015). Gender based EEG before and after acute bout of aerobic exercise. *Asian Journal of Medical Sciences*, *6*, 2, 30–35.

Liu, N. H., Chiang, C. Y. & Chu, H. C. (2013). Recognizing the degree of human attention using EEG signals from mobile sensors. *Sensors*, *13*, 8, 10273–10286.

Lutsyuk, N., Éismont, E. & Pavlenko, V. (2006). Correlation of the characteristics of EEG potentials with the indices of attention in 12- to 13-year-old children. *Neurophysiology*, *38*, 3, 209–216.

Mirsky, A. F., Anthony, B. J., Duncan, C. C., Ahearn, M. B. & Kellam, S. G. (1991). Analysis of the elements of attention: a neuropsychological approach. *Neuropsychology Review*, *2*, 2, 109–145.

Moradi, F., Buračas, G. T. & Buxton, R. B. (2012). Attention strongly increases oxygen metabolic response to stimulus in primary visual cortex. *Neuroimage*, *59*, 1, 601–607.

Murugappan, M., Nagarajan, R. & Yaacob, S. (2010). Classification of human emotion from EEG using discrete wavelet transform. *Biomedical Science and Engineering*, *3*, 390–396.

Nair, D. R., Burgess, R., McIntyre, C. C. & Luders, H. (2008). Chronic subdural electrodes in the management of epilepsy. *Clinical Neurophysiology*, *119*, 1, 11–28.

NeuroSky. (2015). NeuroSky MindWave, Retrieved January 15, 2015, from http://press.neurosky.com/MindWave.html

Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences of the United States of America*, *88*, 6, 2297–2301.

Pincus, S. M., Gladstone, I. M. & Ehrenkranz, R. A. (1991). A regularity statistic for medical data analysis. *Journal of Clinical Monitoring and Computing*, *7*, 4, 335–345.

Rapp, D. N. (2006). The value of attention aware systems in educational settings. *Computers in Human Behavior*, *22*, 603–614.

Rebolledo-Mendez, G., Dunwell, I., Martínez-Mirón, E., Vargas-Cerdán, M., de Freitas, S., Liarokapis, F. *et al* (2009). Assessing NeuroSky's usability to detect attention levels in an assessment exercise. The 13th International Conference on Human-Computer Interaction, Part I: New trends, pp. 149–158.

Riccio, C. A., Reynolds, C. R., Lowe, P. & Moore, J. J. (2002). The continuous performance test: a window on the neural substrates for attention? *Archives of Clinical Neuropsychology*, *17*, 235–272.

Roda, C. & Thomas, J. (2006). Attention aware systems: theories, applications, and research agenda. *Computers in Human Behavior*, *22*, 4, 557–587.
Rosvold, H. E., Mirsky, A. F., Sarason, I., Bransome, E. D. Jr. & Beck, L. H. (1956). A continuous performance test of brain damage. *Journal of Consulting Psychology*, *20*, 5, 343–350.
Rudin, L. I., Osher, S. & Fatemi, E. (1992). Nonlinear total variation based noise removal algorithms. *Physica D: Nonlinear Phenomena*, *60*, 1–4, 259–268.
Sabeti, M. (2009). Entropy and complexity measures for EEG signal classification of schizophrenic and control participants. *Artificial Intelligence in Medicine*, *47*, 3, 263–274.
Sanei, S. & Chambers, J. A. (2007). *EEG signal processing*. Chichester: John Wiley & Sons, Ltd.
Sarter, M., Givens, B. & Bruno, J. P. (2001). The cognitive neuroscience of sustained attention: where top-down meets bottom-up. *Brain Research Reviews*, *35*, 146–160.
Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N. & Wolpaw, J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on Biomedical Engineering*, *51*, 6, 1034–1043.
Smith, L. B., Colunga, E. & Yoshida, H. (2010). Knowledge as process: contextually cued attention and early word learning. *Cognitive Science*, *34*, 7, 1287–1314.
Smola, A. J. & Lkopf, B. S. (2004). A tutorial on support vector regression. *Statistics and Computing*, *14*, 199–222.
Sohn, H., Kim, I., Lee, W., Peterson, B. S., Hong, H., Chae, J. H. *et al* (2010). Linear and non-linear EEG analysis of adolescents with attentiondeficit/hyperactivity disorder during a cognitive task. *Clinical Neurophysiology*, *121*, 11, 1863–1870.
Steinmayr, R., Ziegler, M. & Träuble, B. (2010). Do intelligence and sustained attention interact in predicting academic achievement? *Learning and Individual Differences*, *20*, 1, 14–18.
Stiefelhagen, R., Yang, J. & Waibel, A. (2002). Modeling focus of attention for meeting indexing based on multiple cues. *IEEE Transactions on Neural Networks*, *13*, 4, 928–938.
Toet, A. (2006). Gaze directed displays as an enabling technology for attention aware systems. *Computers in Human Behavior*, *22*, 4, 615–647.
Wager, T. D., Jonides, J. & Reading, S. (2004). Neuroimaging studies of shifting attention: a meta-analysis. *Neuroimage*, *22*, 4, 1679–1693.
Wolpaw, J. R., McFarland, D. J., Neat, G. W. & Forneris, C. A. (1991). An EEG-based brain-computer interface for cursor control. *Electroencephalography and Clinical Neurophysiology*, *78*, 3, 252–259.
Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G. & Vaughan, T. M. (2002). Brain-computer interface for communication and control. *Clinical Neurophysiology*, *113*, 6, 767–791.
Yuan, Q. (2011). Epileptic EEG classification based on extreme learning machine and nonlinear features. *Epilepsy Research*, *96*, 1–2, 29–38.
Yun, K. (2012). Decreased cortical complexity in methamphetamine abusers. *Psychiatry Research: Neuroimaging*, *201*, 3, 226–232.
Zhang, D., Zhou, L., Briggs, R. O. & Nunamaker, J. F. (2006). Instructional video in e-learning: assessing the impact of interactive video on learning effectiveness. *Information & Management*, *43*, 1, 15–27.
Zhao, F., Shi, M. & Xu, T. (2010). A new image restoration model based on the adaptive total variation. International Conference on Digital Manufacturing and Automation (ICDMA), 1, pp. 63–66.
Zheng, Y., Zhu, G., Jiang, S., Huang, Q. & Gao, W. (2008). Visual-aural attention modeling for talk show video highlight detection. IEEE International Conference on Acoustics, Speech and Signal Processing, 2213–2216.
Zumsteg, D. & Wieser, H. G. (2000). Presurgical evaluation: current role of invasive EEG. *Epilepsia*, *41*, 3, S55–S60.