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Article

Real-Time Cognitive Load Measurement in Classroom Environment using a Dry-Electrode EEG system

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Abstract: Cognitive load (CL) theory suggests that instructional materials need to be designed for reducing unnecessary CL and has been regarded as one of the most influential theories in science education. How to measure individual CL is still under investigation. In this study, we developed an eight-channel dry-electrode electroencephalogram (EEG) system and proposed an algorithm to real-time measure the depth of working memory of the N-back task in a classroom environment. The ocular artifact was removed by using the recursive least-square (RLS) method. Time-frequency analysis was applied to extract event-related theta-band activities in the artifact-suppressed EEG signals. Eight participants had the active duration for theta-band activities as 1.44±0.36 mv, 1.70±0.22 mv, and 1.97±0.04 mv for 0-back, 1-back, and 2-back tasks, respectively. In contrast to the previous research that has used spectral power of particular frequency bands as signal features, we found the detection of active duration provides better discrimination power in classifying different CL levels, compared to that of the classification using features of spectral power. The result in this study demonstrates the feasibility of theta-band EEG as an indicator to measure students' cognitive load in a classroom environment.

Keywords: Cognitive load, Electroencephalography, N-back task

1. Introduction

In the learning process, especially in science learning, students are encouraged to utilize science knowledge, skills (problem-solving, reasoning, creativity, and so on), and a positive attitude to solve real-world problems. Students may face several challenges and obstacles while solving new problems. Therefore, determining what students learn and how they feel about the learning throughout the instruction (also referred to as formative assessment), is important, but still under investigation. Cognitive load (CL), sometimes also referred to as learning difficulty, has been regarded as an important issue in science education especially.

The cognitive load theory (Sweller, 1988) [1], which describes the cognitive processes involved in learning and understanding, has been somewhat limited, in regards to addressing said issues. Recent literature in educational psychology provided evidence for the strong link between cognitive loading and academic performance [2,3]. Students may easily feel cognitive overload when facing complex learning material or solving new problems due to the limitation of working memory capacity. Evaluation of cognitive load from students' perceptions in real-time may help teachers adjust or modify their instruction. Evaluating students' subjective cognitive load has been regarded as a difficult and under-investigated issue. Therefore, this study aimed to develop a dry-electrode EEG system for real-time monitoring of an individual's cognitive load in a classroom environment.

How to assess cognitive load perceived in students is important. Schultheis and Jameson (2004) [4] concluded that each cognitive load measurement method can be assigned to one of four classes: (1) analytic measures, (2) subjective measures (self-report), (3) performance measures, and (4) psycho-physiological measures. Among diverse methods, self-rating assessment of cognitive load was used most frequently, owing to the convenience of counting scores and the capability of administering it to large classes (Chang & Yang, 2010) [5]. Most research applies the 9-point rating scale of symmetrical category mental effort developed by Paas (1992) [6] to assess cognitive load. The rating is usually collected immediately after instruction or completion of a task.

As mentioned previously, it is important to keep and maintain students in appropriate cognitive loads during classroom learning. A possible strategy is to assess an individual's cognitive load in real-time and modulate instructional pace/difficulty according to students' perceived cognitive loads. By keeping the cognitive load of learners at appropriate levels, it is an effective way to promote learning efficiency. However, evaluating instantaneous cognitive load over time by subjective measurements has been regarded as a difficult issue because the cognitive processes are hidden behind our observations.

Electroencephalogram (EEG) has the advantages such as real-time monitoring, low cost, high temporal resolution, easy-to-preparation, and portability. Compared to other methods for brain imaging, the EEG system has been chosen mostly for real-time monitoring of cognitive loads in classroom learning [7,8]. Over the past few decades, scientists and engineers have achieved great progress in the development of EEG technology. Traditional EEG utilizes a wet electrode that requires electrolyte gel on a participant's scalp to reduce the contact impedance between his/her scalp and the EEG electrode. The requirement of electrolyte gel makes the EEG preparation time-consuming and lousy, as the electrolyte usually makes subjects feel uncomfortable inconvenient in a classroom environment. Accordingly, in this study, we have developed a dry EEG electrode to facilitate the EEG recording in the classroom. The EEG signals recorded from the dry electrodes were digitized by an eight-channel wearable EEG system and were wirelessly transmitted to a cloud server for cognitive load analyses.

To measure the level of cognitive load using EEG, several algorithms for EEG analyses were developed. Friedman et al. (2019) [9] applied independent component analysis (ICA) to retrieve EEG features and applied Lempel-Ziv complexity (LZC) (Zhang et al., 2016) [10], Multi-Scale Entropy (MSE) (Abásolo et al., 2008) [11] and Detrended Fluctuation Analysis (DFA) (Peng et al., 1995; Rubin et al., 2013) [12,13] to evaluate the cognitive workloads. Kumar and Kumar (2016) [14] designed a mental multiplication task. The EEG features were extracted using ICA and alpha-band power in orbital prefrontal and temporal lobe regions were studied. They found that the spectral power in the alpha band was significantly related to the level of cognitive loads. Mazher et al. (2017) [15] studied the cognitive load in the learning phase by designing a multimedia learning task. EEG complexity was measured by approximate entropy and a partial directed coherence (PDC). Trammell et al. (2017) [16] calculated the ratio of the spectral power of theta and alpha bands. They found the cognitive load was positively correlated with the power ratio between theta and alpha bands. In addition, the theta-alpha ratio (TAR) also presented an age-dependent tendency. Seve cognitive psychology studies have revealed that brain theta and alpha activities are related to task difficulty or cognitive load when dealing with tasks. These studies found that the decreased alpha (8–12 Hz) and the enhanced theta (4–8 Hz) activity were usually observed along with the difficult or complex tasks. In addition, increased alpha activity was detected in easy tasks that require low mental workloads. In event-related task design, cognitive loads were analyzed using event-related desynchronization/ synchronization (ERD/ERS) in the alpha, beta, and theta brain wave rhythms. Antonenko et al. (2010) [17] pointed that increased cognitive load is associated with higher brain wave desynchronization for alpha and beta rhythms. In this study, we developed a dry-electrode EEG system to real-time monitor students' cognitive load in the N-back task. The study results provide a feasible system architecture for cognitive load monitoring in future classroom environments.

2. Materials and Methods

2.1 Subjects and Experiments

Eight graduate volunteers, six males and two females (aged between 23 and 28 years old) were recruited in this study. Each subject was requested to participate in three visual N-back tasks, including a 0-back, a 1-back, and a 2-back task. Visual stimuli were displayed on a 17-inch ViewSonic LCD monitor (model VG724; reaction time < 3ms; 60 frames/s) with a distance of 50–60 cm away from the viewer. Upper-case letters were sequentially presented with 2 s duration and 0.5 s blank duration. Visual stimuli were presented with 6□subtended visual angles. A small cross located at the center of the LCD monitor was also designed for subjects to facilitate the fixation of their eyes. The inter-stimulus interval (ISI) was 2.5 s. For an N-back task, one subject had to remember the upper-case letter that presented N turns back, in which N was chosen as zero, one and two in zero-back, one-back, and two-back tasks, respectively. When an N-back stimulus was identified, i.e., the currently presented letter matched the letter presented in N-back steps, the subject had to press the left button of a computer mouse with the index finger. Figure 1 shows the examples of zero-back, one-back, and two-back tasks. In the zero-back task, subjects had to respond to each visual stimulus. The recorded EEG data of the zero-back task were used as a baseline for comparisons with one- and two-back tasks. In the middle and right figures, subjects only responded to the cases of the same letters presented in one- or two-back steps when one-back or two-back task was performed. The volunteers were all informed explicitly about the plan, protocol, and procedure of this study, and all subjects gave informed consent before performing the study. The study was approved by the Institutional Review Board of National Taiwan University Hospital and ClinicalTrials.gov. (ClinicalTrials. gov identifier: NCT00713570).

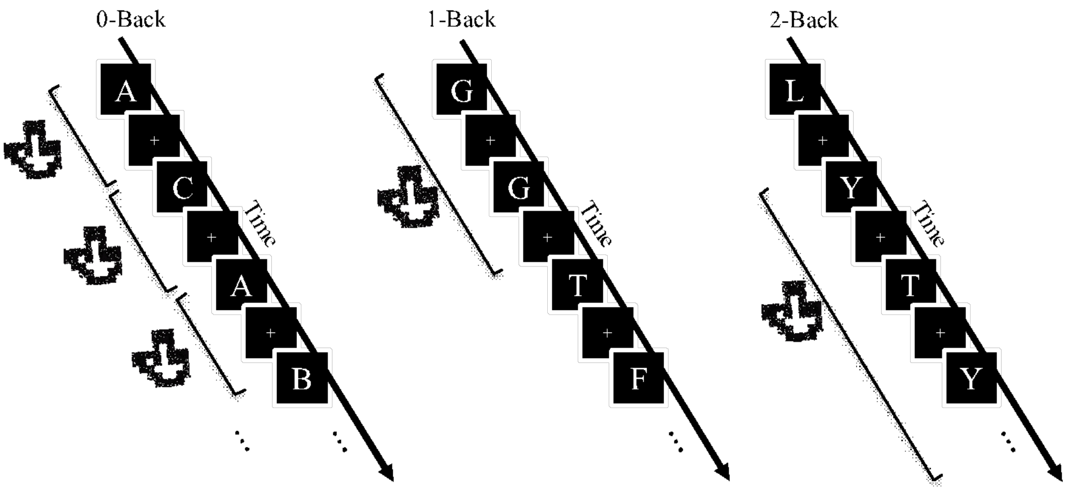


Figure 1. Examples of 0-back, 1-back and 2-back tasks.

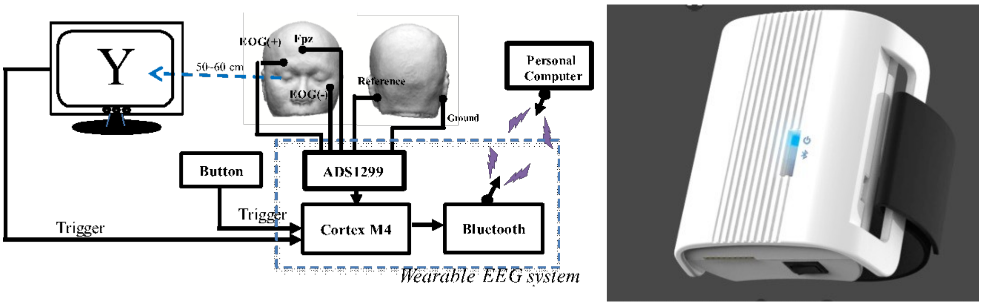
2.2 EEG system and data recording

EEG data were recorded by an eight dry-channel wearable EEG system (InMex EEG system, WellFulfill Co., Taiwan). Each dry electrode has a three-layer design, including a contact layer, a shielding layer (middle layer), and the circuit layer (top layer). The contact layer has ten spring-loaded gold-coated copper pins so that the pins pass through the subject's hairs to contact the subject's scalp comfortably. The top layer has a differential amplifier which magnified the voltage difference between the pins (contact layer) and the shielding layer (middle layer). The size of the dry electrode was designed in disk shape with a 1 cm diameter [18]. Each EEG channel is configured as a monopolar or bipolar channel for different experimental applications. In this study, we measured EEG signal from the frontal region at Fpz position, according to the international 10–20 system, with one reference and one ground electrode placed at left and right mastoids, respectively. Two EEG channels out of the eight EEG channels were configured as a bipolar electrooculogram (EOG) to monitor the subject's eye movements by placing two electrodes above the left eye and right outer canthus. Both Fpz EEG and EOG signals were digitized at 1 kHz with 24 bits data resolution and wirelessly transmitted to the tutor's personal computer (PC) to estimate the participant's cognitive load. The system architecture and the outlook of the wearable EEG system are shown in Fig. 2(a) and 2(b), respectively.

2.3. EEG Signal processing

In this study, we estimated subjects' cognitive load using calculating the ERD/ERS in theta-band power. The theta-band EEG signals were recorded from the subjects' frontal region, located at Fpz position, to avoid the inadequate contact of EEG electrode from blockage of hair coverage. In addition, we applied a recursive least-square (RLS) adaptive filter [19] to the recorded EEG signals, since EEG signals are usually susceptive to electrooculogram (EOG). The EOG-suppressed EEG signals were then segmented into EEG epochs anchored to onset times of visual stimuli (the presence of upper-case letters). Morlet wavelet was then applied to obtain the temporal-spectral analysis of each EEG epoch, and the temporal responses within 4–7 Hz were then summated to represent the subject's temporal changes of theta-band responses. For the theta-band response of each epoch, we defined the mean □2std at $p<0.05$ of theta-band responses between -0.5 and 0 s as baseline threshold. As brain response varies with time and theta-band power rises with the increase of cognitive load, the duration of theta-band responses higher than the baseline threshold was defined as the active duration in this study. Longer active duration indicates that the subject is experiencing a longer cognitive load which reflects the difficulty of the task that the subject is performing.

Figure 3 shows the demonstration of the EEG signal processing. The first and the second graphs show the measured FPz EEG and EOG signals, respectively, and reveal that the EEG was affected by the EOG artifact. The third graph shows the EOG-suppressed EEG signal with RLS. The noise-suppressed EEG signals were then segmented into epochs, and the temporal-spectral responses of each epoch were calculated. In the bottom panel, the active duration was measured as 1.85 s.



(a) **(b)**

Figure 2. Architecture and outlook of the wearable EEG system. (a) Experimental system setup. (b) InMex 8-channel EEG system.

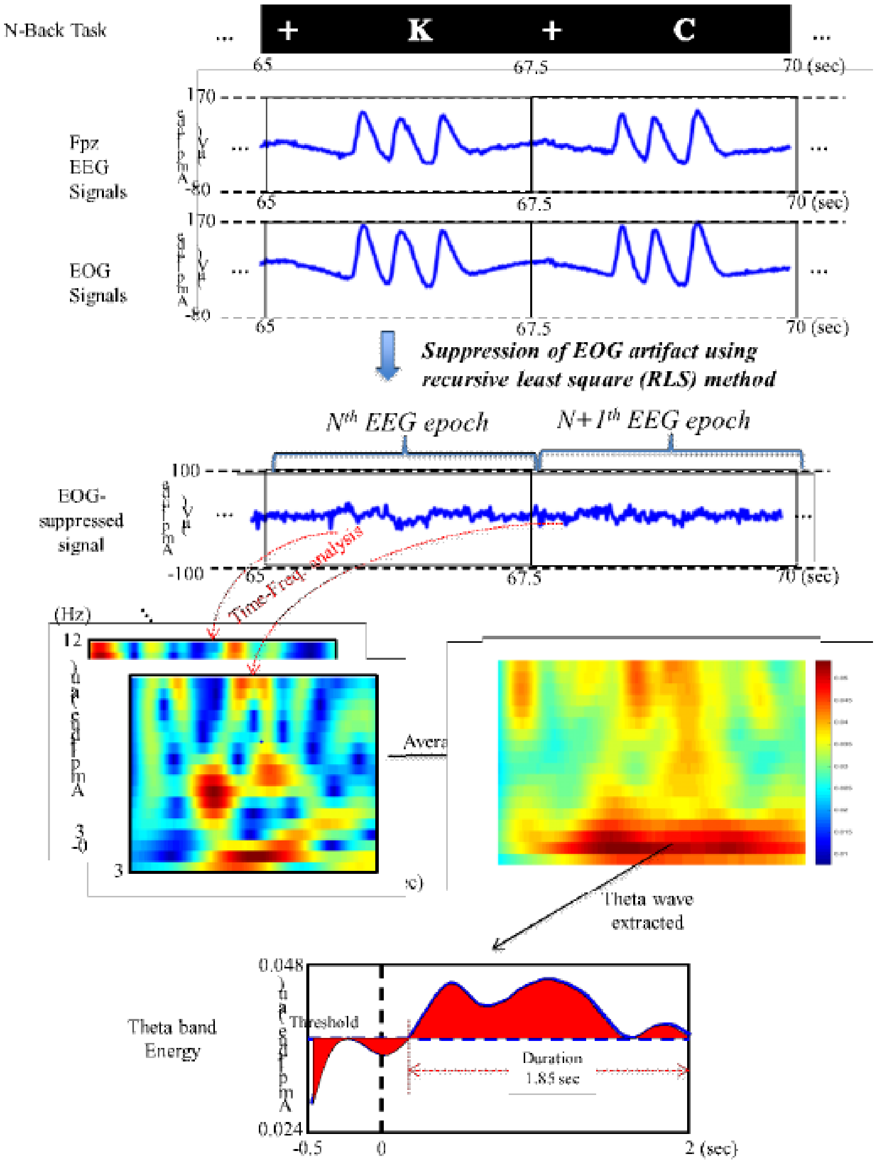


Figure 3. Demonstration of our EEG signal processing. The first and second graphs show the measured Fpz EEG and EOG signals, respectively. The third graph shows the EOG-suppressed EEG signal with RLS. The noise-suppressed EEG signals were then segmented into epochs, and temporal-spectral responses of each epoch was calculated

3. Results

Figures 4(a) and 4(b) show two examples of the active duration detections in subject 2 and subject 4, respectively. The onset time of visual stimulus (the present time of upper-case letter) was marked as zero time index. The threshold values of 0-back, 1-back, and 2-back tasks are calculated as the means plus two-times the standard deviations from the baseline intervals (-0.5–0s) (marked by dashed lines). The active duration of 0-back, 1-back, and 2-back in subject 2 was 1.50, 1.54, and 2.00 s. In subject 4, the active durations were 1.86, 1.93, and 2.00 s. The active duration increased with the increase of difficulty of a cognitive task.

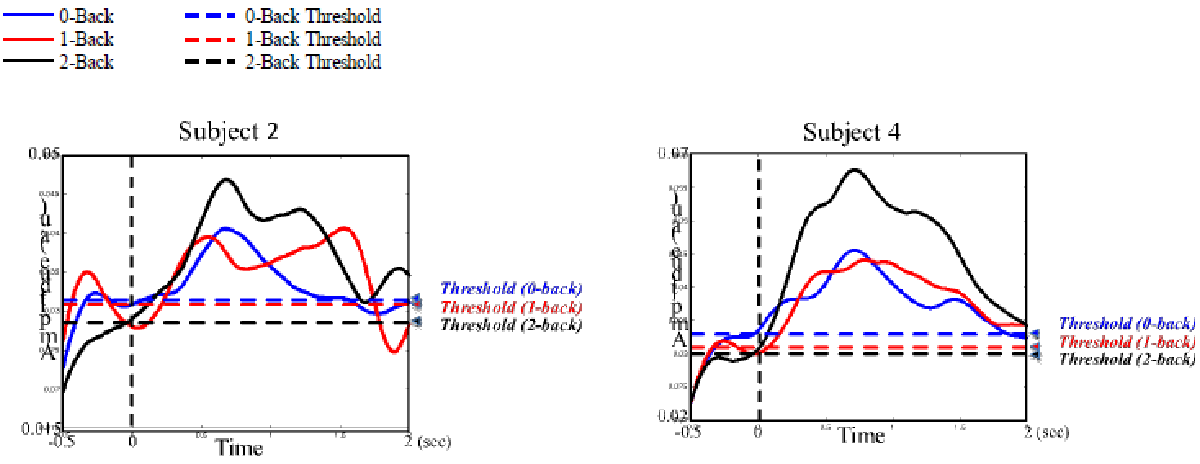


Figure 4. Two examples of the active duration detections in subject 2 and subject 4. The onset time of visual stimulus (the presence time of upper-case letter) was marked as zero time index. The threshold values of 0-back, 1-back and 2-back tasks are calculated as the means plus two-times the standard deviations from the baseline intervals (-0.5s ~0s) (marked by dashed lines). The active durations of 0-back, 1- back and 2-back in subject 2 were 1.50, 1.54, and 2.00 seconds. In subject 4, the active durations were 1.86, 1.93, and 2.00 seconds.

Table 1 lists the results of active durations detected in the eight participants. The active duration of 0-back, 1-back, and 2-back over the eight subjects were 1.43±0.35 s,1.70±0.22 s, and 1.97±0.04 s. The active duration of the 2-back test is significantly larger than the 0-back and 1-back tests (p<0.01; matched-pair Wilcoxon nonparametric test). The active duration of the 1-back test is larger than the 0-back test (p<0.05; matched-pair Wilcoxon sign rank test). It indicates the use of theta-band active duration is an effective tool to discriminate different levels of cognitive loads.

Table 1. Active duration of 0-back, 1-back and 2-back tasks in the eight participants.

Subject Index	Duration (sec)		
	0-Back	1-Back	2-Back
S1	1.12	1.67	1.92
S2	1.50	1.54	2.00
S3	1.44	1.78	2.00
S4	1.86	1.93	2.00
S5	0.87	1.26	1.89
S6	1.53	1.80	1.96
S7	1.93	1.95	2.00
S8	1.25	1.69	1.96

4. Discussions and Conclusions

In the last few years, cognitive science has acknowledged learning structures in terms of an information processing system involving long-term memory (which effectively stores all of knowledge and skills on a more-or-less permanent basis) as well as working memory (which performs the intellectual tasks associated with consciousness). Information may only be stored in long-term memory after being attended to and, information may only be processed by working memory. Human working memory, however, is limited to the amount of information it holds, and the number of operations it performs on that information [20]. If a learning task utilizes excess information capacity, learning will be impeded. As mentioned by Kirschner (2002) [21], cognitive load is based on a cognitive architecture that consists of limited working memory, with partly independent processing units for visual and audio information, which interacts with unlimited long-term memory. In this study, we proposed a wearable EEG device for measuring the capability of working memory in students. Owing to the close relationship between working memory and cognitive load, the proposed EEG approach helps to understand cognitive load in classroom environments and probe students' cognitive load for different teaching materials.

Over the past few decades, a considerable number of studies have been conducted on the correlation between cognitive load and learning performance. Several studies revealed that students' cognitive load was correlated significantly with academic performance [17]. Therefore, how to decrease learners' cognitive load during the learning process has become an important issue. The majority of studies have focused on investigating the effectiveness of the specific instructional intervention on cognitive load. For example, recent studies in science education indicated students showed lower cognitive load in a multimedia assist learning environment than in a conventional instruction (text only) [5]. Yeh et al. reported that the appropriate application of animation is beneficial for reducing extraneous cognitive load and improving students' understanding of complex phenomena [22]. In brief, educational researchers encourage the appropriate design of educational tools to be taken into account as individual factors that might affect cognitive load. These factors, including task complexity, academic experience, cognitive capability, cognitive style, and prior knowledge of students, may reduce cognitive load and enhance student learning.

When considering how to assess the cognitive load in real-time, two factors need to be considered for the measurement of individual instantaneous cognitive load: the suitable instrument to be utilized in the classroom environment and how to develop an efficient algorithm to run in real-time which provides teachers with learner perceived loading in the learning process. It is difficult to assess a learner's cognitive load by self-report strategy in real-time as evaluating instantaneous cognitive load usually needs repeat testing in the learning process. Repeating tests may increase cognitive load and induce test anxiety. New research areas including neuroscience and cognitive science have emerged to provide exciting, progressive, and concrete evidence in the exploration of human behavioral mechanisms. Medical imaging technologies provide an avenue for strengthening the teaching-learning connection.

The relation between the spectral power of the theta band and working memory has been studied in several research. However, the large inter-individual variation usually results in difficulty in determining a threshold for classifying different levels of working memory [23]. As shown in Fig. 4, the maximum amplitude of 0-back was even higher than the maximum amplitude of 1-back in subject 4, which indicates the ambiguity of discriminating working memory levels using simply using the value of spectral power, especially in low cognitive load tasks. Accordingly, in contrast to previous studies, we chose the active duration (the duration of theta power succeeding resting threshold in each individual) as the index to classify different working memory levels. The study result has demonstrated the active duration as an effective method to classify cognitive load levels.

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Conflicts of Interest: The authors declare no conflict of interest.

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