REAL TIME EEG BASED MEASUREMENTS OF COGNITIVE LOAD INDICATES MENTAL STATES DURING LEARNING

Alex Dan
Technion
Israel Institute of Technology
alexda@alumni.technion.ac.il

Miriam Reiner
Technion
Israel Institute of Technology
miriamr@technion.ac.il

One of the recommended approaches in instructional design methods is to optimize the value of working memory capacity and avoid cognitive overload. Educational neuroscience offers innovative processes and methodologies to analyze cognitive load based on physiological measures. Observing psychophysiological changes when they occur in response to the course of a learning session allows adjustments in the learning session based on the individual learner's capabilities. The availability of non-invasive electroencephalogram (EEG)-based devices and advanced near-real-time analysis techniques have improved our understanding of the underlying mechanisms and have impacted the way we design instructional methods and adapt them to the current learner's cognitive load and valence states. We review Cognitive Load Theory, how cognitive load may be measured, and how analysis of EEG data can be applied to enhance learning through real-time measurements of the learner's cognitive load. We show an experiment that provides a proof of concept of real-time measures based on EEG indicators and of mental states during learning.

1. INTRODUCTION

Assessing a learner's engagement and mental load during learning tasks is one of the main topics of educational method design. Educational neuroscience offers a conceptual framework for understanding in detail how the brain builds cognitive systems from sensory input. It offers a physiologically based assessment of variables that may affect these systems and improve the efficacy of learning methods (Ansari and Coch, 2006; Carew and Magsamen, 2010; Devonshire and Dommett, 2010; Immordino-Yang and Fischer, 2010; Goswami and Szũcs, 2011). Neuroscience creates a new challenge for education because it provides new characterizations of learning through the ongoing physiological state of the student that are applicable to instructional design. Real-time measures, such as electroencephalogram (EEG), carry the potential to expand our ability to interface with technology and to acquire data regarding the impact of learning stimuli on the electrical activity of the brain. Through the broad availability of these noninvasive EEG-based devices and analysis techniques, we can determine which brain regions are involved in school-taught skills and how their neural correlates change over the course of study (Ansari, Smedt, and Grabner, 2012). EEG-based physiological measurements that assess learning variables may provide new details with a potential impact on the theory of instructional design methods, and especially on methods of online adaptation of the learning environment the cognitive and valence states of the learner. We will review how analysis of EEG data can be applied to enhance learning through real-time measures of the student's mental load. In the following, we describe the underpinning theory and mental mechanisms, and describe a validated application: we start with a learning experiment to provide a proof of concept of learning and real-time measures of EEG as indicators of mental states.

2. MENTAL LOAD AND COGNITIVE LOAD THEORY

Mental load is a multidimensional concept with components drawn from factors such as age, mental tasks, physical tasks, and stress (Xie and Salvendy, 2000; Pickup, Wilson, Sharpies, Norris, Clarke, and Young, 2005; Wickens, 2008; Meshkati and Hancock, 2011). Borghini, Astolfi, Vecchiato, Mattia, and Babiloni (2012), looking for a complete description of mental workload, quoted an earlier work by O'Donnel and Eggemeier (1986, p. 41-42): "the portion of an individual's limited capacity that is actually required by task demands."

From this perspective, the assessment of mental load is helpful in optimizing the design of the features of a learning session such as pace, order, details, and level of difficulty leading to increased effectiveness in learning. Such analysis may point to sustained periods of mental overload, which ultimately result in a reduction of comprehension, memorizing, and learning, with negative emotional effects (Parasuraman, Sheridan, and Wickens, 2008; Wickens, 2008; Holm, Lukander, Korpela, Sallinenderive, and Müller, 2009).

Evaluation of mental load is based on the understanding of human cognitive processes and methodologies for the acquisition of measures. Individual mental load combines the situational demands with the cognitive efforts derived from the memory structure. Cognitive efforts are not necessarily efficient. The effective mental burden is the mental workload "people must bear while working" and the inefficient workload is the one "that workers may avoid" (Xie and Salvendy, 2000, p. 221). This statement leads to the development of an information-processing model; effective workload enables people to access critical data in the working memory using an optimized cognitive strategy, while the ineffective workload is generated by unnecessary use of mental resources (Sammer, 1996). Implementing the information processing model is the basis of the Cognitive Load Theory.

Cognitive Load Theory is a theoretical concept increasingly involved in the design of instructional methods. The fundamental idea of Cognitive Load Theory is that working memory is limited so that if the learning task requires too much capacity, learning will be slowed down (Sweller, 1988). One of the recommended approaches in instructional design methods is to optimize the value of working memory capacity and avoid cognitive overload (Höffler and Leutner, 2007; Georgeon and Ritter, 2012). Cognitive Load Theory makes a distinction between three types of sources for the learners' cognitive load: intrinsic, extraneous, and germane cognitive load. All three sources are involved in an individual's attempt to solve a problem or to accomplish a task (Sweller, 1988; Chandler and Sweller, 1991; DeLeeuw and Mayer, 2008; Goldman, 2009).

Intrinsic cognitive load is determined by the interaction between the nature of the material being learned and the capacity of the learners (Sweller, 2010). Gerjets, Scheiter, and Catrambone (2004) trace intrinsic cognitive load to the number of elements that must be processed simultaneously in working memory for schema creation (i.e., element interactivity). Extraneous cognitive load is the effect of instructional techniques that require learners to engage in working memory activities that are not directly related to schema construction or automation (Paas, Renkl and Sweller, 2004). Furthermore, because of the intrinsic cognitive load, required for determining interactivity, and the extraneous cognitive load, needed for instructional design, are additive, the result may be fewer cognitive resources left in working memory to allocate to schema construction and automation during learning (Sweller, 1998). Consequently, learning in educational setups is impeded (Paas, Renkl and Sweller, 2004). Germane cognitive load is the result of favorable cognitive processes, such as abstractions and elaborations, that are promoted by the instructional presentation (Gerjets et al., 2004).

Several findings suggest that extraneous cognitive load should be a primary consideration when designing instruction and facilitate knowledge acquisition (van Merriënboer and Sweller, 2005; Tabbers, Martens, and van Merriënboer, 2004; Plass et al., 2013). Extraneous cognitive load, by its definition, is under instructional control and can be varied by the way in which information is presented and the actions required by the students. Optimized efficiency in a learning task can be achieved when the distribution of learning tasks suits the learner's needs and capabilities. The goal is not necessarily minimizing cognitive (or mental) load during learning, but optimizing it for learning.

Optimal management of cognitive resources must distinguish between external control through proper instructional design and internal control based on average learners' strategies for dealing with high cognitive load (Bannert, 2002). Personal cognitive load (i.e., germane cognitive load) may be adjusted by the terms of optimization of the instructional assets subject to the assessment of the learners' needs and abilities. An adequate measurement of the cognitive load may improve the structure of the necessary instructional aids and the personal efficacy in learning (Mayer and Moreno, 2003; Morrison and Anglin, 2005; Cooper, 2008; Eysink and de Jong, 2012).

The novelty of the present study is in the methodology applied for assessing the effectiveness of a learning environment, based on the cognitive load of the user, as extracted from the changes in neural activation during learning scenarios. The relative cognitive load indices introduced in this study expand the current theoretical field of neurophysiological measures concerning cognitive load.

3. Measurements of Cognitive Load

Cognitive load measurement techniques are typically organized into three main domains: subjective measurements, based on perceived mental load; performance measures, based on the output of predetermined scales of normal task performance (including subdivisions of primary and secondary task measures); and psychophysiological measures (Cain, 2004).

Subjective techniques typically involve asking the participant, in very structured ways, how he or she would rate the difficulty of the training material (Whelan, 2007). However, the setting, situation, and context can often affect the rater's score as much as the actual task difficulty. Individual differences play a significant role in the accurate assessment of cognitive load. For example, Hancock and Meshkati (1988) cite research showing that subjects who scored highly on intelligence tests actually rated a problem as harder than subjects who scored less highly, even though the problems were the same.

Subjective questionnaires have a limited sensitivity to changes in cognitive load levels; perceived cognitive load may go up as well as down, while performance remains the same, particularly when tasks present only a low cognitive load. There is also a lack of consistency between performance ratings and subjective ratings of cognitive load, difficulty, and effort.

Performance measures also tend to be task-specific, vary within tasks, and not be easily replicated across unrelated tasks.

Performance measures of cognitive load can be classified into two broad types: primary task measures and secondary task measures (Cain, 2004). The performance of the primary task measures will always be of interest to determine participant cognitive load while performing the task and to examine whether it derives from the task difficulty or the participant's ability to perform it. In secondary task procedures, the performance of the task itself may have no practical value and serves only to measure the cognitive load (Lysaght et al., 1989, Cain, 2004). To have primary task measures that are reliable, tests must have an appropriate context, relevance, and representation.

The combination of performance and cognitive load measures has been identified to constitute a reliable estimate of the mental efficiency of instructional techniques (Paas, Tuovinen, Tabbers, and Van Gerven, 2003). Further research into the sensitivity of the combined design has limited the scope of those methods, however. For example, Paas' cognitive load questionnaire (Lepink et al., 2013) was shown to be sensitive to variations in intrinsic load, and a differential sensitivity to high and low extraneous load conditions was not evident. Workload profile index, a subjective, self-report questionnaire, may be sensitive to intrinsic load results under low extraneous load requirements but susceptible to extraneous load effects under high intrinsic load conditions (Rubio, Díaz, Martín, and Puente, 2004). The conclusion is that none of the methods used is entirely comprehensive in their diagnostic utility and predictive power for all types of load.

Despite those limitations, the combined method, which merges questionnaires of perceived cognitive load (based on effort rating and challenging rating) with a measure of performance (such as response time, scores, etc.), is considered to measure the total cognitive load without distinction between its three sources (DeLeeuw and Mayer, 2008).

4. PHYSIOLOGICAL METHODS

The need to measure cognitive load objectively and validly has encouraged exploration of alternative methods. Physiological indices assume that cognitive load can be measured using the level of physiological activation. These responses are physical signals that make it possible to discover human psychological processes by monitoring the physical changes.

Psychophysiological measures are grouped according to the controlling nervous system they measure (Dirican and Göktürk, 2011). The human nervous system has two parts, the central nervous system (CNS) and the peripheral nervous system (PNS). The CNS consists of the brain, brain stem, and spinal cord. The main measures related to CNS are electroencephalography (EEG), such as event-related brain potentials (ERP), oscillations and electrooculography (EOG). The leading measures of the PNS are heart rate (HR), heart rate variability (HRV), pupil dilation, eye movements, galvanic skin response (skin conductance), and electromyogram (EMG).

The main benefits of the psychophysiological measures of cognitive load are the objectivity of the measures, the sensitivity to the different cognitive processes, the unobtrusiveness of the procedures, and their implicitness and continuity (Dirican and Göktürk, 2011). The last advantage is of crucial importance. Implicitness and continuity of EEG measures allow near real- time assessment of the cognitive load during learning. Thus, observing psychophysiological changes when they occur in response to the course of the learning session allows adjustments in the learning session based on the individual learner's capabilities.

5. PHYSIOLOGICAL MEASUREMENTS AND INDICES

Psychophysiological measures are grouped according to the control nervous system being measured (Dirican and Göktürk, 2011). As noted in the previous section, the human nervous system is mainly classified into two parts, the CNS and the PNS. Instantaneous measurements and methods focused on CNS, such as functional magnetic resonance imaging (fMRI; Buccino et al., 2004), EEG (Antonenko, Paas, Grabner, and van Gog, 2010), eye tracker recording (Reiner and Gelfeld, 2014) and others, have been studied during the last decade as part of an objective frame to establish cognitive load.

Physiological methods are mainly of interest to the extent that they provide indications of neural activity related to the perceptual, cognitive, affective, or motor functioning of the person (Parasumaran, 2003). Physiological indices assume that the cognitive load can be measured using the level of neural activation. These are clear indications that support the determination of individual mental/cognitive processes by monitoring changes in their neural activation (Dirican and Göktürk, 2011). Cognitive processes such as memory, awareness, and decision making may be induced by computations performed by assemblages of synchronously active neurons (Teplan, 2002; Ward, 2003).

The analysis of EEG waveforms, and their decomposition into different frequency bands, has often been used in the evaluation of the variation of the cognitive state of subjects during the execution of cognitive tasks, sensory-motor jobs, or while learning (Borghini et al., 2012; Smith et al., 2001; Gevins et al., 1998). The most useful analysis of the EEG is power spectral analysis, which allows us to determine the extent to which the neurons generating the EEG output are oscillating synchronously at different frequencies. In obtaining the power spectrum for a time series of EEG samples, the voltage fluctuations recorded by an EEG electrode from moment to moment are analyzed into different sine wave frequencies. The fluctuations in spectral power of a particular frequency, with changes in experimental tasks, or over time, may indicate relationships between the mean diversion of groups of neuron and cognitive processes (Ward, 2004; Holm et al., 2009).

The introduction of low-cost wireless EEG headsets allows now extensive use and commercialization and hence, has been recently integrated into research (Das, Chatterjee, Das, Sinharay, & Sinha, 2014). The use of EEG signals in measuring educational states is growing fast, and identifying real-time applications in the educational practice and research is needed (Yuan, Chang, Xu, & Mostow, 2014).

6. EEG MEASURES INDICATE COGNITIVE LOAD

Başar et al. (1999) hypothesized that integrative brain functions are manifested in the superposition of several oscillations. According to a later study, Başar, Başar-Eroglu, Karakaş, and Schürmann (2001) argued that selectively distributed oscillatory systems (Delta, Theta, Alpha, and Gamma frequencies) are activated by cognitive events. They concluded that it was not possible to assign a particular function to a given set of oscillatory activities. Cognitive events (or complex functions) evoke superimposed signals of multiple oscillations.

Parallel to the previous work, Gevins, Smith, Leong, McEvoy, Whitfield, Du, and Rush (1998) and McEvoy, Smith, and Gevins (1998) used EEG indices to assess working memory states. They tested neural activations during pattern recognition. Their results explicitly revealed that there is an increase in frontal Theta frequency activity along with a decrease in Alpha frequency activity when there is an increasing mental load related to the memory task.

The results of Başar et al. (2001) and Gevins et al. (1998) provided the feasibility tests for using EEG-based methods for monitoring cognitive load. From this starting point on, researchers continue to seek the appropriate indices for measuring the cognitive load of learning and memorizing assignments.

EEG measures of Theta–Alpha channels in frontal and parietal brain regions have been found to correlate with the mental/cognitive load. Most studies demonstrated that frontal Theta increases with higher cognitive load and Alpha decreases with a higher cognitive load (Gerě & Jaušcvec, 1999; Grimes, Tan, Hudson, Shenoy, & Rao, 2008; Itthipuripat, Wessel, & Aron, 2013; Maurer et al., 2015; Zarjam, Epps, & Lovell, 2013). This observation led to several studies that linked Theta–Alpha frequency and cognitive load (Chick, 2013; Holm, Lukander, Korpela, Saline, & Müller, 2009; Käthner et al. 2014; Kawasaki, Kitajo, & Yamaguchi, 2010). Following these latest findings, we adopted the results of Holm et al. (2009) that the Theta middle frontal (Fz) to Alpha middle parietal (Pz) ratio is a reliable cognitive load index expressing changes in the cognitive load.

7. APPLICATION EXAMPLE

We reviewed the validity of using EEG-based indices to measure cognitive load, specifically EEG power for increased power of the Theta band power and a decreased power of the Alpha band, that occurred during important mental cognitive load tasks. This provides a technology and method to assess learning variables that potentially improve our instructional methods and adapt them to the ongoing cognitive and valence states of the learner. In the following example, we used this approach to assess in-near-real-time process, the cognitive load of participants during a difficult origami session.

Ten Technion students (*N*=10, Mean Age=24.9 *SE*=0.876) were separated into two groups: A ($n = 5$) and B ($n = 5$). Groups were similar by age (Group A Mean Age=24, *SE*=1.21, Group B Mean Age =25.8 *SD*=1.21, one-way ANOVA $\alpha = 0.05$, $F\ (1{,}9) = 1.01$, $p > 0.32$) and paper-folding abilities (VZ-2 Brace Test: Group A Scores= 14.2, *SD*= 2.07, Group B Scores = 15.4, *SD*= 2.06, one-way ANOVA $\alpha = 0.05$, $F\ (1{,}9) = 0.167$, $p > 0.69$). They sat behind a desk in front of a large 2.80m x 1.80m size screen, while an EEG cap was applied and calibrated. After calibration had been completed, all participants watched a 2D (group A) or a 3D virtual reality (group B) presentation of an instructor demonstrating origami paper folding of a crane for 5 minutes. Participants were asked to memorize the order of the folding steps of the crane while EEG signals were recorded. Recording went on for the entire session. After completion of the observation periods, participants were asked to repeat the folding.

Sessions were divided into four 20-second periods of viewing the origami folding, followed by 30 seconds of actual paper folding, i.e., repeating the demonstrated instructions. The condition of group A was termed "Crane 2D." Participants in Group B went through a similar process. They started by viewing a three-dimensional (3D) virtual world of the instructor demonstrating origami crane paper-folding. This condition was termed "Crane 3D." Period 2 and 4 folding tasks are known by the experts of the origami community as the most difficult steps in folding a crane

We recorded spectral power ($\mathbf{\mu V^2}$).from the middle frontal (Fz) and central parietal (Pz) electrodes. We averaged the spectra power over all periods, for each participant, electrode, experimental condition, and time window. Theta (4–8 Hz) spectral power from the middle frontal (Fz) and Alpha (8–12 Hz) spectra power from the central parietal (Pz) electrodes were measured. For each period, the average oscillations potential for each channel was calculated as the mean of the intervals of the sessions. The Cognitive Load Index (CLI) was calculated based on the Theta Fz/Alpha Pz ratio (Holm et al., 2009). For each participant, we assessed the average CLI for each observation session (n = 1,2,3,4)

$$Equation\ 1: CLI_n = \frac{Theta_{\ Fz\ n}}{Alpha_{\ Pz\ n}}$$

We calculated the relative CLI by calculating the ratio of the average CLI in the observation sessions (n = 1, 2, 3, 4) and CLI in the first (n = 1) session.

$$Equation\ 2: Relative\ CLI = \frac{CLI_n}{CLI_1}$$

The average relative CLI of Crane 2D participants (n = 5, M = 1.2698, SD= 0.045) was significantly higher than the average relative CLI of the "Crane 3D" participants (n = 5, M = 0.7910, variance = 0.114), (t stat = −2.6788, DF=4. p = 0.027). In addition, the figure 1. shows the differences in each observing period for each participant.

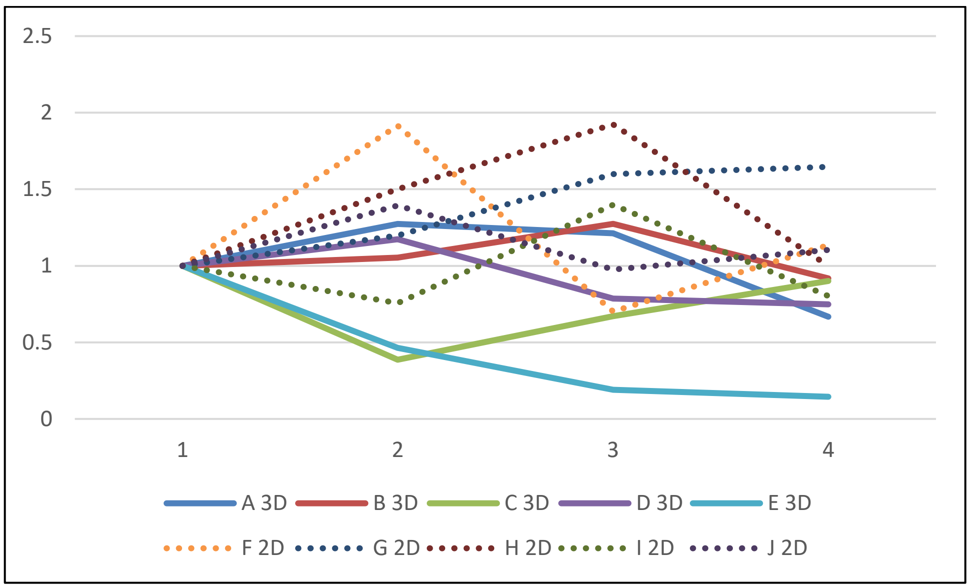

Figure 1. The single Relative CLI of each participant (A…E F…J), while observing 2D/3D instructions of folding a crane during four observing periods. The y-axis represents the relative intensity of the CLI. The x-axis represents the observing period in the learning scenario sequence (1…4). Dotted lines connect the relative CLI of the various participants (F…J) who observed the 2D crane scenario. Solid lines connect the relative CLI of participants (A…E) who observed the 3D crane scenario. The diagram shows clearly that the dotted lines are generally higher than the solid lines, i.e., the mental load associated with 2D is greater than with 3D.

We analyzed the difference between the average relative CLI between 2D and 3D participants in observing periods 2, 3, and 4, using JMP statistical software. We found statistical differences in period 2 and 4. This analysis is described below in Table 1.

Table 1: Relative Cognitive Load Index comparison between learning sessions

	Average Relative CLI		
Period	2D (n = 5)	3D (n = 5)	Robust fit p-value
2	1.35254 (*SD* = 0.169)	0.87029 (*SD* = 0.116)	0.041*
3	1.31959 (*SD* = 0.194)	0.82694 (*SD* = 0.176)	0.06
4	1.13745 (*SD* = (0.125)	0.67586 (*SD* = 0.125)	0.009**

This example shows the potential of online measuring of brain potentials using EEG. Assessing the cognitive load helps to determine the differences between processing data in each environment (3D and 2D). Looking in depth into the learning scenario, we determined that two sessions (the second and the fourth) are significantly different in the mean relative-CLI, measured for all participants, and it is implicit that the difficulty of those step is higher for the 2D Crane than for the 3D Crane demonstration.

8. LIMITATIONS

This study has several limitations. The number of participants in the experimental group was adequate for EEG-based research. However, the affirmation of these findings regarding segments of the experimental group (such as those relevant to participants with low spatial abilities) should be explored in a larger group. This experiment focused on the cognitive load that is associated mainly with a visual task, and, hence, visual working memory processes.

Another research direction might involve adding sensory input other than visual, such as assessing the effect of auditory or haptic load. EEG indices (Cognitive Load Index, and Relative CLI) were designed to measure the students' cognitive load during the observation sessions and provide useful information about the correlation between mental oscillations and learning scenarios. EEG-based indices are sensitive to electrical activity arising from sites other than the brain (artifacts).

Artifacts limit the analysis of EEG output to observation periods only and demand a significant artifacts removal analysis, as performed in this experiment. Technological innovations in EEG equipment and the reduction in the number of necessary electrodes in the near future should improve the research setting and allow expanding to additional performance phases and population. Finally, due to the original nature of the innovation of the stereoscopic 3D Digital Double learning environment, there is a lack of prior research studies. Near real-time physiological measurements in the context of learning methods and environments is insufficiently studied and require additional research.

9. FUTURE STEPS

The experiment in this study was designed s to identify the mechanism involved in changes of cognitive load in real time and provided details on methodologies for real-time EEG-based measures of CLI. The Relative CLI that measures the individual cognitive load of the learner while learning provides real-time data on difficulties. Once such information is available, personal adjustment of the learning order can be made, to avoid a drop-in learning due to excessive extraneous cognitive load. CLI and is especially relevant for assessing VLEs that often expose the user to ambiguous or complex information, resulting in high cognitive load. This is especially important for new gadgets that provide large amounts of streaming information that crucially increases task-related cognitive load, leading to the possible erroneous performance.

10. SUMMARY

We reviewed how near-online physiological measures could improve Education Data Mining in the context of learning technologies and compares two conditions – flat 2D video and 3D immersive virtual reality demonstrations. Using EEG, we can acquire data on electrical the activity of the brain, use a mathematical model of relative-cognitive-load, then correlate with learning. Such correlates can be employed for mining association rules across learning variants and EEG variants from existing data. The opportunity of extracting physiological measurements that assess learning variables provide a valuable tool for the design of instructional methods and support the emerging new brain –computer interfaces, to adapt the features and responses of the technological learning environment to the measured cognitive load and emotional states of the learner.

An additional motivation for this article is the recent emerging friendly and inexpensive technology for EEG measures. Integrating EEG systems with algorithms of near-real-time analysis of EEG-based mental load in e-learning, or MOOCS (Massive Online Open Courses), will potentially revolutionize assessment and allow a highly valid and objective evaluation. Objective assessment provides the cornerstone of Brain-Computer-Interface applied to e-learning.

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