Computerized Brain Interfaces for Adaptive Learning and Assessment

Rosa María Arnaldo(✉), Javier Iglesias, Víctor Fernando Gómez, Javier Crespo, Luis Pérez, José Félix Alonso, and Alvaro Rodriguez Sanz

Aerospace Systems, Air Transport and Airports Department, School of Aeronautical and Space Engineering (ETSIAE), Technical University of Madrid, 28040 Madrid, Spain
{rosamaria.arnaldo,fernando.gcomendador,javier.crespo,l.perez, josefelix.alonso,alvaro.rodriguez.sanz}@upm.es, javier.iglesiash@alumnos.upm.es

Abstract. This paper presents a project, which aims to develop a low-cost Brain-Computer Interface (BCI), whose characteristics may allow educational institutions to improve the learning and evaluation methodologies applicable to a specific student. By collecting reliable electroencephalogram (EEG) data, the system will realize a cognitive state monitoring of the learner and will evaluate its brain activity to adapt the content and visualization of the learning material. Two main objectives have been established in order to determine the success of the investigation: Assess the use of contemporaneous low-cost EEG devices and applications as a proper method to obtain reliable results of the students' cognitive state. Develop signal-processing algorithms that allow identifying the cognitive state of the students as well as their working memory load (WML).

Keywords: Human factors · Learning analytics · Learning assessment tools Adaptive learning · Electroencephalogram · Brain-Computer Interface

1 Introduction

By realizing the *Computerized Brain Interfaces for Adaptive Learning and Assessment* project, the final intention of the authors is to make progress in the process of continuous improvement of the quality of education, which identifies the public universities of Spain, based on the premises of collaboration between teachers and students. Therefore, two fields are considered and related as it illustrates the Fig. 1.

1. *Adaptive learning and assessment*, which is the focus of the research project, is based on the search of methods to adjust the level of demand (WML, fatigue, stress…) to which the student is subjected to the difficulty of tasks, tests or lessons taught. An illustrative scheme is presented in the Fig. 2.
2. The *electroencephalogram* is a noninvasive method to measure the brain wave pattern for the identification of electrical activities in the brain. The distribution of the Alpha, Beta and Gamma brain waves will provide abundant information on the

W. Karwowski and T. Ahram (eds.), *Intelligent Human Systems Integration*, Advances in Intelligent Systems and Computing 722,
https://doi.org/10.1007/978-3-319-73888-8_37

student's brain state while exposed to differentiated learning strategies. This way, researchers can determine how brain patterns reflect the student's level of learning and when the brain patterns confirm that the student has mastered the skills to be acquired.

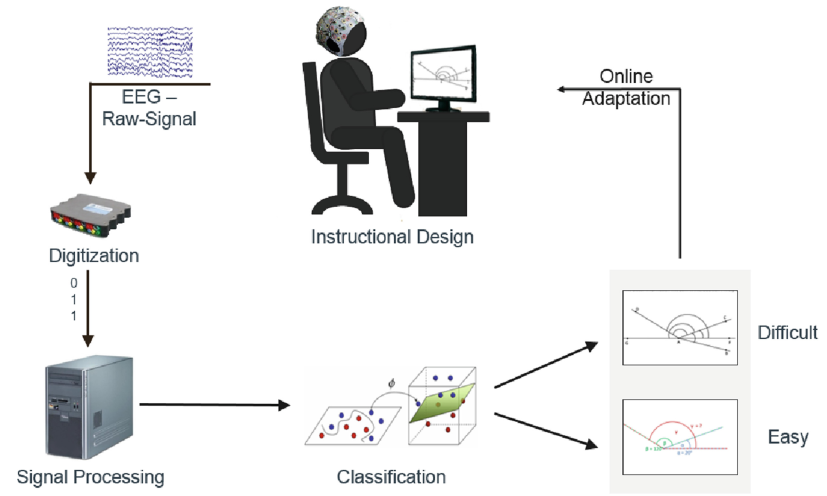

Fig. 1. Schematic workflow of a BCI application - an online adaptive learning environment based on EEG data

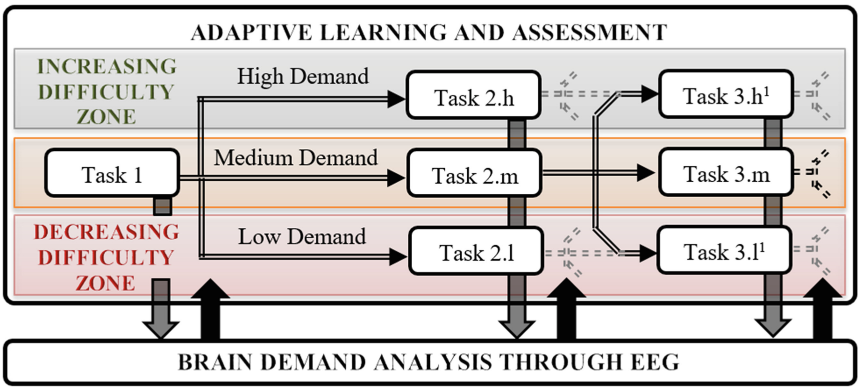

Fig. 2. Illustrative scheme of an adaptive learning method and its relation with EEG

2 Context and Purpose

Context. Until now, learning environments primarily attend to a student's performance and behavior. These systems [1, 2] aim to diagnose the development of the amount of knowledge acquired by a student based on response to questions, selection of links or errors during problem solving. However, online predictions of *workload, fatigue and attention states may be used to tailor the learning material* presented to the subject [3, 4] in a specific and personalized way, helping to maintain the burden of work coped by each student within an optimal range for learning.

The current neurological theory and the more recent cognitive studies of learning allow to set a relation between the brain activity (the brain waves and the areas of the brain where they occur), the difficulty of the learning tasks and the level of performance attained in the activities. The method proposed in this project is based on the monitoring of the brain patterns of the students, through EEG, when they perform tasks of different complexity, to reflect the level of learning and mastery of the skills to be acquired.

Two critical factors have propelled the realization of this project. The first is the current situation of the technological market, more specifically in relation to leisure and video games, which offers the possibility of acquiring simple non-intrusive low-cost EEG measurement devices. The second, the previous execution of projects within the ETSIAE related to the development of cognitive workload models in environments similar to those experienced by an air traffic controller [5], as well as the use of electroencephalography in practical applications such as drone control [6].

Purpose. The main objective is to *analyze the feasibility of applying low-cost electroencephalogram (EEG) based computer interfaces to adaptive learning and assessment strategies and systems*. In conclusion, to evaluate the feasibility of using brain waves to improve adaptive learning tools. Besides, the project has two sub-objectives:

1. Evaluate the usability of low-cost EEG devices for the measurement of brain waves for educational and research purposes.
2. Develop neurological signal-processing algorithms that allow the assessment of the student's cognitive state in the face of learning tasks of different complexity.

3 Methodology and Results

Methodology. A thorough analysis of previous studies has allowed the identification of two promising research lines to incorporate EEG technology in adaptive learning, with the project activities focusing so far on the first. One is the determination of working memory load (amount of mental resources used to execute a specific task), the other the determination of the emotional state and its influence on learning [7–9].

The workload during learning is the result of an interaction between the complexity of the contents to learn, the instructional design and the previous knowledge of an apprentice [10]. So far, methods for detecting workload are based primarily on subjective workload ratings [11], or on dual-task procedures [12]. Nonetheless, EEG measures can be used to estimate the amount of workload of each student during a learning session, based on the following hypothesis. *Increased workload leads to increased activity in the theta frequency band (synchronization) in the electrodes of the frontal zone [13, 14] and to a decrease in activity of the alpha frequency band (desynchronization) on the parietal and occipital area [13, 15].*

To verify the feasibility of measuring mental workload with low-cost EEG devices, a set of experiments have been carried out using accessible technologies and a learning environment based on on-line games [16] of incremental difficulty that do not require previous knowledge by the student. These mini-games test a set of basic cognitive abilities. For example, the game *Shape Tracking*, tests the ability to follow an element on the screen, with each level increasing in difficulty. For the study, level 1 was labeled as low workload, and the maximum level that each subject has reached was high workload.

Measurements were taken with the device *Emotiv Insight* [17], a wireless 5-channel EEG handset that records brain waves and translates them into meaningful data. It uses a patented polymer dry sensor that is safe to use and offers great electrical conductivity. Signal processing was performed with the SW EEGLAB [18], an interactive Matlab toolbox for processing EEG, MEG and other continuous event-related electrophysiological data. Figure 3 shows the measurement device and a snapshot of the experiments performed. Five subjects and three difficulty levels were tested. Figure 4 illustrates the results obtained when calculating the PSD (Power Spectral Density) in θ and α bands.

Fig. 3. Measuring equipment (left) and experiments performed (right)

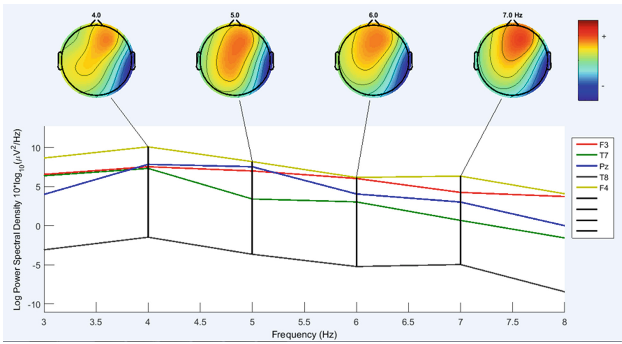

Fig. 4. Example of processed results (PSD of subject 1 in θ band for low workload. Test 1)

Results. Analyzing the behavior of the PSD theta frontal for the different tests and subjects, it is proved that PSD increases in high workload conditions, compared to data extracted for low workload. In addition, the PSD theta frontal variation in subjects is smaller as the session time increases. These data corroborate the hypothesis assumed.

The experiments realized satisfy the initial objectives of the project, since they have allowed the familiarization with the EEG measurement device, proving its value for the intended purpose; and have allowed to identify a methodology and indicators that allow to estimate the workload associated with learning tasks. It is therefore confirmed that this research line has the potential to be further developed in upcoming studies.

References

1. Corbett, A.: Cognitive computer tutors: solving the two-sigma problem. In: Proceedings of the 8th International Conference on User Modeling (2001)
2. Graesser, A., McNamara, D.: Self-regulated learning in learning environments with pedagogical agents that interact in natural language. Educ. Psychol. **45**, 234–244 (2010)
3. Lan, T.: Channel selection and feature projection for cognitive load estimation using ambulatory EEG. Comput. Intell. Neurosci. **2007**, 12 (2007)
4. Pavel, M., Wang, G., Li, K.: Augmented cognition: allocation of attention. In: Proceedings of the 36th Annual Hawaii International Conference on System Sciences (2003)
5. AUTOPACE: Facilitating the AUTOmation PACE. http://autopace.eu/
6. Arnaldo, R., Comendador, F.G., Perez, L., Rodriguez, A.: Motor imagery brain–computer interface for RPAS command and control. In: 8th International Conference on Applied HF and Ergonomics (2017)
7. Kort, B., Reilly, R., Picard, R.W.: An affective model of interplay between emotions and learning: reengineering educational pedagogy-building a learning companion. In: Proceedings of IEEE International Conference on Advanced Learning Technologies (2001)
8. Lepper, M.R., Woolverton, M., Mumme, D.L., Gurtner, J.-L.: Motivational techniques of expert human tutors: lessons for the design of computer-based tutors. In: Technology in Education. Computers as Cognitive Tools (1993)
9. Lepper, M.R., Woolverton, M.: The wisdom of practice: lessons learned from the study of highly effective tutors. In: Improving Academic Achivements. Academic Press (2002)
10. Kalyuga, S., Ayres, P., Chandler, P., Swelle, J.: The expertise reversal effect. Educ. Psychol. **38**, 23–31 (2003)
11. Paas, F., Tuovinen, J.E., Tabbers, H., Van Gerven, P.W.: Cognitive load measurement as a means to advance cognitive load theory. Educ. Psychol. **38**, 63–71 (2003)
12. Cierniak, G.: Explaining the split attention effect: is the reduction of extraneous cognitive load accompanied by an increase in germane cognitive load? J. Comput. Hum. Behav. **25**, 315–324 (2009)
13. Gevins, Y.: High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cereb. Cortex **7**, 374–385 (1997)
14. Pesonen, M., Hämäläinen, H., Krause, C.M.: Brain oscillatory 4–30 Hz responses during a visual n-back memory task with varying memory load. Brain Res. **1138**, 171–177 (2007)
15. Stipacek, A.: Sensitivity of human EEG alpha band desynchronization to different working memory components and increasing levels of memory load (2003)
16. NATS. http://www.nats.aero/careers/trainee-air-traffic-controllers/games/
17. Emotiv Insight. https://www.emotiv.com/insight/
18. Swartz Center for computational neuroscience. https://sccn.ucsd.edu/eeglab/index.php