USING STUDENT MENTAL STATE AND LEARNING SENSORY MODALITIES TO IMPROVE ADAPTIVITY IN E-LEARNING

USO DE ESTADOS MENTALES DE ESTUDIANTES Y MODALIDADES DE APRENDIZAJE SENSORIAL PARA MEJORAR ADAPTABILIDAD EN E-LEARNING

Rodriguez-C Paola-J[1], Paternò Fabio[2] and Jimenez Jovani[3]

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ABSTRACT

In this paper, we present an innovative solution to improve adaptivity in an e-learning system using Brain Computer Interface (BCI) measures (Attention/Meditation) in order to detect changes in students' preferred perceptual modes for learning information (VARK model). Our solution is also able to report course units and learning resources that could be difficult for the students.

Keywords: Adaptivity, Attention, BCI, e-learning, Meditation, Neurosky, VARK.

RESUMEN

En este artículo se presenta una solución innovadora para mejorar la adaptabilidad de un sistema de e-learning utilizando medidas Brain Computer Interface (BCI) (Atención / Meditación) con el fin de detectar los cambios en los modos de percepción preferidas de los estudiantes para el aprendizaje de la información (modelo VARK). Nuestra solución también es capaz de reportar unidades del curso y los recursos de aprendizaje que podría ser difícil para los estudiantes.

Palabras clave: Adaptabilidad, Atención, BCI, e-learning, Meditación, Neurosky

[1]Camaleon reasearh group of Universidad del Valle at Cali, Colombia; (e-mail: paola.rodriguez@correounivalle.edu.co).
[2]Paternò Fabio, is with CNR-ISTI, HIIS Lab at Pisa, Italy, (e-mail: fabio.paterno@isti.cnr.it).
[3]Jimenez Jovani, is with Universidad Nacional de Colombia at Medellin (e-mail: jajimed1@unal.edu.co

1. INTRODUCTION

Adaptativelearning systems which focus on users' Learning Styles (LS) have shown to be able to improve the students learning achievements and even their satisfaction during the learning process [1][2][3][4][5].

Consequently, many proposals about LS identification have been developed in recent years, which arebased on a) questionnaires answered by the students before whatever interaction, b) the server log file in order to monitor resources that have been accessed by the students, their frequency of use and time spent on them. The last ones are classified in the state of art as automatic ways to identify LS applying, inter alia, Bayesian Networks, Fuzzy Logic, Genetic Algorithms, Neural Networks, Hidden Markov Chains, Decision Trees and statistical tendency measurements to adapt the learning system [6][7][8][4][9][10].

Nevertheless, disadvantages still exist : Many of the preceding works depend of large questionnaires (40 items at least) as a prior step in order to establish the student LS and as is mentioned in [11][12]; They use very technical language that can cause misinterpretation or misunderstanding because of their size and in some cases students answer them lightly. On the other hand, automatic detection techniques, reported on the literature, are founded on biased data sincethey correspond to activities planned by the teacher for the course; This means that students access an activity or resource just because the teacher planned the use of that resource, so variables as frequency of use and time spenton activities present some uncertainty for identifying student styles. In addition, only afew contributionshave taken into account potential LS changes over the time. It is worth noticethat it has not been proposed any technique that use student internal state (what a student feels at the moment of the interaction).

Based on the foregoing, we propose a technique that takes advantage of users' brain-activity data (attention/meditation) while they interact with e-learning systems. In this manner, we can predict the grade of user engagement (focus/relaxation) with the interface and detect and monitor the student preferred perceptual mode for learning information.

The article is organized as follows: section 2 presents an introduction to BCI; section 3, describes VARK perception model and the relationship between student engagement and its perceptual mode tendency; section 4 explains the proposed technique to improve adaptivity in an e-learning system and finally, some conclusions and future work are presented.

2. BRAIN COMPUTER INTERFACES - BCI

BCIs are computational systems that permit interaction between users and the environment by means of their brain activity. This is a new way of communication in which users intentions are sending to external devices such as computers, mobiles, prostheses and wheelchairs, etc. [13][14][15][16].

BCI is an AI system that can acquire brain signals, pre-processes them in order to extract information, identify and gather discriminative information, classify and organize those data and translate them into commands understandable by the connected device [17][18][16].

Most frequently used BCI systems are based on Electroencephalography (EEG) signals that via sensors on the scalp can capture brain signals (non-invasive way). In general the quality of the signals are considering acceptable, BCI devices are relatively inexpensive and do not generate any risks for users[16][19][17][20].

EEG technique classifies captured signals in four frequency ranges in accordance with sensor location and biological meaning. Thus, this information can be used in order to infer user metal state (level of focus, relaxation, etc.). Table 1 summarizes frequency ranges and their meaning [16][15][21][22][14][18].

In addition, hardware and software advances have made possible to develop portable and reliable BCI devices incorporating the above aspects and promote their application in several contexts. Although many companies building BCI devices exist, Neurosky and Emotive are the most widely recognized and used in both commercial and academic sphere Table 2 presents a comparative summary of this both technologies [23][24][25][26][27][28][29].

In the HCI context, BCI technology has predominantly assumed as a assistance tool, focused on restoring communication skills,

Tabla 1. EEG FREQUENCY RANGES AND MENTAL STATES

Brainwaves	Frequency Ranges	Mental State
Delta (δ)	< 4 Hz	Unconsciousness, deep sleep
Theta (θ)	4Hz to 7Hz	Relaxation, intuition, creativity, remembrance, Imagination
Alpha (α)	8Hz to 12Hz	Mental effort, relaxed but not sleepy, quiet, conscious.
Low Beta (β)	12Hz to 15Hz	relaxed and focus
Mid Beta (β)	16Hz to 20Hz	Thinking, self-conscious
High Beta (β)	21Hz to 30Hz	Alert, agitation, disturbance
Gamma (γ)	30Hz to 100Hz	Motor functions and high mental activity

Tabla 2. EMOTIV AND NEUROSKY COMPARATIVE

Characteristic	Emotiv	Neurosky
Sensor Type	Wet	Dry
N° sensors	14 around the scalp	1 in the front and an ear contact point.
Data reported	Brainwaves. User mental State: instant emotion, long term emotion, focus, frustration, meditation, boredom. Facial expressions as left-right look, blink, wink, brow lift, grip teeth, smile. Basic head movements (left, right, up, down)	Brainwaves. User Mental State: Attention, Meditation, (Anxiety, Lethargy), and Blink
Software	Expressiv™ Suite for Monitoring facial expressions and head movements. Affectiv™ Suite to infering mental states. Cognitiv™ Suite for deduce users conscious intentions in order to interact with objects.	MindWave Mobile - Brainwave Starter Kit for processs EEG signals and return Brainwaves data and user mental state.
System Requirements	Windows, MAC. USB Access	Windows, MAC, iOS/Android. USB/ Bluetooth access

monitoring the environment and providing mobility for people with severe physical disabilities, so that much of the results of research is framed in the field of accessibility [30][23][31][16]. Nonetheless, some works report aspects relative to BCI usability with the intention to test their power and viability of use in software development. As a result of this review we could find out that: users feel secure wearing those devices; some people find difficulties with Emotiv Cognitive (movement prediction tool); for common mental state variables there are not any noticeable difference between Emotiv and Neurosky[32][33][34][18].

As a complement, at the Camaleon Research group of Universidad del Valle, we have conducted a small test with 50 users randomly selected in order to observe the performance and user comfort level. For this, we used Neurosky Attention and Meditation games and Emotiv suites, and observed and interviewed the users during the interaction. The group was composedof40 university students(10 of arts, 10 of computer science, 10 of sciences and 10 of humanities) and 10 professors (2 of arts, 3 of sciences, 3 of computer science and 2 of humanities); They interacted for 3 minutes with each application and took 4 minutes of break between each one. As a result, we could confirm the findings concluded in the above works and other additional and important aspects as:

- All users prefer wearing Neurosky device because its facility of location on the head and its dry sensor does not cause any discomfort.
- 90% of users expressed displeasure with Emotiv because of its wet sensors.
- Long or abundant hair causes interference with Emotiv device, which became evident since in those cases many sensors worked intermittently or did not work.

Finally and in accordance with the foregoing, we decide to use Neurosky, due to our work is based on Attention and Meditation measures that have similar reliable level in both devices, but users feels more comfortable wearing it and it is less expensive.

3. MODAL PREFERENCES IN LEARNING STYLES

A LS is the pattern of behaviour exhibited by the learner in his learning process, which means LS shows the preferred way apprentices used to approach and appropriate knowledge. LS are important because could improve the teaching process doing learning easier for each student. Accordingly, it is extremely important to identify apprentice LS and monitor its changes over the time [11][5].

Considering the state of art in LS, we find the VARK model very interesting in order to use it in e-learning environments, because of common computer-learning resources can be easily transform to Learning Objects compliant with VARK and the patterns of behaviour can be without difficulty translate into guidelines for potential interactions. Thus, we can take advantage of that for improving presentation adaptivity in e-learning environments.

3.1 VARK LS Model

The VARK model suggests that learners have a preferred perceptual mode for information inputs and outputs. Accordingly, Visual, Aural, Read/Write and Kinaesthetic are the possible modal preferences. Table 3 summarizes the features for each type of modal [35].

This model has been widely used because of many learning resources are available in formats that easily could be trace to each type of modality, as well as, the test used to identify the learning profile is very simple, understandable and ease of use [36], [37].

3.2 User Engagement and Learning Tendency

There are few studies that have shown the relationship between students' engagement or affective response and their LS tendency owing

[1]According to IEEE, Learning Objects are any entity, digital or non-digital, that may be used for learning, education or training. In this context we are interesting in digital resources.

Tabla 3. VARK LEARNING STYLES SUMMARY

Modal Preferences	Main Features
Visual (V)	People that easily understand and assimilate information presented in charts, graphs, and other symbolic modes instead of words.
Aural (A)	People who prefer to use spoken material and talking.
Read/Write (R)	Individuals who easy understand and appropriate information from different kinds of texts.
Kinaesthetic (K)	People who need to go into direct practice, doing muscular movements or having movement sensations in order to understand.

to the difficulty to estimate that in an e-learning environment. Notwithstanding, technological advances have allowed some interesting studies. The most interesting are: a) [38]it was conducted an experiment in order to investigate the relationship between LS, engagement and Visual Programming Languages. Their conclusion was that Visual style learners exhibited higher engagement labels. For the experiment VARK model LS, Venkatesh's questionnaire for measure the engagement and Scrath[1] programming Languagewere used. b) [39]found out that students' emotion (frustration, anxiety, focus, etc.) is affected by the type of materials they use during the learning process, and suggest that students should receive materials compliant with their cognitive learning style in order to stimulate learning interest and performance. This work was tested for Visualizer and Verbalizer styles and used heart rate variability as a measure of emotional state by means of emWave device. c) [40] studied the relationship between students' LS and EEG data when students perform mental rotation tasks. They could determine by means of different statistical measurements that different brain zones were activated according to the student's LS and its gender. They used EGI 64-channel HydroCel Geodesic Sensor and Fielder-Solomon Inventory for LS. d) [41] worked with log-file server data in order to predict disengagement in an e-learning system using data mining techniques. They found that there is a relation between the potential disengagement situation and student's learning performance (evaluation activities). The disengagement prediction took into account data from learners' interaction such number of accessed pages, time spend per activity, etc.

[1]It is a visual programming language designed by the Lifelong Kindergarten team from MIT Media Lab

Considering as well foregoing studies that show the existence of a relation between LS and level engagement, the strength of this proposal is to use Attention/Meditation measurement in order to predict and monitoring learning modal tendency and thus improve adaptivity in an e-learning system.

4. ADAPTIVITY PROCESS

The adaptivity process comprises three components, one runs on the client side and others on the side server. These components are connected as shown in figure 1.

EEG-Capturer: It is an autonomous component that getsBCI data (Attention/Meditation) form TGC (Neurosky controller), via socket connection. When interaction ends the EEG-Captured create and stores a XML file on the server.It isnoteworthy

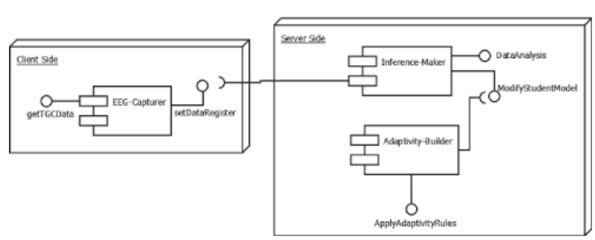

Figura 1. Adaptivity Module - Component View

that Neurosky device reports BCI data every second, so EEG-Capturer could get hundreds of values for each variable by a single interaction.

Inference Maker: It updates Student's Model (SM) according to BCI data.The SM is defined as 5-tuple as follow:

$$SM = \{Id, Cu, Att, Med, DI, VARK\}$$

Where

- Id corresponds to student identifier at the system.
- Cu is the Course-Unit of study. The course content is represented as a hierarchical structure of Cu.
- Att and Med[2] are the statistical tendency of attention and meditation levels for the related Cu.

$$Att, Med = \{x, y \,/\, x \epsilon \mathbb{Z} \wedge y \epsilon \mathbb{Z} \wedge 100 \geq x \geq 0 \wedge 100 \geq y \geq 0\}$$

If $x \in [0,40]$ it means student lost focus or is disengage of the activity.

If $x \in [60,100]$ it means student present high interest in the activity.

If $y \in [0,40]$ it means student lost calm and relaxation.

If $y \in [60,100]$ it means student is calm and relaxed.

Values between $(40,60)$ are considered neutral.

- DI represents the estimate level of difficulty for the current Cu. It could be Low, Neutral or High. We are interesting in High values in order to report the associated Cu.
- VARK represents the student modal preference that was detected.

The Inference-Maker uses an algorithm in order to establish SM. First, the Inference-Algorithm calculates the statistical distribution of the data captured by EEG-Capturer. Then, it could estimate the level of difficulty (DI). For this, the algorithm consider the above intervals defined for Attention and Meditation values.

The student VARK modal preference is determined in two steps: First, when students use the adaptation model for the first time they are asked to answer VARK test (16 questions)[35]. At this moment, the algorithm is able to identify a VARK tendency and applies the first adaptation rules by the course. Second, the Inference-Maker monitors Att and Med variables in order to identify loss of focus and calm in the interaction, which means high degree of disengage and thus a potential change in VARK preference.To calculate the change, the algorithm determine a value (median)for probability distribution of the Att and Med data associated to learning resources used by the student.

Adaptive Maker: It applies the adaptation rules according with the Student Model. Adaption Rules are a set of rules expressed in the format Event/Condition/Action, which represent the way to adapt user interfaces [42]. For this case, we have a main Event and 8 conditions that determinates the possible actions. Table 4, shows main adaptation rule.

Adaptive Maker is able to build the concrete user interface by means of RIA technologies (CCS, JavaScript, and HTML5) and Web Speech API. For best understanding of user interface changes, figure 2 and 3 shows a prototype of a learning resource for Multimodal Read/Write-Aural tendencie and the recommendation for access another resources according with the model.

Tabla 4. ADAPTATION RULES

EVENT	Change in Student Model
CONDITION	ACTION
If there is a V tendency	The user interface turns into an iconic map, chart or graphs, using symbols.
If there is an A tendency	The user interface turns into a vocal modal.
If there is a R tendency	The user interface turns into a mental map, list or table, with strong highlight in text.
If there is a K tendency	The user interface needs to have animation and movement, with balance between symbols, text.
If there is a Multimodal tendency	Multimodal is a combination of VARK, it could be bimodal, or more. In those cases, UI turns into the strongest modal preference for the index page and the others pages levels could take the other modalities. For balance users, it means with low difference between their modalities, the tendency will be selected randomly because that situation point out that user could take advantage of whatever modal option.
If VARK tendency is determined	Link to Cu structure learning resources related to student tendency (as a first priority).
If Attention and Meditation are in a low interval.	Link Cu structure learning resources changes to the next in priority
If student is disengage on a lesson	Refresh statistical information on “Difficulty topics” professor panel.

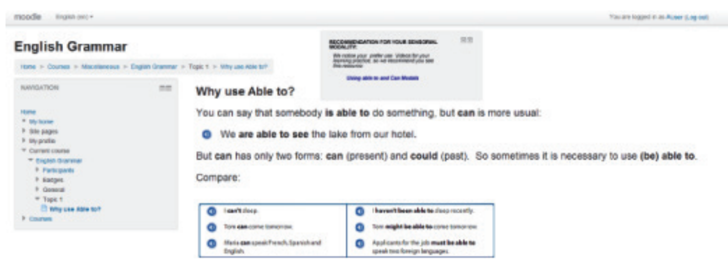

Figure 2. Multimodality Read/Write - Aural and Recommendation for change the resource.

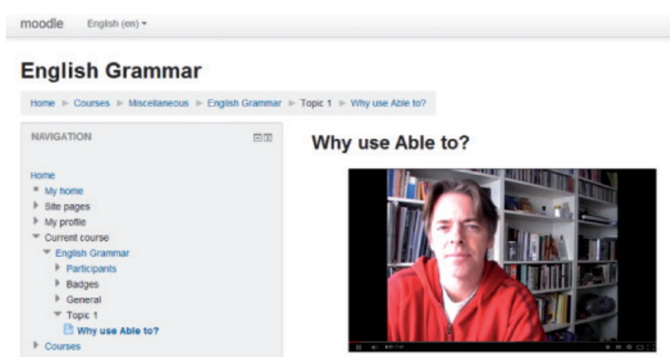

Figure 3. Access of the recommended reosurce.

CONCLUSION

This work describes the use of student’s mental data (Attention/Meditation) as way to monitor VARK modal preferences and thus improve adaptivity. For this type of data, the use of measures of central tendency in the Inference-Maker algorithm was appropriate because it allows to identify to what extent the data is grouped or spread around the intervals defined for the target variables. Additionally, BCI data could be used as a metric for the design of learning resources because they allow to establish the extent to which students are engage in learning activities.

Future work will be dedicated to further applying the adaptivity process in a complete courses supported by Moodle platform to identify the relation between high engagement learning resources and effectiveness of students learning process.

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