MENTOR: A Physiologically Controlled Tutoring System

Maher Chaouachi(✉), Imène Jraidi, and Claude Frasson

Department of Computer Science and Operations, University of Montreal, Montreal, Canada
{chaouacm,jraidiim,frasson}@iro.umontreal.ca

Abstract. In this paper we present a tutoring system that automatically sequences the learning content according to the learners' mental states. The system draws on techniques from Brain Computer Interface and educational psychology to automatically adapt to changes in the learners' mental states such as attention and workload using electroencephalogram (EEG) signals. The objective of this system is to maintain the learner in a positive mental state throughout the tutoring session by selecting the next pedagogical activity that fits the best to his current state. An experimental evaluation of our approach involving two groups of learners showed that the group who interacted with the mental state-based adaptive version of the system obtained higher learning outcomes and had a better learning experience than the group who interacted with a non-adaptive version.

Keywords: Intelligent tutoring system · Engagement · Workload · Real-time adaptive system · EEG · Machine learning · Experience and affect

1 Introduction

The use of physio-cognitive sensing technologies in computer-based learning environments has grown continuously through these last years. More precisely, the emergence of the affective computing domain has made a huge change in the design of such environments by enhancing their capabilities to understand the learners' needs and behaviors [1-5]. Research in the Intelligent Tutoring Systems (ITS) field is increasingly directed towards the integration of new techniques that can provide relevant indicators about the learners' internal and affective states. In fact, one of the main objectives of ITS is to provide an adapted and individualized learning environment to the learner. This adaptation can be operated with regards to several considerations (cognitive, educational, emotional, social, etc.), and can be related to different aspects of the system's interaction strategy (selection of the next learning step, providing an individualized feedback, or help, etc.). The integration of physiological data sources can represent a genuine opportunity for such a system to extract valuable information about the user's state and to proactively adapt to this state.

In this paper, we present a new ITS called MENTOR (MENtal tuTOR), which is entirely based on the analysis of the learner's engagement and workload, extracted from the EEG data, in order to sequence the learning activities. More precisely, the system relies on an adaptive logic that selects the next pedagogical activity which fits

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the best to his current state; this activity can be either a problem solving or a worked example.

This choice between worked examples and problems has often been discussed in educational psychology. On one hand, worked examples tend to have a lower mental load impact compared to problems as all the required steps of the problem resolution are already provided to the learner [6]. On the other hand, the problems are more demanding in terms of mental efforts as the learner has to resolve the problem and in case of a wrong answer, he must also understand the solution. However, providing only worked examples to the learners can have a negative impact. The learner may not identify the relevant information pertaining to the worked example, and focuses rather on useless or secondary information [7]. In this paper, we present a set of rules that we have implanted in our system to adaptively select the best activity for the learner. An experimental study was conducted to evaluate our system. The goal was to verify the following two hypotheses:

(1) The integration of the engagement and the workload brain indexes in an ITS can have a real impact on the learners' outcomes. Our assumption is that if the system controls the learning dynamics according to these mental indicators, then the system's interventions can help the learner understand the tutoring content.
(2) Using a mental state-based strategy in this type of adaptation can improve the learner's experience regarding their tutoring session. In other words, we assume that if the system is aware of the mental challenges the learner is facing, this can be reflected positively on the learner's satisfaction regarding the system.

2 Related Work

Mental workload and engagement are among the most commonly used indicators to dynamically assess changes in the users' states [8-11]. Several physiological sensors such as heart rate variability, oculomotor activity, pupilometry, body temperature, respiration and galvanic skin responses have been employed to detect mental state changes [13-15]. However, the electroencephalography (EEG) is considered as the only physiological signal that can reliably and precisely track restrained changes in mental attention (or engagement) and workload, and that can be identified and quantified on a millisecond time-frame [12].

Developing EEG indexes for workload and engagement assessment is a well-developed research domain. Several linear and non-linear classification and regression methods were used to measure these indexes in different kinds of cognitive tasks such as memorization, language processing, visual, or auditory tasks. These methods rely mainly on a frequency processing approach using either the Power Spectral Density (PSD) or Event Related Potential (ERP) techniques to extract relevant EEG features [12].

In the educational context, the index developed by Berka and his colleague was used within a learning environment to analyze the students' behaviors while acquiring skills during a problem solving session [11]. Recently a workshop was hold to promote the use of EEG input in ITS [16]. This paper represents a straight continuation of these approaches by presenting a tutoring system whose adaptive strategy is entirely based on the values of the engagement and the workload indexes.

3 System Design

MENTOR is a tutoring system that uses indicators extracted from the EEG physiological data to adjust the learning activities according to the learner's mental state. The system uses the Emotiv EEG headset (www.emotiv.com) to collect EEG raw signals. The reasons of choosing this EEG device is that it can be connected wireless to any machine through the receiving USB. The Emotiv device is also light, easy to use and does not require any particular material configuration. The Emotiv headset contains 16 electrodes located according to the 10-20 international standard [28]. It allows recording simultaneously 14 regions (O1, O2, P7, P8, T7, T8, FC5, FC6, F3, F4, F7, F8, AF3 and AF4). Two additional electrodes are used as references, which correspond respectively to the P3 region (called DRL for Driven Right Leg) and the P4 region (called CMS for Common Mode sense). The system's sampling rate is 128 Hz.

Two brain indexes are derived in real-time by MENTOR, namely mental engagement and workload.

3.1 Mental Engagement

The engagement index used comes from the work of Pope and colleagues [17] at the National Aeronautics and Space Administration (NASA). This work is based on neuroscientific research on attention and vigilance [18]. It was found that the user's performance improved when this index is used as a criterion for switching between manual and automated piloting mode. This index is computed from three EEG frequency bands: θ (4-8 Hz), α (8-13 Hz) and β (13-22 Hz) as follows: $\beta/\,\theta+\,\alpha$

The engagement index is computed each second from the EEG signal. In order to reduce the fluctuation of this index, we use a moving average on a 40-second mobile window. Thus, the value of the index as the time *t* corresponds to the total average of the ratios calculated on a period of 40 seconds preceding *t*. The extraction of the θ, α and β frequency bands is performed by multiplying one second of the EEG signal by a Hamming window (in order to reduce the spectral leakage) and applying a Fast Fourier Transform (FFT). As the Emotiv headset measures 14 regions at the same time, we used a combined value of the θ, α and β frequency bands by summing their values over all the measured regions.

3.2 Mental Workload and MENTOR's Training Mode

Unlike the engagement index, there is no a common established method to directly assess mental workload from the EEG data. Therefore, we propose to build an individual mental workload predictive model for each learner. This model is trained using data collected from a training phase during which the learner performs a set of brain training exercises. This training phase involves three different types of cognitive exercises, namely: digit span, reverse digit span and mental computation.

The objective of theses training exercises is to induce different levels of mental workload while collecting the learner's EEG data. The manipulation of the induced workload level is done by varying the difficulty level of the exercises: by increasing the number of the digits in the sequence to be recalled for digit span and reverse digit span, and the number of digits to be added or subtracted for the mental computation exercises (see [12,19] for more details about this procedure). After performing each difficulty level, the learner is asked to report his workload level using the subjective scale of NASA Task load index (NASA_TLX) [20].

Once this training phase completed, the collected EEG raw data are cut into 1-second segments and multiplied by a Hamming window. A FFT is applied to transform each EEG segment into a spectral frequency and generate a set of 40 bins of 1 Hz ranging from 4 to 43 Hz (EEG pretreated vectors). These data are then reduced using a Principal Component Analysis (PCA) to 25 components (the score vectors). Next, a Gaussian Process Regression (GPR) algorithm with an exponential squared kernel and a Gaussian noise [21] is run in order to train a mental workload predictive model (the EEG workload index) from the normalized score vectors. Normalization is done by subtracting the mean and dividing by the standard deviation of the all vectors. In order to reduce the training time of the predictive model, we used the local Gaussian Process Regression algorithm, which is a faster version of the GPR [22].

3.3 Analysis of the Computed Indexes

In order to evaluate the learner's mental state, the system analyses the behavior of the engagement and workload indexes throughout the current learning activity. A slope of each index is computed using the least squared error function of the index's values from the beginning of the activity. For the engagement index, if the slope value is postive, then learner is considered as mentally engaged. Otherwise, the learner is considered as mentally disengaged. For the workload index, if the slope value is between - 0.03 and + 0.03, than the workload is considered as positive. Otherwise, if the slope value is above 0.03, the learner is considered as overloaded, and if the slope is below -0.03 the learner is considerd as underloaded. Thus, the learner's mental state is considered positive, if he is mentally engaged and neither overloaded nor underloaded; otherwise, it is considered negative.

3.4 Learning Mode

The MENTOR tutoring system has been designed to help learners understand the Reverse Polish Notation (RPN), which is also known as the postfix notation. The lesson presented by the system includes four successive parts. After the learner finishes each part of the lesson, the system presents four pedacogical activities so that the learner puts into practice the concepts seen in the previous part of the lesson and enhance his understanding. Each activity uses one of the two following pedagogical resources:

Questions: each question presents a problem that the learner has to resolve. Hints are provided with each problem in order to help the learner find the solution and improve his knowledge acquisition. At the end of each question, the system informs the learner whether his answer was correct or not. In case of a wrong answer, the solution of the problem is given without presenting any explanation of the resolution process.

Worked examples: a worked example describes a problem statement with the detailed steps and explanations leading to the solution. The learner is simply asked to read and understand these examples.

3.5 MENTOR's Adaptive Rules

MENTOR's decisional process lies mainly in the selection of the type of the pedagogical resource (a question or a worked example) to be provided as a next activity. In summary, 16 decisions (4 parts × 4 activities) has to be made by the system according to the learner's mental state. The decision of presenting a worked example or a problem within MENTOR is based on a continuous analysis of the learner's mental engagement and workload. The goal is to select the pedagogical resource that maintain the learner in a positive mental state. More precisely, the system has to keep the learner mentally engaged and avoid overload and underload. If the system detects a negative mental state caused by an engaegement drop, an overload or an underload, it will then try to correct this state by switching the type of the next pedagogical activity.

A total of seven adaptive rules are used by MENTOR as shown in Figure1:

(R1) If the learner's mental state is positive (mentally engaged and neither overloaded nor underloaded), then the system selects a question for the next activity. This rule is applied whatever the current activity is (question, worked example or reading a part of the lesson).

(R2) At the end of a question, if the learner's mental state is negative (disengaged, overloaded or underloaded), then the system provides a worked example in the next activity.

(R3) At the end of a worked example, if the system detects a negative mental state due to disengagement or underload, then it provides a question as a next activity.

(R4) At the end of a worked example, if the system detects a negative mental state due to overload, then it provides a worked example in the next activity.

(R5) After reading a part of the lesson, if the system detects a negative mental state due to disengagement or underload, then it provides a question as a next activity.

(R6) After reading a part of the lesson, if the system detects a negative mental state due to overload, then it provides a worked example for the next activity.

(R7) Whatever the learners' mental state is, if he answers a question incorrectly, then the system provides a worked example in the next activity.

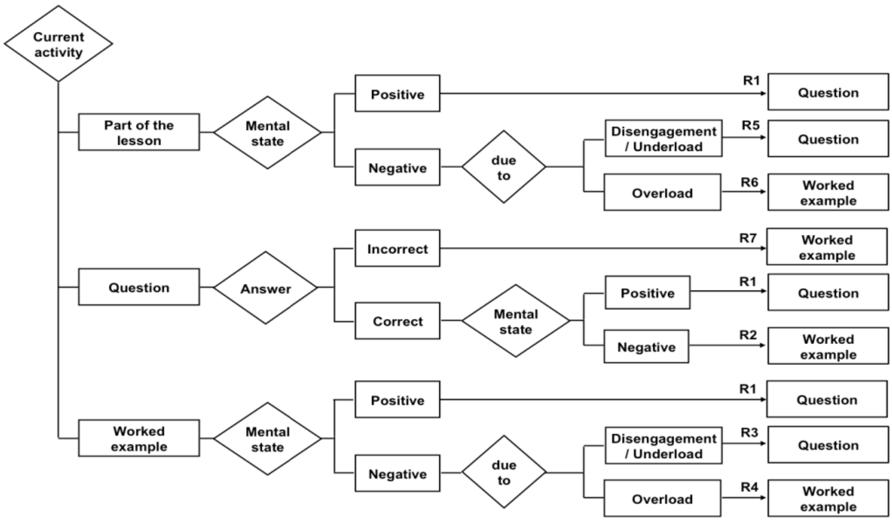

Fig. 1. MENTOR's adaptive logic for selecting the next pedagogical resource

The idea behind the use of these rules is given hereafter.

Decision After Reading a Part of the Lesson. The system uses the questions as a main pedagogical approach to help the learner understand the presented concepts. The rule (R1) makes that the system automatically provide a question if the learner's state is positive. The hypothesis behind this rule is that if the learner reads a lesson while maintaining a positive state, then he likely did not have too much difficulties to understand the presented concepts. So, by choosing a question as a subsequent activity, the system checks the learner's knowledge. However if the learner's mental state is negative, the system analyzes the cause of this state. If this negative state is due to a mental overload, then the rule (R6) makes the system choose a worked example in the next activity. The hypothesis behind this rule is that a mental overload signals generally a cognitive difficulty with regards to the presented concepts. The learner produces then a high level of mental effort to understand what he was reading. So the decision of presenting a worked example after this activity can help the learner to better understand the presented part without producing further mental effort. In this case, we think that giving a problem to solve while the learner is overloaded can worsen his workload level and disturb his learning process. However, if the learner's negative state is due to a disengagement or a mental underload, the system selects a question using the rule (R5). In this case, we assume that this lack of mental investment is either due to the fact that the learner was perfectly mastering what he was reading, or he was rather uninterested and neglecting the lesson. In both cases, a question can be a more stimulating and challenging activity for the learner and can probably enhance his mental investment.

Decision After a Question. At the end of a question, if the system does not detect a negative state, it chooses another question as a next activity using the rule (R1).

We suppose in this case that the learner reacts well mentally and that the strategy based on the questions is currently well suited to the state of the learner. It is important to note that the use of the rule (R1) is limited by the rule (R7). So, in case of a wrong answer, the system automatically switches the next activity to a worked example even though the learner is in a positive mental state in order to prevent the occurrence of a negative state due to a succession of wrong answers.

This same switch is also performed using rule (R2), if the system detects a negative mental state even though the learner's answer is correct. The assumption is that if the learner shows a negative state following the resolution of a problem, changing the type of the activity can be in any case beneficial. More precisely, if the learner is overloaded, switching for a worked example in the next activity can correct or prevent this state of getting worse (this would probably be the case if the system continues with another question). If the negative state is caused by a disengagement or an underload, changing the type of the activity can be stimulating for the learner and may correct this negative state.

Decision After a Worked Example. After presenting a worked example, the system opts for a question as a next activity if the learner's mental state is positive using the rule (R1). The reason of using this strategy is to target an effect known as *the problem completion effect* [6], which is generally obtained by providing a worked example followed immediately by a problem. This type of strategy is used to increase the learning performances and enhance the learner's motivation [23]. For this reason, we decided to choose a question as a subsequent activity to the worked example even if the learner's state is positive, rather than pursuing with another worked example.

Finally, if the system detects a negative mental state caused by an overload, the system continues to present a worked example in the next activity using rule (R4). The assumption behind this rule is that if a learner has some cognitive difficulties to understand the example, or if he is simply tired, it would not be suitable to provide him a problem to solve since that this can worsen his overload. Therefore, another worked example can support his knowledge without beeing mentally much demanding.

4 Experimental Study

In order to highlight the impact of using the learners' mental indicators as an adaptive criterion to manage the system's pedagogical resources, our experimental study relied on two different versions of MENTOR. The difference between these versions lied only in the adaptive logic of the decisional module. The first version left intact the adaptive logic with the seven basic intervention rules described previously. The selection of the resource to be provided was done according to the evolution of the learner's mental state. In particular, the system tends to privilege the questions in case of a positive mental state. In the opposite case, the selection of the type of the resource was made following heuristics that aim to correct the learner's mental state.

The second version of the system did not take into account the mental indexes of engagement and workload in selecting the type of the resource to be provided.

Only the rule (R7) was preserved in the adaptive logic of MENTOR, and the six other rules were ignored. The principle of this version was quite simple: after reading each part of the lesson, the system selected a question for the learner. As long as the learner answered correctly, the system continued to adopt the same strategy: asking questions. However, if an incorrect answer was given, the system selected immediately a worked example as a next activity in order to fix the learner's reasoning. Once the learner finished reading the example, the system automatically followed up with a question in order to increase his motivation and elicit a *problem completion effect*. So the unique parameter that triggered an adaptive action in this version was an incorrect response given by the learner.

The two used versions shared a common point in their operation: if the adaptation parameters are positive, the two versions opt for a question as a next step. The mental state-based adaptive version of the system (the first) represents then an augmented version of the second, insofar as in addition to considering the accuracy of the response (through the 7th rule), it also applies other adaptive actions based on mental parameters.

In summary, we compared two versions of the system, the first used in its adaptive logic an analysis of the mental indexes in addition to the response of the learner, and the second was based solely on the response of the learner. Both versions used, in the same order, exactly the same pedagogical resources.

4.1 Participants and Experimental Protocol

14 participants took part in our study. All were students in the University of Montreal in the same certification program in applied computer science. Upon their arrival, participants were briefed about the experimental procedure and signed a consent form. Each participant was randomly assigned to one of the two following groups. (1) The experimental group (N = 7) used the adaptive version of MENTOR: the learning activities are actively adapted to both the learners' brain indexes and answers. (2) The control group (N=7) used the second version of MENTOR that considers only the learners' answers.

For each participant, the experiment was conducted on two successive days. On the first day, the participant uses the training mode of MENTOR in order to create his individual workload model. In this phase, which lasts about an hour, the participant performs a set of 40 brain training exercices including digit span, reverse digit span and mental computation as described earlier.

On the second day of the experiment, the participant uses the learning mode of MENTOR. The duration of this phase is approximately one hour, including 20 to 30 minutes to learn the four parts of the Reverse Polish Notation lesson. The session starts with a pre-test followed by the lesson, then a post-test, and ends with a debriefing phase. Two 5-minute breaks were taken between the pre-test, the lesson and the post-test.

Pre-Test and Post-Test. These tests use a set of 16 questions relative to the concepts of the lesson. Each of the four parts of the lesson is concerned with four different questions, and the same questions are asked in the pre-test and the post-test. For each question, the learner can answer true or false, or may choose not to respond. A typical example of a question is to check whether two postfix expressions are equivalent. The score in each test is calculated as follows: a correct answer is worth 1 point, while a wrong answer (or a non-response) worths 0.

Debriefing. During this phase, the learner is first asked to report his appreciation of his interaction with the learning environment by rating his *satisfaction level* regarding the lesson, using a scale of seven grades ranging from 1 (strongly disagree) to 7 (strongly agree) on how much he agrees with the following statement: "*Overall, I am satisfied with of my learning experience with the system*".

Then, the learner evaluates the quality of the tutoring provided by the system by reporting his perceived level of *relevance* of the system's proposed activities, using another scale of seven grades ranging from 1 (strongly disagree) to 7 (strongly agree), on how much he agrees with the following statement: "*Overall, I am satisfied with the learning activities selected by the system. The examples and questions are presented at the right time and helped me to understand the lesson. The choice made between asking a question or presenting an example fits my level of understanding*". This scale is therefore an evaluation of the relevance (or the perspicacity) of the tutor's decisions.

5 Results and Discussion

The experimental results are presented in the following subsections. First, we analyze the impact of using the EEG indexes as an adaptive criterion on learning; we compare the learners' outcomes and progression in the two considered groups (experimental group vs. control group) between the pre-test and the post-test. Then, we analyze the impact of using the two versions of the system on the learners' satisfaction level.

5.1 Learning Performance

A 2 (group: experimental vs. control) × 2 (time: pre-test vs. post-test) mixed-model analysis of variance (ANOVA) was conducted to compare the learners' outcomes of the two groups in terms of scores achieved in both tests. The group variable is a between-subject factor that compares the scores between the two experimental conditions, whereas the time variable is a within-subject factor that analyzes, for each participant individually, the score variation (changes) between the pre-test and the post-test. First, the analysis yielded a main effect of the time variable, showing a significant difference of the learners' scores in both groups between the pre-test and the post-test: $F(1, 12) = 2253.353$ $p < 0.001$. Thus, there was significant a learning gain regardless of the group, and hence regardless of the version of the system which was used by the participants.

Second the analysis yielded a significant interaction effect of both factors (group × time) on the learners' outcomes: $F(1, 12) = 29.824$, $p < 0.001$. The results revealed that over time, that is between the pre-test and the post-test, the learners of the experimental group got significantly better learning performances compared to the control group. The means of scores obtained in the pre-test and the post-test for the both groups are listed in Table 1.

The comparison of the learners' scores between the experimental group and the control group revealed that there was no statistically significant differences between the two groups in the pre-test: $F(1, 12) = 4.190$, p = n.s. The overall mean score in the pre-test was $M = 4.21$ ($SD = 1.31$). In contrast, the comparison of the learners' scores in the post-test showed that the scores achieved in the experimental group were significantly higher than the control group: $F(1, 12) = 50.069$, $p < 0.001$. The mean score of the experimental group was $M = 13.86$ ($SD = 0.67$) against $M = 10.71$ ($SD = 0.95$) for the control group.

Table 1. Learners' outcomes in both groups before and after the tutoring session

		Pre-test	Post-test
Experimental group			
	M	4.86_a	13.86_b
	SD	1.07	0.70
Control group			
	M	3.57_a	10.71_c
	SD	1.27	0.95

Values with different subscripts differ significantly.

These results confirm our first hypothesis, that is using the workload and the engagement indexes as a main criterion to control the user's activities can have a positive impact on his learning performances. The learners' whose pedagogical resources were selected according to their mental states were able to provide an average of 86,6 % correct answers after the tutoring session. An increase of 22.7 % in terms of learning outcomes was achieved using this adaptive strategy.

5.2 Subjective Measures

An ANOVA was conducted in order to compare the learners' satisfaction levels between the experimental group and the control group. This ANOVA showed an almost significant difference between the two groups: $F(1, 12) = 4.545$, $p = 0.054$. The learners of the experimental group reported higher satisfaction ($M = 5.71$, $SD = 1.604$) in comparison to the control group ($M = 4.29$, $SD = 0.756$).

A second ANOVA was performed to compare the learners' ratings of the relevance of the activities proposed by the tutoring system in both groups. These ratings were significantly higher in the experimental group ($M = 5$, $SD = 1.414$) versus ($M = 2.43$, $SD = 0.787$) in the control group, $F(1, 12) = 17.673$, $p < 0.05$.

These results confirm thus that incresing the system's adaptive logic with the EEG engagement and workload indexes has a positive effect on the users' satisfaction regarding their learning experience in general, and their appreciation regarding the relevance of the decisions taken by the system in the selection of the pedagogical resources more specifically.

6 Conclusion

In this paper we have presented an intelligent tutoring system called MENTOR (MENtal tuTOR) that adapts its tutoring content according to the user's brain activity. The goal was to show that enhancing the ITS adaptive logic with two physiological mental indicators, namely the engagement and the workload indexes, can improve the learners' outcomes and interaction experience.

MENTOR collects the user's EEG data. The training mode of the system uses different types of brain training exercises to build a workload model for a new user. This model is used to derive in real-time the user's workload index from his EEG signals. The learning mode of MENTOR provides a tutoring environment that adapts its content actively to the learner's brain indexes. The system evaluates the learner's mental state, and selects the pedagogical activity that best suits to his state.

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