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SUMMARY

A model of attention in computer-based assessment exercise in Second Life is presented. Attention is measured considering psychometric inputs based on Electro Encephalogram (EEC) readings using NeuroSky technology. The model of attention considers the readings and combines them with user-generated, performance data [1] (giving-up, answer correctness and time spent) to determine states of attention and trigger strategies to improve or sustain an optimal level of attention. The novelty of this approach is in using NeuroSky technology to read attention levels and in combining this input with user-generated data taken from interaction. This model of attention is based on the ARCS [2, 3] model of motivation and can be later integrated into a model of motivation [4] for virtual worlds learning. The paper discusses the feasibility of using attention to complement existing models of motivation [4] and outlines work for the future.

General Terms

Measurement, Experimentation, Human Factors

Keywords

Attention, motivation, modeling, brain computer interfaces, NeuroSky, EEC.

1. INTRODUCTION

Attention is an important aspect in the learning process both in real life situations and in computer-based instruction and provides the basis that informs motivation modeling [5-7]. Addressing the learner's attention to model motivation in computer-based instruction is a topic in the area of Artificial Intelligence in Education (AIED) that has considered diverse mechanisms to recognize human motivation and react with the aim of improving or sustaining optimal levels of motivation. The approach to attention recognition presented in this paper consists of modeling learner's attention considering measurements taken from a brain computer interface (BCI) in combination with user-generated data taken from the interaction. Modeling attention is important as it could form the basis for enhancing current models of motivation [8, 9]. BCI offer the possibility of reading electric signals generated by neural activity in the brain. The NeuroSky input device is employed since it recognizes states of user's attention. This device has been developed by the NeuroSky company which provides solutions to communicate bio-signals to computers (http://www.neurosky.com). The model of attention described is based on theoretical concepts taken from theories of motivation, in particular Keller's ARCS model [2, 3]. However, our approach combines attention inputs with user-generated, performance data [1] to detect states of attention and react sensibly aiming to improve or sustain learner's attention in computer-based interactions. The novelty of this approach is that it combines inputs from a BCI with user-generated data. The paper is organized in four sections. Section Two frames our approach to modeling introducing the topic of attention and its role in motivation modeling, its importance in AIED and describes methods for modeling. Section Three introduces the principles of attention recognition with NeuroSky technology and justifies its use in AIED research. Section Four presents our approach to modeling combining attention inputs from Neurosky with some theoretical constructs taken from the literature [1]. In the conclusions and future work section we present a discussion of this work, address its appropriateness for being employed for motivation modeling and present the steps to be taken in order to evaluate the validity of this model and the appropriateness and effectiveness of using BCI in AIED research.

2. BACKGROUND

Attention is an important aspect of the learning situation [2, 5-7]. Keller's ARCS [2, 3] model for example, considers attention as the most fundamental element towards achieving motivation in the classroom (ARCS stands for Attention, Relevance, Confidence and Satisfaction). In the ARCS model the four components need to be achieved if the learner is going to be motivated. Keller's strategies for attention emphasize *"getting* and *sustaining* attention" (p. 403) [3] before embarking on other strategies to motivate the learner. In computer mediated learning, both attention and motivation have generated a growing body of research with the aim of recognizing students' attention and reacting appropriately given low states. In order to recognize and react researchers have employed Artificial Intelligence methods that allow personalizing the interaction. Artificial Intelligence in Education (AIED) has thus dealt with two problems: those associated with recognition of attention/motivation and those related to the reaction. On the recognition side, researchers have employed two main methodologies: modeling using physiological clues [10-13] and employing user-generated data [1, 9, 14-17]. The results provide an indication, on the one hand, of the bodily reactions that are associated to different affective, attention or motivation states during the interaction between a learner and an educational system. On the other, the results have provided a useful list of interaction features (such as mouse movements, performance results, help-seeking behavior) that are associated to the learner's attention state. Of particular relevance to our work is the work of de Vicente and Pain [1] who asked expert raters about the motivational state of different learners by watching a replay of their interactions. They inferred a set of 85 rules that associate specific user-generated data (performance data for example) with states of motivation. On the reaction side, researchers have investigated different ways of offering corrective feedback if the detection shows low levels of affective states (including attention and motivation). Typically, AIED research has relied on well established theories to endow the computer-based instruction with a set of pedagogically sound strategies to enhance or sustain an optimal level. The various approaches taken in AIED research have brought about benefits that translated into learning gains. Giving the relevance of attention in motivation modeling and ultimately in the learning gains, our approach considers reading user's attention (recognition) using both physiological inputs and user-generated data. The physiological inputs, however, will be based on a Brain Computer Interface capable of assessing the learners' attention levels based on neural activity. Unlike previous research using physiological inputs, we will employ a Brain Computer Interface (BCI) based on neurological research associating particular brain activity with attention levels. We have chosen to combine these reading with user-generated data since it is not possible to determine what the user is paying attention to only using the BCI. On the reaction side, and giving the importance of attention in motivation and learning, we have based the model's reactions in Keller's [2, 3] ARCS model. The intention with attention modeling is that it will serve as a basis for motivational modeling in future implementations of our model that consider attention as input. In the following section, we present the basis for attention reading.

3. NEUROSKY

Brain Computer Interfaces (BCI), are input devices that use the brains' electrical activity to allow communication between users and computers. Typically, BCI's are used to activate commands based on specific reading or to measure neural activity of interest such as attention, anxiety or relaxation. The use of traditional BCI such as magnetic resonance (NMR), electro encephalograms (EEC) or near infrared (NIR) machines presents problems for AIED research because of their intrusiveness and expense. NeuroSky technologies, however, have developed a non-invasive, dry, bio sensor to read electrical neuron-triggered activity in the brain to determine states of attention and relaxation. NeuroSky is a low-cost, easy to use Electro Encephalogram (EEC) developed for leisure, non-clinical human-computer interaction. Neural activity generates a faint electrical signal that constitutes the basis for EEC-based NeuroSky readings. To do so, it captures these signals using three dried electrodes and decodes them by applying algorithms to disambiguate multiple signals and give coherence to the readings. NeuroSky is used as a headset with the three electrodes touching the skin at three different locations: beneath the ears and the forehead. The electrical signals read at these three points are used as inputs by NeuroSky's algorithms to determine the levels of attention. The algorithms used to translate electrical signals into binary information are able to distinguish and use the electrical activity caused by neural activity associated to 'paying attention' from other sources of electricity such as that generated by the computer. Although the algorithms are able to detect the signals associated to attention or relaxation based brain activity NeuroSky has not evaluated the technology. To us, the novelty of using NeuroSky in research is its portability and easiness of use and the potential to apply it as an input device to for physiological, brain-generated information relevant in AIED. From our point of view, NeuroSky offers the possibility to read neural activity associated with attention and to investigate its connection with factors such as the learner's motivation in computer-based learning situations. By using NeuroSky with research purposes we will throw some light onto the appropriateness and effectiveness of using this BCI in AIED research given the role of attention in learning.

4. ATTENTION MODELING

Our model of attention is built around dynamic variables generated by the learner's brain (attention inputs via a BCI) and the learner's action in a computer-based learning situation. The combination of physiological (attention) and data variables is not new [11, 18]. Our approach, however, is the first to consider BCI claiming to give an accurate reading of the learner's attention. In this sense, our approach does not have to correlate to particular body postures or gaze activity to infer attention levels but directly uses the inputs based on brain activity associated to attention as described in the previous section. NeuroSky reads attention levels in a scale from 0 to 100. There is an initial delay of 4 seconds before the first of these values reach the computer and newer values of attention are calculate at a pace of one value per second. A value of 0 indicates no signal is being read and values greater than 0 indicate increasing levels of attention with a higher value of 100. The closer to 100 a particular reading is, the greater the attention detected by the BCI.

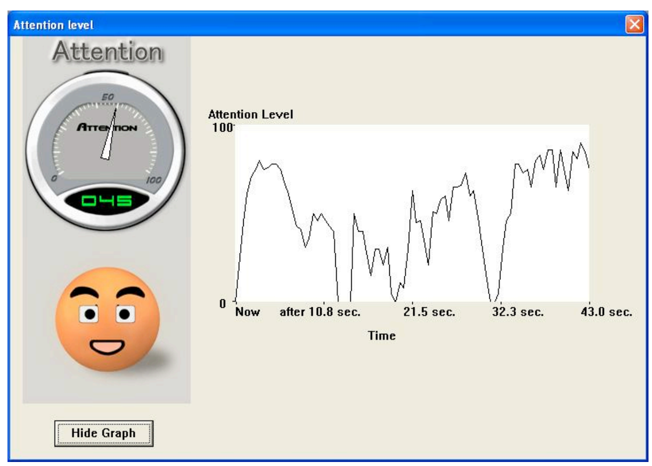

Figure 1 Levels of attention as displayed by NeuroSky "attention meter"

Given the dynamic nature of the readings and the potentially large data sets obtained, in our model one reading of attention is associated to a particular learning episode lasting more than one second. A learning episode consists of the presentation of a learning activity, the solving of a mathematical problem, the answering of a question or the exposure to reflective feedback. To calculate attention for one episode we simply obtain the mean of all the attention readings that occur during the learning episode. Figure 1 shows a diagram displaying readings of attention associated to particular points in time. Figure 2 shows the same diagram split in n learning episodes. However, the model of attention also considers other clues from the interaction that are useful indicators of the learner's attention levels. In the background section examples of user modeling that considers interaction traits such as mouse movements, time taken and errors made [1].

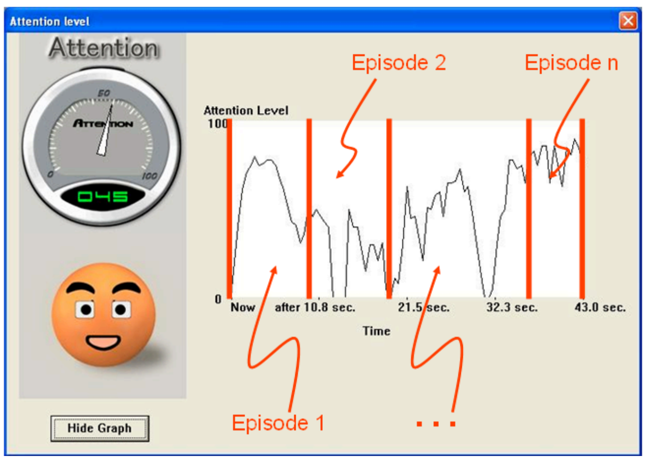

Figure 2 Levels of attention are associated to episodes

In this model, user-generated data that is related to estimating levels of attention is that related to performance [1]: quality, speed and give-up. These interaction-based clues have been found to be relevant sources to determine states of attention and motivation as judged by expert human tutors [1]. To throw some light onto the suitability of using BCI in combination with user-generated data the model of attention will focus on detecting low states of attention to improve or sustain optimal levels of user attention. Table 1 presents the inputs that will inform the attention model.

	Low	High
NeuroSky readings	< 50	> 50
Quality	Errors made	No errors made
Speed	More than 1 minute	Less than 1 minute
Give-up	Yes	No

Table 1 Inputs associated to attention modeling

However, a model of attention should be able not only to determine (detect) low or high levels of attention but also should provide feedback for the learner (react) in order to improve or sustain learner's attention. In the background section the work of Keller [2, 3] has been presented as a series of steps towards improving learner's motivation. In this model of motivation, attention modeling is the first step towards detecting motivation. Our model of attention considers Keller's strategies to sensitively provide feedback aimed at improving or sustaining the learner's attention. Table 2 presents Keller's strategies.

Strategy 1	To increase attention, use novel, incongruous and paradoxical events. Attention is aroused when there is an *abrupt* change in the status quo.
Strategy 2	To increase attention, use anecdotes and other devices for injecting a *personal, emotional element* into otherwise purely intellectual or procedural material.
Strategy 3	To arouse and maintain attention, give people the opportunity to learn more about things they *already know about* or believe in, but also give them moderate doses of the *unfamiliar* and unexpected.
Strategy 4	To increase attention, use analogies to make the strange familiar and the familiar strange.
Strategy 5	To increase attention, guide students into a process of question generation and *inquiry*.

Table 2 Outputs taken from Keller's ARCS (REF) model

When considering interaction traits and BCI inputs the type of task determines, to some extent, the data used for modeling and the reactions that will be provided. In order to try out our ideas regarding attention modeling we chose an assessment exercise since we believe lack of attention to the questions asked might be responsible for low scores in multiple choice questions. To do so, we have programmed a general purpose multiple choice question (MCQ) avatar in Linden Lab's Second Life virtual world.

Figure 3 Student controlled-avatar interaction with an AI-driven one in Second Life

Second Life is an open-ended virtual world which offers users opportunities to define virtual experiences open to other users of the system. In order to model attention we have defined an Artificial Intelligence (AI) driven avatar which is able to pose questions, use a pre-defined set of reactions and have limited conversation with learners in Second Life. The AI-driven avatar was programmed using C# (C-sharp) in combination with lib second life. Lib Second Life is project aimed at understanding and extending Second Life's client to allow the programming of features using C# programming languages. This tool enables the manipulation of avatars behaviors to respond to other avatars or to adapt to changes in Second Life's environment. Figure 3 shows an example of the AI-driven avatar (to the right) interacting with another avatar controlled by a university student. In order to respond to other avatar's actions and behaviors, the AI-driven avatars collects user-generated data during the interaction. Since the current implementation of the AI-driven avatar asks questions in a MCQ format, information regarding the correctness of answers (quality in Table 1), time taken to respond and whether users give-up is gathered dynamically. Physiological data is collected using NeuroSky which is worn by the student controlling the avatar (see Figure 4). The data generated by NeuroSky is transmitted to the computer via a USB interface and organized with using a C# class which communicates with the AI-driven avatar. In this way, the model of attention (AI-driven avatar) is updated dynamically and considers inputs from the BCI and the learner's performance behavior.

Figure 4 Student using the NeuroSky

In order to implement Keller's [2, 3] strategies to improve or sustain the level of attention, our attention model defines 6 types of reactions where type 1 in intended for the lowest levels of attention, type 5 is aimed at sustaining a high attention level and type 6 does not require any reaction:

- **Type 1 reaction**: Change the status quo by making the AI-driven avatar propose a different activity than the current MCQ. Options include asking the learner to return at a later time or take a break.
- **Type 2 reaction**: Use analogies to make the strange familiar. If the answer to the current question is wrong, rephrase the question using different, easier to understand terms. If the answer is right offer to use easier language to frame subsequent questions.
- **Type 3 reaction**: Guide the student into a process of inquiry about his/her experiences. Provoke a simple conversation reflecting on the causes of lack of attention, is the student tired? Does he/she like the topic? Would he/she like to come back at a later time?
- **Type 4 reaction**: Inject a personal, emotional element into the process. The AI-driven avatar shows some emotions of excitement about the current MCQ process and provides feedback about the current question. The avatar uses a range of facial expressions available to denote its delight for the student's progress.
- **Type 5 reaction**: Give students the possibility to learn more about the topic at hand. The AI avatar asks the learner whether he/she wants to explore more resources in connection with the learning material used in the MCQ assessment. Provide web links or Second Life SLURL's so that the student can explore other areas.
- **Type 6 reaction**: The learner's attention is at an optimal level. The AI-driven avatar is not required to react.

As suggested earlier, measurements of attention will be collected during the interaction considering episodes. An episode in the MCQ situation consists of the asking of one question and the answer to that question. As discussed earlier in this section, the BCI's input (I1, NeuroSky reading in Table 1) for attention modeling is calculated as the mean value of all the attention inputs during the episode. On the other hand, the time taken by the learner (I2, speed in Table 1) to respond to the question at hand, the correctness of the question (I3, quality in Table 1) and whether the learner gives-up or not (I4, give-up in Table 1) are also considered as inputs to determine an attention value per episode. The values of I3 and I4 are binary values where as I1 and I2 are not. In the case of I2 (time taken) we consider any time greater than 1 minute to be low (0) and high (1) otherwise. I1 represents the mean value of attention reading during the duration of the episode (I2). To simplify this input I1 will be divided by 100 so its value is lower than or equal to 1. The mean value of I1+I2+I3+I4 for any given episode (i) becomes the value of attention for that particular episode:

$$\textbf{Attention[i]} = \textbf{(I1 + I2 + I3 + I4) /4}$$

Since there are 6 types of reactions (see above), in our model of attention the specific reaction that will be selected for an attention level in episode i, will be dependent on the level of attention as specified in Table 3. For example, suppose that Question 1 in the multiple choice questionnaire was correctly answered by the learner in 43 seconds. The BCI detected an average attention value (calculated considering 43 attention inputs) of 56. The values for this episode (question 1) are: I1 = .56 (56/100), I2 = 1 (short time = 1), I3 = 1 (correct answer) and I4 = 1 (the user did not give up): Attention [question 1] = (.56+1+1+1)/4 = 0.89. There will be no reaction for this particular example since the level of attention is high.

Attention Value	Reaction type
0 – 16.66	1 : Change status quo

16.67 – 33.33	2 : Provide alternative questions
33.34 – 50	3 : Provoke reflection on lack of attention
51 – 66.66	4 : AI-driven avatar shows excitement
66.67 – 83.33	5 : Provide supporting material for this question
83.34 – 100	6 : No reaction is given

Table 3 Levels of attention and their associated reactions

5. CONCLUSIONS

We are not aware of motivational modeling combining neural input with interaction traits. The model of attention proposed on this paper is based on input from a Brain Computer Interface (BCI) called Neurosky. This device offers the possibility of detecting brain waves associated to levels of attention. Given the importance of attention in motivation modeling and in the ARCS model [2, 3] we propose a model of attention in Second Life that will serve as a first step towards more complex modeling of motivation in computer-based learning scenarios [4]. The novelty of our approach consists of combining a novel form of computer input with existing user-generated data to model attention levels. We have also proposed the association of levels of attention with particular reactions taken from motivation theory [2, 3]. Work for the future consists on evaluating this model and the NeuroSky. The objective of a large-scale evaluation (n > 90) will be twofold: on the one hand we will evaluate the NeuroSky technology to determine whether its levels of attention correlate with self-assessed values of attention. On the other hand, this evaluation will throw some light onto the effectiveness of our modeling approach. To do so we will setup a 2 x 1 factorial design experiment where the AI-driven avatar's reactions will vary by giving motivational feedback (experimental condition, the model is used) and not giving motivational feedback (control group no reactions are presented). The results of these evaluations will allow us to determine the appropriateness of using NeuroSky in educational research with computers and whether our model approach can be used to enhance existing models of motivation in computer-based assessment in Second Life.

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