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Recommending Regulation Strategies

Asma Ben Khedher, Claude Frasson
Département d'informatique et de recherche opérationnelle
Université de Montréal, 2920 Chemin de la Tour, Montréal, CANADA
{benkheda, frasson}@iro.umontreal.ca

Abstract

Negative affective states such as boredom and disengagement, experienced in educational environments, cause student disinterest and lack of concentration. In fact, they are harmful to students' progress since they decrease their learning gains. This is why regulating learner's emotions and reengaging him into the learning process, is of primary interest. In this paper, we propose to investigate learner's negative affective states namely frustration and disengagement since they can divert the student from his learning goal. We assessed also his/her position during a game as well as his behavior in term of tasks performed and objects explored in order to recommend regulation strategies. An experimental study was conducted where physiological data as well as additional features extracted from log files were used as inputs in machine learning classification algorithms. An accuracy of *93.18%* was reached by Decision Tree classifier. Results demonstrated that based on students' affects and behaviors we were able to identify the adequate regulation strategy.

Introduction

In the last decade, affect has become a motivating research area in learning especially in Intelligent Tutoring Systems (ITS). Significant researches have emerged on affective states assessment and detection in an effort to investigate their impact on learning outcomes and improving knowledge's acquisition. Affective learner modeling plays an important role in ITS in order to understand tutoring process. For instance, building an affective user model is a way to identify learners' emotions as well as their interaction behaviors in order to assess how they are related to learning gains (Conati and Maclaren 2005, Amershi and Conati 2009, Kardan and Conati 2011).

On the other side, detecting emotions occurring during learning is in increasing interest. Students can experience positive (motivation, engagement, etc.) as well as negative (boredom, frustration, etc.) emotions. Investigating factors that lead to positive emotions is essential since they could be considered as tools to cope with negative affects Some results reported that students, with prior content knowledge or experience about a specific concept, tended to be more engaged (Rowe, Shores et al. 2011, Derbali and Frasson 2012). However, students may exhibit a lack of motivation and attention because of an uninteresting or a difficult learning content. Several approaches were introduced to predict affective states: machine learning techniques for early prediction of user frustration (Mcquiggan, Lee et al. 2007), eye-tracking data for predicting boredom and curiosity (Wang, Chignell et al. 2006, Jaques, Conati et al. 2014) and also using electrophysiological sensors as well as cognitive and personal criteria to predict students' uncertainty (Jraidi and Frasson 2013). All of this work seek to endow ITS with capabilities to reduce negative emotions in an effort to help students focus their attention on learning elements. In fact, early detection of negative affects, enable ITS to plan appropriate interventions and establish corrective strategies. However which strategies would be appropriate? How to determine them? The goal of this paper is to recommend regulation strategies for students who experience negative emotions during their interaction with a game-based learning environment, CRYSTAL ISLAND. These strategies depend upon several factors specific to student's behavior and his affective state during learning process.

The organization of this paper is as follows: In the first section, we present previous work related to our field. In the second section, we detail our proposed approach. In the third section, we present the obtained results, followed by conclusion as well as future work in the last section.

Previous Work

It is widely known that negative affective states influence learner behaviors, leading them to game the system or divert attention from their main focus. Recent works have been addressing these issues by adapting regulation strategies in an effort to provide assistance to promote learning and increase engagement and motivation. Different works in regulation strategies have emerged. Cognitive reappraisal is one of them (Gross 1998, Strain and D'Mello 2011), the ability of the learner to transform negative situations into a positive emotion can lead to the learner's self-efficacy in managing bad emotion and perceiving them as effective experiences. In the same context, off-task behaviors could be used as productive of emotions' self-regulation (Sabourin, Rowe et al. 2013), off-task behavior is when the student become disinterested and disengage from the learning task. On the other hand, McQuiggan and colleagues demonstrated that the empathetic responses and reactions of the narrative-centered learning environment characters had an impact on user affective state (McQuiggan, Robison et al. 2008). In an effort to reengage the student, reduce his anxiety and foster his learning gains an experiment was done to estimate the impact of an affective sensitive pedagogical agent (Amershi and Conati 2009, Woolf, Arroyo et al. 2010, D'Mello, Olney et al. 2012). Although detecting, as early as possible, learner affect has the potential to permit establish efficient interventions, monitoring his goals progression and behavior during learning is an interesting issue to adapt accordingly. In the present research, we focus on detecting two negative affective states namely *frustration and disengagement* from electroencephalograms as well as tracking where the learner is looking at during his interaction with the CRYSTAL ISLAND environment (Rowe, Mcquiggan et al. 2007) and what behavior he/she is adopting such as tasks performed and objects explored. Our approach will investigate these data as well as self-reports fulfilled by the users to recommend regulation strategies.

Proposed Approach

Twenty graduate students from computer science were recruited for the experiment, ranging in age from 17 to 33 years (M = 25.9, SD = 4.34).

Experimental methodology

The experiment was divided into three phases. The first phase was dedicated to the EEG's measures validation in an effort to ascertain its efficiency in giving precise measurements for the frustration and disengagement affective states. To validate the accuracy of these measures, we used the International Affective Picture System (Lang, Bradley et al. 2008). A series of four images per affective state were chosen and displayed to the student while he/she was wearing the headset, to record his EEG signals at the same time. Upon visualizing each series, the participant was asked to fill a self-report on which the most evocative emotion in his/her opinion should be selected from a list of different emotions. For each participant, we compared his responses with the obtained values from EEG. We obtained 70 % of valid responses for frustration and 65 % for disengagement.

In the second phase, upon the participant arrival, he/she is asked to complete a consent form as well as a demographic survey and a personality test namely the Big Five Personality test (Costa Jr and McCrae 2013). After completing the pre-experiment questionnaires, we outfit the participant with the appropriate material as described in figure 1. He was asked to stay in front of the computer monitor and instructed to stay calm and relaxed in order to obtain the baseline recording.

Figure 1: experimental environment (EEG and Crystal Island).

Then CRYSTAL ISLAND is displayed and the participant begins exploring the environment in order to discover the cause of a mystery disease that infects a research station. Upon resolving the mystery or after 50mn of elapsed time for those who didn't resolve the mystery, the players were asked to fill first a post-test to evaluate how much microbiology aspects they learnt from the virtual environment and second, a self-report. In this last report (figure 2) the participant is asked to answer two types of information: 1) he has to evaluate his/her emotions after interacting with the game's character in each scene, choosing the most appropriate one(s) among a list of nine affects, and 2) he has to indicate which help strategy he would have liked to receive during the interaction in the scene. Otherwise, the learner is free to not choose any strategy and select "I don't need help".

After collecting all their choices, we removed data relative to the last strategy since we were focusing only on students in need of help. The next step was also to keep only the strategies that were selected, obtaining thus a final list of five strategies. Finally, the third phase consisted, in data preprocessing and features extraction.

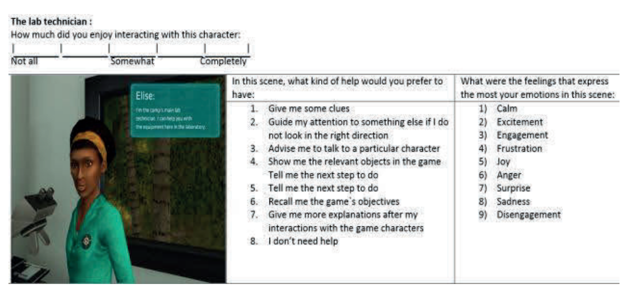

Figure 2: self-report example representing different regulation strategies.

Features' extraction

Seventeen features were extracted from the data gathered during the interaction with CRYSTAL ISLAND, two mental features and fourteen event features. For EEG features, we removed the outliers (invalid or missing) and we performed data preprocessing for emotion labelling as presented in table 1. During the game, several information per participant were recorded in log files in order to assess the player's progress. . We only considered two events features describing the user's behavior: the position of the participant (nursery, laboratory, etc.) and the different actions performed in each room (open a book, close journal, etc.). Since we had already binary EEG features, we used one-hot encoding in order to convert log files categorical features into binary to obtain homogeneous data. Both features were reported periodically over one minute window time.

Table 1: emotions labelling

	EEG value	Baseline value	Results	Discretization
Frustration	a	d	a>d → frustrated	1
			a<d → not frustrated	0
Engagement	b	e	b>e → engaged	1
			b<e → not engaged	0

A total of 88 instances were fed as inputs into machine learning algorithms available in the Weka data mining toolkit. Several classifiers were considered: Naïve Bayes, J48 implementation of Decision Tree, Sequential Minimal Optimization (SMO) implementation of Support Vector Machine, K-Nearest Neighbors with different values of k (k=3, k=5) and Logistic Regression. The k-fold (k=10) cross validation technique was used to evaluate the performance of these classifiers.

Results and Discussion

Our objective, in this paper, was to recommend regulation strategies, based on learners' behaviors and affective states during their interaction with CRYSTAL ISLAND. These strategies will be applied in real-time on a future work. For that purpose, we focused on algorithm's execution time, to choose from the classifiers presented above, those we used in our work. And, the error rate was considered too, since a classifier with a lower error rate produces more efficient classification's results (bin Othman and Yau 2007). Based on these criteria, we finally use Naïve Bayes, Logistic Regression and Decision Tree with their default parameters as in Weka. The later provides the higher accuracy of 93.18% among all classifiers.

We evaluated the classifiers' performance of in term of two measures, overall accuracy and Kappa statistics since we aim to obtain a classifier that generalize well. Table 2 presents the obtained results. In addition, a baseline classifier (ZeroR) was used to assess the performance of the other classifiers (Litman and Forbes 2003, AlZoubi, Calvo et al. 2009) . It predicted the most likely class (strategy 1, accuracy=59.09%). We observed in figure 3 that all other classifiers achieved significantly higher accuracies than the baseline.

Table 2: Classifiers detailed results.

Classifier	*Accuracy (%)*	*Kappa statistics*	*Mean absolute error*
Naïve Bayes	68.18	0.3422	0.1397
Decision Tree	93.18	0.8801	0.0264
Logistic Regression	86.36	0.7545	0.0844

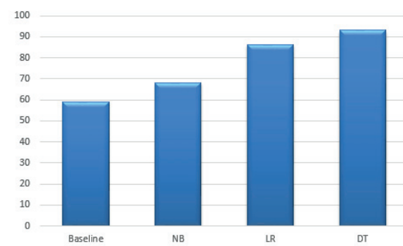

Figure 3: The overall performance in each classifier.

We believe that the results we have obtained are encouraging. In one hand, based on electrophysiological data and students' behaviors, we were able to correctly generating regulation strategies. On other hand, recommending appropriate helps for students during their learning process is a key challenge, since enhancing learning gains is a major goal for almost all the Intelligent Tutoring Systems. All of these findings will enable us to track and monitor learners' actions, performance as well as their affective states to make real-time interventions. During learning, reengaging students and capture their attention is fundamental.

Conclusion and Future Works

Learner attention and engagement are primary interests in Intelligent Tutoring Systems and Serious Games as they are closely related to learning quality. Thus detecting as soon as possible negative affects, can permit early prevention and sufficient time to perform corrective strategies. In this paper, we used electroencephalography to detect two negative affective states namely frustration and disengagement and reported also events features based on log files in order to reach our research objective consisting in recommending efficiently regulation strategies from the user's state and behavior.

An experimental study was conducted in order to record participants' EEG signals during their interaction with the CRYSTAL ISLAND. We then used machine learning classification algorithms to recommend regulation strategies.

The findings were very encouraging: up to 93% of accuracy (kappa = 0.8801) was obtained by Decision Tree classifier. In future work, we plan to add eye tracking data source as well as developing an intelligent agent. This agent will react efficacy to the learner disengagement and frustration by applying the appropriate obtained regulation strategies in order to motivate the student and reengage him into the learning process.

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