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Predicting the Difficulty Level Faced by Academic Achievers based on Brainwave Analysis

Judith AZCARRAGA*, Merlin Teodosia SUAREZ, Paul Salvador INVENTADO
Center for Empathic Human-Computer Interactions
De La Salle University, Manila, Philippines
*jay.azcarraga@delasalle.ph

Abstract: Students who performed well in their college mathematics subjects, referred to here as *academic achievers*, were divided into two groups according to the self-reported level of difficulty faced by them while performing several programming tasks in LOGO - a programming language using turtle-graphics. It is shown that, to some extent, the level of difficulty of tasks faced by academic achievers can be predicted, based on their measured affective levels of excitement, frustration and engagement. These affective states are measured using brainwaves sensors that are attached to the head of the student. Those who assessed the learning experience as easy tend to have higher levels of excitement than those who reported to have experienced difficulty in learning the language. On the other hand, the level of frustration among those having difficulty with the tasks registered slightly higher frustration levels. Three machine learning algorithms were used to predict whether or not a learner finds the tasks to be easy. The average predictive accuracy is 70%.

Keywords: Learning Environment, Affective Computing, Brainwaves Sensors, Academic Achievers

Introduction

When designing computer assisted learning environments, it is useful to be able to predict the level of difficulty and affective state that a specific learner is experiencing for a specific problem or task. This would guide the learning environment when making corresponding adjustments to the learning module in real time. Indeed, it had been shown that the affective states of learners can be predicted with high accuracy using brainwaves information [3]. Guided by another study conducted by Jausovec [4] that found differences among gifted and non-gifted students in the mental effort that they exert, this study delves into the affective behavior of academic achievers while immersed in a learning activity, and seeks to predict the level of difficulty that they face based on an analysis of their brainwaves. The study focuses on high achieving students as these are the students who would benefit most from self-regulated learning using automated, computer assisted learning environments [1][6].

1. Experiment, Results and Discussion

Based on their cumulative grade point average in their college mathematics courses, 17 undergraduate students (10 males and 7 females) who were among the top 10% of their cohort were involved in this study. Each subject was asked to learn the LOGO language [5] in a single session by watching a tutorial video prior to the performance of each task. The tutorial videos teach the basic commands of the language and the tasks involve drawing of various geometric figures. At the end of each session, a student is asked to assess the level of difficulty of each programming task. Group I (easy) was composed of

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those who found the tasks to be "easy" or "less than moderately difficult". Those who found the tasks to be "moderately difficult", "difficult", or "very difficult" were placed under Group II ("challenging").

The whole time that a student is watching a video or performing a task, an EEG sensor is attached to his/her head. Using 14 channels based on the International standard 10-20 locations [7], the EEG sensor is an *Emotiv EPOC*, a commercial product capable of capturing brainwaves signals that translate into three affective states, namely *excitement*, *frustration* and *engagement*. Based on the levels of excitement, frustration and engagement, the experiments were conducted to test the following hypotheses:

i. A learner who finds a task easy would tend to be more excited than someone who finds the task challenging.
ii. A learner who finds a task easy would tend to be less frustrated than someone who finds the task challenging.
iii. A learner who finds a task easy tends to be more engaged than someone who finds the task challenging.

The average levels of the three affective states are presented in Table 1. From these very general, aggregated data, hypothesis i and iii do seem to be plausible. Indeed, those who found the tasks to be easy did seem, on the average, to register higher levels of excitement and engagement while performing the tasks. However, upon closer examination of the data, hypothesis iii may have to be reconsidered.

Table 1. Average excitement, frustration and engagement of the 2 groups of students on all activities.

	Excitement		**Frustration**		**Engagement**	
	Challenging	*Easy*	*Challenging*	*Easy*	*Challenging*	*Easy*
Video	0.45	0.48	0.5	0.59	0.58	0.62
Task	0.44	0.5	0.57	0.57	0.61	0.64
Average	0.45	0.49	0.53	0.58	0.59	0.63

Based on the dis-aggregated data, as shown in Figure 1 and Table 2, only hypothesis i is consistently true for all three tasks, while hypothesis ii holds only for Tasks 2 and 3, and hypothesis iii by the data shown in Figure 1 but not in Table 2. Extending the analysis to include both the watching of videos and performing the assigned programming tasks, the *easy* group tends to be more excited to be assigned programming tasks rather than watching a video - since they register higher excitement and engagement levels. For the challenging group, it is the reverse. As for frustration levels, the students who found the tasks to be easy tend to be more frustrated while watching a video as shown in Figure 1. As for engagement, both groups registered higher engagement levels on programming the tasks than watching videos as shown in Tables 1 & 2 and Figure 1.

On top of the comparisons based on average levels of excitement, frustration, and engagement, the detailed brainwaves data, which were collected from the participants every 3 seconds, were used to predict the level of difficulty that a learner is facing while performing the programming task. The average prediction accuracy was 70% using 3 different WEKA classifiers [2] namely, C4.5 (69.9%), Multilayer Perceptron (70.5%) and Decision Table (69%) with 10-fold cross validation. These classifiers predicted which group, *easy* or *challenging*, a student belongs to. The F Measure of the *easy* group (0.71 - 0.72) is found to be higher than the *challenging* group (0.66-0.68). This may suggest that those students who found most tasks easy to program are more predictable than those who are having difficulty with the tasks.

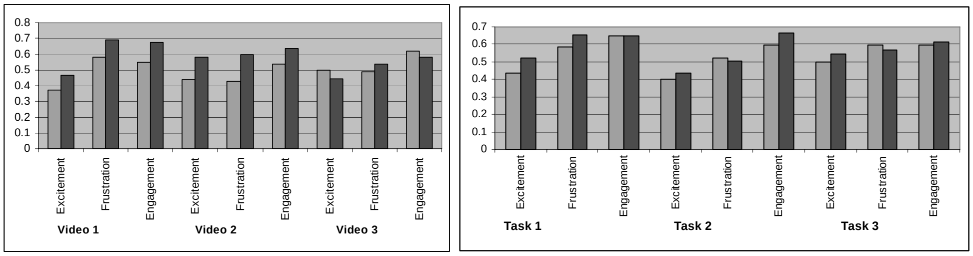

Figure 1. Average affective states for each of the three videos and tasks. Dark bars are for the *easy* group.

Table 2. Outlier percentage for engagement and excitement for each of the three videos and tasks. Low and high outlier is 1 standard deviation from the left and right of the mean, respectively.

	Video						Task					
	Low Outlier			High Outlier			Low Outlier			High Outlier		
Excitement	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Challenging	16.3%	34.1%	30.0%	19.7%	20.4%	27.5%	21.8%	15.3%	23.2%	15.9%	14.9%	18.2%
Easy	25.5%	24.0%	22.0%	16.8%	30.2%	22.7%	17.4%	19.7%	17.8%	19.6%	21.8%	26.8%
Engagement												
Challenging	58.0%	41.7%	36.2%	23.1%	32.5%	29.6%	43.0%	18.3%	19.6%	33.6%	14.1%	22.6%
Easy	40.7%	36.3%	33.3%	27.5%	21.4%	16.5%	40.3%	4.8%	7.0%	25.2%	19.7%	20.5%

2. Conclusion

The academic achievers who were the subjects of this study showed some differences as to their levels of excitement, frustration, and engagement depending on whether they found the tasks to be easy or not. Also, their general affective states differed depending on whether they were passively watching a video or were actively performing some programming task. Moreover, these affective states can be used to predict, with an accuracy of about 70%, the level of difficulty that a learner is facing. Further work would look into the use other input features such as gaze and facial expressions, voice, mouse and keyboard strokes and physiological signals like heartbeat, skin conductance, and body temperature.

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