Recognizing Student Emotions using Brainwaves and Mouse Behavior Data

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ABSTRACT

Brainwaves (EEG signals) and mouse behavior information are shown to be useful in predicting academic emotions, such as confidence, excitement, frustration and interest. Twenty five college students were asked to use the Aplusix math learning software while their brainwaves signals and mouse behavior (number of clicks, duration of each click, distance traveled by the mouse) were automatically being captured. It is shown that by combining the extracted features from EEG signals with data representing mouse click behavior, the accuracy in predicting academic emotions substantially increases compared to using only features extracted from EEG signals or just mouse behavior alone. Furthermore, experiments were conducted to assess the prediction accuracy of the system at points during the learning session where several of the extracted features significantly deviate in value from their mean. The experiments confirm that the prediction performance increases as the number of feature values that deviate significantly from the mean increases.

Keywords: Affect Recognition, Brainwaves, Electroencephalography (EEG), Mouse Behavior, Tutoring Systems

INTRODUCTION

Students experience various emotions while engaged in learning. Such emotions, also referred to as academic emotions (Pekrun, 2002), may affect the flow of learning as well as the motivation to continue with the learning task. This has been the challenge for the human tutors and even for those who develop intelligent tutoring systems (ITS). Indeed, effective tutors, whether human tutors or computer-based intelligent tutoring systems, are those who are not only aware of the cognitive needs of the students but also of their affective needs.

With this in mind, recent research projects in the area of ITS have tried to address not only the cognitive needs of students but their affective needs as well. Such affective systems, also referred to as affective tutoring systems, consider the effect of emotions in the learning process of a learner as well as the typical emotional patterns under different learning scenarios. Academic

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emotions typically experienced by a learner while using a tutoring system are confidence (Arroyo et al., 2009; Azcarraga et al., 2011a, 2011b, 2011c; Ibañez et al., 2011), excitement (Arroyo et al., 2009; Azcarraga et al., 2011a, 2011b, 2011c; Ibañez et al., 2011), frustration (Arroyo et al., 2009; Azcarraga et al., 2011a, 2011b, 2011c; Burleson, 2006; Ibañez et al., 2011), interest (Arroyo et al., 2009; Azcarraga et al., 2011a, 2011b, 2011c; D’Mello & Graesser, 2009; Kapoor, Burleson & Picard, 2007), flow/engagement (D’Mello & Graesser, 2009; Stevens, Galloway & Berka, 2007), boredom (D’Mello & Graesser, 2009) and confusion (D’Mello & Graesser, 2009).

Affective tutoring systems are capable of recognizing student affect based on tutorial information complemented with the user profile. Furthermore, these systems sometimes also include a combination of facial expression, gesture and physiological signals. In (Arroyo et al., 2009), affective states such as confident, frustrated, excited and interested are predicted with high accuracy using special devices such as a camera to capture facial expression, posture chair to monitor the level of engagement, pressure-sensitive mouse and skin-conductance sensor. Similarly, Burleson (2006) uses the same set of devices in order to predict student frustration and the need for help. Moreover, tutorial information such as conversational cues, posture and facial features are used in Autotutor to predict boredom, flow/engagement, confusion and frustration (D’Mello & Graesser, 2009).

Another physiological sensor also explored in detecting student emotions is the EEG sensor which reads brainwaves. Such a device can measure the electrical activity in the brain induced by the electro-chemical processes related to the firing of neurons. Negative emotions, such as “disgust” were found to be associated with right-sided activation in the frontal and anterior temporal regions whereas “happiness” was found to be associated with left-sided activation in the anterior temporal region (Davidson, 2000). Nevertheless, whether a given spike in neuron activities as captured by an EEG sensor is indeed induced by some emotion cannot be ascertained. Muscle movements near the eyes and forehead are typical noise/artifacts in EEG recording. Various other artifacts may also get (wrongly) captured. As explained later, serious care must be given to pre-processing EEG data in order to increase its signal-to-noise ratio and at some point be able to isolate segments of EEG signals, over some sustained period.

Past researches have used brainwaves information to measure user alertness and cognitive workload (Sanei & Chambers, 2007), while others have used these to predict the stress level (Heraz et al., 2009) and emotional dimensions (pleasure, valence, arousal and dominance) (Frantzidis et al., 2010; Heraz, Razaki, & Frasson, 2007). In Stevens, Galloway, & Berka (2007), the student’s level of frustration, distraction and cognitive workload were observed while the student is engaged in different activities in a multimedia-learning environment.

Similarly, in the previous work of the authors (cf. Azcarraga et al., 2010), the level of problem difficulty faced by academic achievers is predicted based on brainwaves. Those who assessed the problems as easy tended to have higher excitement level compared to those who found the tasks to be difficult. Moreover, those who experienced difficulty with the problems tended to be more frustrated.

Other research efforts have been directed at detecting student affective states while using some learning environment with various sensors connected to the head or body of the learner (Azcarraga et al., 2011a, 2011b, 2011c; Chanel, 2009; Ibañez et al., 2011). In Chanel (2009), classification based on EEG led to a higher accuracy for the assessment of the valence dimension of emotions as compared to the peripheral features from GSR, temperature, BVP, HR and respiration. Also, emotion valence and arousal prediction have improved when EEG features are combined with these peripheral features.
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