Affective State Detection in Educational Systems through Mining Multimodal Data Sources

Sergio Salmeron-Majadas
aDeNu Research Group. UNED
Calle Juan del Rosal, 16. Madrid
28040. Spain
+34 91 398 93 88
ssalmeron@bec.uned.es

Olga C. Santos
aDeNu Research Group. UNED
Calle Juan del Rosal, 16. Madrid
28040. Spain
+34 91 398 93 88
ocsantos@dia.uned.es

Jesus G. Boticario
aDeNu Research Group. UNED
Calle Juan del Rosal, 16. Madrid
28040. Spain
+34 91 398 71 97
jgb@dia.uned.es

ABSTRACT

Affective computing in e-learning is playing a vital role, as emotions can strongly impact on learner's results. Detecting affective states and managing them can lead to a learning performance improvement. For this, different sensors can be used to monitor user's interactions and detect emotional changes. Due to the huge varied data volume a multimodal approach based on data mining has been proposed.

Keywords

Affective Computing, Educational Data Mining, Emotions, Adaptive Systems, User Modeling.

1. RESEARCH APPROACH

Given the strong role emotions play on the learning process, by combining in a wise way the use of emotional information and user interactions in an e-learning platform, an impact on user's performance and cognition can be expected [3]. The ongoing research works in the literature aim to progress on managing different information, sources such as physiological sensors or face tracking systems [1]. To this, data mining is applied to provide personalized feedback to learners, which aims at supporting them in achieving better results on their tasks [5].

The approach followed in the MAMIPEC project [4] is focused on addressing the problem of emotion detection from a multimodal viewpoint by using different data sources. Our goal here is to combine those data sources to model the learner's current affective state and improve thus the possible results obtained from a single data source [1]. The learner model, which is based on standards, is thus enriched with new features that are used to provide personalized feedback during the learning process. In particular, the research of this ongoing Ph.D work focuses on identifying and modeling affective states to support adaptive features in educational systems. The top-level hypothesis behind the research is that the application of data mining techniques to different emotional data sources can improve the modeling of the learners' affective state in terms of standards and thus, better provide a personalized support in open educational service oriented architectures (i.e. those that take advantage of standards-based models).

2. INITIAL EXPERIMENTS FOR DATA GATHERING

A large-scale experiment was carried out to get data to feed the data mining system. More than 90 participants came to our lab and were asked to solve a series of mathematical tasks (the mathematical domain was chosen as Maths can awaken different intense emotions in the learner [2]) in a dotLRN platform while being monitored. Physiological, facial and interaction data were gathered during the experiment. Physiological signals recorded were: i) the participant's heart rate, ii) the participant's breath frequency, iii) the participant's galvanic skin response (electrical conductance of participant's skin) and temperature. For detecting changes in the signals recorded, baselines for the involved sensors were computed. Besides physiological sensor devices, a Microsoft Kinect device was used to extract participant's facial characteristic points in order to get their expressions. Additionally, a key-logger and a mouse-tracker were developed in order to track all the interactions performed by the user with the platform during de experiment. A webcam registered the face of the participant during all the session as well as the desktop was also recorded. Also, some questionnaires were offered to the participants, such as Big Five Inventory (BFI) to know the main five structural dimensions of individual's personality, General Self-Efficacy Scale (GSE) to get the self-beliefs of the participants to cope with a variety of difficult demands in life and the Positive and Negative Affect Schedule (PANAS).

To evaluate the emotions experienced by participants during the tasks, participants were asked to fulfill a SAM (Self-Assessment Manikin) scale after each exercise. Moreover, after each mathematical task, participants were also asked to write a self report (as plain text) regarding their feelings when doing the task.

3. DATA MINING

With this collected data, the work on this Ph.D focuses on detecting the emotions felt by the users by processing the different data sources obtained during the experience.

3.1 Data Preprocessing

For the keystroke data, some measures were processed such as mean time between strokes or between stroke and release. For the sensor data, first of all, the data were split into tasks and the noisy values were removed. Once done this, the mean of the physiological baseline recorded before the experiment was calculated so all the other values are compared to this mean. The mean of all these differences is stored for all the tasks solved by each participant. For detecting affective facial information the Kinect is expected to provide facial patterns or gestures and link them to emotional states. To do this a psycho-educational expert is currently viewing the webcam captured videos in order to detect relevant facial expressions during the experiment. The mouse-tracking data have not been processed either. Although some measures can be easily calculated (mean speed, distance moved, etc) from the interactions recorded, there is a need to research how to identify meaningful individual mouse movements (i.e. when the mouse draws differentiated paths).

3.2 Data Mining Methods

Currently, two different approaches are being explored: one for predicting user's emotion from the text typed (in the emotional report) and another where all the processed information was used as input to predict the SAM valence values given by learners.

3.2.1 Text Mining

Three of the tasks consisted in typing participants' emotions (like a typed think-aloud), these tasks were used to gather information from the keyboard interactions, but also to get emotional knowledge from the text. A simple approach was adopted, consisting of processing the text typed by the user searching for positive and negative terms included in the emotional valence labeled MPQA Opinion Corpus affective database to provide an emotional score to each text. A psycho-emotional expert also assigned an emotional valence score to each text after its reading to label the data for its use with supervised learning methods.

When comparing the text mining scores with the experts' score based on the participants' reports, if both are binned into 2 categories (Positive-Negative), a 73.42% of success prediction rate was achieved.

3.2.2 Affective States Detection

Another data mining approach aims to predict the user's emotional valence while dealing with a given task based on the processed records obtained during that task: questionnaires scores, text mining scores, keyboard interactions and physiological data.

To use supervised learning methods, two different labeling systems were used as results to be predicted: the SAM scores given by the participants and experts' emotional tagging based on users' emotional report afterwards.

For the data mining process, prediction trees and naïve bayes predictors were used. The biggest effort on this stage was made by grouping and binning different data sources in different ways to get the best results. Two, three and four-category binning was used when binning valence values and text mining scores (using equal percentile values so all the bins have the same probability and equal spaced intervals over the domain range). After every different combination, naïve bayes and prediction tree (C4.5) nodes were executed with leave-one-out sampling.

The best result were obtained using a naïve bayes algorithm with a 79,72% success rate on predicting the valence given by the experts ignoring the neutral tagged values.

4. OPEN ISSUES

The work reported so far has helped to identify several kinds of open issues to deal with i) the infrastructure for the data gathering and synchronization, ii) the emotions detection of neutral values, iii) the data mining approach itself, and iv) reducing the intrusiveness. Results achieved so far suggest that the way sensor data have been preprocessed might need to be redesigned, focusing not only on using data mining over all the data gathered preprocessed, but also on using data mining to preprocess single signals data (eg. Keystrokes, mouse movements). Finally, a study on which data sources are more valuable for emotions detection should be done, focusing on getting emotional information in a non-intrusive and cheap way.

5. ONGOING WORKS

Several open issues have been identified analyzing the data gathered. In particular, there is a need to redefine certain aspects from the data gathering in order to provide more meaningful information from where to obtain better mining results in future experiments. The approach proposed at the end of this stage must offer an affective state detection strong enough to provide a robust base to the model generated in the next layers.

Proposed work aims to provide an accurate standards-based user model useful to supply personalized assistance taking the learner's affective state into account. The first layer of this work is still being addressed, studying the state of the art in order to meet multimodal approaches on emotion detection and also being able to detect different emotions by using data mining.

6. ACKNOWLEDGEMENT

Authors would like to thank experiments' participants, MAMIPEC project (TIN2011-29221-C03-01) colleagues and the Spanish Government for its funding.

7. REFERENCES

[1] D'Mello, S. and Kory, J. 2012. Consistent but modest: a meta-analysis on unimodal and multimodal affect detection accuracies from 30 studies. Proceedings of the 14th ACM international conference on Multimodal interaction (New York, NY, USA, 2012), 31–38.

[2] Goetz, T., Frenzel, A.C., Hall, N.C. and Pekrun, R. 2008. Antecedents of academic emotions: Testing the internal/external frame of reference model for academic enjoyment. Contemporary Educational Psychology. 33,1 (2008), 9–33.

[3] Moore, S.C. and Oaksford, M. 2002. Some long-term effects of emotion on cognition. British Journal of Psychology. 93, 3 (2002), 383–395.

[4] Santos, O.C., Salmeron-Majadas, S., Boticario, J.G. 2013. Emotions detection from math exercises by combining several data sources. Proceedings of the 16th International Conference on Artificial Intelligence in Education (AIED 2013), in press

[5] Shen, L., Wang, M. and Shen, R. 2009. Affective e-learning: Using "emotional" data to improve learning in pervasive learning environment. Educational Technology & Society. 12, 2 (2009), 176–189.