Affective standards-based modeling in educational contexts from mining multimodal data sources

Sergio Salmeron-Majadas

aDeNu Research Group, Artificial Intelligence Dept., Computer Science School,
UNED, C/Juan del Rosal, 16, 28040 Madrid, Spain
ssalmeron@bec.uned.es

Abstract. With the goal of providing affective triggered feedback in educational contexts, this work focuses on detecting affective states from different data sources. To this end, different signal combinations have to be tested in order to optimize the detection depending on the data sources used. Here, a wide variety of options have been addressed, from physiological signals to mouse and keyboard interaction analysis, looking for a non-intrusive and low cost detection approach. The final goal is to enrich standards-based learner models with affective information, which will be used to provide personalized support during the learning experience.

Keywords: Affective Computing, User Modeling, Data Mining, Emotions, Physiological Signals, Mouse, Keyboard

1 Introduction

The impact of emotions in our lives comes determined in part from the strong relationship existing between emotions and mental processes such as decision making [1]. In learning, it should be made the best of that link, but emotion detection is an indispensable requirement for that. Some research has been done in emotions experienced in an academic context [2], and interesting links have been found between affective states and learning, playing these states a key role in learning [3] and motivation [4].

Moreover, affective computing has addressed the study of the affective dimension of interactions between human and devices and how these should manage the emotions appearing during that interaction [5]. In the last years, thanks to the technological advances, many different ways to measure emotions have appeared (as described in the next section), allowing multiple detection approaches in very different contexts.

The problem addressed by this research is the affective state detection, in order to take advantage of the possibilities affective computing brings on information extraction from learners while in a learning process. The motivation behind for addressing this problem is to use learner's emotions to improve the learning outcomes so, this research focuses on identifying those affective factors that both prevents the learner from a good academic performance and support the learner in achieving positive learning outcomes. To identify these factors, the affective dimension of each individual learner should be modeled. To this there are several processes involved. First there is a monitoring process all along the learning process, which focuses on detecting affective changes in the learner. Second, an emotional data processor infers which affective states are of relevance within the given context. Third, there is a Semantic Affective Educational Recommender that is in charge of providing personalized reaction to the learner in terms of affective feedback or educational oriented recommendations. This personalization approach is to be supported by an affective learner model, that is, the main goal of this work, a user model that takes into account the descriptions of the emotional profile of the learner as well as other affective related issues, such personality traits. In order to support interoperability with other systems (to exchange information between them) when providing the affective support, this affective learner model is also to be compliant as much as possible with existing specifications, such as IMS Learner Information Profile (to model learners' profile), IMS Access for All (to model accessibility preferences) and W3C Emotion Markup Language (to deal with affective information), among others. The paper is structured as follows. In section 2 we present the existing theoretical framework that motivate the presented work. In section 3 we introduce the research approach proposed in this Ph.D. In section 4 we mention the main contributions that the dissertation aims to achieve. In section 5 the progress made to date and current results are presented. In section 6 we discuss the works done and to be done.

2 State of the art

As aforementioned, many different works centered in affective states detection have arisen in the last years, appearing many different ways to address the emotion recognition problem. There are works showing the application of this goal in many different fields, being the educational field one of the most researched. The high interest on affective states detection in educational context relies on the potential impact that an accurate process of emotions could play in learner's results. As we are about to see, different data sources have been proposed with affective purposes.

One of the most common procedures followed are those using physiological signals to detect how the autonomic nervous system manifest some responses to some emotions as this manifestations cannot be falsified. There are works using Electrocardiogram (ECG) to get affective information [5] from variations present heart rate. Galvanic Skin Response (GSR), measuring micro-changes in sweating has also been widely used to detect variations related to affective states [6]. In [7] a combination of GSR with body temperature is used as input to recognize affective states, and in [8] is the combination of GSR with electromyography, measuring the activity of certain facial muscles trying to capture emotional expression. Some other signals as respiration have not been so extendedly explored as they are hard to process but some works have used it with other physiological sources [9].

Other way to capture affective information commonly used is process and extract information from audio or video recording. From the voice affective information can also be extracted, as in [10], where authors try to identify stress from speech and the biometrical signature of voice. From video recordings, a common approach is to detect, from facial expressions, action units related to some affective states [11].

Another non-intrusive way to get information to process with affective purposes is the study of the interactions performed by participant with the interaction devices he is usually using. Some works have been done analyzing the keyboard interactions performed by users. The purpose here is to identify different affective states depending on their behavior typing [12] or moving their mouse [13].As we can see from the existing studies, there is a wide diversity of data sources proposed to detect affective states, but each one has to be deeply studied due to the complexity of the goal. The combination of these sources is an approach that could help not only to improve the results[14], but also to offer affective modeling based adaptation regardless the available data sources. Other common approach seen in proposed literature is the one based on the comparison of different algorithms applied all over the generated dataset, but the combination of these used algorithms has not been widely explored yet.

3 Research Approach

The proposed research relies on the hypothesis that data mining on multimodal data sources can detect affective features for learner modeling in educational contexts.

After seeing all the works done in affective states detection, the point of view presented in this research is based on using different combinations of data sources obtained from bio-feedback devices to offer the best prediction rates possible from the given sources regarding the affective state, characterized in two dimensions (valence or pleasantness and arousal or activation), of the learner. Then the information provided by these sources will be taken into account to provide the personalized affective feedback through the e-learning platform. To get there, a thorough analysis of each and every single processing technique and data source available needs to be done and after that, a study of the different possible ways to merge all that data and get the best rates from those combinations is to be performed. Due to the huge amounts of data to be processed (as the data sources proposed entail capturing data with high frequency), data mining is being used in this work to detect variations in behavior that could reflect some affective information to be included in the user. That affective modeling will be used to guide the personalized response providing affective recommendations.

One critical open issue here is to determine the most appropriate setting to tackle the problem. Based on our own experience in running experiments with final users we are currently changing our initial approach. Thus, after carrying out some experiments trying to get as much data as possible in short time experiences following an initially considered inter-subject approach[15], current steps are given towards an accurate and individualized modeling in mind. In particular, this research is currently focused on the adoption of an intra-subject task-independent approach, where an exhaustive data collecting from a single user is to be done in order to model as precisely as possible this particular user's affective states along a large period in time.

The work described here is to be included in the MAMIPEC project [16], which aims to help learners while using a learning platform by means of providing them affective triggered feedback when some behaviors or affective states detected could lead to worsen the results, looking for causing positive affective flows in learners.

4 Proposed Contributions

The proposed work aims to advance in some aspects from the traditional approach adopted when performing affective states detection. Due to the wide variety of data sources proposed in literature a lot of different approaches have been proposed, but as nowadays the ways to access to learning platforms are been enhanced in terms of a wide variety of interaction devices, different configurations can be used to get affective information from the learner. Usually the proposed works seen in section 2 have focused on studying one or a concrete closed group of sources. A high detailed study of all the possibilities combining sources is to be done in order to offer affective adaptation regardless of the available data sources available for a learner in a given context. This contribution is necessary for the main purpose of this work is the enrichment of the user model with the affective information detected, with standards (as the mentioned in section 1) in mind to guarantee interoperability with other components. This may sound trivial, but there is a lot of research to be done in this aspect such as detecting which aspects should be used to enrich learners' model to reflect their affective states. The affective indicators to be included in the user model could vary depending on the data sources available but some of them should be included for any of them, such as the reactivity of the learner regarding certain signals or the baseline values for every data source used. The first one would be useful to know which data sources would arise more information on that particular learner, while the second one is essential to evaluate the variations on the signals used without the needed of record the baseline every time affective support has to be provided. Other outcome from this research will be the process to be done in order to combine the different data sources as many different sources are used, so the combination techniques used should look for the best accuracy when detecting emotions. These techniques will be based on data mining algorithms, performing an individual analysis for each data source and another analysis to perform over the outcomes from the single data source processing in order to detect the best way to combine every data source available.

5 Results

Following the most common approach presented in literature some experiments have been done. In November 2012 in the frame of Madrid Science Week, near 100 participants came to our laboratory to solve some mathematics problems while monitored. The information gathered from that experiment included: hear rate, galvanic skin response, skin temperature, breath rate, keyboard interactions, mouse interactions, face and recording (using webcam and kinect), screen recording. As in the experiment participants had also to type down their emotions after each mathematical task, a natural language text description of the emotions experienced was also obtained. In the first data mining workflows made, presented in [15] most of the data gathered was used, i.e. heart rate, skin temperature and galvanic skin conductance variations regarding the base line recorded at the beginning of the experiment, some keyboard indicators, and a score automatically generated from the texts were used to identify if the state of the learner was positive or negative according to an expert's opinion. After that, more detailed mouse and keyboard interaction indicators were generated and a study comparing different combinations of data sources processed with different algorithms were done, obtaining prediction rates near 85% accuracy when predicting the positive or negative value of valence dimension. Next steps to be taken include designing new experiments adopting the intra-subject approach, evaluating all the possible ways to process the gathered data to perform an accurate modeling.

6 Discussion

There are some points still wide open in the field of affective state detection. Due to the nature of the studied phenomena, different ways to label the recorded data have been proposed, varying in the people who labels the data (e.g. the own learner or an expert), the format the labels should be (e.g. a closed list of given emotions, an dimensional approach with numeric values, etc), or the moment the data is labeled (e.g. anytime the learner feels like to express an emotion, in a fixed time intervals, in a revision after the experiment, etc.). The last point is also related to the time validity of each tag, where a study on the affective states duration is also needed. Other open issue is detecting different methods to elicit the most common emotions in learning in order to use them in future experiments to get valuable data to mine.

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