# Gathering Emotional Data from Multiple Sources


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## ABSTRACT

Collecting and processing data in order to detect and recognize emotions has become a research hot topic in educational scenarios. We have followed a multimodal approach to collect and process data from different sources to support emotion detection and recognition. To illustrate the approach, in this demo, participants will be shown what emotional data can be gathered while solving Math problems.



## Keywords

Affective Computing, Data Mining, Sensor Data, Emotion Detection, Mathematics


## 1. INTRODUCTION

Currently there is a growing interest in offering emotional support to learners in e-learning platforms through an expanded set of adaptive features. A key issue is to determine learners' affective state, which is related to their cognitive and metacognitive process [4], preferable with low cost sensors [2]. Affective states in our approach are to be defined from mining in a jointly manner subjective, physiological and behavioral data gathered from diverse emotional information sources while the learner interacts on the given e-learning environment. This approach offers possible improvements on emotion detection, which as suggested in the literature may come out from the combination of different data sources simultaneously [5]. Math problem solving scenarios have provided opportunities to investigate this new approach, as from them different emotions may be elicited [7].

## 2. OUR APPROACH

As for emotion detection, our approach is based on the use of data mining techniques. As shown in Figure 1, we follow a multimodal gathering approach based on the combination of the following data sources obtained while the learner carries out learning interactions to solve Mathematical tasks in the e-learning platform and stored in the corresponding user model. To start with, bio-feedback data provide appropriate measures to detect typical physiological reactions that come along with emotions. Although they should not be used for categorizing discrete emotions on its own, they provide useful indicators of the participants' arousal level associated with the ongoing affective state over the learning process. Signals used to this end are: heart rate, breath frequency, galvanic skin response and skin temperature. To evaluate phasic variations on collected signals upon a tonic state, recordings of each learner pre-baseline are done to provide reference values for subsequent analysis.

Another key source for gathering affective information is the non-verbal behavior (e.g. gestures, facial expression, body movements). Facial expressions of participants are recorded by Windows Kinect face features extraction. Kinect for Windows device provides an API able to detect a user's face model based in 100 points. The processing of these data is to identify the learner's head position, inclination and expressions. In addition, a webcam (with microphone) is used to record other sources of information not necessarily located in the participant's face expression, such as verbal expression and speech tone.

Some additional user interactions are also gathered. In particular, keyboard and mouse data sources are recorded to find out behavioral correlates of the emotional intensity. To collect all the events triggered by mouse and keyboard, a key logger and mouse tracker has been developed in Java (with no GUI, so it cannot interfere with the user interactions) using the library provided by kSquared.de. A video of participant's desktop is also recorded to keep track of the session.

As this approach is based on a wide range of information sources, synchronization is a key issue. Due to the number of devices used, several computers may be needed to collect the required information. Thus, the synchronization of the systems involved (given that some of the recorded interactions can last less than a second) is needed. Through this, synchronization data are merged and data mining can be applied.

Information about learners' personality is also considered when processing the data, given the narrow relation between personality traits and affective states with learning styles and strategies [3]. To get this information, some self-reports are used. To gather personality traits, learners fill the Big Five Inventory (BFI), that reveals the main five structural dimensions of personality and the General Self-Efficacy Scale (GSE) that assesses participants self-beliefs in coping with a variety of demands in life. Moreover, as supervised learning techniques are considered due to their well-known benefits for emotions detection [8], some labeling is needed. With this aim, participants are told to rate proposed activities in the valence (from negative to positive) and arousal (from calm to excited) dimensions using the Self-Assessment Manikin (SAM) scale. Other meaningful sources to gather learners' subjective emotions are obtained by self-described emotional reports (participants are asked to write their emotions in natural language) and the 20 emotional states of the Positive and Negative Affect Schedule (PANAS). The learners' performance regarding the Mathematical tasks is another information source that should be taken into account from their learning outcomes.

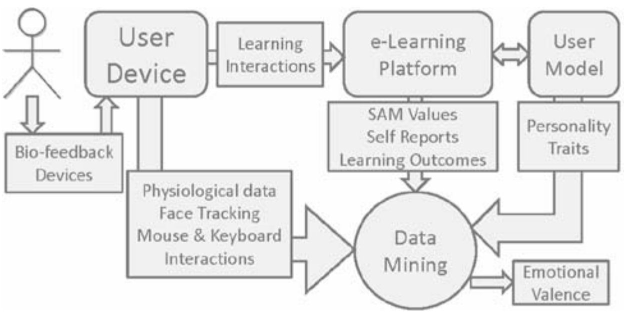


**Figure 1. Data gathering flow**

Once data have been gathered, and before data mining processes are carried out, each kind of data is to be pre-processed in a particular way depending on their nature. Physiological data are being pre-processed to find significant variations on the signals with regard to the pre-baseline. Relations between signal variation patterns found and the self-reported affective labeling given by participants provide valuable information. A similar approach is being followed to the interaction data, relating interaction changes (in keyboard typing or mouse clicking behavior) with the subjective emotional reported values. Text mining techniques have been applied to extract valence values depending on the terms typed by the user when writing the emotional reports. Data recorded with Kinect are being pre-processed to extract emotional patterns according to gestures and movements from detected facial points. The result of these processes is to be used (in the same way as the emotional feedback and subjective information collected from the user commented above) to emotionally label data gathered from sensors in supervised learning systems. The current state of this work will be presented in a demo where participants are to carry out mathematical exercises while some of the above information will be collected and shown, and the data mining process followed discuss with the participant.

## 3. ONGOING WORKS

This approach is supported by the MAMIPEC project, where we are exploring how to combine different information sources from different signals to offer an accessible and personalized learning experience to the learner, which accounts for their affective state and aims to provide, accordingly, affective based recommendations. To progress on this goal, a large-scale experiment was carried out where 72 participants (excluding 10 additional pilots to test the settings) performed different types of individual activities, which consisted in a Math problem solving experience implemented in dotLRN e-learning platform. Text mining techniques are being applied over the emotional report in order to extract valence information. Using the text mining scores (filtering out those reports with a difference of less than 3 words when subtracting positive items from negative items when computing the frequency of affective words from the MPQA database) and the keyboard interactions, our best results were roughly a 70% success rate when predicting positive or negative valence compared to the experts' labeling [6]. New experiments using this approach with a problem solving ITS [1] have been proposed in cooperation with Valencia University.

## 4. ACKNOWLEDGMENTS

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