PRELIMINARY RESULTS OF A PARAMETRIC ANALYSIS OF EMOTIONS IN A LEARNING PROCESS IN SCIENCE

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In the last decades, several studies have highlighted the importance of emotions in the teaching and learning process. The classroom is considered an emotional place, where the learning is influenced by cognitive and emotional-motivational mechanisms. Classically, emotions have been classified in discrete categories. Furthermore, in educational settings, it is possible to evaluate dimensional categories as engagement and attention. According to this vision, we designed an activity to analyse emotions and their flow when students are involved in an inquiry-based activity. To avoid limitations of self-reports and observational methods, we evaluated emotions with an automatic facial coding system. This system detects facial human expressions using facial reference points and classifies their emotional value parametrically. The data shows different flows for each affective parameter. Thus, we obtained a constant high level of attention and intense engagement along the whole activity. Moreover, joy and surprise flows showed a global presence higher than negative emotions. Four parameters' flow graphics are related to characteristic educational behaviour. This work opens to the possibility of objective parametric evaluations of the emotional component in the teaching-learning process.

Keywords: Emotion, Science Education, Conceptual change.

INTRODUCTION AND THEORETICAL FRAMEWORK

In Education emotions may be described as appraisals and reactions to the information received from the context, whose intensity depends on subjective evaluations, influenced by personal prior knowledge beliefs and priorities (Dávila et al., 2021; Graesser, 2020; Harley et al., 2017; Rubin & Talarico; 2009). Emotions may occur due to evocation of events that happened in the past or by anticipating possible future situations (Damasio & Carvalho, 2013; Hutchinson & Barrett, 2019; Pekrun et al., 2014; Russell, 2003). Thus, antecedents as academic successes and failures, may shape students' emotions. Conversely, emotions may impact outcomes, determining a reciprocal influence (Murphy, 2019; Pekrun et al., 2017).

Emotions influence in different ways experiences, strategies, and attitude of students toward learning (Borrachero et al., 2014; Murphy et al., 2019). They may be positive (happiness, hope, etc..) or negative (anxiety, frustration, etc..). In general, positive emotions (such as enjoyment, hope, satisfaction, self-confidence) support the teaching-learning process positively (Pekrun et al., 2017). On the contrary, negative emotions (such as boredom, confusion, frustration, and hopelessness) tend to have negative influences on learning and are negatively related to achievement (Murphy et al., 2019; Marcos-Merino, 2019; Pekrun et al., 2014).

Moreover, the emotional state can be described dimensionally. Dimensions describes emotional experiences along a continual variation of parameters as pleasure and arousal, directly related to core affect (Deckert et al., 2019; Plass et al, 2019). Anyway, dimensions may represent a superior level that includes emotion discrete categories (Loderer et al. 2019). Some prominent dimensions in educational context are attention and engagement (Graesser, 2020; Harley et al., 2017; Loderer et al., 2019; Mrkva et al., 2019).

Introduction to parametric study of emotions

Basically, up to the present days, scientific research in Education has been focused on observational and self-reports methods (Azari et al., 2020; Harley et al., 2019; Loderer et al., 2019; Meindl et al., 2018; Pekrun, 2006). These methodologies, for assessing personal qualities, are the most common approaches in research (Duckworth & Yeager, 2015). They have the capacity to get outcomes in a cheap, quick and versatile way of emotion recognition (Engelman & Bannert, 2019).

Anyway, self-reports are difficult to edit and the declarations of the participants may be affected by biases, as consequences of incapacity to self-estimate or express correctly their own emotions (Engelman & Bannert, 2019; Goetz et al., 2016; Izard, 2009; Pekrun, 2006). As far as observer-reports, coder experts need a long and intense practice to achieve reliable data by observation (Barrett et al., 2019).

In the last decades, the continuous development of technology offers different methodologies and analytical instruments to identify the emotional process. These systems collect and analyse data related to the brain and nervous system. Some among the most investigated are EEG, heart rate, skin conductance, fMRI and eye tracking. Furthermore, recent advanced included no-intrusive techniques to automate facial expression recognition systems using cameras or webcams (Darvishi et al., 2021; Monkaresi et al., 2017), now commercially available for scientific research with high level of reliability (Stöckli et al., 2018, Küntzler et al., 2021). This is relevant in education, considering that the movements of the facial muscles almost always accompany an emotional state, which can be related to discrete emotions and affective dimensions. Thus, the analysis of facial expressions is one of the most appropriate automatized techniques to estimate emotions and behaviours in class (Calado et al., 2017).

Facial automatic detection systems can achieve an appropriate and accurate postural, head movement and facial expression coding recognition around 90%, depending on the conditions of clear and correct illumination of the participant's face (Benitez-Quiroz et al. 2017). That gives us the chance to bring to bear a dynamic perspective on emotional changes over a period of time. Thus, it is possible to analyse profiles of emotional response and behaviour occurring in a given situation (Gross, 2015; Kuppens et al., 2009; Kuppens & Verduyn, 2015).

The first step of the automatic facial expression recognition was to detect the face of the subjects (Kulkarni et al., 2021). For that, the software iMotions (2018) utilised the algorithm Viola Jones Cascaded Classifier (Viola & Jones, 2004). Successively, to estimate the facial expression recorded, it used an automatic coding system based on Facial Action Coding System (FACS) (Barrett et al., 2019; Ekman & Friesen, 1978; Keltner et al., 2019). Eventually, the Affectiva AFFDEX algorithm SDK 4 (Affectiva, 2015, Boston, MA) correlated the facial expressions to the affective states. This system can detect head orientation (yaw, pitch, roll); interocular distance; 34 facial landmarks; 14 facial expression metrics.

In detail, to describe facial movement, the software uses algorithms to detect landmarks as brows, mouth corners, etc., as well as groups of landmarks. When these reference points change their relative position, due to a change of respondent's expression, the system evaluates the new facial configuration in terms of affective metrics. Each movement corresponds to an Action Unit (AU). One or more AUs describe an emotional facial expression based on FACS. It allows to assess basic emotions: Anger, Sadness, Joy, Surprise, Disgust, Contempt and Fear; moreover, affective dimensions as Attention, Valence and Engagement. When an emotional event occurs, it generates an emotional episode that is evident in the change of facial configuration, ending when it goes back to its baseline level (Kuppens et al., 2015). Because respondents differ in their natural expression, the Affectiva algorithm applies a rolling baseline on the neutral expression of the respondent. This process keeps into account the frames preceding and following the current frame, and calculates changes. Each frame get an assigned score, depending on facial expression recognition and its intensity, from the absence of expression (0%) to an expression fully present (100%).

In this work, based on an artificial intelligence system for facial expression recognition, we have set out to develop and apply an experimental design which would allow us to collect and study the emotional and behavioural dynamics in a science education activity.

RESEARCH METHOD AND DESIGN

With the aim to investigate emotional and behavioural dynamics in science education, we proposed an inquiry activity to 24 teaching students (15 women and 9 men) attending the Master in Secondary Education, at School of Education, Complutense University of Madrid. The participants had to predict the contents of a box, with dimensions of 9x6x20 cm. It contained some euro coins: two of 1 cent; one of 5 cents; one of 10 cents; one of 20 cents; one of 1 euro. All these coins moved freely inside it. The participants could not open the box or break it. That is, they had to make use only of their scientific-technical knowledge, such as observing, testing hypotheses, drawing conclusions, etc. They could use some magnets. A similar activity was proposed among others by Lederman & Abd-El-Khalick (1998) and Haber-Schaim et al. (1979).

The participants were divided into pairs. Only one student of each pair had to guess the contents, and they were video-recorded. The other students observed their peers' activity. They checked the right operation of the camcorder, and they warned their peers to remain inside the video framing. In this way they learnt the operational best practice. Each HD video camera was placed on a tripod in front of each observed student, at a distance of one metre to obtain the best recording view of the face and upper body. The activity lasted twenty minutes. We divided the session into ten periods of two minutes each. After each period, students filled a form in which they reported their emotions. Nevertheless, here, we only describe the emotional dynamics obtained from the video recordings.

After data collection, we devised the protocol to process and analyse the data. The videos recorded during the activity were saved and named with a specific code. Later, they had been edited to prepare them for the analysis. Specifically, they were synchronized with the start, the frames recorded outside of the activity's duration were cut off, as well the pause intervals (time utilized by the students to take notes), then the remaining parts were merged. The videos were imported and processed by iMotions® program.

The total processed data constituted our initial signal for analysis, it consisted of 60.856.164 entries, determined by 141 entries per frame. The frames analysed were 35.967 for each respondent (12).

RESULTS

Our preliminary results indicated different dynamics for each affective parameter. Throughout the ten time periods (Table 1), we observed Attention with the highest global average presence value (69,4%), then Engagement (20,8%), Joy (4,8%) and Surprise (3,2%). Other emotions were quite lower (< 1%). Basically, four emotional states were prevalent for all participants. The Standard Deviation (SD) was restrained to a range from 0,05% (Sadness) to 3,91% (Attention). It seems to indicate that emotional states, experienced by the students, maintained their average presence percent along the whole activity. Effectively, the analysis of the parameters in particular with high presence, Attention and Engagement, indicated that all the students were engaged with high attention carrying out the activity.

Table 1. Percent of time for each of the 9 selected parameters, they were measured by the system for each of the periods. "Mean" indicates the mean value of each emotion for all periods within the 12 respondents.

	Anger	Sadness	Disgust	Joy	Surprise	Fear	Contempt	Engagement	Attention
Period 1	0,00%	0,10%	0,30%	9,40%	2,90%	0,30%	1,60%	25,10%	60,30%
Period 2	0,90%	0,00%	0,30%	7,50%	1,50%	0,50%	0,90%	22,30%	66,10%
Period 3	0,70%	0,00%	0,10%	3,90%	1,90%	0,10%	0,90%	17,20%	75,10%
Period 4	0,00%	0,00%	0,20%	4,60%	2,20%	0,40%	1,00%	20,60%	71,00%
Period 5	0,10%	0,00%	0,30%	3,60%	3,10%	1,10%	1,30%	19,40%	71,30%
Period 6	0,10%	0,00%	0,10%	5,00%	4,50%	0,60%	0,40%	21,00%	68,30%
Period 7	0,20%	0,10%	0,30%	2,20%	3,90%	0,50%	0,70%	19,40%	72,70%
Period 8	0,00%	0,00%	0,30%	3,90%	4,20%	0,50%	0,70%	21,90%	68,50%
Period 9	0,10%	0,00%	0,20%	3,30%	3,40%	0,80%	0,50%	19,60%	72,00%
Period 10	0,00%	0,10%	0,10%	4,50%	4,30%	0,50%	0,40%	21,70%	68,30%
Mean	0,20%	0,00%	0,20%	4,80%	3,20%	0,50%	0,80%	20,80%	69,40%
SD	0,30%	0,05%	0,09%	2,02%	1,01%	0,26%	0,37%	2,03%	3,91%

We analysed the graphics of the parameters, focusing specifically on the dynamics of the prevalent four. Then, we observed whether there were profiles which were shared by the respondents. The analysis indicated three different profiles in parameters' graphics. In Figures

1 (Surprise and Engagement) and Figure 2 (Attention) we show the graphics of Respondent 10 as an example.

Profile 1 was correlated to the first part of the activity (in this case till about 6 minutes) and presented Surprise (orange line in Figure 1) with very low presence or absence of peaks. Engagement (light blue line in Figure 1) was characterised by high variability, with sharp peaks and low interval average presence (15%). Attention (Figure 2) was very high for the initial first minute, but then (1-6 minutes interval) it showed high variability with repeated rise and fall, for an interval average presence of 76%.

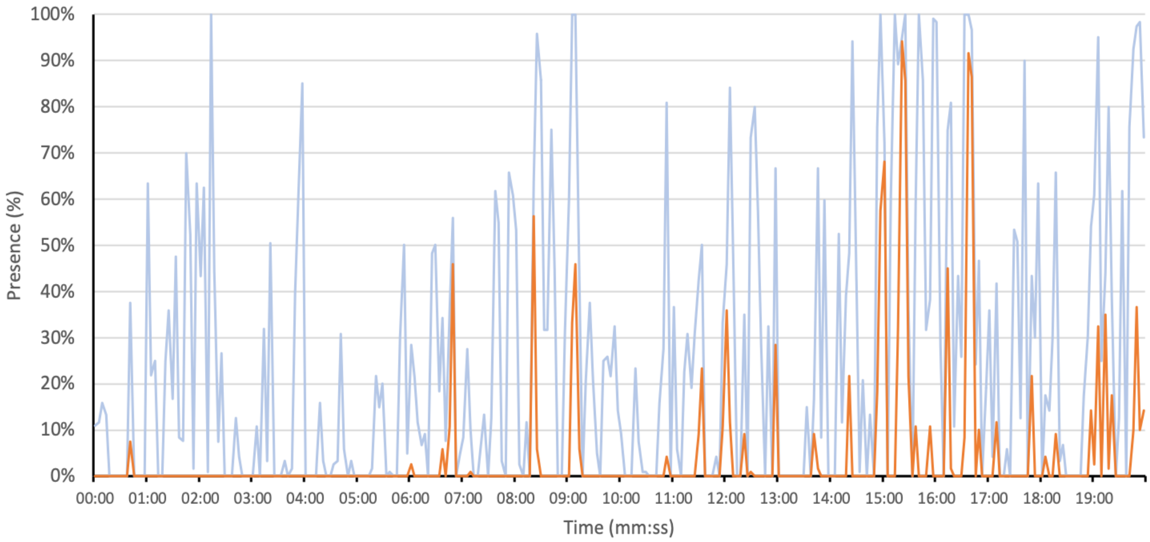

Figure 1. Surprise (orange) and Engagement (light blue) (Respondent 10)

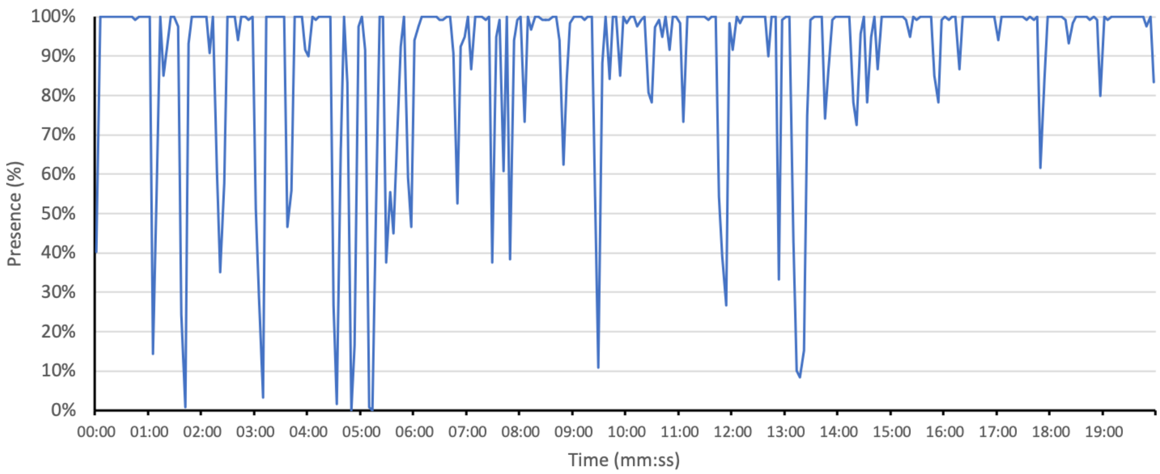

Figure 2. Attention (Blue) (Respondent 10)

Profile 2 was correlated with the central part of the activity (in this case about 6-14 minutes interval). It was characterized by a sequence of isolated sharp peaks of Surprise, of medium and low intensity. It showed covariation with Engagement, that presented variability of peaks succeeding with different intensity and frequency, with an average presence (24%), higher than the previous interval. Attention (Figure 2) presented high presence with variability less evident than the previous profile and showed peaks with either steep or smooth slopes. It showed short tracts with inertia and an interval average presence (89%) higher than the preceding interval.

Profile 3 referred to the last part of the activity (in this case about 14-20 minutes interval). Surprise (Figure 1) showed isolated peaks of different intensity, clustered in the central part of the interval, with some peaks of high intensity of presence (70-90%). It still presented covariation with Engagement, that increased the interval average presence (42%) with higher sharp peaks frequency and roller-coaster trend. Attention (Figure 2) showed an inertia maintained till to describe a plateau, where Attention persisted for several seconds or few minutes at 100% presence, thus achieving the highest interval average presence (97%).

We evaluated the presence and the sequence of the profiles and we could observe different duration depending on the participants. Thus, we could propose common patterns within the respondents, depending on the profiles they showed. This introductory analysis indicated relations of the parameters' patterns (achieved from data analysis) with students' educational actions (inferred from observing the recorded videos).

Pattern 1 showed the sequence of the profiles 1, 2 and 3. Basically, Profile 1 was present at the beginning of the activity, Profile 2 characterized the central part of the time-line, whereas Profile 3 was prevalent on the last part of the activity. This pattern was shared among Respondents 1, 2, 9, 10, 11. This preliminary study of the students' educational actions showed their high capacity of concentration, problem solving and to apply systematically the hypotheses elaborated.

Pattern 2 showed a short tract with the Profile 1 and alternation of Profile 2 and 3, with short (2-3-2-3) or large (2-3-2-3-2-3) sequences, with different intervals for each participant (3, 4, 5, 7, 8). They also showed interest and implication, but more doubts and uncertainty than the previous group.

Pattern 3 didn't present any of the mentioned profiles (Respondents 6, 12), due to reduced engagement and the lack of characteristic trend of Attention and Surprise described for the profiles above. They showed difficulty to elaborate and apply strategy to resolve the task.

This preliminary study seems to point at the existence of emotional dynamics linked with the students' educational behaviours. Nevertheless, more time and data processing are necessary to establish more robust relationships.

DISCUSSION AND CONCLUSIONS

This study indicates the possibility to evaluate parametrically the emotions during an educational activity, overcoming some self-report or observational limitations. We had the possibility to continuously follow the dynamic of students' affective dimensions and emotions by using a facial recognition system.

The data showed the parameters of Attention and Engagement predominant throughout the activity. Positive emotions, Joy and Surprise, displayed global average presence higher than negative emotions. It indicated that the activity was carried out with motivation, implication and positive attitude by the students. Furthermore, the restrained standard deviation implied that the general trend of the different emotional states was consistent throughout the activity.

The analysis of Attention, Engagement and Surprise dynamics permitted to elaborate three graphical profiles. The distinct presence and sequence of these profiles, along the task, drew three patterns shared by different groups of participants. It is remarkable that each pattern's group of students showed a characteristic educational behaviour, related to observation, reflection, systematic exploration and application of strategies. For the students it implied a different ability to carry out the task, such as to develop and test hypotheses, to avoid distraction, capacity of concentration and perseverance.

Basically, the profiles and patterns found are peculiar to this activity. Different tasks would imply rather distinct profiles and patterns classification. Anyway, this study confirms the correlation between emotions and educational behaviours, and encourages us to expand the research to other educational activities.

Concerning the teaching-learning process, this preliminary study underlines the importance of teachers' capacity to correlate educational actions with the affective states that students go through, when they are involved in an educational activity. Evidently, the future teachers cannot still ignore the emotional dynamics in class. Thus, it should be an important part of their training.

It is worth considering some limitations, such as the difficulty for some respondents to avoid covering the face or turn it on a side over a suitable angle, aligned with the camera, to be correctly detected by the system, for the whole time of the activity. Moreover, the large quantity of data implicated the necessity of managing a notable noise reduction. Anyway, this work opens up the possibility for objective parametric evaluations of emotional components during the teaching-learning process.

ACKNOWLEDGEMENTS

This work has been funded by Project: "Identification of scientific contexts in society. Tools for teachers and citizens (SCIxSOC)" (RTI2018-094303-A-I00) of the Ministry of Science, Innovation, and Universities (Spain) in the framework of the National R&D&I Program Oriented to the Challenges of Society, State Plan for Scientific and Technical Research and Innovation 2019-21.

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