Affective Computing to Enhance Emotional Sustainability of Students in Dropout Prevention

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ABSTRACT

In ACACIA project, through its Apoya module seeks to provide means and methods to enhance emotional sustainability as innovative approach to student's dropout prevention. Emotional state of the students at risk of dropout have to be assessed and innovative methods for counselling and curricula adaptation should be applied for getting out the student from the risk zone.

The aim of this study is to propose an innovative solution to meliorate both emotional state and attention of students in risk of dropout. A scenario is presented in which eyetrackers and webcams are integrated in a platform in order to infer and manage students' emotional state in a smart classroom environment.

CCS Concepts

• Applied computing → Education → Computer-assisted instruction.

Keywords

Affective computing, sensors, emotional state detection, student counselling.

1. INTRODUCTION

Cultural and social backgrounds of students may strongly influence the educational process and often lead to marginalization and social exclusion of certain students from meaningful participation in learning activities and community life. Such exclusion further reduces students' perspectives to learn, grow, and develop. Adapted educational systems facilitating the modern level of knowledge and skills are crucial components of positive change and successful development of the society. The use of technologies is not the only requirement of the new century. Educational planning and policy-making are also of great importance. Any educational policy must be able to meet diverse challenges and enable everyone to find his/her place in the community, which they belong to, and at the same time be given the means to open up in other communities.

The roadmap for inclusive education was set forth in 1994 at the World Conference on Special Needs Education in Salamanca [29]. Inclusion is concerned with learning, participation, and equal opportunities for all children, youth, and adults with a specific focus on the groups that are vulnerable to marginalization and exclusion from society life. It could apply to any or all of the following categories:

- girls and boys who have gender issues;
- ethnic and faith minority groups, travelers;
- asylum seekers, and refugees;
- children who need support in learning the language of instruction (second language);
- children with special educational needs, including those considered to have emotional, behavioral, sensory, physical, or mental disabilities;
- gifted and talented pupils;
- children with social difficulties, such as street children, prison inmates;
- people in disadvantaged, remote areas, poorly served by educational services;
- people who missed the opportunity to study in childhood;
- children in need, including those in public care, orphan children;
- other children, such as the ones with specific health needs, young careers, the children whose families are under stress, pregnant school girls, and teenage mothers;
- any pupils at risk of disaffection and exclusion.

These groups are usually excluded from the mainstream education. Therefore, education for them requires special approaches and techniques.

This article is organized as follows: Section 2 presents an overview of the definition of the emotional states, section 3 presents approaches for detection emotional states, section 4 presents the Acacia project and especially the Apoya module dealing with methods for detection emotional states, section 5 presents the architecture proposed for Apoya module while section 6 shows a working scenario within the centers for educational and professional development (CADEP) which will be setup in the Acacia project. Finally, section 6 summarizes the principal conclusions and future work.

2. Emotional States

As humans, our ability to perform every task in our daily life, from work to amusement or any other conscientious task depends on our emotions. Emotions play a central role as they ensure our survival and all activities from the most basic to the most elaborated tasks. Damasio proposed that the relationship between learning, emotion and body state runs much deeper than many educators realize and that the original purpose for which our brains evolved was to manage our physiology, to optimize our survival, and to allow us to flourish [15]. Emotions are as vast as the diversity of persons and their relationship with the environment including objects people and other living beings. Two aspects are important to be taken into consideration: first aspect is connected to the situation when exposed to external stimuli a person has a physiological flow of activity and that will trigger thoughts emotions and acts in response, and second, how a person reacts to threats or to friendly situations in different ways according to his feelings or thoughts towards those persons or environments.

There are several concepts such as emotion, feeling and mood that, sometimes are confused and used interchangeably without regarding to their differences in meaning. According to [18] emotions are cognitive data arising from events (internal and external) used to inform responses, and attributed to concepts and states while feelings are subjective experience of an emotion or set of emotions and mood is an overall state of emotion, which is sustained over longer periods of time and is less changeable than emotions themselves.

Emotions are important in nonverbal communication, and emotions influence cognition in many ways; how we process information, our attention, and our biases towards information [7]. The Plutchik's wheel Figure 1, represents the families of emotions, which can be used as a reference list when one looks to find means of detection.

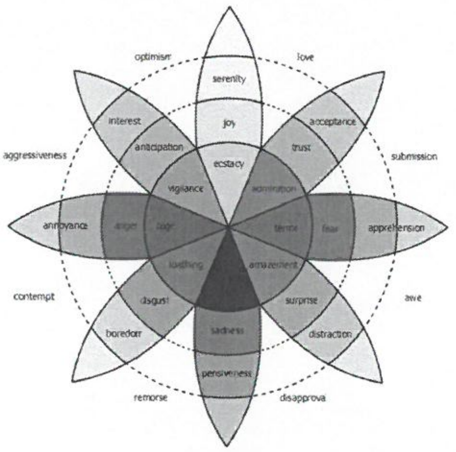

Fig.1 Plutchik's wheel model of emotions (after [23])

The Circumplex Model of Affect proposes that all affective states arise from two fundamental neurophysiological systems, one related to valence (a pleasure–displeasure continuum) and the other to arousal, or alertness. Each emotion can be understood as a linear combination of these two dimensions, or as varying degrees of both valence and arousal as depicted in Figure 2 [24].

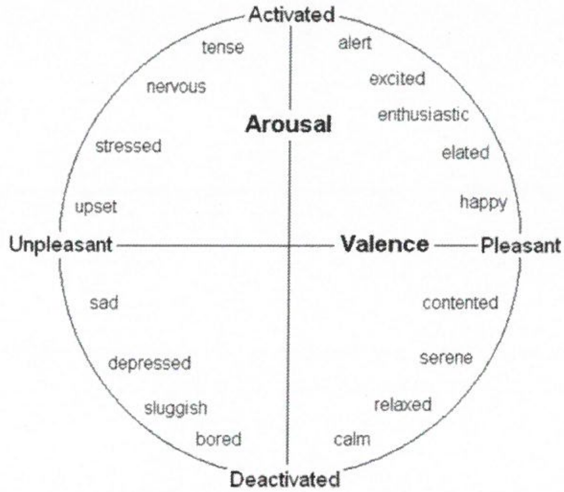

Fig. 2 Arousal and Valence in Circumplex Model of Affect

3. Emotion Detection Approaches

Current research in affective computing combined with learning assessment may control of the affective dimension of the learner that could derive in some variations in motivation [2] or learning effectiveness [20]. In this respect, the first issue is affective detection, and some works have been done, usually centered in using just one data source aimed to get enough information to detect the affective state of learner. Two aspects are of interest and have been analyzed: 1) emotions detection, and 2) data labeling. Facial gestures detection can also provide useful information about the users' emotions as in a research led by one of the psychologists of the aDeNu research group and project partners from the Universidad de Valencia. A review of the state of the art regarding emotions detection with facial gestures has been published in [25].

Psychophysiological sensors. One of the most common approaches on emotion detection relies on the use of Psychophysiological sensors, which consider different measures, including electrocardiography, skin conductance response or skin temperature. In [30] authors use a commercial pulsimeter and alternatively skin conductance to detect stress using continuous wavelet transforms and decision tree algorithms (J48), remarking that the skin conductance presented wider differences in the relaxed and stressed stages. To perform the experiment, the subjects of this experiment were asked to listen to annoying sounds and solve some Stroop tests (i.e., participants are asked to tell aloud the names of colors appeared in a different ink than the color named) [27].

Heart rate is also used in [6], but this time combined with speech to asses people's emotions while watching 30 pictures from the International Affective Picture System (IAPS) [17] and evaluating them with the Self-Assessment Manikin scale - SAM (i.e., a non-verbal pictorial assessment technique that directly measures several emotional dimensions) [3]. In this case some personality traits are also used. The study presented in [10] shows the relationship between hyperventilation and affective states measuring inspiratory and expiratory time, tidal volume, and pulse rate to study their connection with valence (pleasantness) and arousal (activation) measured using also the SAM scale. For elicit emotions in this experiment eight imagery scripts were used: three relaxation (positive valence, low arousal), two fear (negative valence, high arousal), one depressive (negative valence, low arousal), one action (neutral valence, high arousal) and one "desire" script (positive valence, high arousal). In [31] authors use Blood Volume Pulse, Galvanic Skin Response, Pupil Diameter and Skin Temperature to detect stress from 32 subjects while solving a series of Stroop tests [27]. To recognize stress patterns in the captured signals, they use three different learning techniques: decision tree learners, Naïve Bayes classifiers and Support Vector Machines (SVM), showing this last technique the best prediction results (90.10%), followed by decision tree learner (88.02%). The lower prediction rate was achieved with the Naïve Bayes (78.65%). While dealing with e-learning materials [14] links the e-learning material provided to the learner's galvanic skin response as only data source. Their results suggest that SVM (97.06%) and discriminant analysis (94.12%) shows higher accuracy levels than the k-nearest neighbour technique (79.42%). In [5] authors use both facial electromyography and electro dermal activity as a man-machine interface for empathic consumer products. Trying to detect 4 emotions (neutral, positive, negative and mixed), they first apply analysis of variance and principal component analysis to perform the selection of a subset of extracted features. After that, they perform classification using k-nearest neighbours (k-NN), SVM and artificial neural networks (ANN). The average prediction rates obtained (60.71% for SVM, 61.31% for k-NN and 56.19% for ANN) make the authors question the success of the predictors, pointing in their conclusions some steps (covering from a more detailed exploration of time windows to different feature selection approaches to be followed) that should be given to the development of a generic, self-calibrating biosignal-driven classification framework. In [9] electrodermal activity is used to detect the 12 proposed emotions during an 8 session experiment with 3 subjects while using ALEKS, a web-based ITS for math, statistics, science, and other domains. In [16] a framework is proposed to recognize learner's emotions. Using electroencephalography, skin conductance and blood volume pressure during an experiment that included three different environments (trigonometry, backward digit span, and logic) where the participants were asked to rate their experienced levels of stress, confusion, frustration, and boredom. In [21] participants suffering from cerebral palsy are asked to evaluate some affective sounds from the International Affective Digitized Sounds database [4], trying to predict their affective state evaluated as valence and arousal using SVM with galvanic skin response data and electroencephalography data, getting a 51% accuracy rate. In [13] electrocardiography is used together with electroencephalography in order to detect emotions elicited by means of a set of 60 emotional images from the IAPS database [17]. In [13], [22] can be found studies comparing different works using autonomic nervous system responses as data input for emotion detection, classifying more than 60 studies according to the approach followed and the classification techniques used.

There are as well many examples on the progress of affect computing in educational settings. For instance, a framework has been proposed to recognize learner's emotions using electroencephalography, skin conductance and blood volume pressure [16]. In [14] authors made use of the e-learning material provided to learners in relation to their galvanic skin response. Electrodermal activity was used to detect the 12 proposed emotions in [9]. There are also instances on using non-verbal communication, such as body movements and facial expressions, which were used for evaluating learners' states [1].

The aDeNu Research Group at UNED has designed, implemented and evaluated the Ambient Intelligence Context-aware Affective Recommender Platform (AICARP) infrastructure to explore the potential of context-aware affective feedback beyond computer-based recommendation approaches taking advantage of the possibilities of ambient intelligence [26]. The corresponding personalized support is provided without interrupting the learning activity by delivering the recommended action to the learner at the same time she is carrying out the learning activity (e.g. while the learner is talking, the system can tell her to slow down by switching on a light or playing a sound). This requires enriching the system with capabilities to detect changes in the learners' affective state (e.g. from physiological sensors), as well as to interact with the user through the preferred sensorial channel (e.g. sight, hearing, touch, smell) [12]. [8] consider six main perspectives for modeling affect, as a result of different approaches: emotions as expressions, emotions as embodiments, cognitivist approaches to emotions, emotions as social constructs, affective neuroscience, core affect and psychological construct of emotion. All those trends are important for analyzing and characterizing emotional states, and currently influence AC.

AC systems can create different scenarios that help and improve educational conditions. A system for identification of emotions can for example detect signals of frustration during the learning process, or lack of understanding during the study of concepts and definitions. Applications include tracking of emotional trends in groups, detection of emotional interactions, and detection of anxiety or depression patterns. With such identification at the beginning of processes, the educational staff can start individual psychological assistance for students, avoiding future problems that interfere in the learning process, and even more, in their lives.

Some tools are currently available for detecting emotions, such as AffectButton (www.joostbroekens.com), Emotion Research (http://emotion-research.net/toolbox) and Affectiva (www.affectiva.com). Affectiva, in particular, is based on machine learning techniques and provides a non-invasive way to detect emotions, since it is based purely on the images captured via webcam. It considers 42 action units of the face and, from them, 6 major emotional expressions are mapped and analysed. The database of videos (used to train the Affectiva machine learning tool), documentation, software Affdex SDK are freeware, and UFOPA considers Affectiva tools as starting point for investigations related to future AC developments in education in the context of the ACACIA project.

4. ACACIA PROJECT

ACACIA project is grounded on the principle of education for all. Although there have been many advances registered, higher education (HE) in Latin and Central America still faces several problems [28], including: student desertion caused by emotional factors, academic, economic or social marginalization; and the communication gaps between involved members that inhibit the management of collective actions to face transversal problems referred to the access and successful permanence in the university.

The main goal of ACACIA project is to contribute to the dissipation of that exclusion, discrimination and marginalization by disparity or inequality. In this context, the goals of ACACIA are:

- Recognize HE Institutions as social and political means to develop inter, multicultural and multilinguals education programs matching the several real educational needs;
- Strengthen teaching staff qualification and capacitation;
- Use ICT as a tool to complement teaching processes and learning;
- Propose new forms of institutional organization to promote the integration of groups that combine efforts and resources to the solution of problems previously mentioned.

4.1 CADEP

In terms of organization, as a result from the analysis of multiple theoretical approaches that address the problem of student retention, the project setup supporting centers for educational and professional development, namely CADEP. The CADEP has an integrated systems of modules (Empodera, Innova, Cultiva, Apoya, Convoca) which act together in order to: (i) monitor students at risk; (ii) training and support the academic, technical and administrative staff; (iii) use new strategies for university teaching and innovative use of ITC in practical scenarios by stimulating the entrepreneurship between students and professors.

4.2 APOYA

This module has two components. First one is technological and the second one is human. The goal of the technological component is to implement an automated emotion detection system that allows to monitors and supports students by providing automatic recommendations.

The human component seeks to educate, inform and divulge throughout the academic community, guidelines for the recognition and handling of persons in situations of exclusion (attention disorder, including disability, cultural differences, extreme emotional situations, etc.).

This module directly relates to all other development modules, providing valuable information to PT2 (Empodera), PT3 (Innova), PT4 (Cultiva), and PT6 (Convoca). In the final design the module will be integrated in CADEP, and will communicate with PT8 (Disemina). PT8 Disemina provides guidelines for the detection and execution of situations that may generate social exclusion attending the broadcasting actions to raise awareness, for apprehension and for the action.

APOYA tasks descriptions:

T.1 Automatic detection of affective states. The work focuses on the implementation of a system for detecting emotions, also defining a methodology for data collection and methodology for emotional labeling and sys-tem management.

T.2 Tracking and recommendations automation. This work deals with the automation of monitoring the student and the system that generates recommendations to help improve their academic level.

T.3 Promotion of multiculturalism and diversity. The objective of this task is to generate guidelines for the detection and recognition of people at risk of social exclusion, a guide for action (treatment, activities, visibility) and a system of courses to train university and technical personnel (teachers, administrative staff and technical supporters included).

T.4 Integration strategies. The objective of this task is to define the protocol operation and the internal articulation of Apoya module, define the operation of the laboratory module, define the diffusion and disclosure system and the system of internal evaluation of the module itself.

5. Architecture

Physical data comes from the assessed subject and/or ambience, as the environment contains various sensors that capture data. Captured data are stored in a warehouse. The combination and fusion of multiple sensor output can be used. A rule-based expert system transforms this data into relevant contextual data. The problem of sensor fusion is particularly important in the extraction of contextual data: a sensor might not produce sufficient information due to uncertainty and unreliability of the sensor itself. Two types of sensor fusion may be applied: the competitive and the complementary. The competitive sensor fusion is based on sensors which detect equivalent physical data, trying to diminish the errors in the measurements of every sensor. The complementary sensor fusion uses different typologies of sensors to extract high level data. Various sensors and actuators connect the environment to the middleware level. Data and knowledge are transferred to applications and services that are accessed by end users on mobile devices or client-server-type information systems.

The main goal of this environment is to create an enhanced learning and teaching environment. Our process is designed to identify the necessary improvements that will have an immediate positive impact, manage efficient implementation of those improvements, and regularly communicate progress and results to all stakeholders.

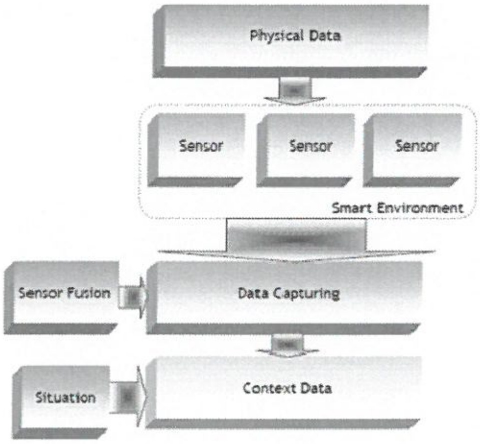

Figure 3. Emotional Gathering Architecture

5.1 Apoya Recommendations

The fundamental issue in a ubiquitous learning environment is how to provide learners with the right material at the right time in the right way. Context aware adaptation is therefore indispensable to all kinds of learning activities in ubiquitous learning environments.

The ubiquitous environment should be personalized according to the learner's situation. Personalization is defined in [11] as the way in which information and services can be tailored in a specific way to match the unique and specific needs of an individual user. While a learner is doing learning task or activity, it usually looks for some knowledge. In a ubiquitous learning environment, it is very difficult for a learner to know who has this knowledge even though they are at the same place. In this case, the learner needs to be aware of the other learners' interests that match his request [11].

There are only a few studies that have attempted to induce the educational affordances of context-aware ubiquitous learning environment. [19] devoted attention to the problem of what educational affordances can be provided by a context-aware ubiquitous learning environment. They proposed a system named EULER that can provide eight educational affordances:

1. knowledge construction,
2. apply,
3. synthesis,
4. evaluation,
5. interactivity,
6. collaborative learning,
7. game based learning,
8. context-aware learning.

Moreover, they stressed that ubiquitous learning provides context-aware information and self-learning opportunities for learners. Therefore, it not only enables students to achieve learning goals anytime and anywhere, it is also cultivating their ability to explore new knowledge and solve problems. This should be considered to be one of most important characteristics of ubiquitous learning.

The process of ubiquitous learning is understood as a social process that happens at a time and place of the learner's choosing, continuing throughout one's life. It is collaborative, evolving and informed by a process of self-paced development.

6. SCENARIO

Student dropout is a problem affecting Higher Education Institutions (HEI) in Latin America and Caribbean. The dropout problematic can be originated by several factors such as emotional factors, academic, economic or social cultural marginalization.

A possible technological solution to avoid student's dropout and increase their performance is to develop a frameworks using the internet of things (IoT) paradigm integrating several devices such as biomedical sensors and eye trackers to collect information from the students. The goal is to use that information collected from different sources to support professors to identify and manage students' emotional state during classroom lessons.

The proposed scenario consists of the evaluation of the student's emotional state, for affective management and prevention of HEI dropouts (Figure 4).

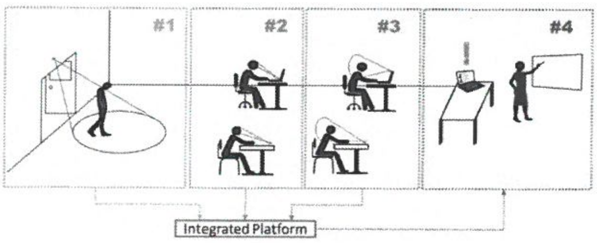

Figure 4. Scenario for affective management in student dropout prevention including four case studies: 1) gait and posture analysis; 2) eye tracking detection; 3) automatic facial emotion detection; 4) emotional record based on data integration.

In that context four case studies were identified as illustrated in figure 4: gait and posture analysis; eye tracking detection; automatic facial emotion detection; emotional record based on data integration;

The gait and posture analysis case study is performed when the student enters or leaves the classroom. To implement this case study a 3D motion capture device will be used, composed by a RGB camera and an infrared depth sensor (i.e. a Kinect device) in order to track the student skeleton key points. It is expected that a change in the student regular gait also indicates a change in his/hers emotional state.

The eye tracking detection case study is performed when the students are sitting at a desk. The eye tracker will be used to track both head and eye movements. This analysis allows both to recognize the student affect states and to measure the engagement level of the student during learning tasks.

The automatic facial emotion detection case study is performed when the student is sitting at a desk. A RGB camera will be used for this case study to record facial expressions. An algorithm will extract and analyze the facial features in order to determine the correspondent emotion or emotions.

Both in the eye tracking detection and in the automatic facial emotion detection case studies there is the possibility of not using a computer, just the emotion tracking device.

In the emotional map based on data integration case study, data from the previous case studies will be collected and processed in real time in order to create an emotional map to detect potential problematic situations, such as disengagement, attention disorder, learning difficulties, emotional stress, and dropouts. This case study is performed in the classroom environment to support teacher manage the class. Technically, this integrative platform provides a real-time early alert system activated when deviations from regular patterns are detected. It will be expected that the system, in the end of each class, generate a report for the interested actors, i.e., teacher, students, parents, and the school.

For this scenario 3 different capturing devices will be used, as mentioned above.

The Kinect is comprised by an RGB camera and a infrared depth sensor, and its SDK allows to track a person's skeleton key points.

The eye tracker is a device usually composed by an infrared light source, an infrared or near-infrared camera and/or an RGB camera. It allows the tracking of head and eye movements as well as pupil variations, which has been proven to be an indicator of cognitive activity.

In the automatic facial emotion detection case study a simple RGB camera is used, and a computer algorithm first detects and isolates the face, then the facial features are extracted and the facial expression classified.

7. CONCLUSIONS AND FUTURE WORK

The goal of ACACIA project is to contribute to prevention of student dropout in Latin America, caused by a variety of factors including emotional factors, academic, economic or social marginalization. The organization of the project promotes the implementation of centers for educational and professional development, namely CADEP. That are supported by a set of integrated modules, in which is included APOYA module which aims to use innovation as driving factor to avoid student dropout.

This paper addresses how affective computing may prevent student's dropout. Specifically, this paper presents a scenario in the context of a smart classroom or environment, in which an innovative technology will be used to detect and manage students emotional state based on Kinect devices, eyetracker and webcam data acquisition. The scenario is composed by four case studies: gait and posture analysis, eye tracking detection, automatic facial emotion detection and emotional record based on devices data integration.

Future work will be the technical design and implementation of the referred framework and the test of the described scenario in the CADEPs. Additionally, other innovative solutions and a methodology for prototype evaluation will be proposed and developed.

8. ACKNOWLEDGMENTS

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