Emotion Analysis in Distance Learning

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Abstract. The COVID-19 pandemic has changed education forever because schools, universities, teachers, and students had to adapt to distance learning. Multiple differences are identified with online learning compared to face-to-face education. First, students must be more responsible. Second, users’ familiarity with using computers varies significantly. Third, the traditional interaction between teacher, student and content are made more complicated by the introduction of technology. The application of new tools related to the student, teacher, content, technology, software, and communication results in the improvement of teaching methods in online learning. When new tools are applied and there is an improvement in the results in online education, the student, teacher, and educational institutions benefit from it. Emotion plays an important role in the knowledge, acquisition, and decision process of an individual. Consequently, they directly influence perception, learning process, and the way people communicate. There is also significant evidence that rational learning in humans is dependent on emotions. In this paper, we presented a solution with a new Intelligent Tutoring Framework, that analyzed emotions in a non-intrusive and non-invasive way.

Keywords: Intelligent system · Sentiment analysis · Distance learning

1 Introduction

Todays, we live in a world where the student do not go to the school, because of pandemic situation. Distance learning is a teaching modality that, due to the Covid-19 pandemic, has now become the alternative. This distance learning was only possible, due to the integration of information and communication technologies (ICT) in the teaching and learning processes. However, when the teacher explains the contents, he does not know if the student is or not motivated to learn.

Emotion plays an important role in the knowledge, acquisition, and decision process of an individual. Consequently, they directly influence perception, learning process, and the way people communicate. There is also significant evidence that rational learning in humans is dependent on emotions.
To analyses emotion, there are several theories, which attempted to specify the interrelationships of all the components involving an emotion and the causes, the reasons, and the function of an emotional response. Some research intended to relate emotion and computer, so for Ortony, Clore and Collins [1] emotion identification is generally used in the field of cognitive science has a connection to affective computing enabling computers to recognize and express emotions.

According to the literature [2], there is a connection between emotion and learning process. Although, this process is not simple or direct, it is accepted that positive and negative emotional states can cause different kinds of thinking and can influence the learning perspective.

Intelligent Tutoring System (ITS) is a learning environment that allows students to acquire knowledge and skills in a targeted manner and adapted to their own pace. ITS contains intelligent algorithms that adapt to users and allow the application of complex learning principles. Some basic activities of this system must incorporate the student’s active learning, interactivity, adaptability, and feedback [3].

In this paper, we proposed a new ITS framework to obtain data from behavior biometric, specially user’s emotional state during e-learning activities.

So, this paper is organized as follows. After this introduction, Sect. 2 introduces the state of the art of ITS and student emotion analysis. Then, Sect. 3 presents a proposed ITS framework. Next, Sect. 4 presents some application methods and results. Finally, Sect. 5 concludes the study by performing a global analysis of the presented research.

2 State of Art

In the last decades, the rapid development of ICT has benefited all areas of knowledge. However, and according to [4], these technologies were applied in education very late. Even so, from these technologies emerged the Virtual Learning Environments (e-learning systems), in which students interact as if they were in a real environment. These environments are combined with other applications that provide intelligent tutoring and are called Intelligent Virtual Environments or ITS. These ITS aim to adapt to the student’s profile, applying techniques that best suit each one, to obtain better learning results.

Currently, there are several such tutors, however, these tutors have not completely achieved the desired goals, as they do not consider an important element that affects students’ learning: their emotional state. There are some of these tutors who assess the student’s emotional state only at the end of the work sessions, which is not enough to improve the learning environment. For better functioning of the ITS, it should perform an analysis of the data presented in Fig. 1, so that, from there, the best teaching mechanism could be applied [5].

2.1 ITS

The typical architecture of an ITS has the following four basic components: the Expert Model, the Student Model, the Tutor Model and the Interface [5, 6].
The Domain Model, also known as the Expert Model, contains all the concepts, facts, rules, and problem-solving strategies for a given domain. This model serves as a source of specialized knowledge, a standard for assessing student performance and diagnosing errors [5, 6]. This model also performs data analysis and can also make predictions about the knowledge of a given student, since it observes the actions performed by that student.

The Student Model is an overlay of the Expert Model. This model contains the cognitive and affective states of the student in association with their evolution as the learning process progresses. As the student works step by step in the problem-solving process, the system analyzes the student’s interaction with the system [5, 6]. This model contains the dynamic monitoring of the student’s emerging knowledge and skills.

The Tutor Model is the part of the ITS that designs and regulates interactions with the student. This model accepts information from the Student Model and the Expert Model. In addition, it is closely linked to the Student Model, since it makes use of knowledge about the student and its own structure of tutorial objectives, to design the pedagogical activity to be introduced. It also monitors student progress, creating a profile of strengths and weaknesses in relation to production rules [5, 6].

The Interface is the front-end interaction with ITS. This system integrates all types of information necessary to interact with the student, through graphics, text, multimedia, video, menus, etc. The Interface is the communication component of the ITS that controls the interaction between the student and the system. The interface is translated between the internal representation of the system and an interface language understandable to the student [5, 6].

### 2.2 Student Emotion Analysis

There are several types of learning. In 1956 Benjamin Bloom [7], identified three domains of educational activities cognitive: mental skills (Knowledge); affective: growth in feelings or emotional areas (Attitude); psychomotor: physical or manual skills (Skills). The combination of all domains influences the way one learns, and the way rational decisions are made.

Behavioral analysis is the scientific area that tries to understand the behavior of individuals, and how it has been affected by the surrounding environment. There are several ways to monitor and obtain information about the user, for example, through the mouse, keyboard, and even cameras and sensors.
Some research indicated that a slight positive mood could produce an effect on memory, well-organized open-minded, flexible problem-solving and thinking as well as more efficiency and thoroughness in decision-making. This can be found in groups of different ages and professions [8, 9]. The effect on cognition is not restricted to positive states of mind. Negative affective states like anger, sadness or fear can influence the brain activity affecting the thought process [9].

Today, we live in a world where the student do not go to the school, because of pandemic situation. Distance learning is a teaching modality that is a quality alternative for students unable to attend a school in person, based on the integration of ICT technologies in the teaching and learning processes as a means for all have access to education. However, teacher do not know if the students are or not motivate for learning.

Sentimental analysis allows the use of tools and techniques to identify the opinion and feeling(s) that a person may have about various entities, namely the learning. With the emergence of social networks in distance learning, there is now a large volume of opinion data that can be analyzed, increasing interest in this area. These techniques are used by organizations to market their products, identify new opportunities, and monitor their online emotions to improve learning.

Once information about the individual’s text exists in these terms, it is possible to start monitoring emotion in real-time [9]. This makes this approach especially suited to be used in learning activities in which students use computers, as it requires no change in their working routines. This is the main advantage because present an emotional analysis module that is more accurate and that can provide and determine the emotions present in a text and calculate the impact of the emotions present in the text on a person. Besides, the system will send the professor indications of the results obtained. It is possible to collect data that describes the text interaction of the students.

Affective Norms for English Words (ANEW) [10] was developed to offer a set of normative emotional ratings for many words in the English language. The objective is to construct a series of verbal materials that were rated in terms of pleasure, arousal, and dominance. ANEW complements the International Affective Picture System (IAPS) [10] and the International Affective Digitized Sounds (IADS), which are collections of photographs and sounds stimuli, respectively, that also contain affective ratings.

Pang and Lee [11] reviewed the concept of sentiment and opinion analysis, which refers to the application of natural language processing, computational linguistics, and text analytics to recognize subjective information, like emotion, in the text.

3 Proposed Framework

Based on the state-of-the-art section, the idea is to create an ITS system adapted to each student. In this first phase, a general structure of an ITS was developed, which is shown in Fig. 2.
The idea is to have an Interface that communicates directly with users and captures the data necessary to create a student profile. From there, the system, based on the content it has to address and the student profile, applies the tools necessary for the student to acquire the necessary knowledge.

Making a more complete description of the system, Fig. 3 presents the ITS system in more detail. In this figure, you can see in more detail the architecture of the Student Model and the Tutor Model.

The Student Model is divided into three levels: student style, student emotion and state of knowledge. In the first level, student style, the student’s learning style and the interaction of the student’s standard behavior are defined. In the second level, student emotion, the student’s emotional profile is created, based on his emotional state. Finally, at the third level, the state of Knowledge, the student’s profile is created regarding their learning evolution. All this information is stored in its database.

The Tutor Model, based on the Student model, should adjust, and adapt the level of learning difficulty to each student, depending on their parameters. In this way, it applies to learn strategies and rules for a given content.

The Interface captures data from the student’s interaction with the ITS. Data capture is done using a non-invasive and non-intrusive approach. There is a log application that runs in the background, saving the student’s necessary events with ITS. This application has a device that generates raw data that describes the student’s interaction with the mouse and keyboard. There are also flexible sensors that use the information available from other measurements and process parameters to calculate and estimate the amount of raw data. The raw data generated is stored locally until it is synchronized with the web server in the cloud at regular intervals, usually every 5 min. In this layer, each event is coded with the necessary information (for example, timestamp, coordinates of the mouse movement, type of click, keypress, etc.).
4 Methodology and Results

To implement the proposed system, it was decided to create an algorithm that based on the student’s profile, on the Emotion Classifier and on the contents to be taught, MOOCs are used to explain the contents and, from there, a set would be applied questions, based on levels of difficulty. In Fig. 4, the ITS operating structure is shown.
4.1 ITS Application

Based on the framework presented in Sect. 3 and Fig. 4, we have created an ITS Application that is presented in Fig. 5. This ITS Application it will be applied at the Technical University of Manabí, Portoviejo, Manabí, Ecuador.

When the student opens the application for the first time, we need to register. To register, it is necessary to indicate the following data: date of birth, gender; course, and address. The system creates a student profile from this data. When the student makes a test, we can indicate the difficulty level of the test to be performed. In Fig. 5 it is presented the second page of a register page and the difficulty level test to be performed.

4.2 Population

To capture the data, the approach followed is based on the dynamics of the mouse and the keyboard, to propose a completely non-intrusive method for evaluating student-computer interaction. To do this analysis, an activity to be carried out on the computer was applied to a class of Statistics subject, from the Technical University of Manabí, Ecuador. Each computer has a keyboard, a mouse, and a monitor. The assessment activity starts at the same time for all students and they log in to the standard software using their credentials and the activity begins.
4.3 Dataset

Before the test started, students were asked a questionnaire with the following information: “How prepared are you for the evaluation?”, “Have you studied for this evaluation?”. All the answer has only the possibility of “Yes” or “No”.

During the evaluation if the studying as a wrong answer, the answer will be at red color. If the answer is correct it will be at green.

At the end of the evaluation, another questionnaire will be applied with the following three questions: “Was the test easy?”; “Will you get a good grade?”; “Write your opinion about the test”. The first two questions only have the possibility of answer of “Yes” or “No”. The third question is a free text write with limit of 70 characters.

Figure 6 presented question example of the ITS application, where the student answer corrected to a question (green mode).

4.4 Results

Figure 7 depicts the type of information that these features provide. It shows the evolution of the performance of a specific student during the lesson through two features: Click Duration and Mouse Velocity. The velocity of the mouse increases until approximately the same point in time and then it starts decreasing. The duration of each
Fig. 6. Question example of the ITS application.

Fig. 7. - Real-time performance: evolution of one student’s interaction performance during a video Class. Left: Click Duration. Right: Mouse Velocity.
click decreases until roughly the middle of the exam and then increases up to a global maximum. Both features point out an initial improvement of performance, followed by a degrading. Figure 7 reveals a classical effect of stress: performance tends to improve for some time after the beginning of the stressor stimulus, with a drop off in performance after some time performing above average.

5 Conclusions and Future Work

This paper presents a first approach to the model of an ITS. The approach is non-invasive and non-intrusive for an ITS. It is proposed based on the biometric analysis of work behavior in different students with different emotions styles. The system monitors and analyzes the dynamics of the mouse, keyboard, and tasks to determine the student’s interaction with the computer.

These results are crucial to improve learning systems in an e-learning environment and to predict student behavior based on their interaction with mobile devices or the computer.

The ITS makes possible the enhanced learning/teaching processes. The architecture of an ambient intelligent learning environment is proposed to address these issues, especially to monitor the students’ emotion students in distance learning. With this architecture it is possible to detect those factors dynamically and non-intrusively, making it possible to foresee negative situations, and taking actions to mitigate them. In this case, the door is then open to allow to analyze students’ emotion profile, taking into account their individual comments and to propose new strategies and actions, minimizing issues such as stress, anxiety, which can influence students’ results and are closely related to the abandonment occurrence. Moreover, it is possible to maximize the performance and attentiveness since the teacher is informed about the emotion of each student.

In future work, we intend to apply two evaluation tests. One with a non-limited time to answer with the possibility to change the answer, and another with time limited for each question with no possibility to change the answer of the question, and when the answer is wrong, the answer will change to a red color. The idea is to improve stress in the second type of test. Another improvement in the work is to make correlations with the two type of questionnaire (before the test and after) and the test results. It also be analyses the last question of the questionnaire, with text mining techniques to obtain a sentiment analysis.

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References

1. Ortony, A., Clore, G.L., Collins, A.: The Cognitive Structure of Emotions. Cambridge University Press (1990).
2. Durães, D., Carneiro, D., Jiménez, A., Novais, P.: Characterizing attentive behavior in intelligent environments. Neurocomputing 272, 46–54 (2018)
3. Durães, D., Toala, R., Gonçalves, F., Novais, P.: Intelligent tutoring system to improve learning outcomes. AI Commun., 1–14 (2019). (Preprint)
4. Méndez Pozo, G., Una arquitectura software basada en agentes y recomendaciones metodológicas para el desarrollo de entornos virtuales de entrenamiento con tutoría inteligente (Doctoral dissertation, Informatica) (2008)
5. Carneiro, D., Novais, P., Durães, D., Pego, J.M., Sousa, N.: Predicting completion time in high-stakes exams. Fut. Gener. Comput. Syst. 92, 549–559 (2019)
6. Ahuja, N., Sille, R.: A critical review of development of intelligent tutoring systems: retrospect, present and prospect. Int. J. Comput. Sci. Issues (IJSI) 10(4), 39 (2013)
7. Best, R.M., Floyd, R.G., Mcnamara, D.S.: Differential competencies contributing to children’s comprehension of narrative and expository texts. Read. Psychol. 29(2), 137–164 (2008)
8. Picard, R.W., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., Machover, T., Resnick, M., Roy, D., Strohecker, C.: Affective learning—a manifesto. BT Technol. J. 22(4), 253–269 (2004)
9. Isen, A.M.: An influence of positive affect on decision making in complex situations: theoretical issues with practical implications. J. Consum. Psychol. 11(2), 75–85 (2001)
10. Bradley, M., Lang, P.: Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings. University of Florida: Psychology (Vol. Technical). The Center for Research in Psychophysiology (1999)
11. Lang, P., Bradley, M., Cuthbert, B.: International Affective Picture System (IAPS): Technical Manual and Affective Ratings. Center for the Study of Emotion and Attention 1997. Psychology (1997)