Affective Environment for Java Programming Using Facial and EEG Recognition

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Abstract. We have developed an affective and intelligent learning environment that helps students to improve their Java programming skills. This environment evaluates cognitive and affective aspects of students in order to define the level of difficulty of the exercises that are more suitable for the them in its current condition. The cognitive aspects are: the number of mistakes, the difficulty level of the current exercise and the time spent in the solution. The affective aspects are: the acquired emotion from a facial expression and the acquired valence from electroencephalogram signals. This environment also uses a neural network for face recognition of basic emotions, a support vector machine to define the valence of emotion and a fuzzy inference engine to evaluate the cognitive and affective aspects.

Keywords: Intelligent learning environment, affective detection, affective computing, face recognition, EEG recognition.

1 Introduction

Traditional learning environments do not provide an individualized learning model; so, it is common having a classroom group of more than 30 members per teacher. This is a disadvantage because individualized instruction is considered the most effective way of teaching [1]. Also in these environments the emotional state of the student during the learning process is usually ignored. A student can easily fall into boredom if what is taught is not a challenge; this can lead to student to consider teaching as uninspiring and therefore show no motivation.

Another case may be that the student is intensely frustrated in trying to understand a topic. If he is sufficiently persistent there is a possibility that he may achieve success, but there is also the possibility that he could desist in his attempts due to the low sense of achievement gained by his effort.

In these scenarios, the work of Woolf et al. [2] shows different types of interventions that a tutor could carry out to consider the cognitive and affective aspect of the student. In the first case, for example, if a student is showing he/she masters a subject but he/she feels bored then it is recommended to increase the difficulty of the exercises. In the second case, if a student fails to progress and is stressed, is recommended that the tutor provide an alternative to the student: changing the exercise or taking a small break.

There have been numerous investigations of the relationship between affection and learning that have demonstrated that positive affective states as concentration, enthusiasm, and joy may lead to better learning [3], and that boredom is associated with poor learning and behavioral problems [4].

Because of the importance of affect in the learning process, detection of affection is a key component in the development of Intelligent Learning Environments (ILE) that are capable of responding to the affective needs of the student.

On the other hand, one of the main problems a computer science student has to face is to learn a programming language. In this kind of courses the percent of failure increases considerably [5].

This paper presents the implementation of an ILE that consider the student's affective and cognitive needs to provide individualized instruction to students learning the Java programming language.

This paper is organized as follows: Related Works with affect recognition is presented in Section 2. Implementation of the ILE is described in Section 3. Section 4 describes the performance of the ILE. Conclusions and future work are given in Section 5.

2 Related Works

In this section, we present research works in the field of affective or intelligent tutors. The Intelligent Tutoring System **Autotutor** [6] helps students to learn Newtonian physics, computer literacy, and critical thinking topics; this system simulates a human tutor by holding a conversation with the learner in natural language. The tutoring occurs in the form of an ongoing conversation, with human input presented using either voice or free text input. To handle this input, the system uses computational linguistic algorithms.

The distinguishing feature of ILE Java Affective with Autotutor is that it uses facial expressions and EEG signals for the emotion recognition.

HelpTutor [7] is an intelligent tutor for seeking help. This system was integrated into Geometry Cognitive Tutor, an intelligent tutor for learning basic geometry that provides step by step guidance to resolve complex problems, estimates the level of knowledge of the student and provides feedback and clues for each of the steps in solving the exercises.

Additionally, with the help of HelpTutor, the system provides feedback cognitive goal enabling students to improve their ability to ask for help.

The distinguishing feature of ILE Java Affective with HelpTutor is that it considers the emotional dimension of the student as well as the cognitive through the emotion recognition from photos and EEG signals of the student. The system makes use of them to determine the level of difficulty of exercises in order to try to avoid negative emotions within the context of learning (boredom, constant frustration) that can result in poor performance.

Gaze Tutor [8] is an Intelligent Tutoring System designed to tutor students on high school biology topics (e.g., cellular respiration, mitosis, ecological succession). The tutor uses an eye tracker to monitor a student's gaze patterns and identify when

the student is bored, disengaged, or is zoning out. The tutor then attempts to reengage the student with dialog moves that direct the student to reorient his or her attention patterns towards the animated pedagogical agent embodying the tutor.

The distinctive feature of ILE Java Affective with Gaze Tutor is that considers cognitive and affective aspects of students. The ILE uses facial expressions and EEG signals for the emotion recognition.

Java Sensei is an Intelligent Learning Environment with affective management for Java, designed to help students of programming to strengthen different areas of knowledge on Java in a web environment. The system evaluates aspects such as cognitive and emotional state of the student to take intervention strategies that made the pedagogical agent and adaptability processes performed by a set of recommendations [9]. ILE Java Affective considers more cognitive elements than Java Sensei and also uses EEG signals for the emotion recognition.

3 Implementation of ILE Affective Java

In this section we present the main architecture of the ILE. Fig. *1* shows the three relaxed or flexible layers of our architecture. The relaxed layers are less restrictive about the relationships between layers. The presentation layer has two components. The Intelligent-Affective layer has five components. The data layer has three components. Next, we explain the operation of each component.
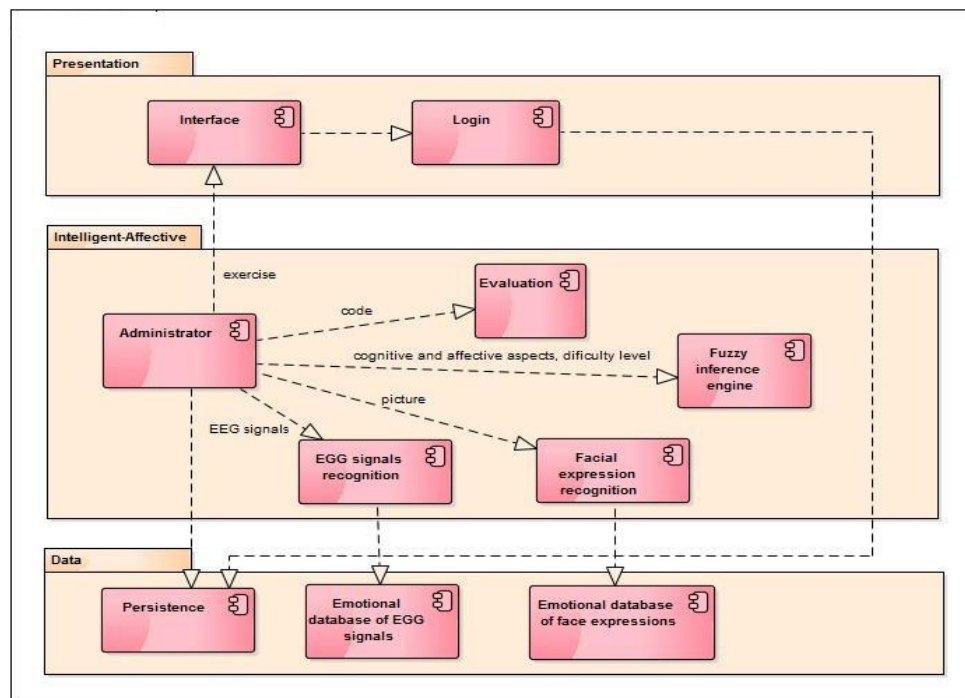
Fig. 1. Architecture of ILE.

Administrator: It is responsible for coordinating the tasks to be performed by the tutor and communicate with other components.

Evaluation: It is responsible for evaluating the exercise solved by the student and report any errors encountered.

Facial expression recognition: Identifies the student's emotion (happiness, anger, sadness, surprise and neutral) at the time of taking a picture of the student face.

EEG signal recognition: Identifies the emotion valence (positive, negative, neutral) of student through the EEG signals recorded during the resolution of the exercise. The ILE Affective Java works with the Brain-Computer Interface (BCI) Emotiv Epoc to obtain EEG signals. To select the appropriate channels that we need in the BCI, we considered the work of Mahajan et al. [10] that use the front channels AF3 , AF4 , F3 , F4, F5, and FC6. Also, the work of Liu et al. [11] that use channels AF3 , F4, and FC6 . At the end, we chose channels AF3, F3, F4, FC5, and FC6 because we concluded that they were closely related to the human emotions.

The main feature extracted from EEG signals is the Hurst exponent. The Hurst exponent, in time series analysis, is used to identify a non-stationary behavior of EEG signals showing identifiable trends in the data. It was chosen because it showed an accuracy rate of 71.38 at work of Wang et al. [12].

Fuzzy Inference engine: It is responsible for assessing cognitive and affective aspects by applying fuzzy inferences to determine the appropriate level of the next exercise for the student. The fuzzy engine manages five fuzzy input variables: level of exercise, amount of errors, time spent in the resolution of the exercise, emotion identified through facial recognition, and valence identified by EEG recognition. The output of the fuzzy engine is the appropriate level of the next exercise. The inference engine works based on 54 fuzzy rules implemented by using library jFuzzyLogic [13]. Some of the rules are shown in Fig. *2*.

1. IF (level is easy) AND (emoEEG is positive) AND (mistakes is few) THEN (dificulty is medium)

2. IF (level is easy) AND (emoEEG is negative) AND (emoRostro is neutral) AND (mistakes is many) THEN (dificulty is easy)

3. IF (level is medium) AND (emoEEG is positive) AND (mistakes is regulars) THEN (dificulty is dificil)

4. IF (level is medium) AND (emoEEG is neutral) AND (emoRostro is happy) AND (mistakes is many) THEN (dificulty is medium)

5. IF (level is medium) AND (emoEEG is negative) AND (emoRostro is neutral) AND (mistakes is few) THEN (dificulty is hard)

6. IF (level is hard) AND (emoEEG is positive) AND (mistakes is many) THEN (dificulty is medium)

7. IF (level is hard) AND (emoEEG is neutral) AND (emoRostro is surprise) AND (mistakes is few) THEN (dificulty is hard)

Fig. 2. Fuzzy rules.

Fuzzy inference engine responds to cognitive and affective states of students. If the student commits errors but their emotional state is neutral, then we conclude that the student is focused, so the same difficulty level is maintained. If the student makes many mistakes and his emotional state is negative, a sign that he is stressed, and the level of difficulty of the exercises decreases. When the student does not make

mistakes and their emotional state is neutral or positive, the level of difficulty increases.

Persistence: Is responsible for managing everything related to the database like writing, querying and updating data.

Emotional database of face expressions: It uses the affective database RaFD (Radboud Faces Database)[14].This database is a set of pictures of 67 models (including Caucasian males and females, Caucasian children, both boys and girls, and Moroccan Dutch males) displaying 8 emotional expressions (angry, disgust, fear, happy, sad, surprise, contempt and neutral). Each emotion was shown with three different gaze directions and all pictures were taken from five camera angles simultaneously. From the set, only 5 emotions were used for this work: angry, happy, sad, surprised, and neutral.

Emotional database of EEG signals: It is an affective database created from EEG signals obtained from test subjects.

3.1 ILE main interface

Figure 3 shows the interface of the ILE where the student performs the exercises presented in Java.
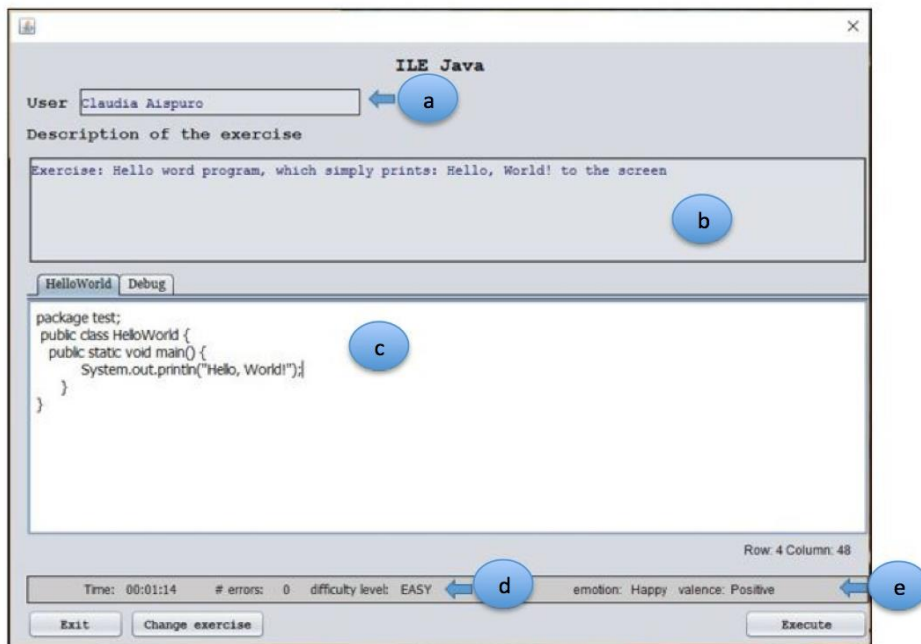
Fig. 3. ILE main interface.

The interface consists of 4 main areas, which are described below:

a. **User**. This section shows the name of the student.

b. **Description of the exercise**. This section shows the description of the exercise to be solved by the student.

c. **Code Section**. It consists of 2 tabs: one that shows the code that the student is writing to solve the exercise and another one (debug) that shows the errors produced at compile time.

d. **Cognitive aspects.** This section shows the indicators used to assess the cognitive aspect of student: time spent in the resolution of the exercise, amount of errors, and the current level of the difficulty in the exercise. There are 3 levels of difficulty to classify the exercises: Easy, Medium and Hard.

e. **Affective aspects.** This section shows the emotion and valence identified by the recognizers.

3.2 The Method

Tests were performed to ten students of the Instituto Tecnológico de Culiacán; five men and five women, who were asked not to be under the influence of caffeine or medicine at the moment of the experiment. Next, we describe each of the steps of the methodology of Bos [15] used to generate the database:

a. **Stimulus**: To evoke emotions an audiovisual medium through short videos was chosen. Recommendations found in the work of Rottenberg et al. [16] were considered to select videos.

Videos classification			
Video	Name	Emotion	Valence(Positive/Neutral/Negative)
Video 1	When Harry Met Sally	Amusement	Positive
Video 2	My Bodyguard	Anger	Negative
Video 3	Pink Flamingos	Disgust	Negative
Video 4	The Shining	Fear	Negative
Video 5	Alaska's Wild Denali	Neutral	Neutral
Video 6	The Lion King	Sadness	Negative
Video 7	Sea of Love	Surprise	Positive

shows the videos used in the experiment, its objective emotion and respective valence.

Table 1. Videos used in the experiment.

Videos classification			
Video	Name	Emotion	Valence(Positive/Neutral/Negative)
Video 1	When Harry Met Sally	Amusement	Positive
Video 2	My Bodyguard	Anger	Negative
Video 3	Pink Flamingos	Disgust	Negative
Video 4	The Shining	Fear	Negative
Video 5	Alaska's Wild Denali	Neutral	Neutral
Video 6	The Lion King	Sadness	Negative
Video 7	Sea of Love	Surprise	Positive

b. **Recording of EEG signals:** To create the emotional database each student was presented with a series of pre-selected videos with the intention to evoke a

particular emotion. As the students watched the videos, the tool TestBench recorded EEG signals.

c. **Filter:** At the end of each video, students were asked to determine the video's valence (positive, negative or neutral). Then, after all videos were classified, EEG signals obtained were filtered to remove noise.

d. **Feature extraction:** We used Java library EEGFrame [17] to extract the recording features to create a feature vector.

e. **Classification:** Video classification was made by considering the expected or estimated valence (see table 1) and the valence stated by the student. The correct classification of the videos was made where those videos that did not match with labeled emotion were discarded.

Finally the affective database obtained comprises 150 records (15 for each student) classified with their respective valence.

4 Performance of the ILE Affective Java

When the system startup, the student has the option to start as a beginner (difficulty level) or take the diagnostic evaluation that will determine its initial level. The system presents a Java programming exercise according with the student's profile level. While the student is solving the exercise, the system is recording his EEG signals. When the student completes the exercise the system takes a picture of its face, and then proceeds to evaluate the exercise.

ILE displays the errors found in the program and waits for them to be corrected. When the exercise is correct, the system does the facial and EEG recognition process.

The facial recognition (See Fig. *4Fig. 4*) consists in extracting the characteristics of the photo and then creating a feature vector, which is evaluated by a neural network trained with Weka [18] to determine the emotion with an effectiveness rate in recognition of 80%.
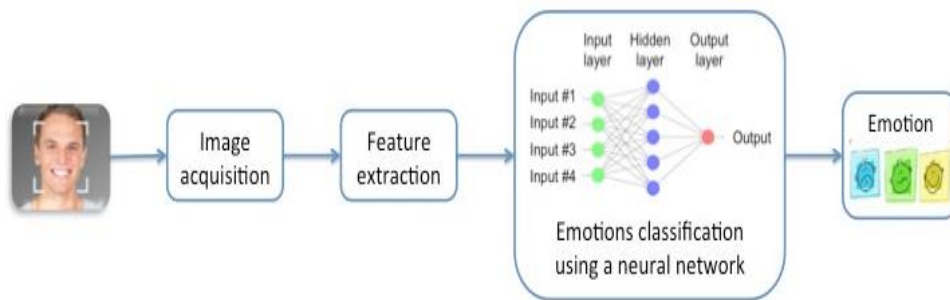

Fig. 4 . Facial recognition.

For the EEG recognition (see Fig. *5*), the system uses Emotiv Epoc headset to register the EEG signals of the student while he is trying to resolve the exercise, then calculates the Hurst exponent, and finally performs signal classification using software from library LibSVM [19]. The library receives as an input a feature vector

composed by the Hurst exponent for each of the five channels in the BCI (Emotiv) previously selected. As the result, the valence of the signal is obtained, with an effectiveness rate in recognition of 70%. We believe that if we increase the number of records of the corpus this rate can be increased.
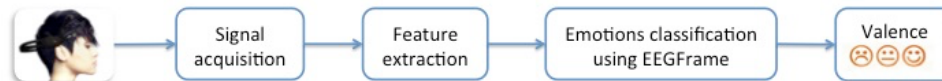

Fig. 5. EEG recognition.

After performing the recognition, the system uses a fuzzy inference engine to define the next problem suitable for the student based on: cognitive aspects, the emotion and valence identified.

5   Conclusions and Future Work

An ILE that manages to give individual instruction to the students, based on their cognitive and affective state was implemented as a result of the integration of several components. The most important are: facial expression recognition, EEG signal recognition and fuzzy inference engine.

Future work intends to perform tests of the ILE to determine the accuracy of the emotion recognition achieved and determine if the ILE manages to help students improve their Java programming skills. It is also expected to implement other ways of emotional recognition to increase the accuracy of the recognizer.

In addition, since the tests were performed only with graduate students with previous knowledge of Java programming language, we hope to make experiments with students who do not have programming skills.

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