Analysis of Student's Context in e-Learning

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***Abstract*—Traditionally, the Teacher-Student relationship is a close one. The student spends several hours of a day in the presence of the teacher and can talk, express doubts and pose questions. These doubts, or the general feeling towards the object of learning, are not only expressed explicitly but also implicitly. Indeed, the teacher is constantly, even if in an unconscious way, reading the state of the student in search for sings of doubt, frustration, stress or fatigue. This information is then used by the teacher to adapt their methods or to personalize their approach in function of each student. These aspects, intuitively central in education, become less efficient when learning takes place in a Virtual Environment. Indeed, the growth of online courses, in which the student and the teacher often never even meet, make learning more difficult for a number of reasons. In this paper we analyse these reasons and put forward an approach for inferring the student's state that aims to minimize the effects of the absence of the teacher.**

Keywords*—*Context-awareness, e-Learning, Stress, Fatigue.

I. Introduction

Traditional teaching processes are characterized by a proximity between teacher and student. A student has an almost daily and personal access to the teacher, either inside or outside the classroom. This has several known advantages: students feel that they are being accompanied closely, that the teacher "cares", that they can get help if and when they need it. This results in an increased motivation from the students. Teachers, on the other hand, benefit from this proximity by having a constant update on the state of the students, on their worries, on their feedback concerning each topic. All this contextual information, much of it analysed in an unconscious way, allows the teacher to intuitively assess the students and steer the methodologies and strategies employed in order to optimize success.

However, when a student attends an electronic course or makes use of an e-Learning platform, generally called Virtual Environment (VE) [7] the interaction between student and teacher, without all these non-verbal interactions [10], is poorer. Thus, the assessment of the feelings, the state and the attitudes of the student by the teacher becomes more difficult [4], [3], [9]. In that sense, the use of technological tools for teaching, with the consequent teacher-student and student-student separation, may represent a risk as a significant amount of context information is lost. Since students' effectiveness and success in learning is highly related and can be partially explained by their mood while doing it, such issues should be taken into account when in an e-Learning environment. In a traditional classroom, the teacher can detect and even foresee that some negative situation is about to occur and take measures accordingly to mitigate it. When in a virtual environment, similar actions are impossible.

With these issues in mind, in this paper we present a novel approach to assess the state of students on an e-Learning platform. It is characterized by being non-invasive, personal and transparent. Our objective is indeed to assess the level of stress or fatigue of students by analysing their behaviour when using the e-Learning platform, i.e., their interaction patterns while using the mouse and the keyboard. For that purpose a total of 12 features are extracted and analysed that fully describe the way students use these peripherals.

To understand these effects several studies were conducted with students of the University of Minho and surrounding high-schools. These studies consisted in an ongoing collection of interaction data while the students performed their tasks throughout the day (using the computer). Specific events or constraints were introduced to induce stress and fatigue. Posterior data analysis allows to understand how these interaction patterns change in function of changes in the student's states.

It is our conviction that the provision of information about the state of the user will allow the teacher to better manage the learning process, bring teachers and students closer together despite the distance imposed by the e-Learning tool.

II. Related Work

Several authors have looked at the drawbacks of VEs, especially in what concerns their inability to convey important contextual information. [1] analysed the influence of five user characteristics - test anxiety, spatial intelligence, verbal intelligence, personality and computer experience - on the

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sense of presence. Also, [13] deal with the idea of the analysis of the user's behaviour and interpretations regarding the cultural background, using accelerometers to uncover the user's cultural background by analysing his/her patterns of gestural expressivity in a model based on cultural dimensions. [6] describe the concept of multi-modal interaction as a way to communicate between humans and computers using more than one modality or communication channel (e.g., speech, gesture or writing).

Also important is the affective aspect of communication [2], [5] that plays a very important role in communication. As noted by [12] affect recognition is most likely to be accurate when it combines multiple modalities, information about the user's context, situation, goal, and preferences.

Stress, fatigue and emotions, in particular, can play an important (usually negative) role in education [11], [14]. In that sense, its analysis in an e-Learning environment assumes greater importance. Generally the assessment of these characteristics is done either through questionnaires (an easily misleading approach and certainly not a dynamic one) or through physiological sensors (very accurate but invasive to the point of making them impractical in e-Learning).

In [15], the authors studied emotion in users of e-Learning platforms. They do it using four physiological sensors: hearth rate, skin conductance, blood volume pressure and EEG brainwaves. Despite its accuracy, this approach will never result in a real-life application due to its invasiveness. Other less invasive approaches also exist. [8] contains an overview of different applications of the so-called Affective Computing [12] field in e-Learning. They point out the use of facial expression and speech recognition as potential ways to detect emotional states. However, facial recognition requires a dedicated camera of some quality to be placed in front of the user otherwise it will be inaccurate. It is thus also invasive. Speech recognition, on the other hand, is less invasive but is also much more prone to error, being difficult to develop an accurate speech model given that each individual has his own speech rhythm, tone, pitch or intonation, aspects that are much cultural-dependent.

III. From the Interaction with the Computer to the Inference of the Student's state

In this paper we seek to show that a relationship between certain mental states and the way one interacts with the computer exists. Specifically, we look at the relationship between states of stress or fatigue and our use of the mouse and keyboard. The idea, in itself, is not new: as the previous section shows, performance measures have been previously used to ascertain the state of an individual. What is however new is the use of the mouse and keyboard for acquiring performance measures, in what constitutes a non-invasive approach for the problem that can be continuously used throughout the day, for example in the workplace or in the classroom.

To this end a very simple logger application was developed that runs in the background collecting system events related to the mouse and the keyboard. These events allow later to compile information describing the following features: Key Down Time, Time Between Keys, Velocity, Acceleration, Time Between Clicks, Double Click Duration, Average Excess of Distance, Average Distance of the Mouse to the Straight Line, Distance of the Mouse to the Straight Line, Signed Sum of Angles, Absolute Sum of Angles, Distance between clicks. The whole process that takes place between the collection of the data and the compiling of the features is described in [16].

IV. Practical Experiments

Two studies were conducted in the area of Braga, Portugal to assess the feasibility and validity of this approach. In these studies students were given tasks to carry out in a computer using an e-Learning tool. Besides this, the previously mentioned logger application was installed in order to continuously collect the necessary data. Two types of studies were implemented, described in the two following sub-sections.

A. Stress

In order to assess the effects of stress on the interaction patterns with the computer, two scenarios were set up. In Scenario A, an activity was performed whose main objective was simply to assess the student's knowledge on the selected topics, with no effect on their marks: it was merely a way for the teacher to evaluate the current state of the students. The activity was performed without any constraints; the students were simply requested to answer the questions that were provided on the Moodle page. In a posterior week, the students were requested to participate on Scenario B. Under this scenario they had to perform another activity, now with some constraints. The students were told by the teacher that this activity would be effectively used for their evaluation, with an impact on the final score. Besides this, students were also told that they would have a time limit to perform the activity. The students were thus given the notion that they would be responsible for managing their activity to maximize their score given the time available. The students were also given personal passwords that they would have to input in order to start the test, an abnormal occurrence. While the students were performing the activity, the teacher insisted regularly on the importance of their performance on their final score and on the decreasing amount of time available.

This experiment allowed to collect student interaction data under two different mental states. Six different classes participated in the study, which resulted in 12 different moments of data collection: one for each class and for each scenario. The study involved a total of 74 students, 49 boys and 25 girls, aged between 13 and 17.

B. Fatigue

Concerning the study of fatigue, the implementation of the study is slightly different. Rather than comparing two moments along the day, we wanted to observe the natural onset of fatigue during the day, as students complete their tasks and the natural effects of the circadian rhythm settle in. In that sense this study consisted in the ongoing collection of data throughout the day, from the morning to the end of the day. With this approach we can not only determine how much fatigue affects the interaction patterns of the students during the day but also the influence of events such as a lunch break. Essentially, we will be looking for decreases in the performance of the students, not only in terms of task performance but also in their interaction with the computer (e.g. slower mouse velocity, longer clickes, etc.). In this study no specific constraints were used. Students had only to carry out the tasks they were given in the e-Learning platform. 24 individuals participated in the study (19 male, 5 female) with their age ranging between 18 and 25.

V. RESULTS

This section summarizes the main results of these studies. Given the space limitations, we do not address here all the features considered. The main result is however clear: stress and fatigue affect interaction patterns with the computer and allow for the development of approaches such as the intended one.

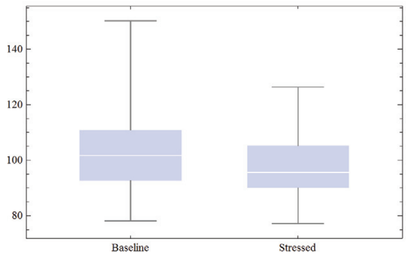
The data gathered was analysed in order to determine statistically significant differences between scenarios A and B, in the case of stress, and between the beginning and the end of each data collection period, in the case of fatigue. Measures of central tendency and variability were calculated for all variables of interest. Provided that most of the distributions are not normal, the Mann-Whitney-Wilcoxon Statistical test was used to test whether there are actual differences between the distributions of the data for the two scenarios. This test is a non-parametric statistical hypothesis test for assessing whether one of two samples of independent observations tends to have larger values than the other.

The null hypothesis is thus: H_0 = *The medians of the two distributions are equal*. For each two distributions compared, the test returns a p-value, with a small p-value suggesting that it is unlikely that H_0 is true. For each feature, the data from the two scenarios is compared. In all the tests, a value of $\alpha = 0.05$ is used. Thus, for every Mann-Whitney test whose p-value $< \alpha$, the difference is considered to be statistically significant, i.e., H_0 is rejected. In this context, a significant difference on the distributions of the data of a given feature between the two scenarios means that the feature is effectively influenced by stress.

A. Stress

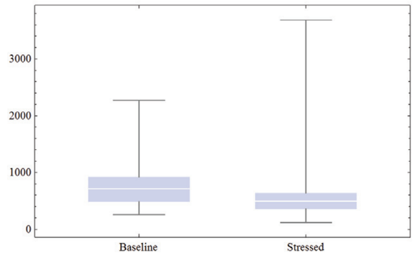
Taking as first example the average time that a key is pressed down while typing, the main conclusion is that a stressed student tends to press the keys during a smaller amount of time. While without stress the mean duration of this feature is of 102.85 ms, under stress the mean value is of 97.8 ms (Figure 1). This same trend was observed in 70.5% of the students. This does not necessarily indicates that the student writes faster when under stress, only that he spends less time pressing the keys.

Fig. 1. The time (in milliseconds) during which a key remains down while typing tends to decrease when students are under stress.



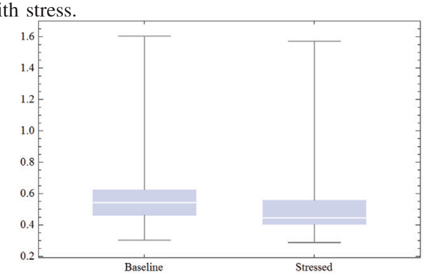
If we consider the distance to the straight line between clicks, its average value is of 782.03 pixels without stressors, decreasing to 549.752 pixels when under stressors. 87.1% of the students behave like this while under stress (Figure 2). The value of the median also decreases in average from 241.1 pixels to 104.07 pixels, with 80.65% of the students showing a decrease in its value. This points out that when stressed, students move their mouse more efficiently.

Fig. 2. The students move their mouses more efficiently when under stress (closer to the straight line between two consecutive clicks).



Evidently, the previous results could be explained by the time limit, i.e., if the students have a time limit to conclude the task, it is expected that they speed up. For this reason, the results concerning the velocity of the mouse came as a surprise. Indeed, both the velocity and acceleration decrease when under stress, which was unexpected. However, if we interpret these results in the frame of the study they make sense. What we observe is that, when under stress, students become generally more efficient. A smaller velocity and acceleration of the mouse is in line with this trend since it allows a more precise control of the mouse (increased velocity would mean less efficient control of the mouse). This explains these findings, in which a decrease in the mean value of the velocity between each two clicks was observed in 77.4% of the students, from 0.58% px/ms to 0.49 px/ms (Figure 3). The difference in the median was even more striking, decreasing in 90.3% of the students, from 0.22 px/ms to 0.189 px/ms. Similarly to acceleration, a large number of students showed this same tendency. Moreover, significant statistical differences between the calm and the stressed data have been observed in 81% of the students.

Fig. 3. Similarly to the acceleration, the value of the velocity of the mouse decreases with stress.



B. Fatigue

In what concerns fatigue, the expected results were observed, i.e., a somewhat gradual decrease in the efficiency of the interaction during the day. This is evidenced, for example when we observe the data for specific students during the duration of a day. Figure 4 depicts how the time each key is pressed down while typing increases from around 87ms at the beginning of the day, to around 90ms at the end of the day.

Fig. 4. The key down time tends to increase throughout the day (example for one student).

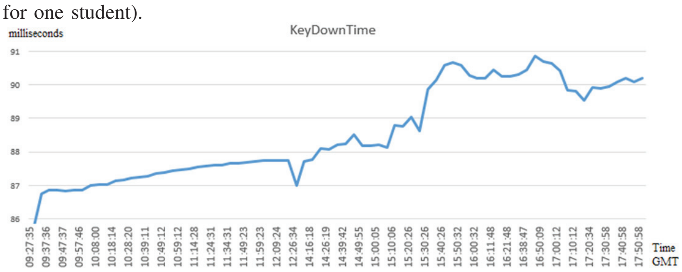
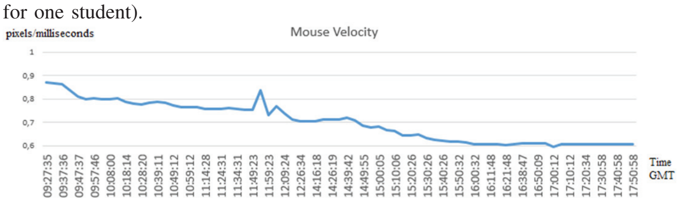


Figure 5, on the other hand, shows a decrease in the velocity of the mouse, equally indicating a poorer performance by the end of the day.

Fig. 5. The mouse velocity tends to decrease throughout the day (example for one student).



VI. Conclusion and Future Work

From the results presented after the carrying out of this research work it is possible to conclude that students' performance decreases during the day and also that students, when under stress, tend to behave in a more efficient way, decreasing the number of unnecessary actions: they are more focused on their task. The results also point out that: 1) generic models can be developed that can, to a large extent, shape the response of students to stress (since generalized trends were observed); and 2) personalized models should not be disregarded as responses to stress and fatigue are very individual , with each student having his own particular response. We also show not only that stress and fatigue do in fact influence performance in the interaction with the e-Learning tool but also, and perhaps more interestingly, that this influence can be quantified in real-time, using non-invasive and non-intrusive approaches. This undoubtedly opens the door to the development of tools that can natively incorporate notions of Context-Awareness to either provide the teacher with information about the state of the students or, in a more futuristic view, to provide the e-Learning tool with such information so that it can itself take actions autonomously towards the improvement of the state of the student and the efficiency of the learning process.

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