Monitoring Level Attention Approach in Learning Activities

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Abstract. In this article we focus on a new field of application of ICT techniques and technologies in learning activities. With these activities with computer platforms, attention allows us to break down the problem of understanding a speculative scenario into a series of computationally less demanding and localized lack of attention. The system considers the students' attention level while performing a task in learning activities. The goal is to propose an architecture that measures the level of attentiveness in real scenario, and detect patterns of behavior in different attention levels among different students. Measurements of attention level are obtained by a proposed model, and user for training a decision support system that in a real scenario makes recommendations for the teachers so as to prevent undesirable behavior.

Keywords: Learning Activities, Attention Level, and Performance.

1 Introduction

Teaching should be solidly grounded to the absolute understanding of how the process of learning occurs, so that instructional strategies could be efficient and lead to persistent knowledge. When students use technologies in learning activities distractions might be occurs with other applications and the acquisition of knowledge can't occur. It's crucial to improve the learning process and to mitigate problems that might occur in an environment with learning technologies. Learning theories provide insight into the very complex processes and factors that influence learning and provide precious information to be used to design instruction that will produce prime results. Besides, each student has its own particular way of assimilating knowledge, that is, his learning style. Learning styles specify a student's own way of learning. Someone that has a specific learning style can have difficulties when submitted to another learning style [1]. When the given instruction style matches the student's learning style, the process is maximized which guarantees that the student learns more and more easily.

adfa, p. 1, 2011.

Technologies that enhance learning environments are ideal for generating learning style-based instructional material in large classes, as they don't have the same limitations as human instructors due to the lack of resources and time to focus on individual students. With this recommendation the teacher can improve some strategies that may increase the level of attention and engagement of the students and they might improve learning.

In this article we focus on a new field of application of ICT techniques and technologies in learning activities. The goal is to propose an architecture aimed at capturing and measuring the level of students' attentiveness in real scenarios and dynamically provide recommendations to the teacher in order to improve the better learning styles for each student.

2 Theoretical Foundations

The concept of attention is commonly used either to describe the active selection of information from the environment or the processing of information from internal sources [2]. It also can be defined as filtering input space to more important spaces in processing. Attention means focusing on thought clearly, among one of several subjects or objects that may capture mind simultaneously. Attention implies the concentration of mental powers upon an object by close or careful observing or listening, which is the ability or power to concentrate mentally. Attention means to cut things to deal effectively to other things. The level of the learner's attention affects learning results. The lack of attention can define the success of a student. In learning activities, attention is also very important to perform these tasks in an efficient and adequate way. In learning activities with computer platforms, computational attention allows us to break down the problem of understanding a speculative scenario into a series of computationally less demanding with visual, audio, and linguistic approach. [3].

Being a cognitive process, attention is strongly connected with learning [4]. When it comes to acquiring new knowledge, attention can be considered one the most important mechanisms [5]. The degree of the learner's attention affects learning results. The lack of attention can define the success of a student and in learning activities, attention is very important in order to perform these tasks in an efficient and adequate way.

Generally, there are some factors that influence attention level: stress, mental fatigue, and anxiety.

2.1 Stress.

When students are subjected to increasing periods of work with a progressive focus on autonomy and continuous assessment, the workload is perceived as stressful and usually leads to emotional disorders, which affects attention and concentration [6]. However, in small periods of time, stress tends to behave in a more efficient way, decreasing the number of unnecessary actions as students are more focused on their tasks [4].

Human stress is a state of tension that is created when a person responds to demands and pressures [7]. However students react in different ways, whereas a situation might be stressful for a student and relaxing for another. Students aren't affected exactly the same way or suffer from the same degree of stress. Although sooner or later in life one goes through a stressful situation [8]. When the students are forced to a higher number of tasks and assessment, they have to set priorities and the level of fear increases, because they don't want to fail. Consequently, the level of pressure increases causing stress.

2.2 Mental Fatigue.

Usually, the term mental fatigue is a cognitive ability that is decreased and used to describe a sequence of manifestations like lack of concentration, loss of attention, and slower reaction in response time. When students are working for an extended period of time, they often end up feeling the effect of inattention, reflected in impaired task performance and reduced engagement to continue working [9, 10]. In addition, one student that feels lower performance also has a harder time concentrating, getting easily distracted [11, 12], an indication that mental fatigue can have effects on selective attention.

Mental Fatigue can occur at any time during the day. Depending on its duration and intensity, mental fatigue can make the carrying out of daily tasks increasingly hard or even impossible [6]. Learning is one of the functions that become impaired when under fatigue. The importance of addressing this issue when students are using learning activities is very important for a teacher. Teachers need to be sensible to the state of mind of their students, impairing their ability to adapt both the contents and the teaching strategy accordingly [13].

2.3 Anxiety.

Anxiety is an aversive emotional and motivational state occurring in threatening circumstances. Generally, anxiety has an adverse effect on attention because it causes inattention [14]. When, in a small period of time, it leads to compensatory strategies like enhanced effort. Anxiety can't change the level of attention [15].

If we consider efficiency the relation between success and the resources spent on a task, anxiety is meant to have a negative influence in the field of cognition and attention through its cognitive interference by preempting the processing and temporary storage capacity of working memory.

3 A Dynamic approach to monitor Attention

When students are affected by positive or negative states, they produce different kinds of thinking and this might hold important implications on the educational and training perspective. This means that students who are caught in affective states such as anger or depression do not process and engage information efficiently. When that occurs it would be important to be able to notify the teacher, so he can be able to dynamically modify the teaching style according students' feedback signals which include cognitive, emotional and motivational aspects.

The first stage of the proposed system is data collection, which was designed and carried out using a logger application developed in previous work [5]. The data collected by the logger application characterizing the students' interaction patterns is aggregated in a server to which the logger application connects after the student logs in. This application runs in the background, which makes the data acquisition process, a completely transparent one from the point of view of the student.

To monitor students' attention level, a log tool was developed, logging some features regarding student-computer interaction through particular operating system events read from the use of the computer's mouse and keyboard. Table 1 summarizes these events.

Symbol	Feature	Description
Mouse Events		
mv	Mouse Velocity	The distance travelled by the mouse (in pixels) over the time (in milliseconds).
ma	Mouse Aceleration	The velocity of the mouse (in pixels/milliseconds) over the time (in milliseconds).
cd	Click Duration	the timespan between MOUSE_UP events, whenever this timespan is inferior to 200 milliseconds.
tbc	Time Between Clicks	the timespan between two consecutive MOUSE_UP and MOUSE_DOWN events, i.e., how long did it took the individual to perform another click.
dbc	Distance Between Click	represents the total distance travelled by the mouse between two consecutive clicks, i.e., between each two consecutive MOUSE_UP and MOUSE_DOWN events.
ddc	Duration Distance Clicks	the time between consecutive MOUSE_UP and MOUSE_DOWN events.
edbc	Excess Distance Between Clicks	represents the excess total distance travelled by the mouse between two consecutive clicks, i.e., between each two consecutive MOUSE_UP and MOUSE_DOWN events.
aedbc	Absolute Excess Distance Between Click	this feature measures the average distance of the excess total distance travelled by the mouse between two consecutive clicks, i.e., between each two consecutive MOUSE_UP and MOUSE_DOWN events.
asdbc	Absolute Sum Distance Between Clicks	this feature measures the average sum of distance that the mouse travelled between each two consecutive MOUSE_UP and MOUSE_DOWN events.
dplbc	Distance Point to Line Between Clicks	this feature will compute the distance between two consecutive MOUSE_UP and MOUSE_DOWN events.
adpbc	Absolute Distance Point Between Clicks	this feature will compute the average distance between two consecutive MOUSE_UP and MOUSE_DOWN events.
Keyboard Events		
kdt	Key Down Time	the timespan between two consecutive KEY_DOWN and KEY_UP events.
tbk	Time Between Keys	the timespan between two consecutive KEY_UP and KEY_DOWN events
kdtv	Key Down Time Velocity	The times that two consecutive keys are press

Table 1. Data acquisition features.

It possible to collected data that describes the interaction with both the mouse and the keyboard [13]. Previous work on this data collection tool and analysis can be found in [6] where a deeper analysis about this process is explained in detail.

4 Proposed Monitoring Architecture

From the features presented in the previous section, we can conclude that it is possible to obtain a measure of the students' attention level. Once information about the individual's attention exists in these terms, it is possible to start monitoring attentiveness in real-time and without the need for any explicit or conscious interaction. 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 of this work, especially when compared to more traditional approaches that still rely on questionnaires (with issues concerning wording or question construction), special hardware (that has additional costs and is frequently intrusive) or the availability of human experts.

Figure 1 depicts the process through which the system operates; it is possible to observe the different classifications of information in order to allow, in the end, the management of attention level.

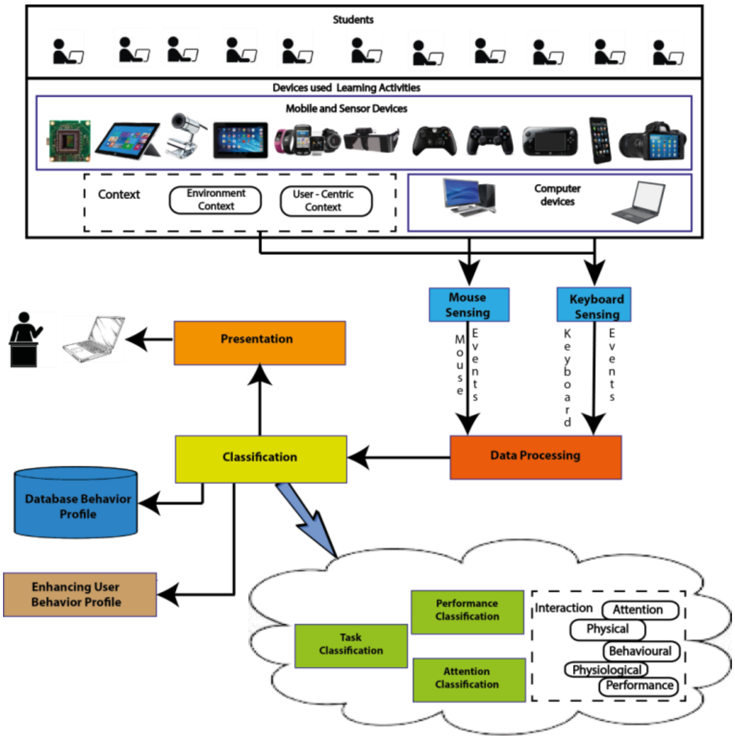

Fig. 1. Dynamic Student Monitoring Architecture for learning activities scenarios.

4.1 Dynamic Student Monitoring Architecture

While the student conscientiously interacts with the system and takes his/her decisions and actions, a parallel and transparent process take place in which the Dynamic Student Monitoring Architecture uses this information. This module, upon converting the sensory information into useful data, allows for a contextualized analysis of the operational data of the students. This framework performs this contextualized analysis. Then, the student's profile is updated with new data, and the teacher receives feedback from this module.

The system developed to acquire data from normal working compiles information from students' learning activities with mouse and keyboard which act as sensors. The proposed framework includes not only the complete acquisition and classification of the data, but also a presentation level that will support the human-based or autonomous decision-making mechanisms that are now being implemented. It is a layered architecture.

The Mouse and Keyboard Sensing layers are charged for capturing information describing the behavioral patterns of the students', and receiving data from events mouse and keyword students'. This layer encodes each event with the corresponding necessary information (e.g. timestamp, coordinates, type of click, key pressed). These data are further processed, stored and then used to calculate the values of the behavioral biometrics. Mouse movements can also help predict the state of mind of the user, as well as keyboard usage patterns.

The Data Processing layer is responsible to process the data received from the Data Acquisition layer in order to be evaluate those data according to the metrics presented. It's important that in this process some values should be filtered to eliminate possible negative effects on the analysis (e.g. a key pressed for more than a certain amount of time). The system receives this information in real-time and calculates, at regular intervals, an estimation of the general level of performance and attention of each student.

The Classification layer is where the indicators are interpreted for example: interpreting data from the attentiveness indicators and to build the meta data that will support decision-making. When the system has an enough large dataset that allows making classifications with precision, it will classify the inputs received into different attention levels in real-time. This layer has access to the current and historical state of the group from a global perspective, but can also refer to each student individually.

For that, this layer uses the machine learning mechanisms. After the classification, the Enhancing User Behavior Profile layer is responsible for providing access to the lower layer. The Database Behavior Profile is also a very important aspect to have control off. This possibility allows to analyses within longer time frames. This layer, whose function detect student's mood preserving those information (actual and past) in the mood database. This information will be used by another sub-module, the affective adaptive agent, to provide relevant information to the platform and to the mentioned personalization module.

Finally at the top, the Presentation layer includes the mechanisms to build intuitive and visual representations of the attentiveness states of the students', abstracting from the complexity of the data level where they are positioned. At this point, the system can start to be used by the people involved, especially the teacher who can better adapt and personalize his teaching strategies. The actual students' mood information are displayed in the Presentation layer, and can be used to personalize instruction according to the specific student, enabling Teacher to act differently with different students, and also to act differently to the same student, according to his/her past and present mood.

5 Conclusions and Future Work

Technology make possible the enhanced of learning/teaching processes, overcoming restrictions such as qualified instructor's availability, time restrictions, and individual monitoring for instance. A framework is proposed to address these issues, especially to monitoring students in learning activities. Narrowing the scope of the study, a model to detect attentiveness is proposed, through the use of a developed log tool. With this tool it is possible to detect those factors dynamically and non-intrusively, making it possible to foresee negative situations, and taking actions to mitigate them. The door is then open to intelligent platforms that allow to analyze students' profile, taking into account their individual characteristics, and to propose new strategies and actions, minimizing issues such as stress, anxiety, and new environments, which can influence students' results and are closely related to the occurrence of conflicts. Moreover its possible maximized performance and attentiveness since the teacher is informed to the behavioral of each student. Enlarge this study to the use of smartphones and tablets, taking advantage of their new features such as several incorporated sensors, and high resolution cameras, is the next step that possible will allow a wider characterization of the student, making it possible to enhance learning experience, though better recommendation and personalization.

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