Quantifying the Effects of Learning Styles on Attention

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Abstract. Monitoring and managing attention in the classroom is nowadays an important aspect where the level of learner's attention affects learning results. When students are using devices connected to the Internet in learning activities in which they send and received notifications, beeps, and vibrations and blinking messages, the ability to focus becomes increasingly important. This is true in many different domains, from the classroom to the workplace. This paper deals with the issue of attention monitoring, with the aim of providing a non-intrusive, reliable and easy tool that can be used freely in schools or organizations, without changing or interfering with the established working routines. Specifically, we look at desk students in learning activities, in which the student spends long time interacting with the computer.

Keywords: Attention Monitoring, Learning Styles, and Human-Computer Interaction.

1 Introduction

Our society is in permanent change and it requires continuous adaptation of the human being to the surrounding environment. The Human being is currently under an increasing demand for attention, result of a society that is moving faster everyday. In most of the so-called developed countries students have nowadays increasingly busier activities. This makes then stretch their limits to find time for classes, homework's, sport activities and other activities. This necessary extra time is frequently obtained at the expense of shorter periods of sleep or rest, and with a cost in terms of pressure and stress [1]. Although this effects may not be readily visible, they have consequences at many other levels than health, including emotions, results, attention, and social behavior, among others [2].

Generally there is no universally accepted definition of attention because there is a diversity of disciplines that are focused on it. In the past, only psychologists studied attention, however in present days attention is highly important for other fields like philosophy, chemistry, anatomy, and even computational science [3].

[1] Please note that the LNCS Editorial assumes that all authors have used the western naming convention, with given names preceding surnames. This determines the structure of the names in the running heads and the author index.

The concept of attention may be defined as the transforming of a huge acquired unstructured data set into a smaller structured one where the main information is preserved. In Computer Science, attention means that there is a filtering input space that selects the most important data in processing and this is a key mechanism of behavioral control for tasks, which is related to planning, decision making, and preventing new situations, however there are limited computation capabilities [3, 4].

Attention means focusing on clear thinking, 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. The lack of attention can define the success of a student. 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. [5].

This paper deals with the issue of attention monitoring, with the aim of providing a non-intrusive, reliable and easy tool that can be used freely in schools or organizations, without changing or interfering with the established working routines. Specifically, we look at desk students in learning activities, in which the student spends long time interacting with the computer.

In preliminary work we have established that the interaction with the computer, measured in terms of the use of the keyboard and mouse, changes when under attention [6]. In this paper we take this work a step forward by presenting a service-based architecture, suited for collecting of data for the purpose of classifying attention. We detail the whole process, from the definition of the architecture to the real-time collecting of data. Finally, from the interaction with the computer we compare the working time with the use of keyboard and mouse in real-time.

2 Related Work

In the last years there has been a growing interest on affective computing of computer users, especially in human-computer interaction giving many possible application domains. One of these application domains is the affective state of computer users, where applications or hardware are developed to adapt to their users [7]. This is an important aspect because the interest of affective computing is not only in the acquisition of information about the human-computer interaction, but also on the knowledge about affective states and how can be used to improve the current state of the user. These are two crucial challenges that exist in this field: how to acquire this information and how to act on the user state. In this paper we use behavior biometrics in the information acquisition and the influence of learning style in the affective state.

Behavioral biometrics defines a field that extracts user's behavioral features from the student interaction of the mouse and the keyboard [8]. Behavior biometrics is a non-invasive and non-intrusive approach that can be used to distribute system for monitoring attention. It can be very useful for teachers to identify potentially distracting events or individuals, as well as to detect other problems (as mental fatigue or stress), which significantly influence the level of attention.

With this tools it's possible to constantly analyze the behavior of the student while he/she interacts with the computer and if the system has the knowledge about the task, it is able to temporally classify attention. This technique is based only on the observation of the use of the mouse and the keyboard, which allows an assessment of the student's attention. In this way we can use this technique to develop the attention level and management initiatives in the context of learning activities, allowing teachers to perceive the student's state of mind and adjust the teaching process to the student's needs and behavior.

2.1 Learning Styles

Learning style is the method that allows an individual to learn best. Different people learn in different ways, each one preferring a different learning style. Everyone has a mix of learning styles, but some people may find that they have a dominant style of learning. Others may find that they have different learning styles in different circumstances. There are several models developed by several authors that try to represent the way people learn [9]. Previous research suggests that, in the context of learning activities, different learning styles can influence learning attention. Learning styles are considered one of the most important factors influencing learning [10].

The learning style not only specifies how a student learns and likes to learn, but it can also help a teacher to adapt to individual students, so that they might learn successfully. When the teacher's methodologies do not support a specific learning style, the student will find it more difficult to learn and acquire knowledge. When students are doing learning activities using new technologies, it is extremely important that the teacher has feedback from the students' work in order to detect potential learning problems at an early stage so he can choose the appropriate teaching methods.

Learning styles can be defined as cognitive, affective, and physiological features that serve as relatively stable indicators of how learners perceive interaction and respond to their learning environments [11].

3 An Intelligent Environment for Attention Management

The architecture of the proposed intelligent environment system depicts the process through which the system operates in order to monitoring attention management. The crucial element in this environment is a data collecting tool that records all events of mouse and keyboard student's interaction with the computer. All this features are described in section 3.1.

These features describing the interaction of each student with each computer, are processed, filtered, transformed and sent to a server, which continuously builds a student interaction profile. This mechanism is described in section 3.2.

3.1 Features Extraction

The process of feature extraction starts with the acquisition of interaction events, which is carried out by a specifically developed application that is installed in each of the computers, laptops or tablets. The first stage in the life cycle of the proposed system takes place in the data generating devices, which was designed and implemented using a logger application. 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. The privacy of the students is ensured, since the necessary data that is collected in the registration process are an ID that does not identify the student, password, and gender. Furthermore, the privacy issues of the system are assured, since the instructor will only have access to the final results on the level of attention.

The Mouse and Keyboard Sensing layers are responsible for capturing information describing the behavioral patterns of the students while interacting with the peripherals. Table 2 and Table 3 describe the features extracted from the use of the mouse and the keyword.

Table 2. Data acquisition mouse features.

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.

This application runs in the background, which makes the data acquisition process, a completely transparent one from the point of view of the student. It collects data from the students' interaction with the mouse and the keyboard, which act as sensors.

This data is further processed, stored and then used to calculate the values of the behavioral biometrics. Mouse movements and keyboard usage patterns can also help to predict the state of mind of the user [12, 13].

Table 3. Data acquisition keyboard features.

Symbol	Feature	Description
		Keyword 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
Kdt	Key Down Time	the timespan between two consecutive KEY_DOWN and KEY_UP events.

Apart from this information, which describes the interaction of the student with the computer, the system also registers the application usage by recording the timestamp in which each student switched to a specific application, by recording a tuple in the form (Id, Username, Timestamp, [AppName, Timestamp]).

3.2 Real Time Analytics for Features

In the context of an organization, the gathering and analysis of metrics describing student's behavior, and the providing of tools for visualization (particularly real time analytics) enables better decision-making and data-driven actions that consider the state and well being of each individual student. Such initiatives can nowadays be scaled to hundreds or thousands of students, through the use of Big Data tools and techniques, without compromising performance and availability. The features described in Section 3.1 describe the behavior of each individual while interacting with the computer. Each of these instances also contains a timestamp.

The architecture of the developed environment described in Figure 1 is divided in three major parts. The lower-level is composed by the devices that generate the raw data (e.g. computers, smartphones). These devices store the raw data locally in SQLite databases, until it is synchronized with the web servers in the cloud, which happens at regular intervals (normally 5 minutes).

The cloud is composed of three layers: storage, analytics, and profile classification. In the storage layer the raw data received from the data generating devices is stored in a data store engine. The analytic layer provides powerful tools for performing analytics and statically analysis in real-time. This layer simplifies the code and limits resources requirements. It is important that in this process some values are filtered to eliminate possible negative effects on the analysis. The system calculates, at regular intervals, an estimation of the general level of performance and attention of each student.

The profile classification layer is where the indicators are interpreted. For example, interpreting data from the attentiveness indicators and build the meta-data, that will support decision-making. When the system has a sufficiently 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 it can also refer to each student individually, creating each student learning profile.

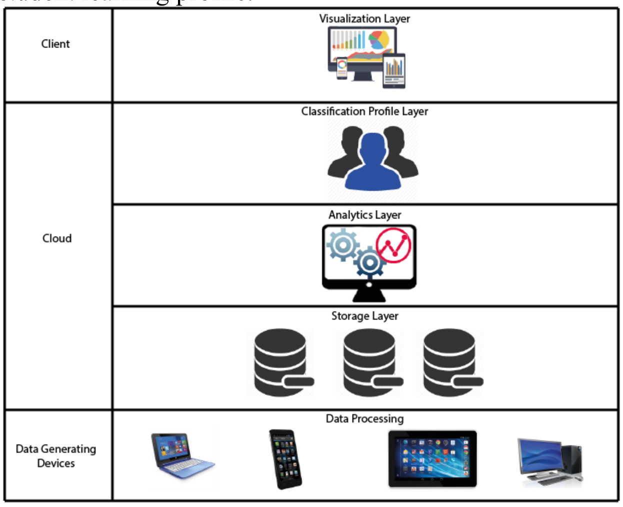

Fig. 1. Architecture of the system.

Profile classification is also a very important aspect to have control of since it allows carrying out analyses within longer time frames. 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, the Client layer is developed as a web app with intuitive and visual representation (diagrams and other graphical tools) of the attentiveness states of the group and each student, 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 teaching strategies. With a focus on individual and group performance and using real time analytics, the intuitive visual tools suggest and facilitate decision-making and student management. The actual quantification of the students' attention is displayed in the visualization layer, and can be used to personalize instructions according to the specific student, enabling the instructor to act differently with different students, and also to act differently with the same student, according to his/her past and present level of attention.

4 Experimental Study

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.

4.1 Study Design

In order to validate the proposed system, we have implemented it for the last past months in Caldas das Taipas High School, located in northern Portugal. In the Portuguese academic context, this system gains increased importance as current policies move towards the creation or larger classes, which makes it increasingly difficult for the teacher to individually address each student.

For this purpose, a group of 22 voluntaries (9 girls and 13 boys) students of the last year of the high school of multimedia technician course were selected to participate, whose average age is 17.6 years old (SD = 1.4 years). In different days, they have a lesson, where they have access to an individual computer and two hours to complete a task and the lessons contained tasks to be completed using Photoshop. All the participants thus have computer proficiency. The room was equipped with similar computers. Each participant was randomly assigned to one computer. The class students have IDs between 12P501 and 12P522.

In order to determine the learning style of each student, four different exercises were applied in four different days where the room had similar conditions in terms of lightning, temperature and humidity. The exercises applied were the following: on the first day a video exercise without audio; on the second day, an exercise only with images; on third day, an exercise only with text; and on the fourth day an exercise only with audio. In the end of each class, the exercise was saved in order to be assessed by the teacher.

4.2 Results

During the lessons the monitoring system was used to assess the interaction of the students with the computer and to quantify their level of attentiveness as well. To quantify attentiveness the following methodology was followed. Apart from capturing the interaction of the students with the computer, the monitoring system also registers the applications with which students are interacting. Attention is calculated at regular intervals, as configured by the teacher (e.g. five minutes). The teacher may also want to assess, in real-time or a posteriori, the evolution of attention of the whole class.

The level of attention of each student was quantified in this section. However, in the beginning it is necessary that the teacher defines the task-related applications that the students will use during the class. The team administrator uses a graphical interface to set rules such as "starts with Photoshop" or "Contains the word Photoshop" which are then translated to regular expressions that are used by the algorithm to determine which applications are and are not work-related. In this sense it is necessary to measure the amount of time in each interval, that the student spent interacting with task-related applications. By default, applications that are not considered task-related are marked as “others” and count negatively towards the quantification of attention. When the student uses an application that does not match any of the known rules for a specific task, the application name is saved so that the teacher can later decide if a new rule should be created for it. The teacher may also determine the regular intervals at which attention is calculated. Figure 2 shows the output of the evaluation of attention of a specific student, which allows the teacher to assess the temporal evolution of attention. These results consider the entire length of a class and give the percentage of time spent in task-related or other applications, for each student.

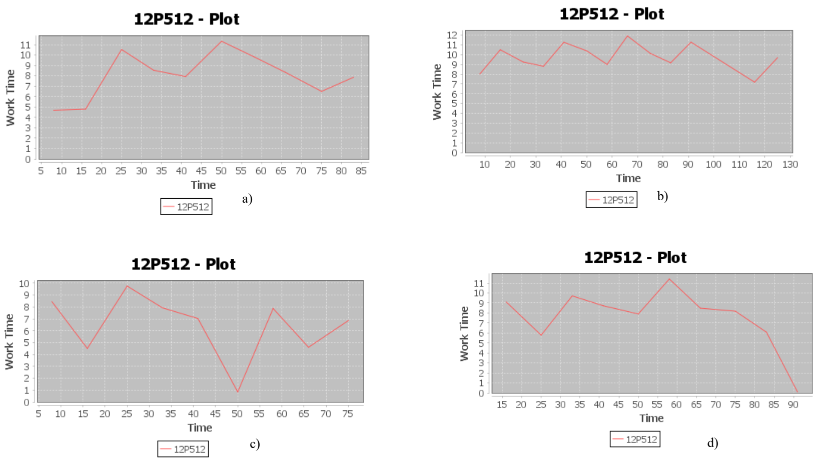

Fig. 2. Detail of evaluation of attention for a specific student in the four different days: a) video; b) image; c) text; d) audio.

In Figure 2 we observed the interacting time with task-related applications in the different lessons, which indicated his/her time focused on the task. The result of this student has a clearly different attitude in the four lessons. When being evaluated with different types of exercises we observed that for this student (12P512) the better learning style applied was for the exercises with images where the students obtain a high level of attention.

In Figure 3 it’s presented the global time spent on the work-related tasks in the four different lessons. The teacher may also find it very important to assess in real time or a posteriori, the evolution of attention of the whole class. In order to obtain this visual representation, the teacher may select which group of students to compare. In this Figure it shows the global evolution of attention in the class: (a) with video exercise; (b) with images exercise; (c) with text exercise; and (d) with audio exercises. This graphical representation is built combining data from the students in each class and computing a running average.

Fig. 3. Detail of evaluation of attention for a class in the four different days: a) video; b) image; c) text; d) audio.

5 Discussion and Conclusion

The main goal of this paper was to present an approach for the nonintrusive analysis of performance in groups of students. This approach was implemented in the form of a distributed architecture that constantly collects, processes, stores, analyzes and monitors data describing individual behavior, a method in line with the Big Data approach. We have shown the expected requirements of this kind of architecture as the number of users and the time of the data collecting grows, which allows for a precise planning of the system in terms of its scalability.

In order to validate this environment and to support the claim that external factors may influence performance and should be considered in attention monitoring approaches, we implemented an experimental study to demonstrate the effect of learning styles on student's attention.

Regarding learning styles, the system only analyses the student's actions by the percentage of work-related tasks and the interaction with the mouse and the keyboard. It is possible to apply a preliminary questionnaire in order to detect the learning style of each student. When the system has enough data for each student, it will be possible to advise the teacher with the aim to improve the attention level. It will also be possible to analyze the students' profiles, taking into account their individual characteristics, and to propose new strategies and actions. Given that the teacher is informed about the behavior of each student and each one's learning style, she/he will be able to maximize students' attention and, consequently, the performance of the teaching-learning process.

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