Quantifying Attention in Computer-based Tasks

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Abstract. Attention-to-task is one of the most important Human cognitive abilities, allowing an individual to selectively focus on a specific issue (among many possible sources) and effectively carry out a task. Without this ability to focus, the individual would constantly switch between stimuli, hardly concluding any task. While attention can be influenced by many internal and external factors, the purpose of this paper is not to analyse them but rather to propose an approach to monitor the attentional behaviour of computer users. The proposed approach may improve the individual's self-awareness as well as the team manager's knowledge about the state of the workforce. It may thus improve the definition of better attention-management strategies, with expected improvements in variables such as on-task behaviour, productivity or work quality.

Keywords: Human-Computer Interaction, Keystroke Dynamics, Mouse Dynamics, Attention

1 Introduction

Nowadays, working, as well as many other activities (e.g. education) take place wholly or partially at the computer. This represents a major shift that took place in the span of a few years, but that definitely changed our relationship with the workplace or the classroom.

This new way of working or studying has, therefore, new characteristics that can represent, at the same time, challenges and opportunities. On the one hand, working for long hours at the computer may have a negative impact in the individual's health, namely due to the lack of physical exercise. For the same reason, these jobs also tend to be considered as more boring when compared to traditional more physical and active ones [1]. Asides from other aspects, this means that these jobs may cause a certain lethargy, fatigue or sleepiness, especially when carried out for long hours [2].

One of the common ways of countering these negative effects is to advise people to make breaks and pauses at regular intervals, taking small walks or simply exiting the working space for a while, as a way to activate the mind and the body. However, this is done either at rigid intervals (e.g. every hour) or left at the responsibility of the individual.

The first approach has the drawback that we are not all equal: while one individual may maintain performance even after working for some hours straight, another may feel bored after an hour. Moreover, the same individual may behave differently in different days, depending on factors such as motivation, task characteristics, time of the day, and many other internal and external factors.

The latter approach may also have drawbacks. Namely, the notion of attention is a rather subjective one and dependent on the individual's interpretation. Moreover, despite the individual's state, she/he may continue working because there are deadlines to meet.

In all these situations, the main problem is the lack of an effective measure of attention [3], that can objectively quantify this concept. The definition and quantification of such a measure is the key element in this paper, provided through real-time analytics [4]. It is especially suited for milieus where people work with the computer for long periods of time (e.g. software houses, banking, call centres, academia). It is designed with the purpose to provide team managers or human-resources personnel with important knowledge about how each individual behaves throughout the day or how each individual reacts to events (e.g. increased/decreased workload).

2 Approach

The measure of user attention proposed in this paper is based on task characteristics, keystroke and mouse dynamics, activity level and application usage tracking.

Task characteristics are defined by the team manager or responsible and include, among others, the names of the applications that are related to the task. These names are defined using an approach close to natural language, which is then translated to regular expressions. As an example, the team manager can provide rules such as "Contains 'Microsoft'" or "Starts with 'Adobe'". These rules are then used by the system to determine which applications are work-related, allowing to quantify the time spent interacting with them versus with others, non-work-related applications.

Keystroke and mouse dynamics include ways to characterize the user's interaction with the computer through the mouse and the keyboard. The system extracts 16 features that include mouse velocity, typing rhythm, distance travelled by the mouse, writing latency, among others, that fully characterize the user's interaction patterns. In previous work we have explored, to a large extent, how these features relate to worker performance or how they are influenced by stress, namely in the academic context [5, 6]. In this work, these features are revisited to define a way of quantifying the level of activity of the user.

Indeed, the level of activity is a very important factor to consider when analysing attention as it provides the necessary context to interpret the otherwise poor information regarding attention (i.e. application usage). For instance, a given user may have a work-related application in foreground but leave the computer and come back after an hour. This does not mean that the user was devoted to the task for that hour since the application was focused but there was no interaction going on. This approach allows to point out these situations as well as to provide a level of activity. All in all, it improves the accuracy of the quantification of attention.

Finally, application usage tracking considers the analysis of how users spend their time at the computer. The developed system tracks changes in the active application, recording its name and the time at which the change took place. This allows to quantify the amount spent interacting with each application, in a given period of time. The knowledge about task characteristics allows thus to infer how much time was spent interacting with work-related applications. Moreover, it also allows to infer other behaviours such as listening to music while working or to identify moments in which the worker is no longer producing or has completely abandoned the task.

3 Architecture

In order to implement this approach, a system was developed with an architecture as described in Figure 1. It is divided in three major components. The raw data is generated in the devices, then pre-processed (by redundancy elimination) and stored locally whenever possible (as in personal computers) in a SQLite database. Then data is synchronized with the web servers in the cloud. The target database is MongoDB (object-oriented DB). MongoDB[4] is a database that is half way between relational and non-relational systems. It provides indexes on collections, it is lockless and provides a query mechanism. MongoDB provides atomic operations on fields like relational systems MongoDB supports automatic sharding by distributing the load across many nodes with automatic failover and load balancing, on the other hand CouchDB achieves scalability through asynchronous replication. MongoDB supports replication with automatic failover and recovery. The data is stored in a binary JSON-like format called BSON that supports boolean, integer, float, date, string and binary types. The communication is made over a socket connection (in CouchDB it is made over an HTTP REST interface).

One of the most interesting applications of this system is to monitor student's attention in the classroom. In fact, this system has been in the past year in the Caldas das Taipas Higher School, located in northern Portugal. Different classes, with different characteristics, are being continuously followed throughout the year. This vast data-collection will allow teachers to assess the influence on attention of aspects such as the time of the day, breaks, classes' contents, classes' objectives, and learning styles. The aim is that with this knowledge, teachers are able to improve their teaching strategies, adapting them to improve student attention.

[4] https://www.mongodb.com

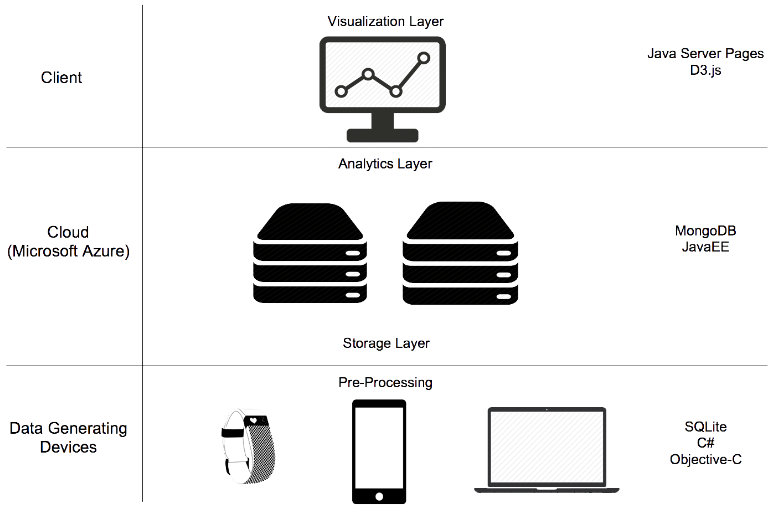

Fig. 1. Architecture of the attention monitoring system.

As an example, we briefly analyse the data collected for two different classes: a bells-letters class (12F) and a vocational class (12I). Both classes took place at the same time but in different rooms and the contents and aims of each class were the same: an application to teach algorithmic concepts. The teacher defined the applications that were necessary to carry out the task as those containing the strings "code.org" and "Microsoft Word".

The Visualization layer provides intuitive ways for the team manager (in this case the teacher) to assess the behavioural differences between these two classes. Figure 2 shows the evolution of the general attention of each class, calculated through the running average (bells-letters class (a) and vocational class (b)). It is possible to conclude that attention in the bells-letters class is generally higher but with a tendency to decrease while in the vocational class it starts relatively lower but with a tendency to increase over time. The teacher may have access to this information in real time or after the class takes place. In either case, the teacher may interpret this knowledge in its proper context (e.g. characteristics of the group of students, aims of each course, etc.) and look for ways to improve student attention.

The system also provides easy access to information regarding the level of activity of the users, which quantifies the degree of interaction between the user and the computer. For example, Figure 3, which considers the same data described before, shows that the general level of activity is higher in the bells-letters class (12F) than in the vocational class (12I), as evidenced by a faster use of the mouse.

With this kind of information, the teacher is able to better understand students, and perceive not only which students or groups of students are more

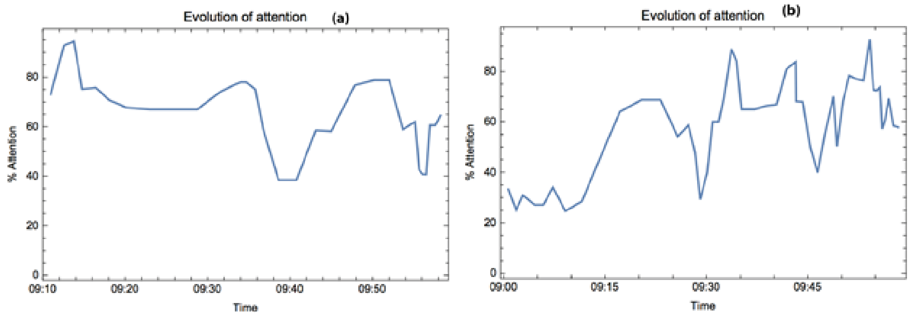

Fig. 2. Evolution of attention in both classes.

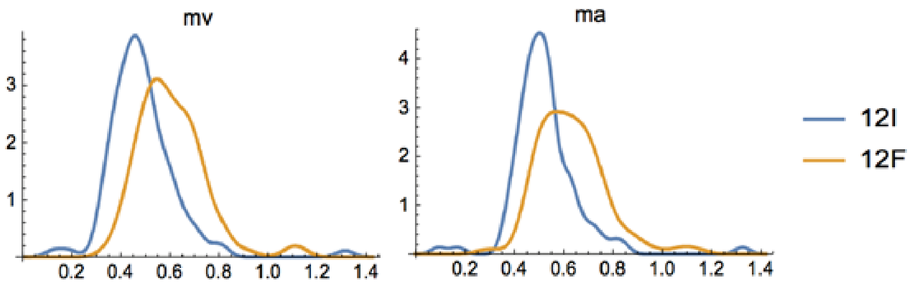

Fig. 3. Comparison of Mouse Velocity and Mouse Acceleration in both classes.

attentive to tasks but also, and perhaps more important, which tasks are more motivating and engaging, allowing to better steer classes in the future.

4 Conclusions

Concluding, the proposed system is able to quantify the level of attention of a group of people, in real time. Moreover, it also measures the level of activity using keystroke and mouse dynamics, through features such as mouse velocity, keyboard typing speed, among others. This, together with information about the task (e.g. required applications) allows to quantify the actual attention of each computer user to the current task, in real-time. Such information can significantly improve existing approaches, by providing an accurate measure based on which better decisions can be taken to manage attention.

When compared to existing approaches, the main advantage of this system is that it is not based on productivity measures, i.e., it is not based on how much the worker is producing but rather on how the worker is producing. This is an advantage as productivity-based initiatives often have a negative impact on productivity that stems from the added pressure on the worker. Moreover, user privacy is protected by masking sensitive information such as the keys pressed or the specific applications used. That is, the team manager has only access to the compiled data and not to the raw data. For these reasons, we believe that this approach may constitute an effective and interesting approach to implement attention monitoring initiatives, in milieus such as the workplace or the classroom.

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