Detection of Distraction and Fatigue in Groups through the Analysis of Interaction Patterns with Computers

André Pimenta, Davide Carneiro, Paulo Novais, and José Neves

Abstract. Nowadays, our lifestyle can lead to a scatter of focus, especially when we attend to several tasks in parallel or have to filter the important information from all the remaining one. In the context of a computer this usually means interacting with several applications simultaneously. Over the day, this significant demand on our brain results in the emergence of fatigue, making an individual more prone to distractions. Good management of the working time and effort invested in each task, as well as the effect of breaks at work, can result in better performance and better mental health, delaying the effects of fatigue. This paper presents a non-intrusive and non-invasive method for measuring distraction and fatigue in an individual and in a group of people. The main aim is to allow team managers to better understand the state of their collaborators, thus preparing them to take better decisions concerning their management.

Keywords: Distraction, Fatigue, Task Performance, Behavioural Biometrics, Distributed Intelligence, Pattern Analysis.

1 Introduction

When people are working in a demanding cognitive task for an extended period of time, they often end up feeling the effects of fatigue, reflected in impaired task performance and reduced motivation to continue working on the task at hand [9, 10]. In addition, an increase in the amount and severity of errors being made can often be observed. Indeed, fatigue is considered one of the major causes for human failure and error [3]. An individual experiencing fatigue will also have a harder time

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concentrating, getting easily distracted [2, 5], an indication that mental fatigue can have effects on selective attention.

Attention can be considered one of the most important mechanisms when it comes to acquiring new knowledge: being a cognitive process, attention is strongly connected with learning and assimilating new concepts either at school or at work [7]. The lack of attention can thus be problematic in some activities such as attending lectures, multimedia learning or car driving [1, 8]. Asides from learning, attention is also very important to perform any task in an efficient and adequate way and to distinguish between important and superfluous information for a given task at hand.

Our ability to focus on a task for prolonged periods is however at risk in a time in which our surroundings are constantly flooded with notifications, alerts and messages, coming from the operating system, friends, social networks and a myriad of (sometimes useless) applications, actively running or constantly in the background. Our brain, which did not evolve towards such a high-level of multitasking, may feel overwhelmed with the amount of sources information. This leads back to the importance of remaining focused on the task at hand, once that such ability is vital for any cognitive function, especially when there might be potential interference from distractors non pertinent to the task [6].

In this work it is detailed a monitoring system for distraction and fatigue based on the patterns of switching between leisure and work applications. Through the use of behavioural biometrics, specifically Keystroke Dynamics and Mouse Dynamics, we analyse the type of task performed by each user as well as the time spent in performing it. With this information we train classifiers that are able to distinguish scenarios in which the user shows sings of fatigue and distraction. This approach can be deemed both non-invasive and non-intrusive as it relies solely on the observation of the individual's use of the mouse and keyboard. This makes it more suited to be used continuously in work or academic environments than other available approaches as it requires no conscious or specific actions from the part of the user. Moreover, it is multi-modal as it relies on features that include the physical and behavioural modalities, potentially holding better results than single-modality approaches.

2 A Non-intrusive Approach to Monitoring Distraction and Fatigue

This paper introduces an approach for determining the type of task being performed on a computer by an individual or by a group. Tasks such as reading, writing reports or programming are examples of tasks that require a significant amount of attention and can be performed using a wide range of different tools. However, what all these tools have in common, is that they are interacted with using mouse and keyboard. The use of these peripherals, as addressed in [4], allows to acquire contextual features that describe the interaction patterns of the user with the computer. These features reflect the behaviour of the user and how it changes under certain conditions, such as when the user is fatigued. In his particular case, we look at how these features change when the user starts becoming distracted.

Particularly, we look at how the user distributes the time devoted to each application, and at which of these applications are related with the task at hand. We thus complement and improve the previously developed fatigue monitoring approach (task-independent, based solely on the performance of the interaction with the computer) with a measure of attention, which can be used as a reliable indicator of fatigue [7].

2.1 Methodology

In order to analyse the proposed problem, a study was set up aimed at collecting the necessary data. The methodology followed to implement the study was devised to be as minimally intrusive as the approach it aims to support. Twenty seven (20 men, 7 women) participants, students from the University of Minho, were selected to participate. The participants were provided with an application for logging the system events related to the mouse and keyboard as described in [4].

It is based on these events that we build the features that described the interaction of each individual over time. Moreover, the provided application also logs the application being used at any moment. This application, which maintained the confidentiality of of the users and of their interactions, needed only to be installed in the participant's computer and would run on the background, starting automatically on system start. The only explicit interaction needed from the part of the user was the input of very basic information on the first run, including the identification and age.

This application was kept running for approximately one month, collecting interaction data whenever there was interaction with the computer. During the whole process, participants did not need to perform any additional task and were instructed to perform their activities as usual, whether they were work or leisure-related, as they would if they were not participating on the study.

When the period of one month ended, participants were asked to send in the file containing the log of their interaction during the duration of the study. The resulting dataset as well as the process by means of which data were analysed is described in the following sub-sections.

The events generated by the mouse and keyboard were divided into 4 categories: (1) *Chat*, concentrating inputs in applications such as Skype, Hangouts, Facebook Mensseger; (2) *Browsing*, including inputs in browsers such as Internet Explorer, Firefox and Google Chrome; (3) *Work* , with inputs regarding applications such as as Eclipse IDE, Microsoft Office Suite, TexMaker, Adobe Reader, Evernote or Netbeans; and (4) *Games*, with records of gaming applications.

2.2 Analysis of Results

In this section we show the existence of different behaviours in using the keyboard and mouse according to the type of task being performed. We do so, as previously discussed, through the analysis of the interaction patterns of the individuals. Specifically, we look at the distributions of the data collected for each category of application and analyse the statistical significance of their differences. To this aim, the following approach was implemented.

First, it was determined, using the Pearson's chi-squared test, that most of the distributions of the data collected are not normal. Given this, the Kruskal-Wallis test was used in the subsequent analysis. This test is a non-parametric statistical method for testing whether samples originate from the same distribution. It is used for comparing more than two samples that are independent, and thus prove the existence of distinct behaviours. The null hypothesis considered is: H_0 : all samples have identical distribution functions against the alternative hypothesis that at least two samples have different distribution functions.

For each set of samples compared, the test returns a p-value, with a small p-value suggesting that it is unlikely that H_0 is true. Thus, for every Kruskal-Wallis test whose $p - value < \alpha$, the difference is considered to be statistically significant, i.e., H_0 is rejected. In this work a value of $\alpha = 0.05$ is considered, a standard value generally accepted by research.

This statistical test is performed for each of the features considered, with the intention of determining if there are statistically significant differences between the several distributions of data, which will in turn confirm the existence of different behaviours in using the keyboard and mouse on the type of task being performed through interaction patterns.

For 90% of the users all the features showed statistically significant differences. Figure 1 depicts these differences clearly for two different features: writing velocity and mouse velocity. It is possible to conclude, for example, that participants write the fastest when in chat applications and move their mouses faster when playing games.

3 Distributed Intelligence Architecture

As can be seen in Section 2 the use of keyboard and mouse reveals distinct behaviours when participants are working or when they are distracted. Based on the results briefly described it was developed a prototype of an application that aims to classify the attention of the user according to their interaction patterns.

The proposed framework aims to assess the level of attention in scenarios of work or study of individuals. Nonetheless, the main objective is to support the decision-making processes of team managers or group coordinators. In this perspective, each element of a group is seen as part of a whole which contributes to the general level of fatigue and the distraction of the group. We will call each member of the group a

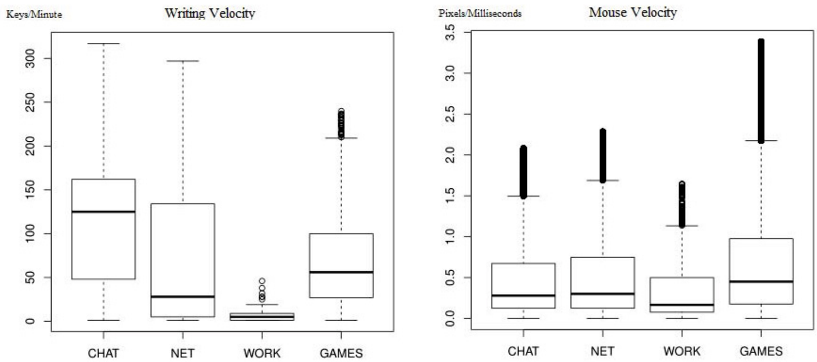

Fig. 1 Differences in the use of mouse and keyboard between the different categories of applications

"Monitored User", with the exception of the coordinator/manager who will is called "Coordinator". Figure 2 depicts the distribution of the roles and the flow of information from raw data to the classification of the state of the individuals.

Each monitored user provides raw data about their interaction patterns to the coordinator. The information provided results of registering the events related to keyboard and mouse. The data collected is processed and transformed in order to be evaluated in terms of the features mentioned. One of the most important tasks is to filter outlier values that would have an undesirable effect on the analysis (e.g. when we continuously press the backspace key to delete a group of characters).

After the data has been processed it is classified and it is used to build the metadata that will support decision-making. To do it, the machine learning mechanisms detailed below are used. At this stage the process of classification can be improved with the inclusion of information from work settings and other scenarios. The information compiled can be presented to the respective user and to the coordinator, for improving routines and decision-making.

The computer of the coordinator receives this information in real-time and calculates, at regular intervals, an estimation of the general level of fatigue and attention of the group. The coordinator has access to the current and historical state of the group from a global perspective, but can also refer to each user individually (Figure 4).

The process described can be found in Figure 3, which details the process of monitoring.

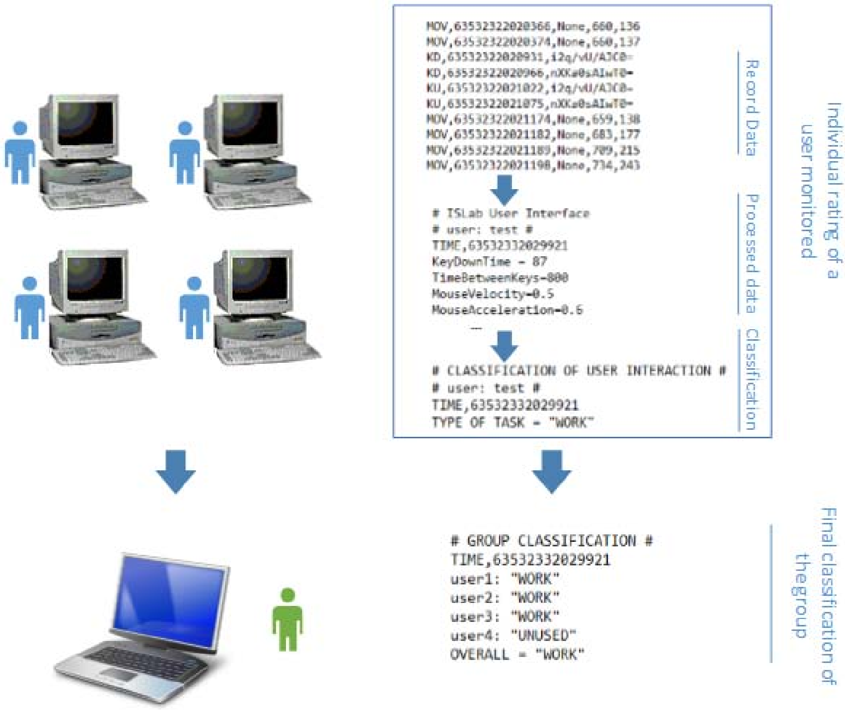

Fig. 2 Flow of information from raw data to the classification of the state of the individuals. The coordinator is depicted in green while users are depicted in blue.

3.1 Classifying Behaviours Associated with Work Tasks

Having proved the existence of distinctive behaviours in the use of the keyboard and mouse in tasks of different types, a classifier was built and trained to determine the type of task being carried out by the users from their interaction patterns.

The classification of the type of task being performed by the user is obtained through use of (k-NN) k-Nearest Neighbor algorithm. It is a classification method based on closest training examples in the feature space. The data used to train the model used by the k-NN algorithm were collected in an experiment described in Section 2. The classification of the state of the group is the result of the average of all monitored users.

The following section describes a case study in which the classifier trained was tested and validated with different participants, in the context of a classroom.

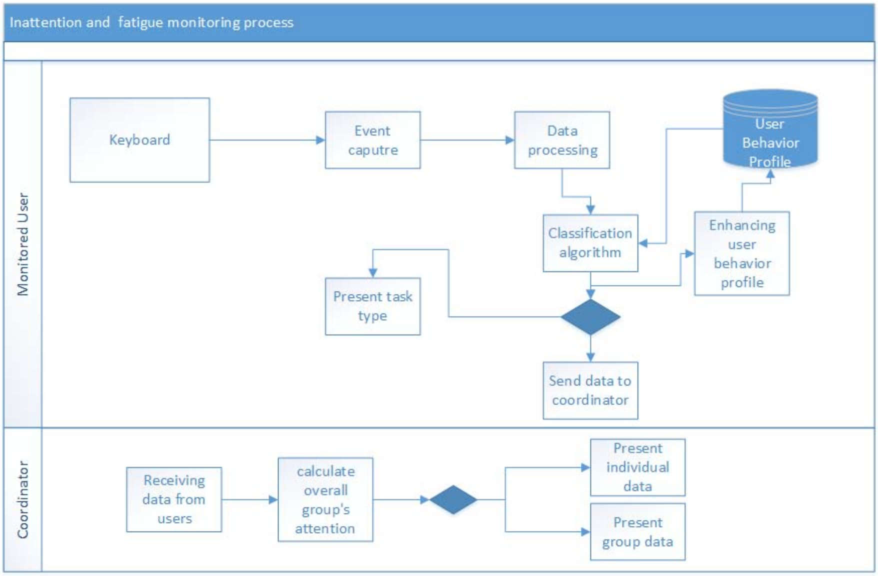

Fig. 3 Work-flow of information in the monitoring process

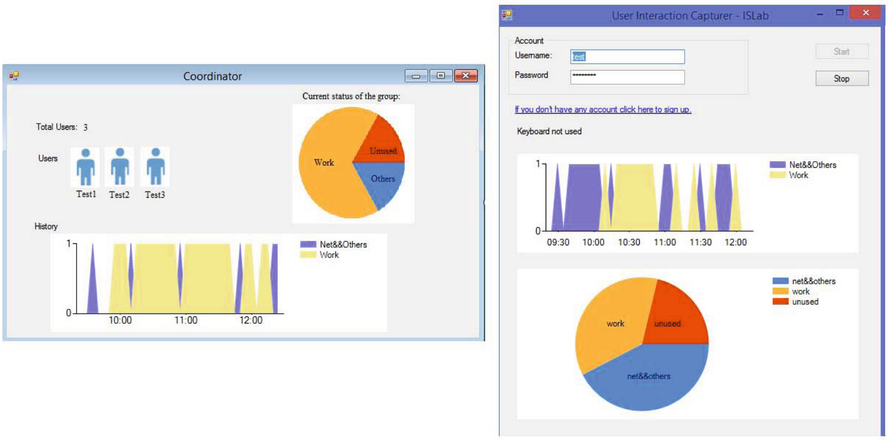

Fig. 4 The presentation layer of the monitoring system detailing the state of the group (right), and the individual details of a user (left)

4 Case Study

In order to test the developed system and approach a case study was set up, including the roles of users and coordinator. We meant to analyse to which extent the coordinator could find the information provided interesting.

In addition to testing and validating the system we were also looking for effects of distraction and fatigue. In that sense we searched for potential activities that needed a significant amount of attention for its correct execution.

A training course on programming was chosen for testing this approach in a real scenario. The course takes place physically in a classroom and comprises a coordinator who is responsible for teaching a programming language (in this case C) to a group of participants. The participants in the case study, eighteen in total (13 men, 5 women) were students from the University of Minho of the field of physical sciences. Their age ranged between 18 and 25.

Each session of the training course has a duration of 3 hours, which always follow the same "protocol": some theoretical concepts are introduced at the beginning of the class and the rest of the session is spent practising and solving exercises using the computer and a specific IDE.

At the end of each session a practical evaluation exercise is carried out for each individual, aimed to determine how well the concepts thought were perceived. The computer is accessible and the students may use it as they wish during the duration of the session, both while the coordinator provides the theoretical background and while students use the IDE. Participants frequently use the computer to take notes, search additional information, send emails or visit social networking sites. There is no restriction on the use of the computer expect for its mandatory use for solving exercises.

4.1 Results

During a training session, the developed monitoring system was used to assess the level of attention of the participants, as well as its performance. Given the domain of the case-study, the participant's usage of the peripherals was classified as belonging to a work-related application or to any other one. At the end of the class, participants were evaluated with specific exercises. Our aim is to find a relationship between distraction, fatigue, interaction performance and scholar performance. Participants were also requested to rate their level of attention during the session using a value between 0 (very distracted) and 5 (attentive), in order to validate the results from a subjective point of view.

The results achieved are available in Table 2. It can be observed that participants with the lowest attention during the session had worse evaluations unlike participants who were more attentive and obtained better results. The participants number 4, 6, 8, 14, 15, 17 are examples of participants who did not pay much attention during the session and had worse results. These same participants also confirmed, through their answers in the questionnaires, that they were not very focused on the class.

Considering the correlation between variables, the following positive correlations were identified: correlation between the percentage of time spent interacting with work-related applications and final score (0.54), correlation between the percentage

Table 1 Overall results of all participants, where one can see the values of the monitoring, evaluation and values of the subjective level of attention to each participant

user	Minutes in work tasks	Minutes others tasks	Minutes unused	% work	% others	% subjective attention	% final evaluation
1	96	36	48	73%	27%	5	90%
2	60	36	84	63%	38%	4	100%
3	72	12	96	86%	14%	4	100%
4	54	48	78	53%	47%	2	50%
5	90	0	90	100%	0%	3	50%
6	54	90	36	38%	62%	3	30%
7	90	12	78	88%	12%	4	100%
8	60	42	78	59%	41%	4	70%
9	96	42	42	70%	30%	4	100%
10	108	0	72	100%	0%	5	80%
11	84	24	72	78%	22%	4	90%
12	96	24	60	80%	20%	5	100%
13	84	24	72	78%	22%	3	70%
14	48	42	90	53%	47%	3	50%
15	54	36	90	60%	40%	3	0%
16	60	30	90	67%	33%	4	90%
17	48	54	78	47%	53%	3	20%
18	114	30	36	79%	21%	5	80%
Mean	76	32	71	71%	29%	4	70%

of time spent interacting with work-related applications and subjective evaluation of attention (0.51) and correlation between subjective evaluation of attention and final score (0.68).

4.2 Validation

In order to validate the results obtained by the monitoring system during the experiment, the applications used by the participants were recorded, as well as the time spent in each one.

The only application that had to be mandatorily used was the Dev-C++ IDE. Nonetheless, some participants used alternative text editors such as Microsoft Office, TextMaker or Evernote. Thus, we looked at what type of application was being used in each moment and what type of application the classifier was providing as output to validate its efficacy.

The results obtained during the scan for all classifications from all users during the formation validate the classifications made by the monitoring system. As depicted in Table 2, 96% of classifications as work tasks through the use of work tools were successful, while the remaining 92% of applications had successful classifications as well. It was also observed that the keyboard was used for tasks other than work-related ones, mostly chat applications and browsers.

Table 2 Results of the classifications algorithm

task type	instances	% correctly class.	% incorrectly class.
work tasks	228	96%	4%
others	97	92%	8%
Unused	215	100%	0%

5 Conclusion

This paper described a prototype for monitoring the type of task being carried out by an individual or a group of individuals. The main aim is to detect patterns associated to distraction and fatigue in scenarios of classrooms or workplaces. The information compiled is provided to team managers and coordinators so that they can improve their decision-making skills. In the example of the case-study, the coordinator of the class gains a better notion of how long he can talk before starting to loose the attention of the class. Students, on the other hand, learnt that there is a direct relationship between the attention they devote to the contents of the class and their final score.

The results also show that carrying our different types of task results in entirely different interaction patterns. These interaction patterns are different enough to train classifiers that are able to classify the type of task being carried out. This can then be used to determine the distribution of time of the individual among the several types of applications. Within the context of CAMCoF project, which founds this work, the long-term goal is to develop environments that are autonomous and take measures concerning their self-management to minimize fatigue and increase the performance and well-being of a group of individuals.

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