A multi-modal architecture for non-intrusive analysis of performance in the workplace

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ABSTRACT

Human performance, in all its different dimensions, is a very complex and interesting topic. In this paper we focus on performance in the workplace which, asides from complex is often controversial. While organizations and generally competitive working conditions push workers into increasing performance demands, this does not necessarily correlates positively to productivity. Moreover, existing performance monitoring approaches (electronic or not) are often dreaded by workers since they either threat their privacy or are based on productivity measures, with specific side effects. We present a new approach for the problem of performance monitoring that is not based on productivity measures but on the workers' movements while sitting and on the performance of their interaction with the machine. We show that these features correlate with mental fatigue and provide a distributed architecture for the non-intrusive and transparent collection of this data. The easiness in deploying this architecture, its non-intrusive nature, the potential advantages for better human resources management and the fact that it is not based on productivity measures will, in our belief, increase the willingness of both organizations and workers to implement this kind of performance management initiatives.

1. Introduction

The change in the job offers in the last decades, caused by technological evolution, brings along many significant and broad changes. Some of the most notorious ones can be pointed out by the emergence of indicators such as stress or mental fatigue which, in extreme cases, can endanger the life and well-being of the employees. In more moderate cases it will impair performance, general cognitive skills and productivity. In addition to these factors, many of these jobs are the so-called desk-jobs, in which people frequently sit for more than 8 h [1].

Until now, the performance of the employees has been evaluated through their productivity: the more one produces, the better the performance at work. While the true nature of this relationship is yet to be thoroughly studied (properly contextualized in each work domain), there are other issues that need to be addressed. First of all, the worst aspect about this approach is that it only points out a potential decrease of performance after a productivity loss. This means that the "damage" is already done and that it is most likely too late for the employee to cope with whatever caused the performance loss. An approach that could point out, in advance, upcoming breaks in performance (e.g. through the observation of behavioral patterns) could allow for

preventive interventions rather than reactive [2].

Another major aspect that current approaches fail to consider are the side effects of productivity or performance monitoring in the workplace [3]. Indeed, as research in the last years has pointed out, this kind of approach might act as an additional stressor on the employee, which adds to the existing pressure in the workplace and to its negative consequences. In a study conducted in 1995 by researchers of the State University of New Jersey, it was analyzed the impact of electronic performance monitoring and its social context on the productivity and stress of employees [4].

Electronic Performance Monitoring (EPM) systems are one of the many technological developments employees face in today's workplaces. These systems provide managers a wide range of information about employees' routines including real-time information such as the pace of work, degree of accuracy, log-in and log-out times, and even the amount of time spent on bathroom breaks. This study examined how productivity and subjective experiences are affected by EPM systems and how the social context of the workplace moderates that influence.

In a survey involving the monitored workers, 81% of the respondents declared that electronic observation made their jobs more stressful [5]. Another study compared the behavior of monitored and non-monitored workers and found that monitored workers felt more

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stressful [6].

The introduction of EPM systems can transform ordinary jobs into high-stress jobs. It can also reduce the opportunities for employees to socialize with each other at work, leading to a loss of social support, partially responsible for the stress associated with EPM [7,8].

In this paper we present a new approach on the problem of performance monitoring in desk jobs, in line with the Ambient Assisted Living view [9], that quantifies performance independently of the amount of work produced by the employee. Namely, we develop a multimodal approach that incorporates different sources of information to allow the extraction of behavioral and physical features to characterize the performance of the user. These features are extracted from the keyboard, the mouse and the chair of the user.

As the results point out, the selected features vary consistently throughout the day, showing a decrease in the performance of interaction as the day of work goes by and an increase in the movement of the chair, pointing out increasing discomfort. This multimodal approach allows a quantification of performance decrements without requiring productivity measures. In that sense, employees will be more prone to accept such an approach. It is also non-intrusive as it requires no specific actions by the employees: they simply need to carry out their regular work.

Our goal is that team managers make use of such information to implement better human resources management strategies, that take into account (possibly in real-time) the state of the employees, allowing the development of individualized working schedules, warnings when performance decreases or the implementation of automatized coping strategies. As an example, we developed a simple desktop application that produces a warning when significant decreases in performance are observed on the user.

2. Architecture

The architecture of the proposed system was developed as a Service-Component Architecture (SCA): a group of OASIS specifications that has become an industry standard. It is intended for the development of applications based on SOA, which defines how computing entities interact to perform work for each other. Originally published in November 2005, SCA is based on the notion that all the functions in a system should exist in the form of services that are combined into composites to address specific business requirements. In other words, it allows to build service-oriented applications as networks of service components. SCA is used for building service components, assemble components into applications, deploy to (distributed) runtime environments and reuse service components built from new or existing code using SOA principles.

SCA provides a good basis for applications under the umbrella of the Ambient Intelligence (AmI) field [10], such as this one, and it fulfills major AmI deployment requirements by promoting late bindings at deploy time and runtime with the support of several relevant technologies including POJO, SOAP, REST, BPMN, BPEL, JMS, Camel or Rules services. But most of all it is currently supported by several major commercial and open source products such as Jboss Switchyard, IBM WebSphere or TRENTINO (C++). From the several available

implementations of SCA we have chosen JBoss SwitchYard since it is an open source solution in a relative mature state, and also enhances some of the SCA advantages.

A service-based approach was followed to develop an architecture logically divided into several packages that encapsulate a set of features and tasks. Fig. 1 pictorially depicts, from a high-level point of view, the proposed architecture.

Three main components can be identified. The first is the component that is on the user-area. It provides, in an non-intrusive way, features about the employees' behavior. Two of these features are extracted from two accelerometers placed in the chair, as detailed in Fig. 1. These accelerometers aimed to record the movements of the workers during the day (8 h workday), while sitting in front of the computer. Accelerometer 1 was placed at the level of the worker's back while accelerometer 2 was placed in one of the wheeled arms of the chair, with the aim to record acceleration generated by the moving of the chair. Specifically, Axivity's WAX3 wireless accelerometers were used.

The remaining features are extracted from the mouse and keyboard of the computer and fully characterize the employee's interaction with these peripherals. Although these features and the process of their extraction have been detailed in the past [11], we provide a brief overview. From the keyboard we extract features such as the typing speed or rhythm, the number of errors or the time of each key press. In previous studies we have noted that key presses, for example, may vary in duration from 80 ms at the beginning of a session, to as much as 100 ms at the end, depending on the user and on the type of task being performed. From the mouse we extract features such as velocity, acceleration, distance between clicks, duration of the click or excess of distance traveled, just to name a few. Once again, we consistently find decreases in performance on these features as the workday progresses [12].

Simultaneously with the acquisition of the behavioral features, employees answered a questionnaire about mental fatigue on a hourly basis (USAFSAM Fatigue Scale [13]). This was implemented with the aim of studying, in parallel, the daily evolution of mental fatigue given the well-known relationship between this indicator and performance [14].

The second component of the architecture is placed on the server side of the system. It is responsible for the continuous acquisition of behavioral data and its persistence in the database. Moreover, it also provides very important functionalities in the form of services. Namely, it allows for behavioral models to be trained based on individual user data and the results of the questionnaire (as depicted further below), namely using machine learning algorithms. It also allows for these models to be used in real-time for classifying user performance from behavioral data, which is essential given the aims of this research line.

Finally, the third major component of the architecture concerns the use of the performance models, in real-time, for improving performance throughout the day or preventing performance breaks. This considers both automatic and human-driven decision mechanisms. On the one hand, and as implemented in the developed prototype, the system can autonomously point out to the user or anticipate significant breaks in performance, providing a warning that encourages the user to
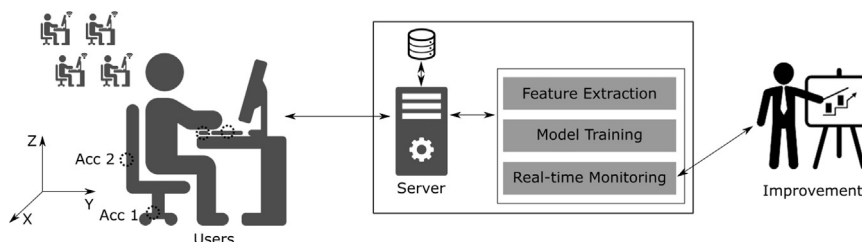
Fig. 1. High-level view of the architecture, highlighting the 4 sources of information in each user: the mouse, the keyboard and two accelerometers placed on the chair as well as their placement and directions of the axes.