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Using smart offices to predict occupational stress

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ABSTRACT

Occupational stress is increasingly present in our society. Usually, it is detected too late, resulting in physical and mental health problems for the worker, as well as economic losses for the companies due to the consequent absenteeism, presenteeism, reduced motivation or staff turnover. Therefore, the development of early stress detection systems that allow individuals to take timely action and prevent irreversible damage is required. To address this need, we investigate a method to analyze changes in physiological and behavioral patterns using unobtrusively and ubiquitously gathered smart office data. The goal of this paper is to build models that predict self-assessed stress and mental workload scores, as well as models that predict workload conditions based on physiological and behavior data. Regression models were built for the prediction of the self-reported stress and mental workload scores from data based on real office work settings. Similarly, classification models were employed to detect workload conditions and change in these conditions. Specific algorithms to deal with class-imbalance (SMOTEBoost and RUSBoost) were also tested. Results confirm the predictability of behavioral changes for stress and mental workload levels, as well as for change in workload conditions. Results also suggest that computer-use patterns together with body posture and movements are the best predictors for this purpose. Moreover, the importance of self-reported scores' standardization and the suitability of the NASA Task Load Index test for workload assessment is noticed. This work contributes significantly towards the development of an unobtrusive and ubiquitous early stress detection system in smart office environments, whose implementation in the industrial environment would make a great beneficial impact on workers' health status and on the economy of companies.

1. Introduction

The pace of modern-day life, the competitiveness in the workplace, poor working conditions and the immense number of tasks with inaccessible deadlines that are assigned to workers are causing work-related stress to become increasingly frequent in our work environment.

The International Labour Organization (ILO) defines stress as the harmful physical and emotional response caused by insufficient perceived resources and abilities of individuals to cope with the perceived demands, and is determined by work organization, work design and labour relations (I. L. O, 2016). It is the second most frequent work-related health problem in Europe (European Agency for Safety and Health at Work, 2013a), presenting in 2005 a prevalence of 22% among working Europeans. In a recent opinion poll (European Agency for Safety and Health at Work, 2013b), 51% of the workers confessed that stress is common in their workplace and the 6th European Working Conditions Survey (European Foundation for the Improvement of Living and Working Conditions, 2016) exposed that 36% of European workers deal "(almost) all of the time" with high pressure to meet tight deadlines.

If timely action is not taken, occupational stress can provoke serious physical and mental problems on the worker (Milczarek et al., 2009), but also important economic losses in the companies. Musculoskeletal disorders, depression, anxiety, increased probability of infections (Wijsman et al., 2013), chronic fatigue syndrome, digestive problems, diabetes, osteoporosis, stomach ulcers and coronary heart disease (Marlen Cosmar et al., 2014; Peternel et al., 2012; Bickford, 2005) are only a few examples of occupational stress' long-term health consequences. Occupational stress can also result in increased absenteeism and presenteeism, reduced motivation, satisfaction and commitment, along with a greater rate of staff turnover and intention to quit, costing high amounts of money to the enterprises (Drivers and Barriers, 2012). An estimate of €617 billion a year is what work-related depression costs to European enterprises, including costs of absenteeism and presenteeism (€272 billion), loss of productivity (€242 billion), healthcare costs (€63 billion) and social welfare costs in the form of disability

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benefit payments (€39 billion) (European Agency for Safety and Health at Work, 2013a). An estimate of 50–60% of all lost working days in European enterprises are due to work-related stress and psychosocial risks (European Agency for Safety and Health at Work, 2013a).

In this context, methods to detect occupational stress in time so as to take the required measures and to avoid its negative health-related and economic consequences are necessary. Often, stress levels are evaluated by means of self-reported questionnaires, which are performed from time to time, and therefore, are not adequate to detect subtle changes that might end up in a more serious problem (Alberdi et al., 2015). Usually, the diagnosis comes too late with these methods, when damage has been done. Moreover, self-reported questionnaires are subjective and rely on subjects' recall abilities and awareness of the situations, which is not guaranteed (McDuff et al., 2012), leading sometimes to incorrect stress level measurements.

In recent years, technology to unobtrusively and ubiquitously monitor users' behavior is being developed as Smart Environments (Ramos et al., 2010). Future work environments are supposed to be intelligent, adaptive, intuitive and interactive (Strömberg et al., 1007). In this sense, a smart office has been defined as an environment that is able to adapt itself to the user's needs, release the users from routine tasks they should perform, change the environment to suit their preferences and access services available at each moment by customized interfaces (Marsá Maestre et al., 2006). In addition, we also see an opportunity based on its potential to avoid health-related problems for workers and improve their quality of life. As a great percentage of workers develop their tasks in an office environment, smart offices represent a useful infrastructure to continuously monitor workers' behavior in a completely transparent way, gathering real work-life data throughout the working day and therefore, to overcome the main disadvantages of the usual assessment methods. The collected data can provide a complete view of workers' behavior in a real-world work environment, the efficiency and ecological validity of the resulting stress assessments and reducing stress detection delays.

Our goal in this paper is to build and validate stress and mental workload prediction models based on unobtrusively collected physiological and behavioral data in a smart office environment. As all other disorders, stress progresses over time. Usually, in stress detection research, the temporal nature of the disorder is not taken into account, and only a snapshot of the symptoms is considered for prediction. In contrast, in this work we hypothesize that changes over time of these symptoms can predict the mental states of the subjects and the conditions they are undergoing.

To support this hypothesis, we propose the use of the Clinical Assessment using Activity Behavior (CAAB) approach adapted to smart office environments to create stress prediction models (Dawadi et al., 2015). This algorithm consists of the application of a sliding window to extract five different time-series statistics from physiological and behavioral data, describing the change and variability of these patterns. This allows the construction of models to predict self-assessed stress and workload levels from the change features instead of using the usual instantaneous feature values. Although it is out of the scope of this work, the computation of these behavioral and physiological change parameters not only provides a method to take the temporal nature of stress into account, but it is also a way to standardize data coming from different subjects, facilitating generalization of the models over a population group.

As a second goal of this work, we also determine the possibility of automatically detecting a workload condition change using these changes in physiological and behavioral data.

The CAAB algorithm has been validated in other scenarios and has been shown to be useful for cognitive state and everyday functioning assessment (Dawadi et al., 2015). The validation of the approach for early stress detection would result in a system that could alert both workers and managers enabling to take timely action. Moreover, this would define the path to follow towards the final development and implementation of a global early detection system for disorders that provoke behavioral changes, among which stress is just an example.

Therefore, the research questions we aim to address in this paper are:

- Can we predict users' perceived stress and mental workload level from changes in their unobtrusively collected behavioral and physiological data?
- Which physiological or behavioral changes are the most informant about stress and mental workload levels?
- Can physiological and behavioral variability as monitored by ambient sensors be used to detect the conditions under which a participant is working, both from a predefined set of conditions and from reliably differently perceived conditions?
- Can these data be used to detect a change in workload settings? Can they also detect the direction of these changes? And a reliably perceived workload change?

The main contributions of this paper are: 1) Use of the CAAB algorithm to evaluate the possibility of measuring self-assessed and standardized stress and mental workload from changes in unobtrusively collected real-life smart office data. 2) Analysis of the predictability of a wide variety of stress and mental workload assessment scores. 3) A feature selection-based analysis of the contribution of each type of behavioral and physiological change to the prediction of each of the self-assessment test scores. 4) Analysis of the predictability of an objective and reliable workload condition, change in these conditions and their directionality from unobtrusively collected data. 5) Testing of specific algorithms (*i.e.* SMOTEBoost (Chawla et al., 2003) and RUSBoost (Seiffert et al., 2010)) to boost models' sensitivity for mental workload detection.

The remaining part of the paper proceeds as follows. First, Section 2, begins by reviewing the related literature. Section 3 explains the methods used for the data collection, preprocessing and model building process. Next, in Section 4, prediction models' results are presented. Finally, in Section 5, results are discussed and the conclusions drawn are presented.

2. Related work

Smart offices have already been implemented and used for a variety of purposes, being the area of energy efficiency a highly popular field of application (Akbar et al., 2015; Choi et al., 2015a, 2015b; Rottondi et al., 2015). Moreover, research aimed at improving workers' quality of life based on this technology are also present in the literature (Kaklauskas et al., 2011; Kiyokawa et al., 2012; McDuff et al., 2012).

To date, stress detection research has mainly focused on the use of physiological signals that could objectively measure stress-levels while replacing the well-accepted but highly inaccessible methods such as salivary cortisol measurements. Even if a wide variety of physiological signals have been analyzed, the most successful results have been achieved with the monitoring of skin conductance levels (SCL), as well as with heart rate (HR) and heart rate variability (HRV) extracted from electrocardiograms (ECG) (Alberdi et al., 2015). Stress and emotions have also been associated with some objectively-measured behaviors (Sharma and Gedeon, 2012). These include computer use patterns (Eijckelhof et al., 2014), posture (McDuff et al., 2012; Arnrich et al., 2010), facial expressions (McDuff et al., 2012; Dinges et al., 2005), speech (Kurniawan et al., 2013; Hagmueller et al., 2006; Lu et al., 2012), mobile phone use (Sano and Picard, 2013; Muaremi et al., 2013), writing patterns (Vizer et al., 2009; Saleem et al., 2012) and global activity-level parameters measured in smart environments (Suryadevara et al., 2012). Nonetheless, the reported conclusions do not result from real office-work settings but from experiments under artificial conditions where participants were not performing their usual work and/or stress was elicited with atypical stressors for an office worker.