Monitoring psychological stress

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ABSTRACT

We propose a method for monitoring stress in real-life. First, experiments were performed in laboratory conditions. 21 subjects were monitored with a wrist device equipped with physiological sensors while performing mental-arithmetic tasks under time and evaluation pressure. On the laboratory data, a laboratory stress detector was built using machine learning techniques. Next, the laboratory stress detector was applied on a real-life data. In addition to the laboratory stress detector, a real-life context information was needed for the method to be successfully applied on the real-life data. The context-based model detects (recalls) 70% of the real-life stress events with a precision of 98%

1. INTRODUCTION

Being able to detect stress as it occurs can importantly contribute to dealing with its negative health and economic consequences. In 2002, the European Commission calculated the costs of work-related stress at €20 billion a year. This is because work-related stress leads to increased absenteeism and decreased productivity. Therefore, a stress-detection system would be useful for self-management of mental health of workers students and others in the stressful environment of today's world [1].

2. METHOD

The proposed method (see Figure 1) builds upon the advanced approaches [2] for stress detection by analyzing the problem of stress detection using machine learning and signal processing techniques first in laboratory conditions, and then applies the extracted laboratory knowledge on real-life data.

The laboratory dataset was collected using a standardized stress-inducing method. 21 subjects participated in the experiments and were monitored with a wrist-device equipped with bio-sensors. Numerous features were extracted from the device's bio-sensors and selected using a feature-selection algorithm. Finally, a machine-learning method was applied to learn a laboratory stress detector. The laboratory stress detector detected stress with an accuracy of 85% for a two-class problem ("no stress" vs "stress").

The real-life dataset consisting of 55 days of data was collected by monitoring 5 subjects who were wearing the wrist device 24/7 and were keeping track of their stressful events. For this experiment, the laboratory stress detector was augmented with another two modules in order to capture the user's activities and context. Therefore, the method consist of three machine-learning components: the laboratory stress detector that detects short-term stress; an activity recognizer that continuously recognizes user's activity; and a context-based stress detector that exploits the output of the laboratory stress detector and the user's context in order to provide the final decision for 10-minute intervals. The best-performing context-based model detects (recalls) 70% of the stress events with a precision of 98% [3].

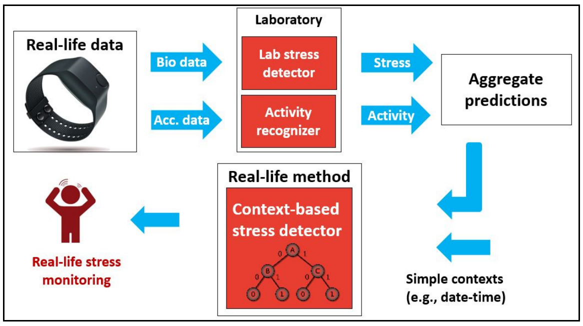

Figure 1. Proposed method for stress detection in real-life.

3. CONCLUSION AND DISCUSSION

We proposed a method for stress detection in unconstrained environments (real-life). At the beginning, the challenges were identified (subjectivity, fuzzy ground truth and unavailable direct monitoring). Having these challenges in mind, the problem of stress detection was first analyzed in laboratory conditions using off-the-shelf wrist device equipped with bio-sensors, and the extracted laboratory knowledge was applied on a real-life data. In addition to the laboratory knowledge, a real-life context information was needed for the method to be successfully applied on the real-life data. The context information was required to distinguish between psychological stress in real life and the many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.). Adding a context information to the stress detection system is a novel idea which significantly improved the performance of the system on the real-life data.

Even though the proposed context-based method for stress detection was tested on 55 days of real-life data, this data belongs to only to 5 subjects. To confirm the obtained results we need a bigger population. In addition, stress is highly dependent on physiological signals that depend on age, gender physical fitness. To check the robustness of the method, it needs to be tested on a bigger population with higher variety in terms of health, gender and age. Finally, the overall data in the study is collected using the Empatica device, thus the proposed context-based method is biased towards that device. In future we plan to test the method cheaper devices (e.g., Microsoft Band).

REFERENCES

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