Monitoring Physical Activity and Mental Stress using Wrist-worn Device and a Smartphone

Božidara Cvetković, Martin Gjoreski, Jure Šorn, Pavel Maslov, Mitja Luštrek

Jožef Stefan Institute, Department of Intelligent Systems, Jamova 39, 1000 Ljubljana, Slovenia
boza.cvetkovic@ijs.si

Abstract. The paper presents a smartphone application for monitoring physical activity and mental stress. The application utilizes sensor data from a wristband and/or a smartphone, which can be worn in various pockets or in a bag in any orientation. The presence and location of the devices are used as contexts for the selection of appropriate machine-learning models for activity recognition and the estimation of human energy expenditure. The stress-monitoring method uses two machine-learning models, the first one relying solely on physiological sensor data and the second one incorporating the output of the activity monitoring and other context information. The evaluation showed that we recognize a wide range of atomic activities with an accuracy of 87 %, and that we outperform the state-of-the art consumer devices in the estimation of energy expenditure. In stress monitoring we achieved an accuracy of 92 % in a real-life setting.

Keywords: Machine-learning, Activity Recognition, Estimation of Energy Expenditure, Mental Stress Detection, Wrist-worn device, Smartphone

1 Introduction

A typical worker in a competitive labor market in developed countries spends long hours in the office (sitting disease) under high mental stress. Since it is acknowledged that the lack of physical activity and mental stress contribute to the development of various diseases, poor mental health and decreased quality of life, it is crucial to increase the self-awareness of the population and provide solutions to improve their lifestyle. Wearable devices and mobile applications with accurate monitoring of physical activity and mental stress modules could offer such solutions.

Popularity of physical activity monitoring is seen in the number of smartphone applications, dedicated devices and smartwatch applications available on the market. The majority of smartphone-only or wristband-only applications are either based on step counting, or use a metric called activity counts which correlate motion intensity with the human energy expenditure (EE) using a single regression equation [1]. Such approaches are somewhat effective only for monitoring ambulatory activities. More accurate approaches recognize the users activity using activity recognition (AR) and utilize it as a machine-learning feature for estimation of EE (activity-based approaches). However, these approaches do not handle the varying location and orientation of the smartphone, which limits their real-life performance.

Monitoring mental stress using commercial and unobtrusive devices is a new and challenging topic, which is why few dedicated devices are available on the market. Until now, the most advanced approach was cStress [2], which utilizes the ECG sensor and is suitable for everyday use. However, the authors proposed replacing the somewhat uncomfortable ECG sensor with a wrist device, and better exploiting the information on the users context.

We present a mobile application that uses machine learning on smartphone- and wristband sensor data for real-time activity monitoring and mental stress detection. The monitoring automatically adapts to the devices in use and to the orientation and location of the smartphone on the body. The stress detection uses the outputs of the activity monitoring and other information as context to improve the performance.

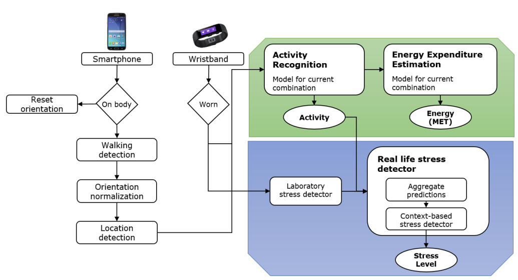

Fig. 1. Pipeline for physical activity and stress monitoring.

2 System Implementation and Methods with Evaluation

The system is implemented on a standard Android smartphone. It connects to the Microsoft Band 2 wristband over Bluetooh, collects and processes sensor data from both devices. It performs activity and mental stress monitoring in real time. The results are shared over MQTT protocol with a web application for demonstration.

2.1 Physical Activity Monitoring Method

The physical activity monitoring method is composed of six steps (left side and green-shaded modules of Fig. 1). The inputs are accelerometer and physiological data from a smartphone and/or wristband. The outputs are the recognized activity and the estimated energy expenditure in MET (1 MET is defined as the energy expended at rest, while around 20 MET is expended at extreme exertion). The first step uses heuristics to detect the devices currently present on the user's body. If the smartphone is present, the method anticipates a walking period of 10 seconds, which is detected using a machine-learning model (second step). The walking segment is used for normalizing the orientation of the smartphone (third step). The normalized data is fed into the location detection machine-learning model, which is trained to recognize whether the smartphone is in the trouser pocket, jacket pocket or a bag (fourth step). The present devices and the recognized location serve as context for the selection of the appropriate machine-learning model for activity recognition. We trained eight models, one for each location and combination of the devices, and one for the smartphone before orientation is normalized. The AR is performed on 2-second and the EE estimation on 10-second data windows. The reader is referred to [3] for details.

The evaluation of the method was performed on the dataset of ten volunteers performing a scenario of predefined activities (lying, sitting, standing, walking, Nordic walking, running, cycling, home chores, gardening, etc.). The volunteers were equipped with smartphones, a wristband and an indirect calorimeter for obtaining ground-truth EE. The evaluation was done with the leave-one-subject-out approach. We achieved AR accuracy of 87 %, and the mean absolute error of the EE estimation of 0.64 MET which outperforms the state-of-the-art commercial device Bodymedia (error of 1.03 MET).

2.2 Stress Monitoring Method

The mental stress monitoring method is composed of two steps presented in blue-shaded modules of Fig. 1. The first step is a laboratory stress detector, which is a machine-learning model trained to distinguish stressful vs. non-stressful events based on physiological data recorded in the laboratory, where stress was induced by solving mathematical problems under time pressure [4]. The detection is performed on the 4-minute data windows. In real life, there are many situations that induce a similar arousal to stress (e.g., exercise), so the laboratory stress detector is inaccurate. The algorithm is enhanced with a context-based stress detector which uses the predictions of the laboratory stress detector, as well as the information on the physical activity and other context information (e.g., time of the day, history of predictions), to perform stress detection every 20 minutes.

The evaluation of the method was performed on a dataset of 55 days of four volunteers leading their lives as normal. They were equipped with a wristband and the mobile application to label ground-truth stress. The evaluation was done with the leave-one-subject-out approach. We achieved classification accuracy of 92 % and the F-measure of 79 % (the results without the context were 17 percentage points worse).

3 Demonstration

To demonstrate the performance of the application, the visitor will be offered an Android smartphone and a wristband. He/she will choose the location of the smartphone and whether both devices or only one will be used. The visitor will perform activities of his/her choice and observe the stress level, estimated energy expenditure, recognized activity and location in real time through the web application shown in Fig. 2.

Fig. 2. Web application presents the processed data from the smartphone in real time.

4 Conclusion

We presented the state-of-the-art application for physical activity and mental stress monitoring, which relies on commercial devices many people already use. It is designed to handle real-life situations, and features real-time visual presentation via a web application, which is suitable for demonstration.

References

1. Crouter, S.E., Kuffel, E., Haas, J.D., Frongillo, E.A., Bassett, D.R.: Refined Two-Regression Model for the ActiGraph Accelerometer. Med. Sci. Sport. Exerc. 42, 1029-1037 (2010).
2. Hovsepian, K., AlAbsi, M., Ertin, E., Kamarck, T., Nakajima, M., Kumar, S.: cStress: Towards a Gold Standard for Continuous Stress Assessment in the Mobile Environment. Proc. ACM Int. Jt. Conf. Pervasive Ubiquitous Comput. (UbiComp 2015). 493-504 (2015).
3. Cvetkovic, B., Szeklicki, R., Janko, V., Lutomski, P., Lustrek, M.: Real-time activity monitoring with a wristband and a smartphone. Inf. Fusion. (2017).
4. Gjoreski, M., Gjoreski, H., Lutrek, M., Gams, M.: Continuous stress detection using a wrist device: In laboratory and real life. In: UbiComp Adjunct, pp. 1185-1193 (2016).