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

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Abstract. This 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 the 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 the 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 the competitive labor market of developed countries spends long hours in an office (sitting disease) under high mental stress. Since it is acknowledged that a 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 offer a promise of such solutions, with a crucial part being accurate monitoring of physical activity and mental stress.

The popularity of physical activity monitoring is seen in the number of smartphone applications, dedicated devices and even smartwatch applications already 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 correlates motion intensity with the human energy expenditure using a single regression equation [1]. However, such approaches are somewhat effective only for ambulatory activities. Activity-based approaches [2], which recognize the user's activity and use it as one of the features in a machine-learning model for energy expenditure estimation, are more accurate. However, until today, we have not come across any application using such an approach. Research system do use them, but they 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 relatively new and challenging topic, which is why few dedicated devices are available on the market [3][4]. Healey and Picard [5] were the first to detect stress using physiological sensors, which required intrusive wires and electrodes. Until now, the most advanced approach was cStress [6], which utilizes an 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 user's 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.

2 System Implementation and Methods with Evaluation

Our system is implemented on Android and runs on an average smartphone. It connects to the Microsoft Band 2 wristband over Bluetooth. The application collects and processes the sensor data from both devices, and perform the activity and mental stress monitoring in real time. The results of both modules are shared over MQTT protocol with a web application for visual presentation and 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 trousers pocket, jacket or a bag (fourth step). The present devices and the recognized location serve as context for the selection of an 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 activity recognition is performed on 2-second data windows and the energy expenditure estimation on 10-second data windows. For more information on the method using a different device, the reader is referred to [7].

The evaluation of the method was performed on 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 in all relevant locations, a wristband and an indirect calorimeter for obtaining ground-truth expended energy. The evaluation was done with the leave-one-subject-out approach. We achieved the activity-recognition accuracy of 87%, and the mean absolute error of the energy expenditure estimation of 0.64 MET. The state-of-the-art commercial device Bodymedia achieved the error of 1.03 MET.

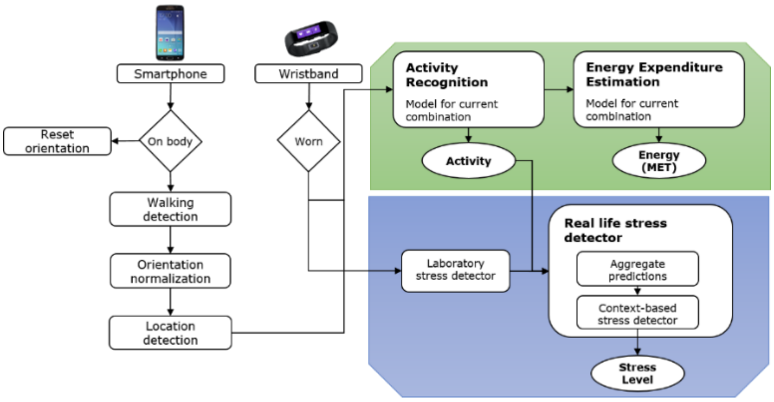

Fig. 1. Pipeline for physical activity and stress monitoring.

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 a laboratory, where stress was induced by solving mathematical problems under time and evaluation pressure [8]. The detection is performed on 4-minute data. In real life, there are many situations that induce a similar physiological arousal to stress (e.g., exercise, eating, hot weather), so the laboratory stress detector is inaccurate. In the second step, we thus introduce a context-based stress detector. This detector is a machine-learning model that uses as input the predictions of the laboratory stress detector, as well as the information on the physical activity from the respective module and other context information such as the time of the day and a short history of predictions, to provide a final 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 a mobile application to label ground-truth stress. The evaluation was again done with the leave-one-subject-out approach. We achieved the 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 weather 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 web application shown in Fig. 2.

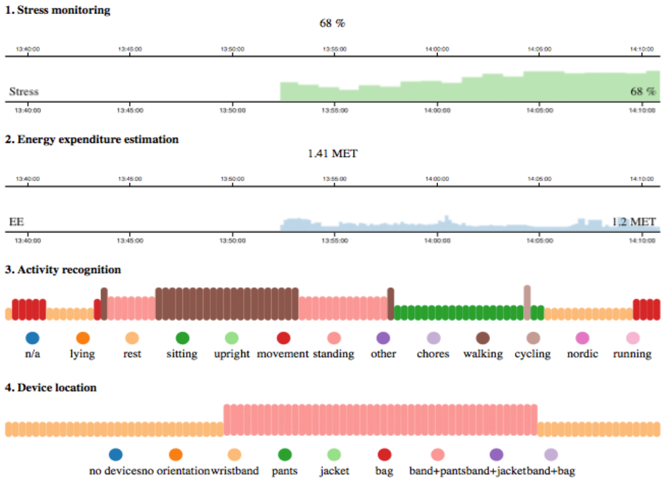

Fig. 2. Web application presents the processed data from the smartphone in real time.

4 Conclusion

We presented a state-of-the-art application for physical activity and mental stress monitoring, which relies on commercial devices such as 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.

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