Real-time Physical Activity and Mental Stress Management with a Wristband and a Smartphone

Božidara Cetković
Martin Gjoreski
Jure Šorn
Pavel Maslov
Department of Intelligent Systems
Jožef Stefan Institute
Ljubljana, Slovenia

Michał Kosiedowski
Maciej Bogdański
Aleksander Stroiński
Poznań Supercomputing and Networking Center
Poznań, Poland

Mitja Luštrek
Department of Intelligent Systems
Jožef Stefan Institute
Ljubljana, Slovenia
mitja.lustrek@ijs.si

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Abstract
Modern lifestyle is largely sedentary and often stressful, giving rise to extensive research and development of solutions for the management of these two lifestyle aspects. Physical activity monitoring is a mature area of ubiquitous computing, with many devices and mobile applications available on the market. Mental stress monitoring is still a hot research topic with few commercial solutions. This demo presents technology that goes beyond the state of the art in both areas, and powers a mobile application for lifestyle management.

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Activity; Stress; Management; Well-being; Machine learning; Wristband; Smartphone

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Physical Activity Monitoring
The physical activity monitoring is composed of activity recognition and the estimation of human energy expenditure (in MET = metabolic equivalents of task, 1 MET corresponds to the energy expended at rest). While the research on activity recognition with wristbands and smartphones is extensive, it generally

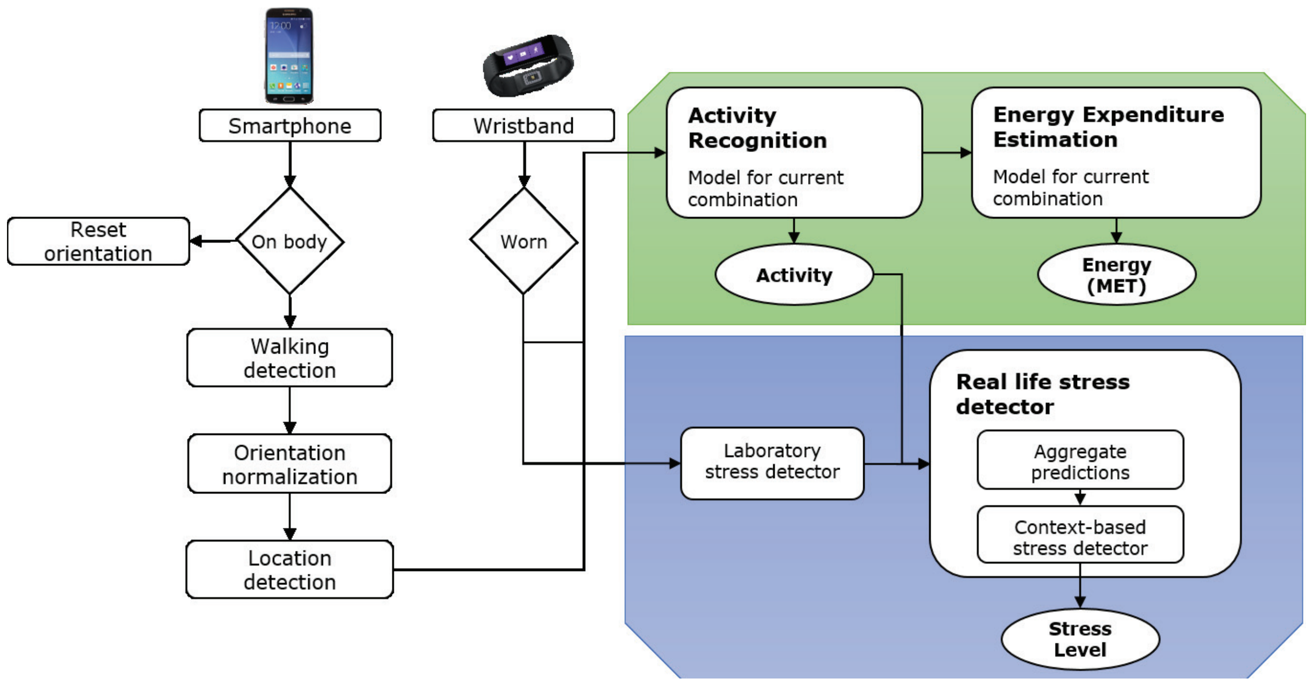

Figure 1. Workflow of the algorithms. Left side presents the preprocessing, data normalization and context detection. Top right side is the activity monitoring module and bottom right is the stress monitoring module.

does not address the practical problems related to people carrying their phones (and sometimes wristbands) freely on the body in different orientations and locations. These problems have been investigated by a few researchers [1], but to the best of our knowledge, the algorithm to be demonstrated here is the first that automatically adapts the activity recognition to the presence, orientation and location of single or both devices. The research on the estimation of energy expenditure until now relied on fixed-location and orientation-dependent features, which limited its flexibility and accuracy.

We developed an algorithm for real-time activity recognition and the estimation of energy expenditure [2] which can utilize acceleration and physiological data from the wristband, smartphone or both devices. The workflow of the algorithm is presented in Figure 1. The algorithm first detects the presence of the devices, and then uses an orientation- and location-independent machine-learning model to recognize 10 seconds of walking. This walking segment gives information about the direction of the gravity and is used for the normalization of the orientation of the smartphone, if present.

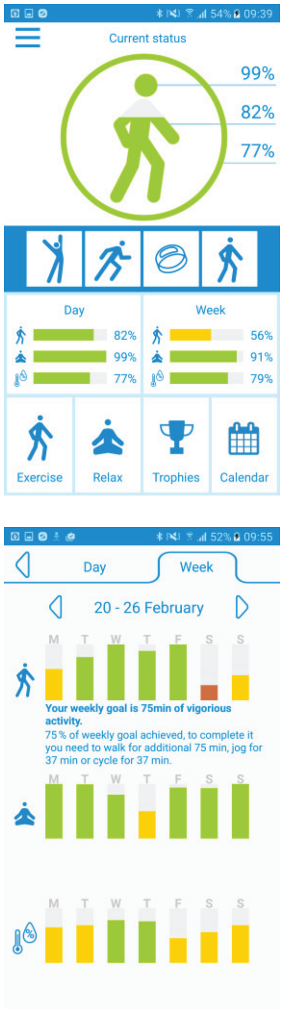

Figure 2. Fit4Work application.

Once the orientation of the smartphone is normalized, the location (trousers, jacket, bag) is recognized using an additional machine-learning model. The information about the present devices and the smartphone location are afterwards used as a context for the selection of the appropriate machine-learning models for activity recognition and the estimation of energy expenditure. The accuracy of the activity recognition ranges from 80 to 95%, and the mean absolute error of the energy expenditure estimation from 0.5 to 0.75 MET (the error of the BodyMedia state-of-the-art consumer device on our data was 1 MET). The reader is referred to [2] for more details.

Mental Stress Monitoring

Most research on mental stress detection with physiological sensing devices has been done in laboratory conditions with few confounding factors that produce similar physiological responses as stress. Until now, the best approach for everyday stress detection was cStress [3], which relies on a wearable ECG monitor. However, the authors proposed replacing the somewhat uncomfortable ECG monitor with a wristband, and better incorporating the information on the user's context in the stress detection, which is what we did.

We developed an algorithm for mental stress detection [4] that utilizes heart rate, heart rate variability and galvanic skin response data from the wristband, as well as the outputs of the physical activity monitoring. The physiological sensor data are first fed into a laboratory stress detector. This is a machine-learning model trained on data where stress was induced by solving mathematical problems under time and evaluation pressure. The outputs of the laboratory stress detector together with the data on the physical activity, time of the day and other contextual information are fed into a real-life stress detector. This is another machine-learning model trained on data collected in the wild and self-labeled by the subjects. Its purpose is to distinguish genuinely stressful situations from situations that produce similar physiological responses (e.g., physical exertion). The algorithm detects (recalls) 70% or real-life stress events with the precision of 95%.

Mobile Application for Lifestyle Management

The mobile application was originally developed in the Fit4Work project (http://www.fit4work-aal.eu/) for older workers, but is suitable for general non-technical population. Participative design was used to develop a simple interface that enables the users to see their physical and mental state at a glance (the body and head of the user in top of Figure 2). The percentage relating to the physical activity (body) informs the user how much of the daily goal for physical activity they have achieved. Until the goal is reached, the application recommends the user to exercise. The percentage relating to the mental state (head) informs the users how relaxed they are – it uses a relaxation score that decreases when stress is detected, and increases when the user is relaxed. In case of stress, the application recommends a relaxation exercise, which further increases the relaxation score. The user can also view historic data in terms of achieved weekly relaxation scores (bottom of Figure 2).

Demonstration

The demonstrators/visitors are given a Microsoft Band 2 and a smartphone. They can choose which devices they want to use (one or both) where the smartphone can be worn in any orientation at three locations

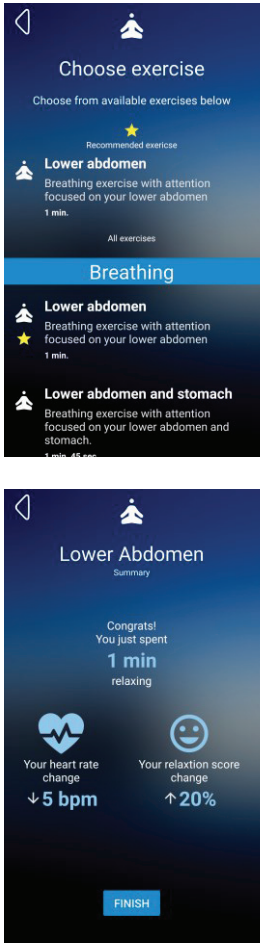

Figure 3. Fit4Work stress relief exercises.

(trousers, jacket, bag). The data from the devices are processed in real-time on the smartphone, and the results are transmitted via the MQTT protocol to a server. The demonstrators/visitors are shown the interface of the mobile application as seen in Figure 2. The interface shows physical activity progress and detected mental stress of the visitor during the conference days. In addition, the mobile application enables the demonstrators/visitors to perform relaxation exercises. After the relaxation exercise is performed it presents the relaxation effect of the chosen exercise on their stress level as seen in Figure 3. A web application (Figure 4) presents the real-time results of the algorithms. It shows the detected present devices, the recognized location of the smartphone, the recognized activity (current and history), the estimated energy expenditure and the estimated level of mental stress. The application also presents the workflow of both algorithms, highlighting the active components, so that the visitor can understand the inner working of the algorithms.

Conclusion

We present a mobile application for physical activity and mental stress management using machine-learning models on wristband and smartphone sensors data. The recognized activities, its intensities and detected mental stress level are used for generating recommendations in terms of motivation to be more physically active or to perform relaxation exercises.

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Figure 4. Web application showing the processed data.

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