Monitoring and Management of Physical, Mental and Environmental Stress at Work

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ABSTRACT
In this paper, we present the design of the Fit4Work system for monitoring and management of physical, mental and environmental stress at work. In addition, preliminary results of the monitoring modules are presented. The goal was to design a low-cost system that can use commercial sensors to monitor several aspects of the users' lifestyle and to provide recommendations for improving it. The system is designed for older workers who are subject to sedentary stressful work in an office environment. The preliminary results show that the system can sufficiently detect sedentary, stressful and unhealthy environment and provide information in the form of recommendation to the user.

Categories and Subject Descriptors
D.3.3 [**Human-centered computing**]: Ubiquitous and mobile computing – *ambient intelligence, mobile computing, ubiquitous computing*

Keywords
Physical activity monitoring, mental stress detection, environment quality management, wearable sensors, ambient sensors

1. INTRODUCTION
The pace of life has been increasing with each day in the developed world, resulting in a lot of health risk factors. Most of the active population spends large amount of time at work in closed environments under productivity pressure, which contributes to different aspects of stress, such as unhealthy amount of sedentary activity, high mental stress and in many cases low quality of the environment. If such lifestyle is maintained over longer period of time and even becomes a regular lifestyle of a person it can severely contribute to development of other behavioral changes and chronical or even deadly diseases.

Physical stress or physical inactivity is the fourth leading cause of death worldwide. It contributes to increased mental stress, development of cardiovascular diseases, diabetes, obesity and other unhealthy behavioral changes. Exposure to *mental stress* at the workplace is not necessarily a negative thing since right amount of stress is needed for better productivity, however, prolonged exposition to stress can result in chronical stress which is a trigger for slower body recovery, other mental illnesses and vulnerability to infections due to decreased immune system. *Environmental stress* is related to overstaying in the environment with low quality conditions. The term Sick Building Syndrome (SBS) is used for buildings that cause the occupants various health and comfort problems, and is most commonly linked with air quality. It has been shown that in addition to health related problems, the bad environmental conditions can cause decreased productivity. Inappropriate temperature decreases the productivity by 10%, humidity by 5% and air pollutants by 6-9%, which can result in a higher level of mental stress due to productivity pressure [1][2][3]. The objective of the Fit4Work system [4] is to detect sedentary, stressful and unhealthy environment and provide information in the form of recommendation to the user.

The smartphone industry is constantly developing and with each new product the difference between the computing power of a computer and a smartphone is being blurred. Today's average smartphone is equipped with sensors for motion monitoring (e.g., accelerometers, gyroscopes, GPS, etc.), ambiance monitoring (e.g., microphones, light, etc.) and with each next generation this list is extended. If we take into account that by the end of 2017, over a third of the world population is projected to own a smartphone (2.6 billion users) it makes it the most appropriate device for mobile sensing and computing. Furthermore, with increased availability of commercial sensors and even dedicated devices that can connect with a smartphone and sense environmental parameters or physiological parameters of a person, the possibility of applications has become almost infinite.

Monitoring of persons' physical activity is not new and is in fact very popular in terms of number of smartphone applications, dedicated devices and even smartwatch applications already available on the market. Smartphone only applications for activity monitoring use smartphone accelerometer to estimate the burned calories and amount of movement based on the number of steps the user takes over a day. Dedicated devices such as Microsoft Band 2 [6] use simplified activity recognition and machine-learning to improve the estimated calorie burn. Apple Watch [7] goes one step further and contains hourly reminders if the person is sedentary and provides feedback and motivation to reach the daily goal. However, if the user wants to be monitored accurately it is required to input the current activity which is being performed. The applications and devices available on the market are satisfactory for most of the active users who want to track their activities such as running or just to get an insight into their lifestyle. If the application/device also provides a feedback and a motivation the price gets too high, thus being too expensive for an average person.

Monitoring mental stress using commercial and unobtrusive devices is relatively new and challenging research topic. Healey and Picard [8] were first to show that the stress can be detected using physiological sensors which required intrusive wires and electrodes. Hovsepian et al. [9] proposed cStress which continuously monitors stress level using an ECG sensor, and were looking forward to use smartwatches in the future. With the advancement of the technological devices equipped with physiological sensors, such as Empatica [10] and Microsoft Band 2 [6], these obtrusive methods could finally be implemented for everyday use. Various studies exist, where researchers combined signal processing and machine-learning to implement stress detection. The studies were utilizing different sources of signals, obtrusive sensors such as camera, microphone or unobtrusive wearables [11] such as wrist device which is acceptable for most of the people.

The monitoring and control of indoor environment parameters is a popular topic in smart–building research where they mainly focus on the trade-off between the occupants' comfort in terms of environment quality, and energy consumption [12]. In this research it is prerequisite to have an automated building and fully equipped rooms with HVAC systems which can be a substantial investment and mainly indicates that most of the people living in older buildings will not be able to use such system. To develop a system which does not need very expensive equipment one must develop several virtual sensors for detection/estimation of parameters that cannot be sensed directly and develop prediction models for environmental parameters. A correlation between the environmental values and the occupancy state or window state has been reported in previous research [13] which proves that it can be modeled. Estimation of the number of occupants was successfully achieved with using the data of single or multiple environmental parameters [14]. We did not come across any relevant methods for window state detection. The prediction of the dynamics of the parameters is usually done with the predictive control technique [15] which requires the user to describe the environment in detail (e.g., material of walls, windows, etc.) which is not very user friendly.

The Fit4Work system will utilize sensors from an accelerometer equipped smartphone, Microsoft Band 2 and a commercial weather station NetAtmo [16] to monitor and detect increased physical, mental and environmental stress at workplace and provide recommendations through the dedicated smartphone application which will assist in management of the stresses. To be able to successfully achieve this goal we designed a system which utilizes multiple machine-learning models to monitor physical activity, mental stress of the user and predict the state of the workplace and predict future dynamics of the environmental parameters.

The paper presents the design of the final Fit4Work system for monitoring and management of physical, mental and environmental stress, and refers to preliminary results of the modules which were obtained independently of other modules.

2. FIT4WORK SYSTEM OVERWIEW

The Fit4Work system for monitoring and management of physical, mental and environmental stress is composed of three data analysis and recommendation components and is presented in Figure 1. The physical activity monitoring utilizes data from the smartphone accelerometer and Microsoft Band 2 to recognize the current activity of the user and to estimate the energy expenditure while performing the recognized activity. The mental stress monitoring utilizes data from the Microsoft Band 2 and physical activity as recognized by the physical activities module to detect the level of mental stress. The quality of the environment module utilizes data from the commercial weather station NetAtmo to detect whether the quality of the environment has decreased. Each of the data analysis components has its own recommendation component which utilizes results from the data analysis to generate recommendation. The generated recommendations are sent back to the users' smartphone.

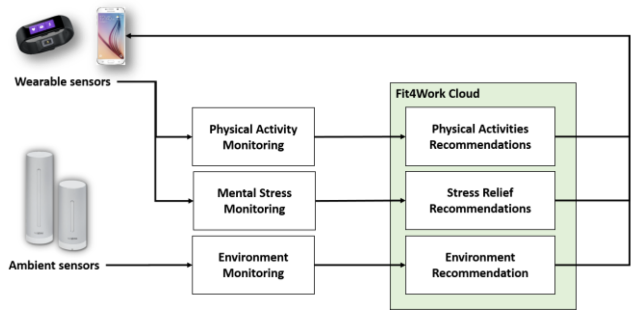

Figure 1. Fit4Work system for monitoring and management of physical, mental and environmental stress overview.

2.1 Physical Activities

The goal of the physical activity module is to recognize current state of the user is terms of activity and expended energy. Additionally, the output of the physical activity module is aggregated and used for generating recommendations which will guide the user to successfully achieve daily and weekly activity goals.

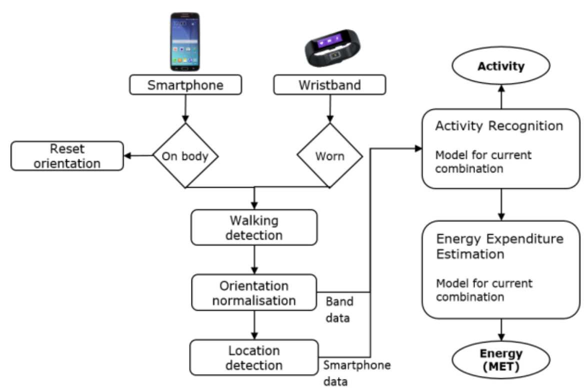

Figure 2. Workflow of the physical activity monitoring data analysis component

The physical activities method is composed of six tasks and is presented in **Figure 2**. The devices we use are the accelerometer equipped smartphone and the Microsoft Band 2 wristband capable of measuring acceleration and physiological signals such as heart rate, galvanic skin response, skin temperature and R-R interval. First, we check whether each of the two devices is present on the user's body. Second, if the smartphone or wristband is on the body, we wait for a walking period. Walking is detected with a machine-learning model in a location- and orientation-independent manner. The walking signal is a prerequisite for normalizing the orientation of the smartphone and the wristband and for recognizing the location of the smartphone. Third, when a 10-second period of walking is detected, we normalize the orientation and detect the location of the smartphone utilising location machine-learning model. If the smartphone ceases to be on the body because the user has taken it out of the pocket or bag, the information on the orientation and location is no longer valid and we have to wait until the next period of walking. Fourth, depending on the devices which are on the body and the location in which the smartphone is, we invoke the appropriate classification model for activity recognition (AR) and regression model for estimating user's energy expenditure (EEE). For more information the reader is referred to [17].

In this paper we present preliminary results for AR (lying, walking, running, standing, sitting, cycling, mixed) and EEE with the wristband only if the wristband is present and smartphone only if wristband is not present. The results are presented in Table 1. The experiments were performed on the data obtained with Empatica in scenario presented in [17]. The results of AR is presented in terms of accuracy and the EEE in terms of mean absolute error (MAE). The results of the EEE are compared against the commercial device SenseWear [19], one of the most accurate consumer devices for EEE.

Table 1. Preliminary results of the activity recognition and estimation of energy expenditure.

		Smartphone			
	Wristband	Trousers	Torso	Bags	SenseWear
AR [%]	88.4	87.9	78.9	79.5	/
EEE [MET]	0.87	0.87	0.92	1.15	1.0

Future work includes use of both devices if both are present as done in our previous work [17].

2.2 Mental Stress

The stress monitoring module continuously monitors user's stress and provides overview of stressful events to the user. Additionally, the output of the stress-monitoring module is used by a stress-relief module for suggesting appropriate exercises at appropriate time.

For the stress-monitoring module we developed a machine learning method which is applied on data collected via sensor-equipped device worn on the wrist, Microsoft Band 2. The method for detection of mental stress is presented in Figure 3 and consists of three machine-learning components (a base stress detector, an activity recognizer and a context-base stress detector).

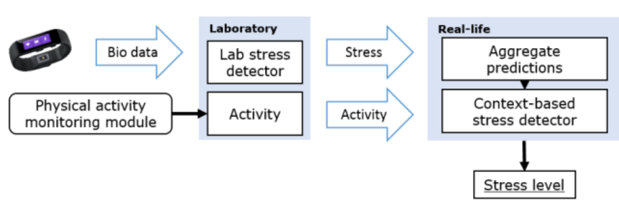

Figure 3. Method for mental stress detection.

The laboratory stress detector is a machine-learning classifier trained on laboratory data to distinguish stressful vs. non-stressful events in 4-minute data windows with a 2-minute overlap. As input it uses features computed from the physiological signals (blood volume pulse, heart rate, R-R intervals, skin temperature and electrodermal activity), and it outputs a prediction for possible stress event. In addition, the activity is retrieved from the physical activity monitoring module and provides a context information for the context-based stress detector. The context-based stress detector aggregates the predictions of the laboratory stress detector, uses context information and provides a prediction every 20 minutes. The interval of 20 minutes was chosen empirically. We decided to use the context-based classifier to distinguish between true stress and the many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.). By introducing the context-based classifier we can provide more information about the real-life circumstances and the user, thus to improve the detection performance.

The preliminary experiment of the module was done using the Empatica wristband and the results are presented in Table 1. For more details the reader is referred to [21].

Table 2. Confusion matrix for leave one user out evaluation of the mental stress detection module.

	No Stress	Stress
No Stress	790	23
Stress	51	63

Future work includes investigating the relation between labelled stress level, recognized stress level and cortisol levels and personalization of the models.

2.3 Quality of the Environment

Monitoring of the quality of the environment detects worsening of measured parameters and recommends appropriate actions which will return to or keep the parameters in optimal range. The module for monitoring and management of the quality of the environment is composed of three components - a sensing component, an ontology with a reasoner, and a simulator, as presented in Figure 4.

The sensing component is composed of hardware sensors and virtual sensors. The hardware sensors are the real sensors which measure the environmental parameters such as temperature, humidity, CO_2, noise, etc., while virtual sensors use machine – learning models on the raw parameter values to estimate room-specific properties that cannot be sensed directly such as estimating the number of occupants and detecting the state of the devices. The outputs of the sensing component are fed into the ontology, from which the reasoner infers actions that can improve the state of the environment, based on the current state and present devices. The list of actions returned by the ontology is fed into the simulator. The simulator is composed of prediction models and the quality rating module (Q–rating) which predicts the environmental values for all combination of actions and evaluates the resulting parameter states (values range between -1 and 1). The action resulting in the best state is finally recommended by the system. The reader is referred to [22] for more details.

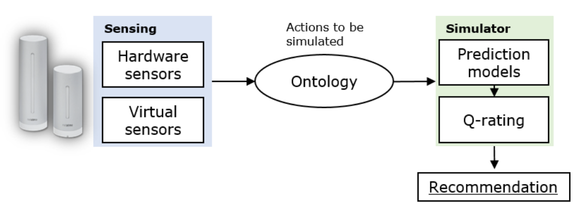

Figure 4. Method for monitoring and management of the quality of the environment.

The preliminary results on the winter data are shown in Table 3. First two rows present the results of the virtual sensors, one for detecting the window state and the second for estimating number of occupants, last three rows present the results of the prediction models. The result for the classification is presented in terms of accuracy and results for the regression in terms of mean absolute error (MAE) and root mean squared error (RMSE).

The future work includes development of the virtual sensors for other devices, such as humidifier, air conditioning etc. and improvement of the prediction models by using additionally collected data.

Table 3. Results of the machine-learning models used for virtual sensors (window state and number of occupants) and for prediction of environmental parameters.

	ACC		MAE		RMSE	
	E	V	E	V	E	V
Window state [%]	91	81	✗	✗	✗	✗
No. of occupants	✗	✗	0.6	0.5	1.2	0.8
Predict T [°C]	✗	✗	0.4	0.5	0.5	0.6
Predict H [%]	✗	✗	0.6	0.3	0.9	0.5
Predict CO_2 [ppm]	✗	✗	55	45	104	61

3. CONCLUSION

We present a work-in-progress system for monitoring and management of physical, mental and environmental stress which utilizes machine-learning models on the data from commercial devices (accelerometer equipped smartphone, Microsoft Band 2 and NetAtmo weather station) to detect the state of the user and recommend appropriate actions to improve users physical, mental and environmental state.

The goal of the Fit4Work project is to develop a low cost system which can be used in any environment (without the need to renovate or automate the environment). The preliminary results of each module show that selected devices in combination with intelligent algorithms can sufficiently detect sedentary, stressful and unhealthy environment and provide information in the form of recommendations to the user.

In the future, we plan to integrate the three modules into a single system in form of a smartphone application and develop first recommendation prototypes. We will upgrade the machine-learning models for recognition of the activities and estimation of energy expenditure to utilize both devices (the smartphone and the wristband) as seen in our previous work, personalize the stress detection method and upgrade its machine-learning models to utilize other contextual information and enhance the environment quality monitoring with additional machine-learning models.

4. ACKNOWLEDGMENTS

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