Energy Expenditure Estimation DEMO Application

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Abstract. The paper presents two prototypes for the estimation of human energy expenditure during normal daily activities and exercise. The first prototype employs two dedicated inertial sensors attached to the user's chest and thigh and a heart rate monitor. The second prototype uses only the accelerometer embedded in a smart phone carried in the user's pocket. Both systems use machine learning for the energy expenditure estimation. The focus of the demo is the convenience of using a smart phone application to provide the user with real-time insight into his/hers current status of the expended energy and also for on-the-spot encouragement based on the status. The evaluation and validation of both systems were done against the Cosmed indirect calorimeter, a gold standard for energy expenditure estimation and against the SenseWear, a dedicated commercial product for energy expenditure estimation.

Keywords: human energy expenditure, physical activity, wearable sensors, embedded smart phone sensors, smart phone application

1 Introduction

It is widely accepted that sufficient physical activity can have a positive impact on one's life [1]. Regardless of this fact, only small fraction of the modern population dedicates time to sufficient exercise. Physical inactivity is becoming one of the main premature death causes [2]. This calls for a quick and smart solution.

To motivate people to increase their physical activity, it is important to quantify it first. The intensity of physical activity or the expended energy (EE) is usually expressed in a unit called metabolic equivalent of task (MET), where 1 MET corresponds to the energy at rest. The MET values range from 0.9 for sleeping to over 20 for extreme exertion. To accurately measure the EE, one has to use methods such as direct calorimety [3], which measures the produced body heat, indirect calorimetry [4], which measures the amount of carbon dioxide production and oxygen consumption using the breathing mask, and doubly labelled water [5], which measures the exhaled carbon dioxide by tracking its amount in water labelled with deuterium and oxygen-18. None of these methods can be used in everyday life to continuously monitor the EE, moreover they are very expensive. Wearable sensors do not have these problems, although they are somewhat less accurate.

Inertial sensors are very popular in different domains [6–8] due to their accessibility and understandable concept of accelerometry. An average smart phone contains an inertial sensor and today we hardly leave our home without it. As a result, we can observe a growing trend in development of mobile applications that use sensor data for monitoring.

Mobile application markets already offer a number of application for EE estimation. These applications either estimate the EE based on the number of steps the user does over one day [9] (essentially pedometers), or estimate the intensity of phone movement caused by the activity [10]. The weakness of pedometers is that they can be used only to detect the ambulatory activities such as walking or running. Applications that detect the intensity of the activity usually require the user to manually define which activity is being performed.

EE estimation is also a popular topic in the research community. Recent papers by Pande et. al. [11] report good results on estimation using smartphone data, personal information and artificial neural network. However, this paper presents EE estimation for walking up and down the stairs, standing and walking. This is only a subset of activities a person performs during a normal day. Other papers are also limited to a small subset of activities.

This paper present two prototypes: the first one uses two commercially available accelerometers and a heart rate monitor, and the second one uses only the accelerometer embedded in a smartphone. We compare these two prototypes against the gold standard Cosmed [12] indirect calorimeter and Senswear [13], a dedicated EE estimation device. The activities performed by the user are normal daily activities such as office work, cooking, cleaning, light exercising and sports activities such as lying, walking, running, cycling. A prototype application running on a smart phone provides helpful tips and encouragements to the user in addition to the EE estimation.

2 Human Energy Expenditure Estimation Systems

We considered five different sensors as shown in Figure 1: a) a wireless tri-axial Shimmer accelerometer [14]; b) an accelerometer and heart rate monitor integrated in the Zephyr Bioharness chest strap [15], which also measured heart rate; and c) an accelerometer embedded in a smart phone, in our case a Samsung Galaxy SII [16]. The reference energy expenditure values, which were used to develop and evaluate the EE estimation models, were measured using d) Cosmed $k4b^2$ portable indirect calorimeter [12]. Finally, we used e) SenseWear, a commercial EE estimation armband developed by Bodymedia [13] as another result for comparison.

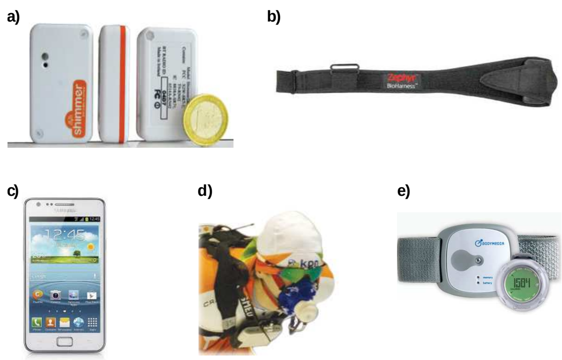


Fig. 1: Sensors used: a) Shimmer accelerometer, b) Zephyr Bioharness chest strap, c) a Samsung Galaxy SII smart phone, d) portable indirect calorimeter Cosmed $k4b^2$ and e) SenseWear EE estimation device.

Both prototypes use machine learning for the estimation of the EE, therefore a high quality dataset was collected for this purpose. The data was collected in a laboratory using all the sensors mentioned above. The laboratory was equipped with fitness equipment, such as treadmill and indoor bicycle. The person being measured performed a scenario containing activities ranging from lying to running, and from office work to shovelling, with the intention to collect a wide sample of typical daily activities and exercise. The scenario was performed by ten healthy people.

2.1 Energy Expenditure Estimation Using Dedicated Sensors

This system uses two types of sensors: two tri-axial accelerometer placed on the chest and thigh, and a heart rate monitor. Data from all the sensors are collected in real time using a dedicated APIs and software provided by the manufacturers. Sampling frequency of the accelerometers is 50Hz, while the heart rate monitor returns one hart rate measure per second. The data is received by a Java client running on a PC. The client pre-processes the data using a low-pass and a band-pass filter.

The activity recognition is performed every two seconds. The preliminary tests [17] showed that a 2-second window size for the sliding window is a reasonable trade-off between the duration of the activities and the recognition delay. The stream of collected data is split into 2-second time windows. For each time window, 41 features are computed. This feature vector is then passed to the machine learning model which was computed from the data gathered during the experiments using the Random Forest algorithm, as implemented in the

Weka suite [18]. The machine-learning model is trained to classify following ten activities: lying, sitting, walking, standing, running, allfours, kneeling, leaning, transition and cycling. Evaluation of the classification model used for activity recognition has achieved a classification accuracy of 92.0 %.

The estimation of the EE is performed every 10 seconds. The stream of collected data is split into 10 seconds windows, each window overlapping with the previous one by one half of its length. For each window a set of features is computed. The features form a feature vector that is fed into a regression model for the estimation of the EE. The feature vector consists of one heart rate feature, the prevalent activity provided by the activity recognition module and 68 other features calculated from the accelerations. The regression model was trained with the support vector regression machine-learning algorithm as implemented in the Weka suite.

The evaluation of the machine learning model was done using two types of error measure. The first error measure is the mean absolute error (MAE). Absolute error is the absolute difference between the predicted and true value. The second error measure is the mean absolute percentage error (MAPE). It measures the ratio between the absolute error and the true value. SenseWear MAE is 0.86 MET and MAPE 33.53%. This system outperformed the SenseWeare with MAE of 0.60 MET and MAPE 26.71.

2.2 Energy Expenditure Estimation Using Smart Phone

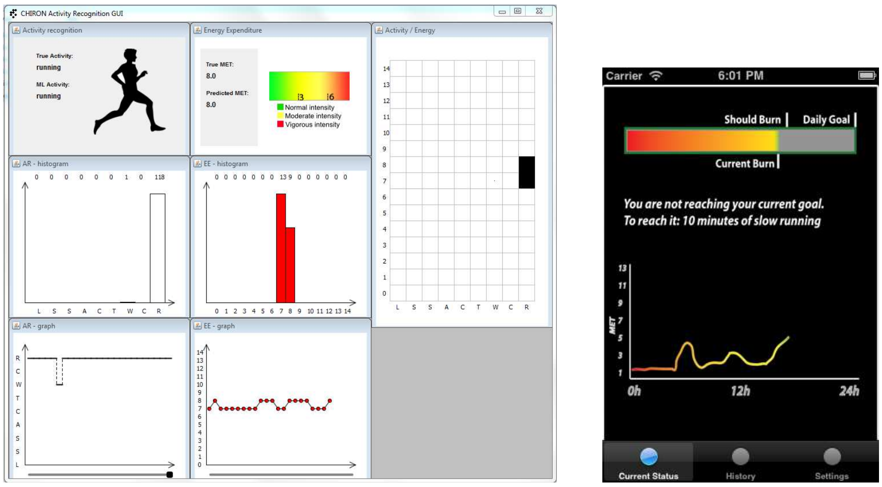
This prototype uses the accelerometer embedded in the smart phone, and runs entirely on the phone. The smart phone should be carried in the right pocket downwards with screen towards the body, although the prototype works in other orientations as well but with a lower accuracy.

Similar to the previous prototype, the estimation of the EE is performed every 10 seconds from the stream of data split into 10 second overlapping windows. For each window a set of features is computed. The feature vector consists of 64 features calculated only from the accelerations. The machine-leaning algorithm of choice was again support vector regression. This prototype does not have the activity recognition module, due to orientation problems of the smart phone.

The prototype using smart phone outperformed SenseWear according to MAE, 0.83 MET, and was a bit worse according to MAPE, 33.97%.

3 Demo

The demo application with the prototype EE estimation systems using dedicated sensors can be seen in Figure 2 a). The left part of the application is the activity recognition graphical interface, where the system has recognised current activity as running. The middle part is the estimation of EE, where we can observe the predicted MET value (as well as the true MET value when the application is running offline on data with gold standard EE measurements from the indirect calorimeter) and some statistics of the prediction.



(a) EE using dedicated sensors. (b) EE using smartphone.

Fig. 2: User interface for estimation of EE when using dedicated sensors a) and when using smartphone sensors b).

The smart-phone prototype can be seen in Figure 2 b). The user interface shows the current status on how much energy was expanded until current time point. It also shows the daily goal and how much energy should be burned by now. It contains a graph of average hourly EE for the current day. In addition to the EE estimation, the prototype contains an encouragement module, which encourages the user to achieve the daily goal.

For encouragement module, the user has to provide his/hers weight, height, age and gender. Based on these information the basal metabolic rate (BMR) is calculated. BMR equals to the number of calories the body would burn if a user would stay in bed all day and is defined as follows: $bmr_{male} = 10 * weight + 6.25 * height - 5 * age + 5$ and $bmr_{female} = 10 * weight + 6.25 * height - 5 * age - 161$

In the demo application, the expected daily consumption equals to BMR plus 1000 calories. This is a rough estimate of how much calories a user should burn during one day and is used only in a prototype version of the application. At each time point we can determine the calories burnt by metabolic processes and by movement (with EE) and if the user will reach the daily goal by the end of the day. If the goal will not be reached, the application warns the user and proposes one of the predetermined exercises and the duration in order to achieve the daily goal. If the daily goal is surpassed the application rewards the user. The application computes the amount of snacks the user can consume and remain in the scope of the daily goal.

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