Activity Recognition and Human Energy Expenditure Estimation with a Smartphone

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Abstract— **This paper presents a novel method for activity recognition and estimation of human energy expenditure with a smartphone and an optional heart-rate monitor. The method detects the presence of the devices, normalizes the orientation of the phone, detects its location on the body, and uses location-specific models to recognize the activity and estimate the energy expenditure. The normalization of the orientation and the detection of the location significantly improve the accuracy; the estimated energy expenditure is more accurate than that provided by a state-of-the-art dedicated consumer device.**

Keywords- activtiy recognition; human energy expenditure; smartphone; accelerometer; heart-rate monitor

I. Introduction

Regular physical activity can have a positive impact on one's life [1], yet only a small fraction of the modern population exercises sufficiently. To appropriately 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 expended 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 or indirect calorimetry or doubly labelled water (DLW) [2][3]. Direct calorimetry measures the body heat, indirect calorimetry measures the carbon dioxide production and oxygen consumption using a breathing mask, and DLW 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, and they are also quite expensive. An alternative are also consumer devices in the form of wristbands or armbands for tracking fitness activities, which correlate the measured acceleration with the EE. More advanced devices include additional sensors for measuring heart rate, skin and near-body temperatures, galvanic skin response, etc. These devices are definitely more appropriate for everyday life than (in)direct calorimetry and DLW, since they are more convenient and less expensive, but are somewhat less accurate.

An average smartphone, which most people already have, contains a tri-axial accelerometer, making it arguably the most convenient device to estimate the EE. It can also connect to additional devices such as a heart-rate monitor for even more accurate estimations. Application markets already offer a number of application for EE estimation. These typically either estimate the EE based on the number of steps the user takes over a day [4] (essentially pedometers), or according to the intensity of the phone's movement if the user inputs the activity [5]. The EE is afterwards estimated according to a table such as the one in the Compendium of Physical Activities [6]. However, more flexible estimation is clearly desirable, and it should incorporate automatic activity recognition (AR).

While AR with dedicated sensors is fairly mature, AR with a smartphone is more difficult because the phone can be carried in different locations with different orientations. Sirtola et al. [7] studied orientation- and location independent features, reporting high AR accuracy for five activities. Several researchers developed AR approaches that normalize the orientation of the smartphone, resulting in an increased accuracy [8][9]. Sun et al. [10] studied AR when the location of the smartphone varied. They reported only a modest increase in the accuracy when location-specific classifiers were used, probably due to recognizing only ambulatory activities and driving, where the intensity of the phone's movement is correlated with the activity in a relatively straightforward manner. They did not detect the location of the phone automatically. An example of EE estimation with a smartphone is the work by Pande et. al. [11], who reported accurate EE estimation for a subset of regular daily activities. They did not take the location or orientation of the phone into account, and we are aware of no work on EE estimation that did that.

This paper present a smartphone application for activity monitoring when the smartphone is worn freely on the body. The application performs AR and uses the recognized activities as an input for EE estimation. It automatically detects if the smartphone is worn or not, normalizes the orientation, detects the location, and uses AR and EE-estimation models specific to the detected location. The application can use an additional device such as heart-rate monitor to increase the accuracy of the AR and EE estimation. The EE-estimation accuracy of the application was compared against the gold standard Cosmed K4b2 indirect calorimeter [12], and Sensewear [13], an EE-estimation armband.

II. System Implementation and Methods

A. System Implementation

The application is implemented in Java for Android and runs on Android smartphone. It connects with the Zephyr BioHarness [14] chest-worn heart-rate monitor with an embedded tri-axial accelerometer, when available. The AR and EE estimation are performed in real-time. The application displays the results of the AR and EE estimation on graphs that can be viewed by the user to get an insight on the amount of activity performed over a selected interval of time (day, week, month, etc.).

B. Activity Monitoring Methods

The method for activity monitoring is composed of six tasks and is presented in Fig 1. First, the method detects the **presence of the devices** with simple heuristics. The smartphone is considered present on the body unless one of the following is true: the screen is on, there is an ongoing call or the phone is still (the number of peaks in the absolute acceleration signal is zero). The Zephyr heart-rate monitor can self-report whether it is being worn. If the smartphone is present, the orientation of the smartphone has to be normalized. The **normalization of the orientation** is based on the assumption that the average acceleration during walking corresponds to the Earth's gravity. For that purpose, the method seeks to detect 10 seconds of walking (walking detection is discussed in the next paragraph). The average acceleration during that time is used to normalize the orientation with the quaternion rotation transformation according to Tundo et al. [15]. The normalized values are further used for location detection, AR and EE estimation. The same orientation is used until the presence state of the phone is changed, since we assume that the phone's orientation changes only when it is used or put away.

Walking detection, **location detection** and **AR** are done in essentially the same way, using machine learning. First, the stream of acceleration data is split into two-second windows. Then, a number of features are computed for each window, forming a feature vector. The feature vector is fed into a machine-learning algorithm, which outputs a classifier for one of the three tasks. Random Forest, as implemented in the Weka machine-learning suite [16], was chosen as the best algorithm for all three tasks. **EE estimation** is performed on a features calculated from the stream of acceleration data split into ten-second windows, the recognized activity and the average heart rate if the Zephyr heart-rate monitor is present. Support Vector Regression, as implemented in the Weka machine-learning suite, was chosen as the best algorithm for this task. There are too many features to list, but briefly, the features characterize the intensity and variation of the acceleration, distribution of the acceleration across each window, correlations between the axes of a single accelerometer and both accelerometers, the orientation of the accelerometers etc. Table I presents the classes for the three classification tasks of the activity monitoring. In some cases certain activities are merged into a single activity due to the identical orientation of the phone: standing and sitting are merged in case the accelerometer is positioned somewhere on the torso (Z or T), lying and sitting are merged into rest when the phone is in the trousers pocket, and lying, sitting and standing are merged into other when the phone is in the bag.

III. Experimental Validation

The proposed method was validated on a dataset composed of recordings of 10 volunteers performing a predefined scenario. Each volunteer was equipped with a Cosmed indirect calorimeter to measure the reference EE, the Zephyr heart-rate monitor and smartphones in different orientations at four locations: in the torso pocket, trousers pocket, shoulder bag and backpack. The leave-one-person-out cross-validation was used for both the AR and EE estimation, which means that all the models were trained on the recordings of 9 volunteers and tested on the recording of the final one, repeated once for each volunteer.

The predefined scenario consisted of all the activities of interest (lying, sitting, standing, walking, running, cycling) performed in different ways (e.g., sitting still and sitting writing, typing and doing other office activities, standing, walking slowly, walking uphill, running, stationary cycling). Five times during the scenario the information on the location and orientation of the smartphone was invalidated, followed by a period of walking, so that the location could be detected again and the orientation normalized.

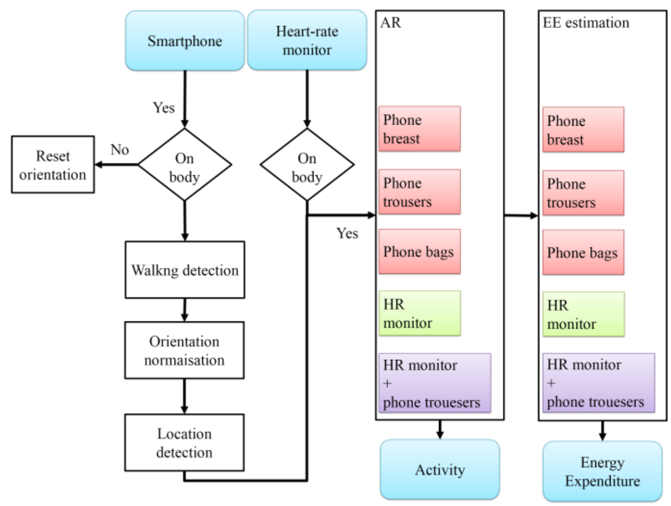

Fig 1. Algorithm for activity monitoring

TABLE I. Classes for the models used for the classification tasks in the activity monitoring.

Task	***Class labels***				
Walking	Walking, Other				
Location	Trousers, Torso, Bag				
AR	***Z*** [a]	***P*** [a]	***T*** [a]	***B*** [a]	***Z + P*** [a]
	Lying Upright Walking Running Cycling	Rest Standing Walking Running Cycling	Lying Upright Walking Running Cycling	Walking Running Cycling Other	Lying Standing Sitting Walking Running Cycling

a. Z – Zephyr heart-rate monitor, P – phone in trousers pocket, T – phone in torso pocket, B – phone in bag, Z + P phone in trousers pocket and Zephyr

The results of the validation of the walking and location detection tasks are presented in Table II. The results of the validation of the AR and EE estimation with or without the orientation normalization and location detection are presented in Table III. The results of the complete method with the phone in various locations are presented in Table IV. Walking detection, location detection and AR are evaluated with the classification accuracy, while the EE estimation is evaluated with the mean absolute error (MAE). The EE estimation was compared to the SenseWear armband, whose MAE was 1 MET, while the average MAE of our method was 0.76 MET.

IV. DEMONSTRATION

To demonstrate the performance of the application, the visitor will be offered an Android smartphone and a Zephyr heart-rate monitor. 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 recognized activities and estimated EE in real time on a computer, which will be connected to the smartphone via Wi-Fi solely for screen sharing. The demonstrator will also be using a prototype. Prototype screens can be observed in Fig 2.

TABLE II. RESULTS OF VALIDATION OF WALKING AND LOCATION DETECTION.

Task	
Walking detection	***Location detection***
92.6	85.8

TABLE III. RESULTS OF VALIDATION OF AR AND EE WITH/WITHOUT ORIENTATION AND LOCATION.

	AR	**EE**
Without orientation, without location	63.4	0.98
With orientation, without location	68.7	1.17
Without orientation, with location	74.7	1.04
With orientation, with location	91.3	0.76

TABLE IV. RESULTS OF VALIDATION OF AR AND EE ESTIMATION

Task	**Location**[a]					***Average***
	Z	***P***	***T***	***B***	***Z + P*** [b]	
AR [%]	90.0	89.0	92.0	92.5	92.8	91.3
EE [MET]	0.68	0.87	0.8	0.81	0.64	0.76

a. Locations: Z – Zephyr heart-rate monitor, P – phone in trousers pocket, T – phone in torso pocket, B – phone in bag, Z + P phone in trousers pocket and Zephyr

b. Other combinations of two devices improved neither AR nor EE estimation

V. CONCLUSION

We presented a smartphone application for activity monitoring, which recognizes the users' activities and estimates his/her EE. The method automatically adapts to the presence, orientation and location of the phone and an optional heart-rate monitor. Results show that the application's accuracy is comparable to a state-of-the-art dedicated consumer device and can be confidently used even without the heart-rate monitor. It thus makes accurate EE estimation more accessible than ever, enabling new applications to track and encourage physical activity. Future work will be focused on energy management, since the drain on the phone's battery is a major barrier to the acceptance of continuous activity monitoring.

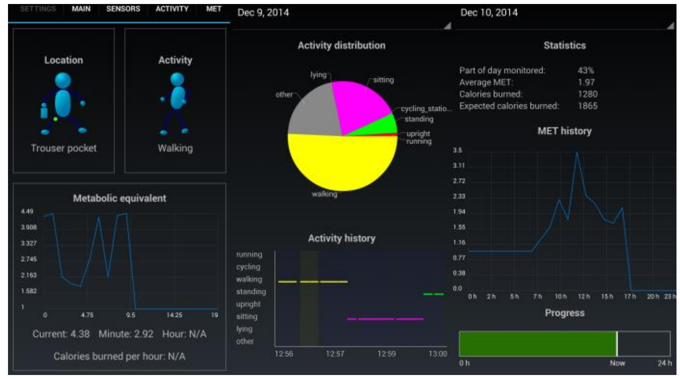

Fig 2. Screenshots of the activity monitoring application. Leftmost screen represents the current phone location, activity and EE. Middle screen shows the activity statistics and the rightmost screen the EE statistics.

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