Estimation of Human Energy Expenditure Using Inertial Sensors and Heart Rate Sensor

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Abstract. This paper presents a method for estimation of human energy expenditure during normal daily activities as well as sports activities using wearable inertial sensor attached to the person's thigh and chest as well as feasibility analysis of this method to be used as an application on an average smartphone. This is done by using one inertial sensor attached to the person's thigh (standard smartphone placement) and performing feature selection that selects only relevant attributes with low computational complexity that can be processed on smartphone and still keep high estimation accuracy. In addition to that, we tested a combination of thigh inertial sensor with hart rate monitor, usually worn by athletes, to collect more relevant data and gain on accuracy.

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

1 Introduction

Mobile devices are used for almost everything these days from talking and texting to event scheduling, daily life monitoring, finding direction, etc. Two of the reasons for such a fast success of the mobile devices and mobile applications are the embedded sensor and their significant improvement with each new model that appears on the market and availability and ease of development. Average smart phone has a rather powerful processing unit. It comes with variety of sensors, for example global positioning system (GPS), camera, proximity sensor, ambient light sensor, gyroscopic sensor and accelerometer. The accelerometer measures the movement acceleration and is therefore the most interesting in terms of analysis of human physical activity, more precisely the human energy expenditure, which is a focus of this paper.

Over the years, research in medical field has shown that a sufficient amount of physical activity can have a positive impact on one's health and well-being regardless of age [1][2][3] and that the physical inactivity is one of the leading causes of death worldwide [4]. Although this is widely accepted as a fact, only small amount of population has regular or sufficient exercise. Key reason for this is the limited time, due to the fast pace of life. If one was able to measure amount of performed physical activity during the regular day and present the difference according to the sufficient physical activity, than this could serve as a motivation for the person to do additional exercise and reach the daily goal. Most importantly, the amount of physical activity can be also used to monitor one's diet, either being healthy individual or someone who suffers from dietary disease. This raises a question; How can we measure the amount of physical activity.

Cost of physical activity is usually expressed in a unit referred as metabolic equivalent of task (MET), where 1 MET is defined as energy expended at rest. MET range is from 0.9 (sleeping) to 23 (running at 22.5 km/h). There are several methods used to reliably estimate energy expenditure. Direct calorimetry [6] measures the heat produced by human body while exercising. This is the most accurate method of estimating human energy expenditure, however it can be used only in a controlled environment such as laboratory. Indirect calorimetry [7] measures the amount of carbon dioxide production and oxygen consumption during rest and steady-state exercise. This method can be used outside the laboratory, however it cannot be used in everyday life since its usage requires a breathing mask. Doubly labelled water [7] is a gold standard, it measures the amount of exhaled carbon dioxide by tracking its amount in water which is labelled by deuterium and oxygen-18. This method can be used in everyday life, however it measures the energy expended over longer periods of time and is rather expensive. And finally, the most affordable system is using wearable inertial sensors or other wearable sensors that are moderately accurate and reliable. These can be used in everyday life and the estimation can be done over shorter periods of time.

This paper presents a method for estimation of human energy expenditure during normal daily activities as well as sports activities using wearable inertial sensor attached to the person's thigh and chest as well as feasibility analysis of this method to be used as an application on an average smartphone. This is done by using one inertial sensor attached to the person's thigh (equivalent to pocket, the standard smartphone placement) and performing feature selection that selects only relevant attributes with low computational complexity that can be processed on smartphone and still keep high estimation accuracy. In addition to that, we tested a combination of thigh inertial sensor with hart rate monitor, usually worn by athletes, to collect more relevant data and gain on accuracy. The heart rate monitor contains one more inertial sensor and can be easily connected to smartphone.

The rest of the paper is structured as follows. Section two presents the related work; Section 3 presents the hardware and the method. Section 4 contains the experiment and the results and finally the Section 5 concludes the paper.

2 Related Work

Estimation of energy expenditure is an interesting domain for mobile application development, according to the number of applications that can be found on application markets of individual operating systems. These applications can be divided into two categories; those that use accelerometer sensors and estimate energy expenditure based on number of steps the user does over one day [12]; and those that use embedded accelerometers to estimate the intensity of the performed activity, thus estimate the expended energy, for example MyFitnessCompanion [13]. Pedometers can be used only to detect the ambulatory activities such as walking or running and not their intensity. MyFitnessCompanion app can detect the intensity since it uses the accelerometers but it has one major shortfall, the user has to define which activity will be performed. Estimation of energy expenditure is afterwards based on the predefined energy estimation value taken from the Compendium of physical activities [14].

Most methods that use artificial intelligence techniques to estimate energy expenditure using wearable sensors seek linear or nonlinear relations between the energy expenditure and the accelerometer outputs. The most basic methods use one accelerometer and one linear regression model. The estimation accuracy can be improved by multiple regression models [8] and complex attributes [9]. The regression method by Crouter et al. [10] is currently among the most accurate. It uses one accelerometer attached to the hip. In the first step it classifies a person's activity into sitting, ambulatory activity or lifestyle activity. In the second step it uses a linear regression model for the ambulatory activity and an exponential regression model for the lifestyle activity. Sitting is always considered to have the energy expenditure of 1 metabolic equivalent of task (MET, 1 MET is the energy expended at rest). The weakness of this method is the exclusion of some activities such as cycling, and a larger error for the upper body due to the sensor placement.

This paper will present a method that uses three regression models that are based on the current users' activity. The activity is automatically recognised using the activity-recognition classifier. The recognized activity will also be used as one of the attributes in the energy expenditure regression models

3 Sensors and Data Pre-processing

To develop and test the method for estimation of energy expenditure we used one tri-axial inertial sensor and chest-strap worn by 10 people performing predefined activities. Besides our dedicated sensors each person was using Cosmed the indirect calorimeter [15] to measure actual expended energy.

3.1 Dedicated Sensors and Translation to Embedded Smartphone Sensors

Smartphone contain several sensors one of which is one tri-axial inertial sensor. For the purpose of this research we used simple tri-axial inertial sensor developed by Shimmer [16] attached to the users thigh, mimicking the placement of the smartphone, which would be carried around in the trousers pocket. Inertial sensor is orientation-sensitive; therefore we had to determine the exact orientation for the sake of simplicity. For example, the smartphone has to be carried in the right pocket downwards with screen towards the person's body. Each person wore the inertial senor the same with a freedom of few centimetres up or down the thigh. The placement and orientation of the Shimmer inertial sensor is shown on Figure 1.

Figure 1. Shimmer inertial sensor attached to the thigh.

In our previous research we have observed that the estimation of the energy expenditure can be improved with heart rate data. For that purpose we used Zephyr chest-strap [17], very popular with athletes, which can be easily connected to the smartphone via Bluetooth. Zephyr chest-strap contains additional tri-axial accelerometer, which can be used to gain on activity-recognition accuracy.

3.2 Data Collection and Data Processing

Data collection

Ten people equipped with our dedicated sensors, inertial and chest-strap, were additionally given a Cosmed indirect calorimeter to measure the real expended energy. The person performed the predefined activities presented in Table 1.

Each activity was performed several times and the duration of the activity is 6 minutes. The range of reference energy expenditure measured by Cosmed is 12 MET.

Table 1. Predefined activities.

Lying	Kneeling
Sitting	On all fours
Standing	Lying doing light exercises
Walking slowly (4 km/h)	Sitting doing light exercises
Walking quickly (6 km/h)	Walking doing light exercises
Running slowly (8 km/h)	Scrubbing the floor
Stationary cycling lightly	Shovelling snow, digging
Stationary cycling vigorously	

Data Processing

The stream of data of ten people was split into 10 seconds windows, each window overlapping with the previous one by one half of its length. For each window 136 attributes were computed, 135 from the acceleration data and one from heart rate. These attributes formed a vector, which was fed into a machine-learning algorithm to train a regression model. To reduce calculation complexity, since the goal is to run the method on a smartphone, we performed feature selection using ReliefF method [18]. The feature selection method returned the attributes in the ranked order. The selection of attributes was preformed as follows. Each attribute was removed one-by-one from the entire set starting with the one with lowest rank score. After each removal the regression was tested using cross-validation. This was performed 10 times for each person. The point where the accuracy started decreasing rapidly was chosen for the selection point leaving 23 attributes.

Descriptive example of selected attribute would be: Interquartile range of sorted magnitudes, where magnitude values are sorted and the result is a difference between the magnitude value at ¾ and the ¼ of the window, squared sum of the signal values, different amplitudes of signal, sum of absolute values, velocity, sum of impacts, mean values, average heart rate, prevalent activity, etc.

In our previous research we have observed that when using only one regression model for all activities result in higher estimation error in case of running and cycling [19]. Based on this finding we divided the data in three sets: running set, cycling set and rest of the activities set. The activity-recognition classifier was taken from our previous research [19]. Regression model was build for each set, to be used for particular recognised activity.

4 Experiment and Results

The experiment was done using data of ten people performing activities as described in Section 3.2. For each person we trained three regression models Weka suite [20] and six regression algorithms: M5PRules, M5P, REPTree, MultiLayer Perceptron. Linear Regression and SMOreg. The results were validated using leave-one-person-out approach. We have validated each regression model; for running activity; cycling activity; and for all other activities with algorithms presented in Table 2.

We have chosen the best performing algorithm per set for our final application using the dedicated sensors with possibility to transfer the method to the smartphone. The best performing algorithm is SMOReg, for other activities and MLP for running and cycling activities. The mean absolute error for this combination is 0.65 MET.

Table 2. Mean absolute error per regression model with six machine-learning algorithms.

	M5PRules	M5P	REPTree	Linear Regression	MLP	SMOReg
Other activities	0.55	0.54	0.55	0.58	0.86	**0.52**
Running activity	0.94	0.96	1.02	0.98	**0.78**	0.99
Cycling activity	0.78	0.99	0.74	0.98	**0.66**	0.87

5 Conclusion

The paper presents low computational complexity method for estimation of human energy expenditure. The focus of the paper is to develop a method that can be easily transferred and used on an average smartphone.

Presented method uses three regression models. Separate model is used for running activity, separate is used for cycling activity; and separate is used for all other activities. The regression models were built ten times on data of 9 people using several machine-learning regression algorithms and evaluated on 1 person using leave-one-person-out approach.

Accurate estimation of energy expenditure and its integration into the device that can interact with the user, can have positive impact on quality of life of each individual, regardless of age and health state.

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For wider interest

Mobile devices are used for almost everything these days from talking and texting to event scheduling, daily life monitoring, finding direction, etc. Two of the reasons for such a fast success of the mobile devices and mobile applications are the embedded sensor and their significant improvement with each new model that appears on the market and availability and ease of development. Average smart phone has a rather powerful processing unit and it comes with variety of sensors, for example global positioning system (GPS), camera, proximity sensor, ambient light sensor, gyroscopic sensor and accelerometer, being the most interesting in terms of analysis of human physical activity, more precisely human energy expenditure which is a focus of this paper.

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