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Context-based ensemble method for human energy expenditure estimation

Hristijan Gjoreski [a,b,*], Boštjan Kaluža [a,b], Matjaž Gams [a,b], Radoje Milić [c], Mitja Luštrek [a,b]

[a] Jožef Stefan Institute, Department of Intelligent Systems, Jamova cesta 39, 1000 Ljubljana, Slovenia
[b] Jožef Stefan International Postgraduate School, Jamova cesta 39, 1000 Ljubljana, Slovenia
[c] University of Ljubljana, Faculty of Sport – Institute of Sport, Gortanova 22, 1000 Ljubljana, Slovenia

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ABSTRACT

Monitoring human energy expenditure (EE) is important in many health and sports applications, since the energy expenditure directly reflects the intensity of physical activity. The actual energy expenditure is unpractical to measure; therefore, it is often estimated from the physical activity measured with accelerometers and other sensors. Previous studies have demonstrated that using a person's activity as the context in which the EE is estimated, and using multiple sensors, improves the estimation. In this study, we go a step further by proposing a context-based reasoning method that uses multiple contexts provided by multiple sensors. The proposed Multiple Contexts Ensemble (MCE) approach first extracts multiple features from the sensor data. Each feature is used as a context for which multiple regression models are built using the remaining features as training data: for each value of the context feature, a regression model is trained on a subset of the dataset with that value. When evaluating a data sample, the models corresponding to the context (feature) values in the evaluated sample are assembled into an ensemble of regression models that estimates the EE of the user. Experiments showed that the MCE method outperforms (in terms of lower root means squared error and lower mean absolute error): (i) five single-regression approaches (linear and non-linear); (ii) two ensemble approaches: Bagging and Random subspace; (iii) an approach that uses artificial neural networks trained on accelerometer-data only; and (iv) BodyMedia (a state-of-the-art commercial EE-estimation device).

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1. Introduction

Human energy expenditure (EE) directly reflects the intensity of physical activity, which makes it important for sports training, weight control, management of metabolic disorders (e.g., diabetes), and other health goals. There are various approaches that can reliably estimate the EE. Direct calorimetry measures the total heat output of a person in an accurate way, but is only usable in laboratory conditions. The slightly less accurate indirect calorimetry analyzes the respiratory gases and requires wearing a breathing mask, making it impractical for everyday use. Doubly labeled water is both accurate and convenient, but can measure only long-term EE. Finally, self-reporting is highly unreliable. Therefore, if both accuracy and convenience are required, a different approach is needed.

With the increasing accessibility and miniaturization of sensors and microprocessors, ubiquitous monitoring systems are becoming a practical solution for measuring the EE. Such systems primarily measure the physical activity with accelerometers, but can include additional sensors that indirectly measure the metabolic activity, such as a heart rate monitor or thermometer. The main challenge is how to estimate the EE from wearable sensor outputs accurately, irrespectively of the participant's activity, ambient conditions and other circumstances, i.e., contexts.

Recent studies in the EE-estimation field showed that machine learning (ML) techniques applied on sensor data can accurately estimate the EE [1–3]. In these studies, the EE estimation is defined as a process of transforming the sensor data into METs (Metabolic Equivalent of a Task), where one MET is defined as the energy expended at rest. MET values usually range from 0.9 (sleeping)

Abbreviations: MCE, Multiple Contexts Ensemble; EE, energy expenditure; HR, heart rate; BR, breath rate; GSR, galvanic skin response; MET, Metabolic Equivalent of a Task; MLR, multiple linear regression; SVR, support vector machine for regression; GPR, Gaussian processes for regression; M5P, model trees; ANN, artificial neural network; ANN-Acc, ANN trained only on accelerometer data; RMSE, root mean squared error; MAE, mean absolute error.

* Corresponding author at: Jamova cesta 39, 1000 Ljubljana, Slovenia. Tel.: +386 1 477 3812.
E-mail address: hristijan.gjoreski@ijs.si (H. Gjoreski).

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to over 20 (extreme exertion). Researchers usually use an indirect calorimeter to estimate the actual EE in METs with a high accuracy, which is later used as the ground truth during the ML phase.

In this study, we propose a novel, Multiple Contexts Ensemble (MCE) approach, which is applied to the task of EE estimation. The MCE approach uses multiple contexts extracted from sensor data and performs context-based reasoning in order to estimate the EE. In general, context is any information that characterizes the circumstances in which an event/situation occurs [4]. In our application, the context information is represented by the eight features extracted from the sensor data: activity, heart rate (HR), breath rate (BR), acceleration counts, chest skin temperature, galvanic skin response (GSR), arm skin temperature and near-body ambient temperature. Each of these features is used as a context in which ML models are built using the remaining features as training data. More precisely, for each value of each context feature, a regression model is trained using the subset of the dataset that corresponds to that particular context (feature) value. For example, for the activity of the user, a regression model is trained for each activity (sitting, walking, running, etc.) using the rest of the features as training data (HR, BR, body temperature, etc.). When evaluating a data sample, a custom ensemble of regression models is assembled from the previously constructed set of models, i.e., the models that correspond to the context (feature) values in the evaluated sample. The final estimation is provided by aggregating the outputs of the assembled models. This way, context-based reasoning is performed, which provides the benefit of combining multiple “viewpoints” when estimating the EE, resulting improved accuracy compared to previous approaches.

The remainder of this paper is organized as follows: Section 2 presents the background of the study and reviews the related relevant methods; Section 3 describes the proposed MCE approach; Section 4 presents the experimental setup, including the description of the activity scenario, the sensor equipment, the evaluation technique, and the description of the competing approaches; Section 5 presents the experimental results and a discussion; and lastly, Section 6 offers concluding remarks.

2. Background and related work

The first automatic methods for EE estimation included supervised ML, i.e., regression learning techniques. In particular, linear regression was used to map a single accelerometer output to EE [5–8]. The accelerometer output was often expressed in “counts”, an aggregate acceleration measure reported by devices such as ActiGraph. To estimate the EE, investigators used these “counts” to develop linear regression models. Although numerous studies showed reasonably good correlation between the counts and the EE [5,9], the estimation accuracy of accelerometer count-based linear regression was shown to contain systematic errors and vary with the type of activities, resulting in overestimations for the walking activity and underestimations during the moderate intensity lifestyle activities [10]. This limitation is probably due to the insufficient information provided by the counts and the simplicity of the linear model. Efforts were made to improve the estimation accuracy by using a richer representation of the accelerometer output consisting of multiple features [11,12], as well as non-linear regression methods such as artificial neural networks (ANNs) [1,13,14] or support vector machine for regression (SVR) [15,16]. These approaches were experimentally shown to substantially improve the accuracy compared to earlier work [17].

Researchers soon realized that single-regression approaches cannot accurately estimate the intensity of physical activity across a range of activities, and that different activities require different EE equations [18,19]. Crouter et al. [20] used the acceleration counts in order to divide the activities into three categories and assigned the following EE estimations: 1 MET to inactivity and two regression equations for light and intense activity, thus achieving a better estimate than previous single-regression methods. The advances in the accelerometer-based recognition of activity type allowed finer-grained activities as the context for EE estimation [2,21,22]. Lester et al. [23] used a Naive Bayes classification model to first recognize three activities (rest, walking and running) from the accelerometer's data, and then to apply the appropriate regression equations in order to estimate the EE. They also considered GPS and barometer information to estimate the slope of walking/running, and showed that additional sensor information improves the EE estimation. However, even with these three types of sensors (accelerometer, GPS, and barometer) they still encountered two problems: (i) EE underestimation of activities that are not characterized by acceleration, but are still energy demanding, e.g., carrying a box and (ii) EE underestimation of activities that follow an intense activity, i.e., the “cool-down” effect (sitting after intense running). Both problems can be solved by sensing other physiological parameters such as the HR and BR [24,25]. In our previous work [26], we showed that by using data from multiple sensors one can more accurately estimate the EE. This may seem as an additional burden to the user, because it requires additional sensors attached to him/her. However, today's commercial wearable devices already provide multiple sensors packed in a single enclosure, e.g., BodyMedia, Basis, Empatica wristband, etc.

The BodyMedia armband sensor uses both multiple sensors and multiple regression models. Vyas et al. [3], the research team of the BodyMedia, proposed a method that uses an activity recognition model that recognizes dozens of activities which are used as the context, and then it combines multiple regression models according to the probabilities for the recognized activities. They showed that by using multiple sensors: an accelerometer, two thermometers, GSR and heat-flux sensors, the estimation of the EE significantly improves. Additionally, a recent review showed that it is the most accurate EE estimation consumer device [27].

The aforementioned studies showed that: (i) using multiple regression models for different user's activities (i.e., context) outperforms single-regression approaches, and (ii) using multiple features extracted from multiple sensor data provides more accurate EE estimation than using only acceleration data (even when multiple acceleration features are extracted). In this work we improve upon these findings and propose a method that uses multiple features extracted from multiple sensor data, and uses not only the activity as the context, but multiple contexts, so that each measurement can be placed in multiple contexts simultaneously (e.g., activity = running, HR = high, BR = moderate, etc.).

3. Multiple context ensemble approach

The proposed MCE is a general approach which can be applied to various reasoning tasks about the user's health and condition. The only requirement is that the data to reason about can be represented by multiple context features. This is usually the case when the reasoning task includes multiple sources of information, for example data streams provided by multiple sensors.

The application of the MCE approach to the task of EE estimation is shown in Fig. 1. It consists of three phases: context extraction, context modeling and context evaluation. In the first phase the data provided from multiple sensors is used in order to extract eight features. In the second phase, each of these eight features is individually exploited as the user's context, and the other seven features are used to model the EE in the context of the first feature. That is, for each value of each feature a regression model is trained on the subset of the dataset that corresponds to that particular value using a regression learning method. In the evaluation phase a custom ensemble of regression models is assembled from

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