Demonstration Paper: Accurate Energy Expenditure Estimation using Smartphone Sensors

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ABSTRACT

Accurate and online Energy Expenditure Estimation (EEE) utilizing small wearable sensors is a difficult task with most existing schemes. In this work, we focus on accurate EEE for tracking ambulatory activities of a common smartphone user. We used existing smartphone sensors (accelerometer and barometer sensor), sampled at low frequency, to accurately detect EEE. Using Artificial Neural Networks, a machine learning technique, a generic regression model for EEE is built that yields upto 83% correlation with actual Energy Expenditure (EE). Using barometer data, in addition to accelerometry is found to significantly improve EEE performance (upto 10%). We compare our results against state-of-the-art Calorimetry Equations (CE) and consumer electronics devices (Fitbit and Nike+ Fuel Band).

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Barometer, Energy Expenditure, Artificial Neural Networks

1. INTRODUCTION

Obesity is an epidemic both in the United States and all around the world. It is predicted to be the number one preventive health threat in the future [7]. Moderate and vigorous physical activity can greatly contribute to health promotion and disease prevention.

The most accurate way to Estimate Energy Expenditure (EEE) is to use direct or indirect calorimeters, however these apparatus are not conducive to track daily intake and expenditure.

Accelerometer based algorithms have found high degrees of correlation with EEE in scenarios such as walking, running and standing. However, active lifestyle often involves climbing up or down stairs. In these scenarios, accelerometer or pedometer based approaches tend to be inaccurate.

New smartphones like Galaxy S3, Galaxy Nexus, iPhone 5 and later models have an integrated barometer sensor in the phone which passively measures atmospheric pressure. Slight variations in atmospheric pressures can be detected by these algorithms to detect work done against gravity, hence improving the results. We also want to develop a practical deploy-able framework for EEE which samples sensors at low frequency.

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2. METHODOLOGY

Our primary aim was to build an application capable of accurately providing EEE without leveraging significant computational resources on the smartphones. Low computational and power requirements will make such an algorithm more usable and attractive to consumers.

Researchers have used a sampling frequency of 10-800 Hz [8, 6, 3] for activity detection. However, studies have shown that 0.1-20 Hz is decent range for most human activities [3]. In this study, however, we restrict our measurements to the default smartphone sampling rate of 2Hz which corresponds to low battery consumption and processing overhead. Both accelerometer and barometer sensors are sampled at 2Hz (corresponding to 2 samples per second).

We use a window of time equivalent to 4 seconds (8 samples) to obtain different feature vectors required for our analysis. We divide these features into two basic categories: basic and derived. The basic features involve direct calculations of mean values from the tri-axis accelerometer and barometer sensor and these computations are power-efficient. The derived features are obtained from basic accelerometer data, used in other studies in this domain and provide advanced features, which we believe will improve the accuracy of our algorithm. However, they require significant computational overhead beyond the requirements of the basic features. We also collect logistics inputs about the users and use them as feature vector in our machine learning algorithm.

The gender, age, height, weight and BMI (Body to Mass Index) of the participants is used as logistics information and input to ANN models. We also use mean values of x, y, and z axis of accelerometer signal and barometer readings as inputs to ANN (Artificial Neural Network) algorithm.

3. PREDICTION MODELS

In this section, we briefly introduce the two regression models we use in this work for EEE using accelerometer and barometer data. One is a linear model while the other is non-linear.

3.1 Linear Regression

Table 1: **Improvement in EEE using ANN and Barometer sensor**

Features used	ρ	RMSE	MAE
MODEL - Linear Regression			
Accelerometer	0.6028	1.8251	1.4611
Accelerometer + Barometer	0.5807	1.8643	1.4797
MODEL - Artificial Neural Network			
Accelerometer	0.7189	1.6235	1.2244
Accelerometer + Barometer	**0.8326**	**1.2991**	**1.0029**

Simple linear regression is the least squares estimator of a single explanatory variable. It minimizes the sum of squared vertical distances between the observed responses in the dataset and the responses predicted by the linear approximation.

3.2 Artificial Neural Networks

We use Artificial Neural Network (ANN), a non-linear, non-parametric and data driven machine learning approach in addition to simple regression technique. These non-linear techniques have been successfully used in a number of domains [4, 9, 1] for successful prediction.

Inspired by biological nervous systems, ANNs are simplified representations of the model used by human brain for intelligent functions. It allows one to fully utilize the data and let the data determine the structure and parameters of a model without any restrictive parametric modeling assumptions.Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Many such input / target pairs are needed to train a network. These functions are available for implementation as standard routines in Weka toolbox [5] and were used in this work.

4. EXPERIMENTS AND RESULTS

In this section, we present our results using ANN and linear regression models on data collected from field experiments. The smartphone sensors logged their data using Androsensor app into a csv file while COSMED K4b2 calorimeter was used to validate the readings and measure actual EE. The smartphone was held straight by the participants. For each participant, the following set of ambulatory activities were designed:

1. Standing (at rest) for 2 minutes
2. Walking two laps of a 50m corridor
3. Climbing up and down on a staircase, 4 flights at a time, for four times

Seven male individuals participated in the tests. Healthy graduate students of different ethnic backgrounds from our research group contributed to these experiments and we ran multiple trials. The range of bodily features are as follows: Weight (56-109 Kg), Height (173-184 cm), Age (22-29 years) and BMI (18-36 kg/m^2).

We obtained all the values and then extracted the feature vectors mentioned earlier. Matlab and Weka software tools were used for computational analysis. Unlike, activity specific classification and EEE algorithms [2], our focus here is on designing a single robust EEE algorithm.

Table 1 gives the performance improvements obtained by (1) Using an ANN model over linear regression model and, (2) Additionally using barometer sensor with accelerometer. Using ANN instead of linear regression technique gives us an increased correlation of 71% instead of 60% for accelerometer sensor only. Adding a barometer sensor does not give any improvement with the linear model. However, with ANN, the correlation improves to 83%. The Root Mean Square Error (RMSE) is 1.3 and Mean Absolute Error (MAE) is 1 for this model.

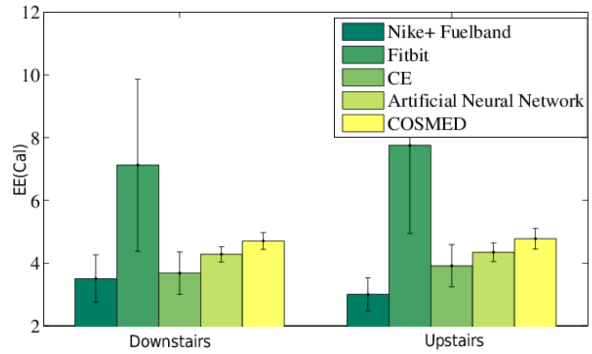

Figure 1: Overall EEE comparison of COSMED and ANN with Nike+, Fitbit and Calorimetry equation

Comparison with other products: It is not possible to obtain second by second EEE from commercial devices such as Fitbit or Nike+ Fuel band. However, we did calibrate these values before and after each trial. We present the summary results in Figure 1. CE refers to Calorimetry equations used by Calfit system. ANN values are within 10% of the range of COSMED values. The error bars in the figure show the standard deviation for each device/ algorithm. Our algorithm has a smaller deviation over the population considered, which is comparable to actual COSMED values.

5. CONCLUSIONS AND FUTURE WORK

In this work, we proposed usage of smartphone accelerometer and barometer sensors for accurate EEE in ambulatory settings. Due to space constraints, we could not go into details of our methodology and machine learning models. It is seen that using barometer we get upto 83% of correlation and RMSE of 1.29.

As a part of future work, we plan to use different combinations of feature vectors to achieve high correlation, in faster time and with low power usage. Another direction for the future is to build a smartphone application which can be used for accurate EEE by using ANN with minimum battery consumption.

6. REFERENCES

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