Energy Expenditure Estimation with Smartphone Body Sensors

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ABSTRACT

Energy Expenditure Estimation (EEE) is an important step in tracking personal activity and preventing chronic diseases such as obesity, diabetes and cardiovascular diseases. Accurate and online EEE utilizing small wearable sensors is a difficult task, primarily because most existing schemes work offline or using heuristics. In this work, we focus on accurate EEE for tracking ambulatory activities (walking, standing, climbing upstairs or downstairs) 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, we build a generic regression model for EEE that yields upto 89% correlation with actual Energy Expenditure (EE). Using barometer data, in addition to accelerometry is found to significantly improve EEE performance (upto 15%). We compare our results against state-of-the-art Calorimetry Equations (CE) and consumer electronics devices (Fitbit and Nike+ Fuel Band). We were able to demonstrate the superior accuracy achieved by our algorithm. The results were calibrated against COSMED K4b2 calorimeter readings.

Categories and Subject Descriptors

J.3 **[Computer Applications]**: Life & medical sciences - *Health*

General Terms

Experimentation, Algorithms.

Keywords

Accelerometer, Barometer, Energy Expenditure, Artificial Neural Networks

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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 [18]. Recent estimates indicate that two-thirds of U.S. adults are overweight. Poor dietary habits and lack of physical activity are two main contributors to this growing health crisis. New smartphone applications and research projects aim at helping people track their daily food intake [12] and a number of smartphone apps are available for consumer download. It is generally very difficult to know exactly how many calories people exhaust during daily physical activity as it depends on the age, gender, weight, height, type and intensity of activity.

Moderate and vigorous physical activity can lead to health promotion and disease prevention. Increased portion sizes and high caloric intake are great contributors to overweight and obesity. Provision of tools to accurately measure EEE would allow people to actively track expenditure of calories relative to the amount of calories ingested, creating awareness of personal habits that can be modified to promote personal health.

The most accurate way to measure Energy Expenditure (EE) is to use direct or indirect calorimeters, however these apparatus are not conducive to track daily intake and expenditure. COSMED K4b2 calorimeter uses pulmonary gas exchange to measure caloric expenditure with a very high correlation of 98.2% [16] but is impractical for use in daily life because of the high cost, complexity and difficulty of use [14]. Pedometers and accelerometer based approximation algorithms offer an alternative solution that is gaining popularity. Many wearable devices, such as Fitbit, Jawbone Up and Nike+ Fuelband provide a practical solution to monitor the dynamic energy expenditure by unobtrusively collecting data required to make EEE. In our objective trials, we found many of these devices were accurate in step counts but inaccurate in EEE. Additionally, people need to purchase and carry these devices with them all the time to get a comprehensive assessment of energy expenditure value.

Table 1: EEE (Cal) and step counts using commercial devices (Nike+ Fuelband and Fitbit one)

Walking type	Up	Down
Steps (Nike+)	54.46 ± 22.58	59.83 ± 11.45
EEE (Nike+)	3.32 ± 2.15	4.38 ± 0.67
Steps (Fitbit)	61.96 ± 20.44	71.38 ± 13.18
EEE (Fitbit)	7.82 ± 2.85	9.14 ± 2.92

The main shortcoming of pedometers or any step-counting algorithms is their poor accuracy in detecting steps at slow speed and insensitivity to gait differences such as the length of the stride leading to unreliable estimation of energy expenditure. Another approach is to use accelerometer values directly. The existing algorithms used to estimate EE from accelerometers attempt to find an empirical relation between accelerometer data and energy expenditure data measured by a calorimeter, e.g. COSMED K4b2.

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. For example - in a sample trial we asked some volunteers to climb up 4 flight of stairs and then to climb down the same number of stairs. The EEE obtained using commercial products such as Fitbit and Nike+ Fuelband (which use pedometer based approach) are shown in Table 1. It is counterintuitive that one will spend more calories climbing down than upwards. The algorithms used in these devices appear to count steps and speed of the movement and attribute higher expenditure based on these variables. Given that our volunteers moved faster when climbing down stairs versus up stairs these devices measured higher caloric expenditure for the less vigorous activity of climbing down versus up.

With smartphones becoming ubiquitous devices, we assert that they are the most convenient devices for EEE, rather than introducing than introducing dedicated wristbands, heart rate monitors or other tracking devices. However, work needs to be done to improve EEE accuracy using smartphone sensors. Accelerometry equations don't work well in climbing upstairs / downstairs where altitude change is involved.

New smartphones such as 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. Another motivation behind our work is to develop a practical framework for EEE estimation. Existing accelerometry equations require heavy computations or require high sampling frequency, either of which will drain the battery of smartphones quickly.

The main contributions of this paper are as follows:

1. We advocate the use of machine learning techniques for EEE. We build a linear regression and multi-layer perceptron-based regression model to obtain a 89% correlation (ρ) accuracy. We obtain high accuracy and low error (RMSE=1.07).

2. Multiple trials were conducted over 7 individuals and validated using COSMED K4b2 calorimeter. We can obtain high correlation using basic features and low sampling frequency, which will lead to battery efficiency.

3. We demonstrate that using barometer sensor, in addition to accelerometer, improves accuracy (ρ increases by 15%) without computational overhead.

Before going into the description of the methodology in details we would like to point out the scopes and limitations of our described model. First and foremost, our analysis have been built and analyzed on the basis of the most basic activities of a normal human being. The results can be extended to other physical activities like running, biking, etc. Secondly, our proposed model requires an individual to carry a smartphone at all times. This can be problematic as a smartphone may not always be carried by individuals and the sensor location will not always be known. Recognizing the activity type with a non-fixed location of sensor on the body is complex.

The rest of the paper is organized as follows: Section 2 gives an overview of related works in this area. Section 3 discusses the methodology used to process sensor data from the smartphones. Section 4 gives a brief summary of the prediction models used in the paper followed by experimental results in Section 5. Section 6 states conclusions and discusses directions for future work.

2. RELATED WORK

2.1 EEE Using Body Sensors

Fitbit is a highly popular commercial device which uses accelerometer and altimeter sensors to capture personal activity, a significant improvement over traditional pedometers. However, some experiments have demonstrated that Fitbit is not very accurate as it lacks activity-classification algorithms [6]. Nike+ Fuelband has the same limitations. Exiting body sensor related energy expenditure estimation mostly employs a body-worn accelerometer and performs signal analysis to estimate calories expended in real-time using regression formulas. However, using a single sensor on the body is not enough to provide accurate measurement for body movement. Instead, multiple sensors are needed to improve the activity estimation performance [3].

Heart rate monitors have been used as stand-alone devices or along with accelerometer sensors to collect data and predict energy expenditure. Some devices such as Wahoo heart rate monitor, acquire heart rate data by measuring pulse rate and use a linear relation between heart rate and oxygen uptake to predict energy expenditure. However, heart rate monitors have low accuracy during sedentary behavior and require individual calibration [14, 2].

2.2 EEE Using Smartphones

Accelerometer sensor in smartphone has been used for activity recognition in many studies like in [19]. CalFit is a widely used Android application that tracks time, location and physical activity patterns of users for health and wellness studies [19]. It uses smartphones GPS receiver to get the location information and the accelerometer for obtaining motion data. It uses an algorithm presented in [5] to estimate energy expenditure strictly based on accelerometer data. Another previous work [21] shows how smartphones, along with GPS data, can be used to effectively calculate the EEE of individuals during biking.

2.3 Barometer sensor and its application

Traditionally, the barometer sensor is used in meteorology to measure atmospheric pressure. It is also used as pressure sensor which measures relative and absolute altitude through the analysis of changing atmospheric pressure. The barometer sensor can be used for motion detection, but it is mostly used by location-based applications to evaluate elevation. Ohtaki et al. have first introduced the concept of combining barometer with accelerometer for detecting ambulatory movmements [15], where authors embed a barometer sensor into a portable device to evaluate daily physical activity and classify the activity type.

3. 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 [20] for activity detection. However, studies have shown that 0.1-20 Hz is decent range for most human activities [4]. 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 and selected from existing studies in this domain [14], 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.

3.1 Logistics

We use subjective user information as feature vectors (FV 1-5) in our machine learning algorithm.

- Gen: Gender of the person (1 for male, 2 for female)
- Age: Age of the person in $years$
- Hei: Height of the person in m
- Wei: Weight of the person in kg
- BMI: Body to Mass Index of the person, calculated as division of height (squared) with weight and measured in kg/m^2

3.2 Basic Features

We use the following feature vectors (FV 6-9) obtained from the accelerometer sensor values over a window.

- μA_x: Mean of x component of Accelerometer signal.
- μA_y: Mean of y component of Accelerometer signal.
- μA_z: Mean of z component of Accelerometer signal.
- μ_P mean of barometer signal.

The FV above are calculated easily from sensor data and are referred to as basic FVs.

3.3 Derived Features

Next, we define the additional FVs we derived from triaxial accelerometer data. These features have been useful in human activity recognition and possibly also improve accuracy in our scenario [14]. These are termed as derived FVs (FV 10-34).

- μACA_x, μACA_y, μACA_z: absolute mean of energy deviation from average of A_x, A_y and A_z signals. (for example, μACA_x = mean of $|A_x - \mu A_x|$)
- SVM: Signal Vector Magnitude is the root mean square value of AC component along all three axis.
- $\rho_{x,y}$, $\rho_{z,y}$, $\rho_{x,z}$: Correlation between A_x, A_y and A_z signals (pairwise).
- P_x, P_y, P_z: Pitch of A_x, A_y and A_z signals.
- $\sigma^2 ACA_x, \sigma^2 ACA_y, \sigma^2 ACA_z$: variance of energy deviation from average energy of A_x, A_y and A_z signals. (for example, $\sigma^2 ACA_x$ = variance of $(A_x - \mu A_x)$)
- R_x, R_y, R_z: Range of A_x, A_y and A_z signals in given window.
- E_x, E_y, E_z: Energy of A_x, A_y and A_z signals in given window.

- H_x, H_y, H_z: Entropy of A_x, A_y and A_z signals in given window.
- σ_P^2: variance of barometer signal.
- Ran_P: Range of barometer signal (in given window).
- mgh: Work done against gravity. $mgh = Ran_P \times Wei$

3.4 Calorimetry equations

The activity counts or acceleration values collected using accelerometers can be combined with demographic information and regression techniques [7, 5] or physical models of the human body [11] to produce energy expenditure estimates. We use the popular equation proposed by [5] to obtain EEE. This model is also deployed in Calfit [19] used by researchers in California to assess associations between the built environment and physical activity in many case studies. EEE estimates given by this method uses the following heuristic relation:

$$\widehat{EEE} = aA_H^k + bA_z^m, \tag{1}$$

where,
∘ $A_H = (A_x^2 + A_y^2)^{0.5}$,
∘ a=.01281**Wei* + 0.84322,
∘ b=.0389**Wei* - 0.68244**Gen* + 0.69250,
∘ k=.0266**Wei* + 0.14672,
∘ m=-0.00285**Wei* + 0.96828

Researchers have reported 60-95% correlation using Equation 1 for ambulatory activities such as walking or running. However, the performance degrades when used for activities involving change of altitude. We use this as FV(35) in our algorithm.

3.5 Instruments

Another critical task is to measure accurate EE values. Direct calorimeter [17] requires observations in a confined metabolic chamber and is therefore impractical in our scenario. Doubly labeled water techniques are inappropriate because they calculate EE over a long duration instead of for a single activity. To calibrate exact energy expenditure values, we used COSMED K4b2 [13] indirect calorimeter, which is portable and can be used with our setup.

We used Samsung Galaxy Nexus smartphones to record observations of barometer and smartphone sensors.

4. PREDICTION MODELS

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

4.1 Linear Regression

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. The resulting estimator can be expressed by a simple formula, especially in the case of a single regressor on the right-hand side. If X denote the vector of inputs (obtained or derived from accelerometer and barometer readings) and Y denotes EE obtained using COSMED calorimeter, $\overline{Y}$ denotes EEE values obtained from the model:

$$\overline{Y} = X\beta + \varepsilon, \tag{2}$$

where β and ε are constants.

4.2 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 [8, 1] for successful prediction. Inspired by biological nervous systems, ANNs are simplified representations of the model used by human brain for intelligent functions.

The number of input layers is determined by the modality of X i.e. the number of feature vectors extracted from accelerometer and barometer data. We use one hidden layer, composed of simple elements (called neurons) and each neuron uses a non-linear transfer function to map inputs into outputs [9]. The connections between neurons largely determines the network function. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. The final layer produces the ANN's output. The output of a feed-forward neural network with one hidden layer and one output neural network is given by

$$\overline{Y} = \Gamma\left[\sum_{j=1}^{N_{hidden}} \omega_{j,o} \times \Gamma\left(\sum_{i=1}^{N_{input}} \omega_{i,j} \times X_i + b_j\right) + b_o\right]$$

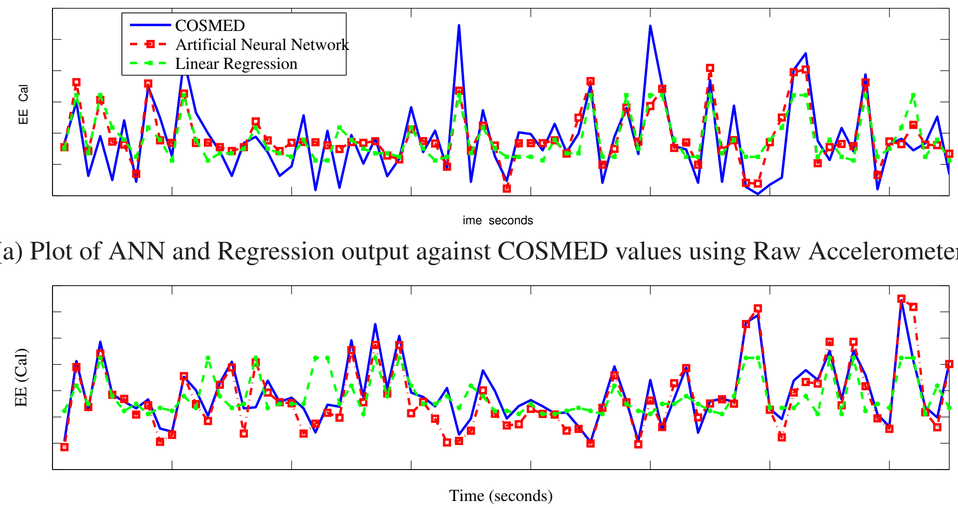
where, $\omega_{i,j}$ denotes weight between link i and j; all the inputs to a node are summed and passed through transfer function Γ. Input layer neurons uses $tansig$ (Tan-Sigmoid) transfer function.

These functions are available for implementation as standard routines in Weka toolbox [10] and were used in this work.

5. 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 in hand by the participants. For each participant, the following set of ambulatory activities were designed:

- Standing (at rest) for 2 minutes.



(a) Plot of ANN and Regression output against COSMED values using Raw Accelerometer output

(b) Plot of ANN and Regression output against COSMED values using all FVs

Figure 1: Plot of EEE using ANN and Linear Regression with actual EE values for one individual.

Table 2: Regression Results

Model used	ρ	RMSE	MAE
ANN			
Raw Accelerometer (only)	0.7189	1.6235	1.2244
All Feature Vectors (FV)	0.8794	1.1266	0.7347
Linear Regression			
Raw Accelerometer (only)	0.6028	1.8251	1.4611
All FVs	0.5807	1.8643	1.4797

Table 3: Impact of Calorimetry Equation (CE) on ANN performance

Model used	ρ	RMSE	MAE
CE	0.606	1.9044	1.4634
Raw Accelerometer	0.7189	1.6235	1.2244
Raw Accelerometer + CE	0.6738	1.7642	1.3347
All FV - CE	0.8653	1.2104	0.7456
All FV	0.8794	1.1266	0.7347

- Walking two laps of a 50m corridor.
- Climbing up and down on a staircase, 4 flights at a time, for four times.

Seven individuals participated in the tests. Healthy male graduate students of different ethnic background from our lab 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, that can be applied to a combination of all regular physical activities in a combined manner.

Table 2 gives the performance results using Artificial Neural Networks and Simple Linear Regression models. ρ indicates correlation between predicted output and actual EE values. RMSE is the Root Mean Square Error while MAE is Mean Absolute Error. Raw Accelerometer means that only the mean accelerometer values are provided as inputs to machine learning algorithm. 'All FV' refer to the case when all 35 FVs mentioned earlier are included in ANN.

It can be clearly seen that linear regression gives very poor performance in all cases. There is no improvement in linear regression performance with increase in Feature Vectors. Thus, the utility of using non-linear models for regression is clear. Using ANN model, we are able to achieve 72% correlation with actual EE values with a RMSE of 1.62 using only accelerometer equations. When all FVs are used, correlation increases to 88% and RMSE reduces to 1.13.

Figure 1 gives a plot of output values using ANN and linear regression, as compared to COSMED values. The errors are less in ANN than by the Linear Regression model, and less in cases where more FVs are used.

5.1 Impact of Calorimetry equations

Calorimetry Equations (CE) proposed in literature, such as the one used in [5, 19] have very high computational complexity as they involve fractional arithmetic and are not feasible on smartphone processors. We want to quantify the impact of these calculations (which are otherwise accurate for walking and running) on the accuracy of ANN model. We ran the ANN model with and without this equation for both Raw Acc. and All FV models. The results are presented in Table 3. Using only CE gives us a correlation of 60%. It can be seen that including CE has a negative impact on the accuracy of ANN model with Raw Acc. while there is in-

Table 4: Impact of barometer values on EEE prediction using ANN

Model used	ρ	RMSE	MAE
Raw Accelerometer (only)	0.7189	1.6235	1.2244
Raw Acc. + Bar.	0.8326	1.2991	1.0029
All FV	0.8794	1.1266	0.7347

significant improvement with other FVs. Hence we remove this input from our selection of feature vectors.

5.2 Impact of barometer sensor

The experimental results validated our assertion that barometric sensor (Bar.) has high correlation with EEE accuracy. Appending the mean of barometer values (μ_P) improve the correlation of EEE to actual energy expenditure from 71% to 83% as shown in Table 4. However, the results can be further improved using other FVs. 'All FV' refer to the case when all 35 FVs mentioned earlier are included in ANN.

5.3 Influence of Feature Vectors

Extracting each feature vector from raw sensor inputs can be time consuming. Particularly, on an embedded device like a smartphone, such operations may drain the battery.

We first profile the different FV extraction algorithms in terms of their computational complexity. Since the exact speed of computation is device dependent, we report relative speed (time of execution relative to time of execution of Raw Acc. values). The values are reported in Table 5. These computations are performed with a desktop processor running at 2.6 GHz and averaged over 200K computations. We show relative performance trend which should scale well to mobile processors. Next, our goal is to prune the FVs with higher computational cost without sacrificing the accuracy of EEE.

We ran multiple trials and found interesting observations:

- Unlike activity classification [14], EEE accuracy is not impacted by pitch, range, axes correlation or entropy. In fact, these FVs have a negative impact on ANN performance. By removing these FVs our classifier correlation improved to 89% and MAE dropped to 0.7886. This, set of features, where we select μAC, SVM, energy and variance along with raw accelerometer values, is referred to as 'Moderate FV' in Table 6.

- Using only Signal Vector Magnitude and μAC coefficients energy along with Raw sensor values gives reasonable accuracy and low computational requirements. This case is referred to as 'Simple FV' in Table 6.

The summary of these results is given in Table 6. The correlation of EEE using Raw Accelerometer values increases by up to 15% using Raw barometer sensor values. Similarly, barometer sensor value impacts performance with Simple FV and Moderate FV by 21% and 24% respectively without

Table 5: Relative Computational Time of FV extraction step (relative to accelerometer data)

Name	Time	Name	Time
Correlation	18.7X	μAC	1.2X
Pitch	158X	SVM	0.21X
Variance	3X	Energy	0.5X
Range	12X	Entropy	0.71 X

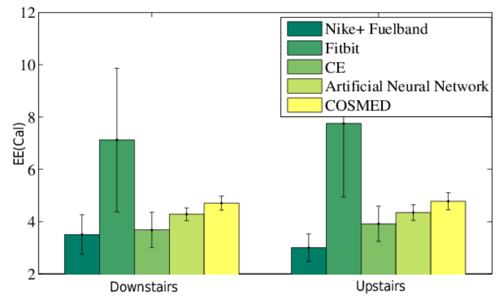


Figure 2: Overall absolute EE comparison of COSMED and ANN with Nike+, Fitbit and Calorimetry equation

incurring any significant computation cost. Also the RMSE values show significant improvement in each of these cases.

We are now in a position to recommend 3 ANN models for best performance tradeoffs: (1) using only accelerometer and barometer mean values, (2) adding simple FVs and (3) adding moderate FVs. The exact choice will depend on accuracy required and available computational power.

5.4 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 2. The errors in individual measurements seem to sum up and CE algorithm (calorimetry equation used in Calfit) presents an estimate which is within 25% of the COSMED values. ANN values are within 10% of the range of COSMED values. We can see that Nike+ Fuelband tends to underestimate the EE while Fitbit tends to overestimate the value. The error bars in the figure show the standard deviation for each device/ algorithm. Fitbit has an abnormally high deviation. Our algorithm has a smaller deviation over the population considered, which is comparable to actual COSMED values.

6. CONCLUSION AND FUTURE WORK

In this work, we proposed usage of the accelerometer and barometer body sensors of smartphones for accurate EEE in ambulatory settings. To emulate a practical setting, we used a smartphone sampling accelerometer and barometer sensors readings at 2Hz only. We then used these values to obtain FVs and fit an ANN which can yield up to 89% correlation and RMSE of 1.07. with very small computational over-

Table 6: Understanding trade-off between computational requirements and accuracy for EEE using ANN

Model used	Computation Time	ρ	RMSE	MAE	% Improvement ρ	% Improvement RMSE
Raw Accelerometer (only)	1X	0.7189	1.6235	1.2244	REF	REF
Raw Acc. + Barometer	**1.3X**	**0.8326**	**1.2991**	**1.0029**	**15.8**	**20**
Raw Acc. + Simple FV	2.2X	0.7837	1.47	1.06	9	9.5
Raw Acc. + Bar. + Simple FV	**2.5X**	**0.8726**	**1.1358**	**.8466**	**21.3**	**30**
Raw + Moderate FV	5.2X	0.7668	1.55	1.09	6.6	4.5
Raw + Bar. + Moderate FV	**5.5X**	**0.8909**	**1.07**	**.78**	**23.9**	**34.1**
All FV	194X	0.8794	1.1266	0.7347	22.3	30.6

head. We observed significant benefits in fusing the input of barometer sensor to an accelerometer sensor as it allows, with use of simpler FVs, achievement of higher correlation and accuracy.

The algorithm we have employed here for our prediction model, ANN, is relatively slow when it comes to building the model. However, the smartphone, will be trained using this model offline and the actual prediction in real-time will be fast and hence, not energy extensive. However, for building the model in real time, decision trees can be used.

Motivated by these strong results, we plan to collect a more extensive dataset, using a higher number of individuals, along with other physical activities like biking and running. Using this dataset, we wish to build a more representative model for EEE (using Artificial Neural Networks or other machine learning algorithms like decision tress), which will improve EEE accuracy. Another direction of future work involves building a smartphone application which can be used to accurate estimate energy expenditure of individuals by using Artificial Neural Networks, without draining smartphone energy.

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