Impact of Sensor Misplacement on Estimating Metabolic Equivalent of Task with Wearables

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***Abstract*—Metabolic equivalent of task (MET) indicates the intensity of physical activities. This measurement is used in providing physical activity intervention in many chronic illnesses such as coronary heart disease, type-2 diabetes, and cancer. Due to the small size, portability, low power consumption, and low cost, wearable motion sensors are widely used to estimate MET values. However, one major obstacle in widespread adoption of current wearable monitoring systems is that the sensors must be worn on predefined locations on the body. This imposes much discomfort for users as they are not allowed to wear the sensors on their own desired body locations. In addition, non-adherence to the predefined location of the sensors results in significant reduction in the accuracy of physical activity monitoring. In this paper, we propose a framework for sensor location-independent MET estimation. We introduce a sensor localization approach that allows users to wear the sensors on different body locations without having to adhere to a specific installation protocol. We study how such an algorithm impacts the performance of MET estimation algorithms. Using daily physical activity data, we demonstrate that an automatic sensor localization algorithm decreases the estimation error of the MET calculation by a factor of 2.3 compared to the case without sensor localization. Furthermore, our sensor localization algorithm achieves an accuracy of 90.8% in detecting on-body locations of wearable sensors. The integration of sensor localization and MET estimation achieves an accuracy of 80% in calculating the MET values of daily physical activities.**

I. Introduction

Metabolic equivalent of task (MET) is an approximation of energy expenditure and indicates the intensity of physical activities. This measurement is used to detect activities with many chronic illnesses such as coronary heart disease, type-2 diabetes, and various types of cancers [1]. Healthy lifestyle changes such as diet control and exercise, which maintain a balance between dietary intake and calories burned, are key approaches reducing the complication due to these diseases. This requires the difficult task of real time monitoring of physical activities that individuals at high risk for chronic diseases perform daily [2]. There are several ways to calculate food intake and level of physical activity, including traditional self-reported questionnaires, indirect calorie meters, doubly labeled water techniques, and electrocardiographs [2], [3]. In recent years, however, accelerometers, gyroscopes, pressure sensors, and heart rate monitors have been deployed for physical activity detection and energy expenditure [4] due to their small size, portability, low power consumption, and low cost [2], [3].

Accelerometers are widely used to estimate energy expenditure and metabolic equivalent of task for physical activities [2]–[5]. Current approaches for estimation of MET values using wearable sensors, although accurate [4], [5], do not consider possible misplacement of the sensors on different body locations. Therefore, the claimed accuracy of current MET estimation approaches is dependent on adhering to deployment protocols; users must wear sensors on predefined body locations. This location requirement is limiting in practical use and potentially imposes discomfort for end users, since they are not allowed to wear sensors on their own desired body locations. To address the aforementioned challenges of the current technology, we develop a location-independent MET estimation approach and study the impact that sensor localization can have on enhancing performance of MET estimation. To the best of our knowledge, the impact of sensor localization on calculation of MET estimates has not been studied previously. Our specific contributions in this paper are as follows: 1) we propose a framework for estimating MET numbers without any information about the location of the sensors on the body; 2) we develop a sensor localization algorithm based on machine learning techniques to automatically detect the location of the wearable sensors; 3) we develop regression-based algorithms for estimating the MET values of physical activities; 4) we assess the performance of individual algorithms as well as the entire framework using real-data collect with 6 adults performing physical activities in a metabolic laboratory.

II. Related Work

Our study in this paper bridges two areas of research, namely MET calculation and unreliability mitigation, as related to body sensor networks.

Several studies have been conducted to approximate energy expenditure and MET values of physical activities. The study in [2] develops a regression model to estimate the MET values when playing a soccer game. It demonstrates that the MET value of soccer exergaming movements can reach the value of 7, which is a standard value for actual casual intensity soccer. In [4], authors compare a wearable multi-sensor with a single sensor approach for energy expenditure estimation. Their results show that a wearable multi-sensor approach outperforms the single sensor solution using the ActiGraph GT3X+ and linear regression model. The study in [3] proposes two MET estimation methods, one traditional single and multiple regression models, and one mono-exponential MET estimation method. The results validate the effectiveness of the mono-exponential MET estimation equation for the non-steady and steady states.

Studies on sensor unreliability mitigation can be divided into 3 groups of: 1) sensor placement on different parts of the body (for example back pocket of trousers versus side pocket of jacket) [6]–[11]; 2) sensor displacement within a given coarse location (for example shifting from top upper arm to middle upper arm) [12], [13]; 3) change in the orientation of sensors [14], [15]. In particular, there exist several recent studies that develop localization techniques based on machine learning algorithms [6]–[8], [11]–[13], [16]–[18]. However, none of them investigate the effects of localization in MET estimation systems.

None of the previous studies examines the join problem of sensor localization and MET estimation in a unified framework. Even the recent work in [19], which performs sensor localization prior to calculating energy expenditure, has the limitation of detecting sensor locations only during walking.

III. System Architecture

We propose a system that estimates the MET values corresponding to physical activities without requiring the sensors to be placed on specific locations on the body. The MET estimation system contains four main modules: 1) Data collection; 2) Sensor localization using feature selection and data classification; 3) Linear regression model which uses the raw acceleration data of the sensors placed on various body locations (e.g. ankle and hip) to estimate the MET values; 4) Investigation of impacts of sensor localization integrating sensor location information, determined by the sensor localization algorithms, with MET estimation mode; As shown in Fig. 1, in the training phase, the accelerometer signals labeled with their locations are fed into a classifier to build a classification model to detect the location of the unlabeled accelerometer signals. We then develop a linear regression on the magnitude of the accelerometer signals to estimate MET numbers. In the execution/test phase, the location of the sensors are automatically detected by the sensor localization algorithm that provides location information to the underlying MET estimation algorithms. Using our sensor localization model, we determine whether each segment of the accelerometer signal, which has been extracted from a sliding window of 3 seconds, belongs to each particular sensor worn on the body. Finally, we compute the MET values using the linear regression model on the magnitude of the previously labeled accelerometer signals.

A. Data Collection Platform

In order to evaluate the effect of sensor localization on MET values of physical activities, we conducted a data collection for exergaming movements [2]. The data was collected from six male subjects from age 21 to 30 during a clinical experiment. In the experiment two types of data collector devices were attached to each participant. First, two GCDC +/- 2g accelerometer with $100Hz$ sampling rate were attached to the body, one on the hip and the other on the ankle to collect acceleration signals from the ankle and the hip during each activity. The second device is a metabolic cart attached to each participant during the experiment. The metabolic cart measures the volume of oxygen breathed into the lungs while doing activities. We used the following equation to compute the actual real value of MET corresponding to each activity.

$$MET = \frac{VO_2}{f \times m} \tag{1}$$

where $VO_2(\frac{ml}{min})$ and m denote the oxygen uptake and the mass of the user in kilograms, respectfully. In equation (1), f denotes a factor that depends on the general fitness features of the group participated in the experiment. In our case, the value of f considered to be 3.5, which is the number for healthy and active adults [20].

Table I shows the list of experimental movements. The participants were asked to repeat each movement for a full 3 minutes in the experiment. We allowed the participants to perform each activity for 3 minutes to achieve a steady state in breathing and allowed them to have their own desired intensity while doing activities. We extracted the intensity of each soccer action based on the work in [2], which requires repeating an action for 3 minutes.

TABLE I. Movements Description

No.	Movement	Description
1	Run	Running in place
2	Sprint	Sprinting in place
3	Pass	Passing the ball directly left
4	Chip	Chipping a ball up and to left
5	Medium Shot	Medium Powered Laces Shot
6	Full Powered Shot	Full Swinging Shot
7	Simulated Game	Simulated Exergame-play

The set of actions in Table II simulates soccer ball movements in a soccer game environment. Each action contains movements such as running, shooting, and passing that happens in normal game play.

TABLE II. Sequence of Actions in Simulated Game

No.	Actions
1	pass, pass, medium shot
2	pass, pass, strong shot
3	sprint for 5 seconds (defense)
4	pass, chip, shot
5	running, fake shot, pass, strong shot
6	sprint for 5 seconds (defense)
7	pass, sprint, shoot
8	sprint for 5 seconds

B. Sensor Localization

We collected 3-axis raw accelerometer signals from two accelerometer sensors attached to the 'ankle' and the 'hip' of each participant. In order to find out whether each segment of accelerometer signals is generated by the hip accelerometer or the ankle accelerometer, we develop sensor localization algorithms based on machine learning algorithms that operate on statistical features calculated from the collected signals. Several features can be extracted from the human activity signals. We extract the features shown in Table III from each

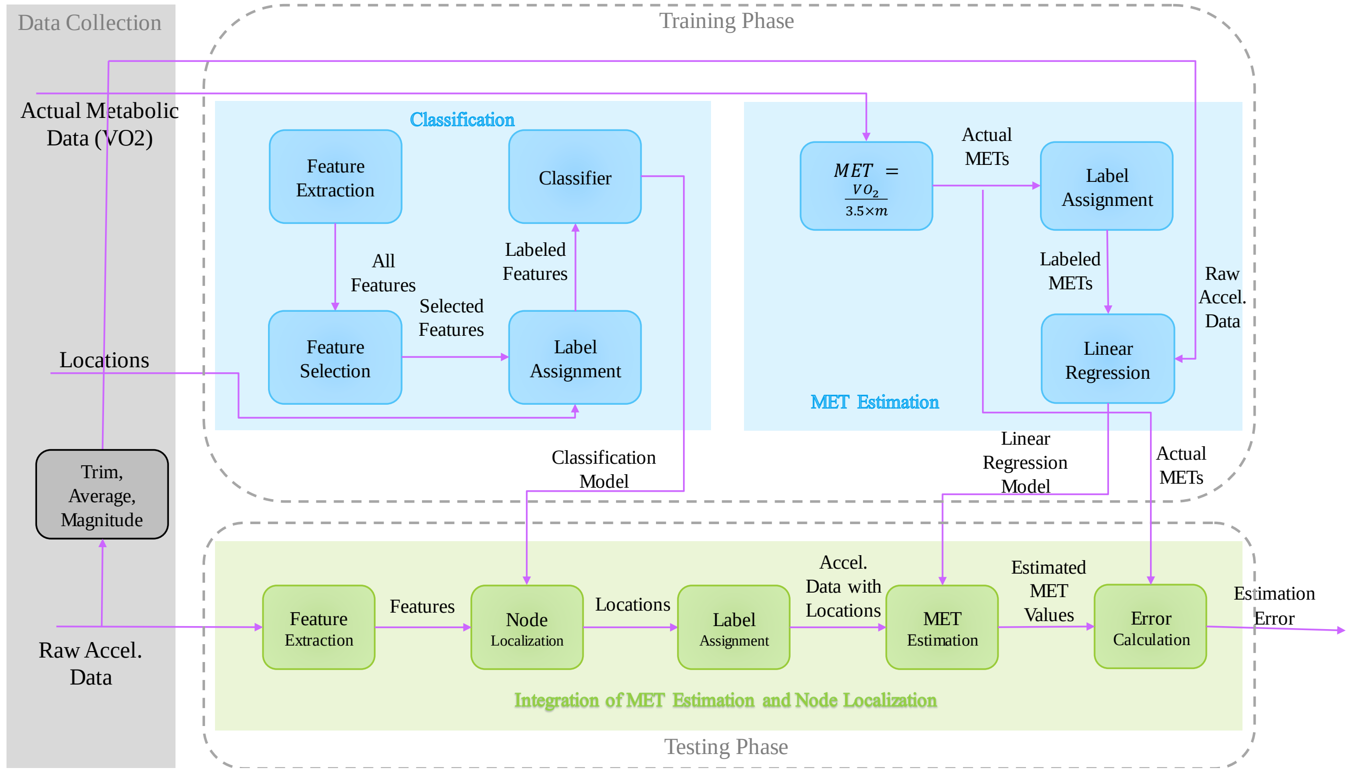

Fig. 1. Process of evaluation of sensor localization on MET estimation linear model

axis of the accelerometer signal. The effectiveness of these features in physical activity monitoring applications has been demonstrated through our prior research [16].

TABLE III. EXTRACTED FEATURES FROM EACH ACCELEROMETER SENSORS

Feature	Description
AMP	Amplitude of Signal Segment
MED	Median of the Signal
MNVALUE	Mean of the Signal
MAX	Maximum Value of Signal
MIN	Minimum Value of Signal
P2P	Peak to Peak Amplitude
STD	Standard Deviation
VAR	Variance
RMS	Root Mean Square Power
S2S	Stand to End Value

The output of feature extraction is 60 features from both ankle and hip accelerometers in feature matrix F, which contains features calculated from the accelerometer signals at time t. The total number of extracted features is relatively high which, decreases the accuracy and can also overfit the sensor localization model. Using high-ranked feature matrix also requires high energy sources for real time execution. In order to solve this problem, we use a forward feature selection algorithm to select the best subset and to remove the irrelevant features based on the maximum relevancy and minimum redundancy. The resulting matrix only includes a subset of all the features extracted from both ankle and hip accelerometer sensors.

$$F = \begin{pmatrix} {f_0}^0 & {f_1}^0 & \dots & {f_{m-1}}^0 \\ {f_0}^1 & {f_1}^1 & \dots & {f_{m-1}}^1 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ {f_0}^t & {f_1}^t & \dots & {f_{m-1}}^t \end{pmatrix}$$

In matrix F, each row contains a subset of m features corresponding to a signal segment captured at time t. The feature set is used to train a classification model that detects sensor locations based on the captured accelerometer data in real-time.

C. MET Calculation Model

As mentioned previously, participants in our experiment were attached to a metabolic cart to measure oxygen volume taken into lungs while performing activities. They were also asked to wear two accelerometer sensors, one on the ankle and other on the hip. Therefore, we have two streams of 3-axis accelerometer signals collected by accelerometer sensors on body and the MET values from the metabolic cart each participant was attached to. Since each individual's breathing patterns differ from each other, the oxygen uptake is collected and averaged over a duration of 30 seconds. We also needed to synchronize the VO_2 data with the accelerometer data, therefore the collected data from accelerometer sensors can be used collectively for sensor location and MET calculation. We also computed the magnitude of each accelerometer sensor device. In this way, we extract the intensity of each action by combining the x-axis, y-axis, and z-axis of accelerometer signals. As a result, each axis of the accelerometer signals is first averaged over 30 seconds (same as the VO_2 data), then the magnitude of the signal vectors is calculated below:

$$\mu = \sqrt{x^2 + y^2 + z^2} \tag{2}$$

where μ in equation (2) denotes the magnitude of the each accelerometer data segment. We calculated the magnitude of each 'ankle' and 'hip' accelerometer signal segment. The peak of these signal segments, which were collected over time span of 3 minutes, were correlated to MET value points computed from the metabolic data. We developed a linear regression model to fit the best line on intensity points as input and MET values as output. Each intensity point includes an ankle accelerometer peak point and a hip accelerometer peak point as features.

$$I = \begin{pmatrix} {\Phi_a}^0 & {\Phi_h}^0 \\ {\Phi_a}^1 & {\Phi_h}^1 \\ . & . \\ . & . \\ . & . \\ {\Phi_a}^\tau & {\Phi_h}^\tau \end{pmatrix}$$

In the above equation, I is a matrix that contains peak points of accelerometers. Φ_a and Φ_h are the peak points of the ankle and hip accelerometers, respectively. τ demonstrates each 3 minute time interval segment.

D. Robust MET Calculation

We extracted a linear regression model form the magnitude of accelerometer signals and actual MET values computed from the VO_2 data. In real life, there is no guarantee that patients or other users wear sensors on the body parts where they are meant to. Therefore, we integrate sensor localization with MET calculation to develop a robust MET calculation algorithm. In order to compare the result of MET value estimation, first we assume the location of each signal segment is known using localization algorithm proposed in previous sections and perform the regression on our data. Second, we consider the most probable situation in which user might wear the hip accelerometer sensor on ankle and ankle accelerometer sensor on hip by mistake. We can show this on our data by changing the detected label for each signal segment, hip to ankle and ankle to hip. As a result, we have 2 data sets including same features as input but opposite labels as output. We build a linear regression model, including estimated MET values and corresponding coefficients from the first data set. The extracted model from the regression is a linear formula such as below:

$$MET^t = c_1^t \times \mu_a + c_2^t \times \mu_h + c_3 \tag{3}$$

In equation (3), c_1, c_2 are the corresponding coefficients to the magnitude of the accelerometers. μ_a and μ_h are the magnitude of the ankle and hip accelerometer signals, respectively.

IV. Results

In this section we compare the performance and accuracy of our location-independent MET calculation system with a baseline MET calculation system that does not use sensor localization. First, we discuss the results of the sensor localization algorithm and then describe the results regarding the MET calculation model. Finally, the accuracy of a location-independent MET estimation system including our sensor localization algorithm, and the MET calculation model will be demonstrated.

A. Sensor Localization

The data collected from accelerometer signals were used to extract 60 features from the 'ankle' and 'hip' sensors. The data were then used to find a subset of features that are relevant to the sensor localization task. Therefore, 14 features out of 60 were selected to perform sensor classification. We used WEKA tools [21] to develop the sensor localization algorithms and to classify the sensor signals into two classes of 'ankle' and 'hip' locations.

As shown in Table IV, the average recall and precision of the classifiers range from 68.57% support vector machine (SVM) to 88.35% 1-nearest neighbor (1-NN) and from 66.3% radial basis function networks (RBF networks) to 88.35% 1-NN respectively. Comparing the F-Measure and ROC Area the artificial neural network (ANN) and 1-NN have the biggest values and SVM and RBF Network have the lower values among all the classifiers. Based on the information in Table IV 1-NN and ANN classifiers give more promising results in detecting the location of the sensors.

In Table V the accuracy of the classifiers in correctly identifying the location of the sensors are shown. We could classify the sensor signal segments with average accuracy of 78.2%. Among all the classifiers, 1-NN shows the best performance with 91% while SVM reaches the least accuracy of 68.05% in classification. The mean absolute error (MEA) and root mean squared error (RMSE) in the Table IV also emphasize the superiority of 1-NN and ANN classifiers in detecting the location of the sensors. Since the 1-NN classifier gives the most promising results in our case, among all the classifiers, we applied it to our system as a localization algorithm. In order to validate the result of classification a 10-fold cross validation is used. Since the KNN classifier shows more accuracy and less mean error, it used as a localization algorithm for our system.

B. Linear Regression

In order to find the most accurate regression model in computing MET values, we performed linear regression on various possible combination of the sensors on ankle and hip. In [2] sum of magnitude of the accelerometer signals was used as one single feature for linear regression. While we use the magnitude of the accelerometer signals as two separate features to perform the regression. Table VI compares the accuracy and error of possible different combinations of the sensors such as using a single sensor ankle, hip, using summation of both ankle and hip sensors and using ankle and hip sensors separately together. As shown, our approach which is the separate use of ankle and hip signals, improves the average R^2 statistic from 0.71 to 0.80 and reduces the amount of the error from 1.37 to 1.15 on average compared to the previous approach used in [2].

C. MET Calculation with and without sensor localization

Table VII shows the result of performing linear regression on each participant separately. We used the linear regression model to extract a linear equation from the accelerometer signals of each subject in the experiment assuming the location of the sensors are known to the model. In Table VII the R^2 statistic denotes the fit of our model. As shown, there is variability among the models per subject. This difference

TABLE IV. PERFORMANCE OF THE SENSOR LOCALIZATION ALGORITHMS USING FEATURES IN TABLE III

(a) KNN Classifier with K = 1

Node	Precision	Recall	F-Measure	ROC Area
Ankle	88.3%	88.8%	88.6%	90.8%
Hip	88.4%	87.9%	88.2%	90.8%
Average	88.35	88.35	88.4	90.8

(b) RBF Network

Node	Precision	Recall	F-Measure	ROC Area
Ankle	75.9%	48.4%	59.1%	73.8%
Hip	61.4%	84.2%	71%	73.8%
Average	68.65	66.3	65.05	73.8

(c) SVM Classifier

Node	Precision	Recall	F-Measure	ROC Area
Ankle	72.5%	59.6%	65.4%	68.2%
Hip	64.9%	76.6%	70.3%	68.2%
Average	68.57	68.1	67.85	68.2

(d) ANN Classifier

Node	Precision	Recall	F-Measure	ROC Area
Ankle	86.2%	83%	84.6%	91.7%
Hip	83.2%	86.4%	84.7%	91.7%
Average	84.7	84.7	84.65	91.7

TABLE V. ACCURACY OF THE SENSOR LOCALIZATION OF KNN WITH K = 1, RBF NETWORK, SVM, AND ANN CLASSIFIERS

Classifier	Accuracy	MAE	RMSE
KNN	92%	0.081	0.283
RBF Network	66.08%	0.402	0.453
SVM	68.05%	0.32	0.56
ANN	84.67%	0.2	0.34
Average	78.2%	0.25	0.41

could originate from different possible intensities in the same activity performed by individuals or even distinct patterns of body movements during the same activity per subject. For example, some people may move their hip during walking while others do not. Based on the results, our linear regression model represents all the subjects with R^2 value of 0.76.

Since the R^2 correlation coefficient of a regression model only reports how well the line fits to the data, in order to better report the accuracy, we defined an estimation error (EE) parameter by differentiating the actual MET values computed from the metabolic data (MET) and estimated MET values ($\hat{MET}$) from regression mode, which is shown by ϵ in the equation (4):

$$\epsilon = |\hat{MET} - MET| \tag{4}$$

Table VIII compares the accuracy of the linear model fitted on the intensity of accelerometers and actual MET values with and without sensor localization. The R-squared statistic of linear regression models with sensor localization ranges from 71% to 92%, while it dramatically decreases down to negative values when the location of the sensors are unknown. Negative value for R^2 correlation is a result of a highly poorly fitted model on the dataset. As a result, based on the computed average estimation error, locating the position of sensor nodes on different body parts improves the accuracy of the MET estimation system with a factor of 2.3 comparing to when there is no prior knowledge about the location of the sensors.

V. DISCUSSION AND FUTURE WORK

This work illustrates how misplacement of sensors on different body locations can affect the result of MET estimation of some exergaming movements. The variability in the linear regression results indicates the necessity to increase the number of the participants in the experiment with more trails including more locations on the body. On the other hand, we can think of a real-time user-oriented model that monitors an individual's activity patterns in order to update the MET estimation model at the same time the user performs activities. Sensor misplacement is not the only concern when it comes to wearables. There are several other unreliable factors to them such as displacement and misorientation of the sensors. Therefore, we are also planning to conduct our research considering the possible misorientation and displacement of the sensors on the body.

VI. CONCLUSION

In this paper, we proposed a location-independent MET estimation system, which collects VO2 and accelerometer data from participants. Using collected data, it detects the location of the two accelerometer sensors, on the hip and ankle, with proposed localization algorithms. The MET estimation system also deployed a regression model to determine the MET values corresponding to some soccer exergaming movements. The main contribution of our study was comparing the result of estimating MET values of physical activities in two different situation. 1) The location of the sensor nodes on body are known using localization algorithms; 2) The location of the sensor nodes are unknown. Based on the result, the average error of estimating MET values corresponding to exergaming movements with sensor localization, is 2.3 times less than it without sensor localization. We proposed a localization algorithm based on the KNN classifier to detect the location of the sensors on the body with accuracy of 92%.

TABLE VI. COMPARISON BETWEEN THE ACCURACY OF THE REGRESSION ON DIFFERENT COMBINATION OF THE ANKLE AND HIP SENSORS

Sub.	Stats.	Ankle	Hip	Ankle+Hip	Ankle,Hip
1	R^2	0.11	0.71	0.71	0.83
	RMSE	3.25	1.85	1.58	1.61
2	R^2	0.22	0.84	0.53	0.84
	RMSE	2.5	1.2	1.94	1.25
3	R^2	0.63	0.84	0.86	0.92
	RMSE	1.58	1.02	0.96	0.79
4	R^2	0.23	0.60	0.71	0.71
	RMSE	2.01	1.43	1.23	1.37
5	R^2	0.60	0.53	0.80	0.82
	RMSE	1.02	1.11	0.71	0.75
6	R^2	0.76	0.44	0.72	0.79
	RMSE	1.23	1.17	1.88	1.23
All	R^2	0.60	0.32	0.63	0.76
	RMSE	1.38	1.81	1.34	1.09
Average	R^2	0.45	0.61	0.71	0.80
	RMSE	1.85	1.37	1.37	1.15

TABLE VIII. COMPARING R^2 VALUES AND ERROR OF LINEAR REGRESSION ON MET VS ANKLE AND HIP ACCELEROMETERS WITH AND WITHOUT SENSOR LOCALIZATION

Subject	R^2 with NL	EE with NL	R^2 without NL	EE without NL
1	0.83	0.29	0.68	0.30
2	0.84	0.12	-19.30	0.34
3	0.92	0.09	-0.10	0.34
4	0.71	0.18	-14.41	0.96
5	0.82	0.13	0.34	0.15
6	0.79	0.20	0.50	0.37
Average	0.80	0.18	-4.98	0.41

TABLE VII. R^2 VALUES FROM LINEAR REGRESSION ON MET VS ANKLE AND HIP ACCELEROMETERS

Subject	R^2	Linear Equation
1	0.83	$11.7\mu_a + 16.9\mu_h - 25.9$
2	0.84	$-2.3\mu_a + 30.3\mu_h - 24.8$
3	0.92	$2.7\mu_a + 7.3\mu_h - 7.4$
4	0.71	$2.2\mu_a + 17.9\mu_h - 18$
5	0.82	$1.8\mu_a + 1.7\mu_h - 2.5$
6	0.79	$3.0\mu_a + 2.5\mu_h - 3.2$
All	0.76	$4.9\mu_a + 4.0\mu_h - 8.0$

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