Towards Practical Energy Expenditure Estimation With Mobile Phones

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***Abstract*—Regular physical activity plays a significant role in reducing the risk of obesity and maintaining people's health conditions. Among all the physical activities, walking is a commonly recommended intervention for combating lifestyle diseases. The capability to accurately measure the energy expenditure of walking provides foundations to base the corresponding intervention. In this paper, we develop a set of signal processing and statistical pattern recognition techniques to estimate energy expenditure of walking in real-life settings using mobile phones. We examine the robustness of our proposed techniques to variations in location on the human body and across body types. We show that our proposed techniques can estimate step frequencies for three common locations of phone usage and achieve promising energy expenditure estimation accuracy with limited training data.**

I. Introduction

Behavior and lifestyle choices are the key factors that contribute to the increasing prevalence of chronic diseases and premature deaths in our modern society. In particular, the worldwide obesity phenomenon and associated diabetes are becoming the main epidemic of the 21st century [1]. Largely as a result of changes in the modern lifestyle, this growing phenomenon is placing a heavy burden on today's healthcare system [2]. In the face of the current obesity epidemic, research findings suggest that encouraging physical activities especially walking on a daily basis so as to reduce sedentary behaviors has been playing a significant role in effectively reducing the risk of obesity [3].

Equipped with powerful communication, sensing and computational capabilities in portable forms, wireless mobile technologies are able to continuously monitor people's daily physical activities and thus have the great potential to raise people's awareness of their sedentary lifestyle and promote behavior change to prevent obesity and its associated chronic diseases [4]. Therefore, in recent years, significant research efforts have been made to develop signal processing and pattern recognition techniques that use sensors embedded inside wearable and mobile devices to track daily physical activities and estimate the corresponding energy expenditure (EE) [5], [6], [7], [8], [9]. Among all the sensors used in this research field, inertial sensors (accelerometers and/or gyroscopes) and electrocardiography (ECG) sensors are the most widespread. The inertial sensors are very sensitive to the motion of human bodies and thus have been widely used for recognizing physical activities and estimating EE. For ECG sensor, the heart rate extracted from ECG signals has been proved to have a strong correlation with EE [10]. However, many mental and physiological activities such as stress could also affect heart rate [11], which makes ECG not a reliable source to infer EE information. Furthermore, wearing a ECG sensor is intrusive in people's daily life, making it impractical to collect EE information on a daily basis.

In this paper, we present a practical solution for estimating an individual's energy expenditure using mobile phones in real-life ambulatory settings. We specifically focus on estimating energy expenditure due to walking in free living conditions. This is because walking is the most common type of activity among people who are physically active [12] and a commonly recommended intervention for combating lifestyle diseases. Specifically, we use the accelerometer and gyroscope present in mobile phones to describe intensity of walking. Mapping movement descriptors measured with such sensors to energy expenditure from walking can be framed as a regression problem. There are two main challenges in this domain. The first challenge is identifying suitable descriptors of walking that are robust to mobile phone placement on individuals. The second challenge is accurately predicting energy expenditure from walking given minimal or no information about an individual. To tackle these issues, we propose an algorithm that robustly estimates an individual's energy expenditure regardless of the location in which the mobile phone is carried. In addition, we use body weight as a similarity measure to minimize training data. By doing so, we aim to expand the the state of the art in energy expenditure with mobile phones using inertial sensors alone in free living scenarios.

II. Methods

A. Energy Expenditure Prediction as a Regression Problem

Given a D-dimensional descriptor of movement $\mathbf{x}_{n_p} \in \mathbb{R}^{D\times 1}$ measured with a mobile phone for a time epoch n_p and a certain anthropometric characteristic $\mathbf{Anth}_p$, for person p, our goal is to determine the energy expended $y_{n_p} \in \mathbb{R}$ for that epoch. Consider a test population consisting of P participants. For each person p, from this population, we collect training data points in the form of input-output pairs $\left\{\mathbf{x}_{n_p}, y_{n_p}\right\}_{n_p=1}^{N_p}$. Using these data, we build a statistical model that indicates what the statistical distribution of energy expenditure, i.e., $p\left(y_{n_p}|\mathbf{x}_{n_p}, \mathbf{Anth}_p\right)$ is given their movement and anthropometric characteristics. This is framed as a regression problem: $\left(\mathbf{x}_{n_p}, \mathbf{Anth}_p\right) \overset{p\left(y_{n_p}|\mathbf{x}_{n_p}, \mathbf{Anth}_p\right)}{\rightarrow} y_{n_p}$.

B. Robustness Across Locations

1) Capture of Center of Mass Movement: Walking is a quasi-periodic (periodic in the short term, with period gradually changing in the long term) physical activity involving highly correlated movement of limb segments. This periodic nature can be captured using an inverted simple pendulum model [13]. According to the inverted pendulum model, a person is modeled as a point mass connected to a rigid beam with the foot as a pivot. During each leg's stance phase, the point mass vaults over the pivot point while the other leg swings when not in contact with the ground. This is repeated alternately between legs. Thus the center of mass of the body moves up and down in a cyclical fashion. The typical usage of a mobile phone include conditions where it is stowed away in a fixed location like a pocket, placed next to the ear for a call or looked at constantly so as to access an application. In these scenarios, phone movement is coupled with the periodic up-down movement of the center of mass. Given that the up-down movement is quasi-periodic, the change in vertical position over a short time instant can be represented using a set of sine-waves. The double-differential of this signal, namely, vertical acceleration will also be cyclic and thus can be represented by the same set of sine waves. Tracking the vertical acceleration could thus provide a robust signal to describe overground walking intensity across multiple locations.

2) Capture of Vertical Acceleration: The principle behind calculating the vertical acceleration on the phone depends on converting the local accelerations on the phone to a canonical reference frame in the world coordinate space and extracting the vertical acceleration from this frame. We use the phone's sensors to calculate a unit quaternion $q = \{q_0, q_1, q_2, q_3\}$ to provide the orientation of the phone. We used the default orientation sensor available within the Android operating system to determine this quaternion.

Given the quaternion q, we calculated the z axis components of direction cosines of the normals of the three planes of the phone (corresponding to x, y and z directions) with respect to the world coordinate frame using the transformation:

$$\{\hat{n}_x, \hat{n}_y, \hat{n}_z\} = \left\{ \begin{array}{c} 2(q_1q_3 - q_0q_2) \\ 2(q_0q_1 + q_2q_3) \\ q_0^2 - (q_1^2 + q_2^2 + q_3^2) \end{array} \right.$$

where $\hat{n}_x$,$\hat{n}_y$ and $\hat{n}_z$are the corresponding z axis components.

After calculating $\{\hat{n}_x, \hat{n}_y, \hat{n}_z\}$, we then obtained the vertical acceleration a_v, by calculating the weighted sum of triaxial accelerations using the z axis components as weights:

$$a_v = \frac{a_x\,|\hat{n}_x| + a_y\,|\hat{n}_y| + a_z\,|\hat{n}_z|}{|\hat{n}_x| + |\hat{n}_y| + |\hat{n}_z|}$$

The intuition behind this approach was that when a particular local axis of the phone is vertical (say Y-axis) with respect to the world frame the magnitude of that z-axis component ($\hat{n}_y$) would be close to 1. By virtue of orthogonality, the other components would be close to zero. Thus this weighting factor, would provide maximum weightage to the z-axis acceleration. The use of a weighted sum allows a smooth location in transitional cases where the phone is diagonal. This results in the normalized vertical acceleration data. Figure 1a illustrates typical raw data when the phone is placed in one's back pocket. Figure 1b illustrates the values of z-axis components of the direction cosines of the three planes. Based on these components, we calculate the vertical acceleration time series shown in light grey in figure 1c.

The resultant time series was then passed through a band-pass filter with cut-off frequencies $[1, 2.1]$ Hz. For the back pocket, the resultant series is shown in black in figure 1c. In order to extract the frequency component from the weighted data, we considered a ten second window of samples, subtracted the mean of the data from each point within that window and extracted a 1024 point periodogram. In this periodogram, the walking frequency was associated with the largest peak within $[1, 2.1]$ Hz (as shown in figure 1d). This frequency corresponding to the value of the maximum peak is used as a representation of movement intensity for walking.

C. Predicting EE with Minimal Training Data

1) Weight as a Similarity Measure: Given a robust descriptor of movement, we use the principle that individuals with similar anthropometric descriptors, in particular, similar body weights, will expend the similar amounts of energy given the same movement. Using weight as a descriptor of similarity between individuals, we utilize a previously validated hierarchical linear model [14] to predict energy expenditure. Weight-based approaches have been used by Altini et. al [15] to normalize across populations. We extend previous work by understanding what kind of data are best suited for learning a regression model for an individual with limited training data.

2) Generalized Energy Prediction using Hierarchical Models: To consolidate information across people, we adopt a two-level approach with hierarchical linear models (HLMs) [16]. For each person p, we model each output energy expenditure value, y_{n_p} as linearly dependent on a representation of movement intensity x_{n_p}. In our case, the x_{n_p} is the step frequency of walking. This can be expressed as:

$$\begin{aligned} y_{n_p} &\sim \mathcal{N}\left(y_{n_p}; \mathbf{w}_p^T x_{n_p}, \beta_p^{-1}\right), \\ &\quad \forall n_p \in \{1, 2, \ldots N_p\}. \end{aligned}$$

β_p is a noise term.

We are also given each participant's weight $\mathbf{Weight}_p$. We model top-down dependence of each person's model parameters,$\mathbf{w}_p$ on their weight $\mathbf{Weight}_p$, i.e. each component $\{w_{p,l}\}_{l=1}^{D}$ of $\mathbf{w}_p$ follows the relation:

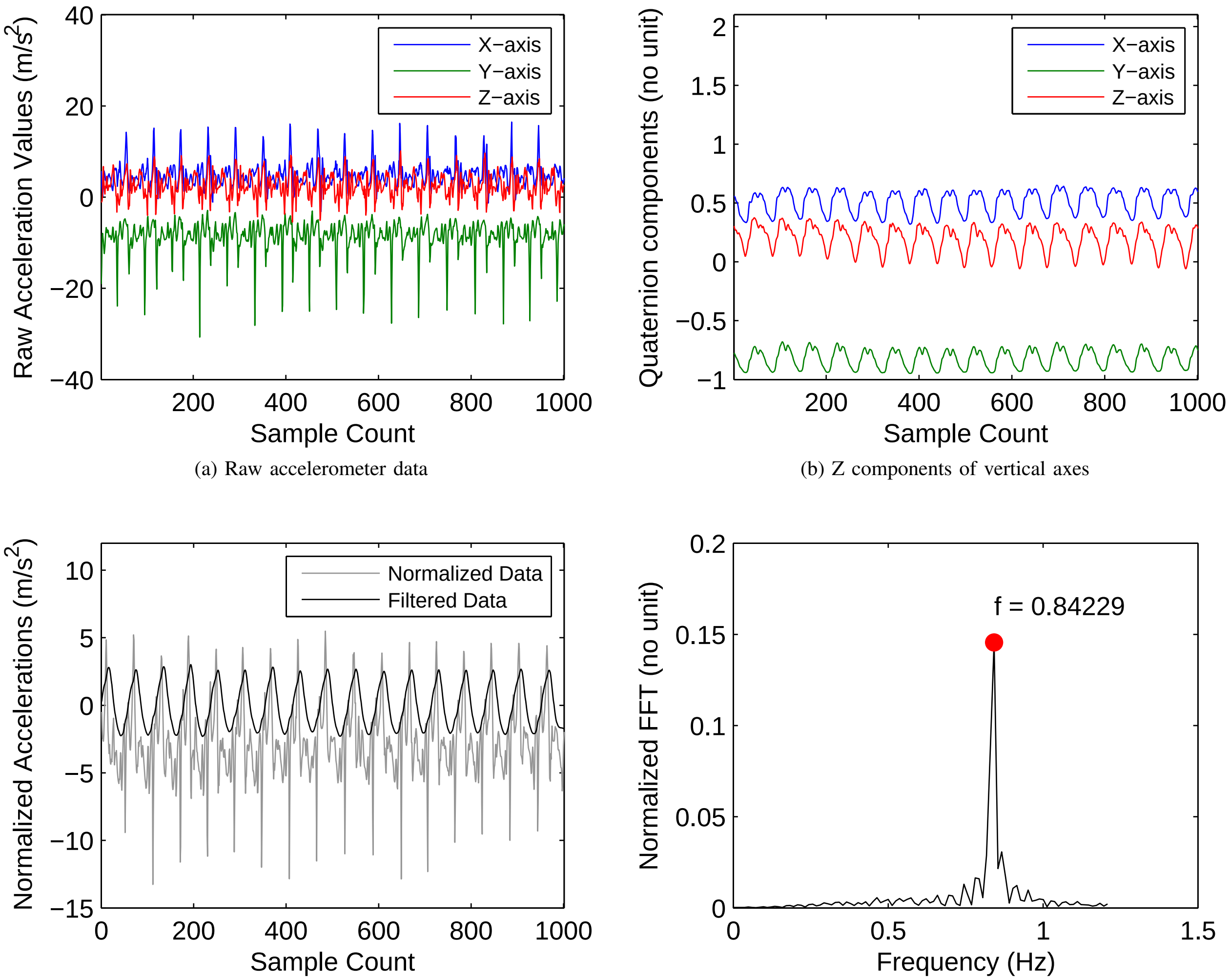
$$\begin{aligned} w_{p,l} &\sim \mathcal{N}\left(w_{p,l}; \mathbf{k}_l^T \mathbf{Weight}_p, \alpha_p^{-1}\mathbf{I}\right), \\ &\quad l \in \{0, 1, \ldots, D\}. \end{aligned}$$

α_p is a noise term.

This model enforces consistency among P local regression models through the population-level parameters $\{\mathbf{k}_l\}_{l=1}^{D}$. The complete log-likelihood function is:

$$\begin{aligned} L &= log \prod_{p=1}^{P} p\left(\mathbf{Y}_p, \mathbf{w}_p | k, \alpha_p, \beta_p\right) \\ &= \sum_{p=1}^{P} \Bigg(\frac{N_p}{2} log\beta_p + \frac{M}{2} log\alpha_p \\ &\qquad - \Bigg(\frac{\beta_p}{2} \left\|\mathbf{Y}_p - \mathbf{X}_p\mathbf{w}_p\right\|^2 \\ &\qquad + \frac{\alpha_p}{2} \sum_{l=1}^{L} \left\|\mathbf{w}_{p,l} - \mathbf{Weight}_p^T \mathbf{k}_l\right\|^2 \Bigg) + const \Bigg) \end{aligned}$$

To maximize this likelihood, each and α_p and β_p must achieve the right balance by being as large as possible while minimizing the relative sum of intra-person least squares error terms $\left\|\mathbf{Y}_p - \mathbf{X}_p\mathbf{w}_p\right\|^2$ and the inter-person least-squared



(a) Raw accelerometer data

(b) Z components of vertical axes

(c) Normalized data and resultant time series after filtering

(d) Normalized FFT obtained from filtered signal

Figure 1: Illustration of normalization technique used to track the vertical component of acceleration. The phone was worn in the back pocket.

terms $\left\|\mathbf{w}_{p,l} - \mathbf{Weight}_p^T \mathbf{k}_l\right\|^2$. The inter-person error describes how accurate a model learned from other participants can be in predicting energy expenditure y_{n_p}. The intra-person error approximates how close the a model learned from that particular participant can predict y_{n_p}. This model is trained using an EM-like algorithm [17].

3) Prediction: Given the model, we predict energy values for a new person $P+1$ with morphological parameters given by $Phys_{P+1}$, using the equation:

$$\begin{aligned} w_{P+1,l} &\sim \mathcal{N}\left(w_{P+1}; \mathbf{Weight}_{P+1}^T k_l, \alpha_{P+1}^{-1}\right), \\ & \quad \forall l \in \{1, 2, \ldots D\}. \\ y_{n_{P+1}} &\sim \mathcal{N}\left(y_{n_{P+1}}; \mathbf{w}_{P+1}^T \mathbf{x}_{n_{P+1}}, \beta_{P+1}^{-1}\right), \\ & \quad \forall n_{p+1} \in \{1, 2, \ldots N_{P+1}\}. \end{aligned}$$

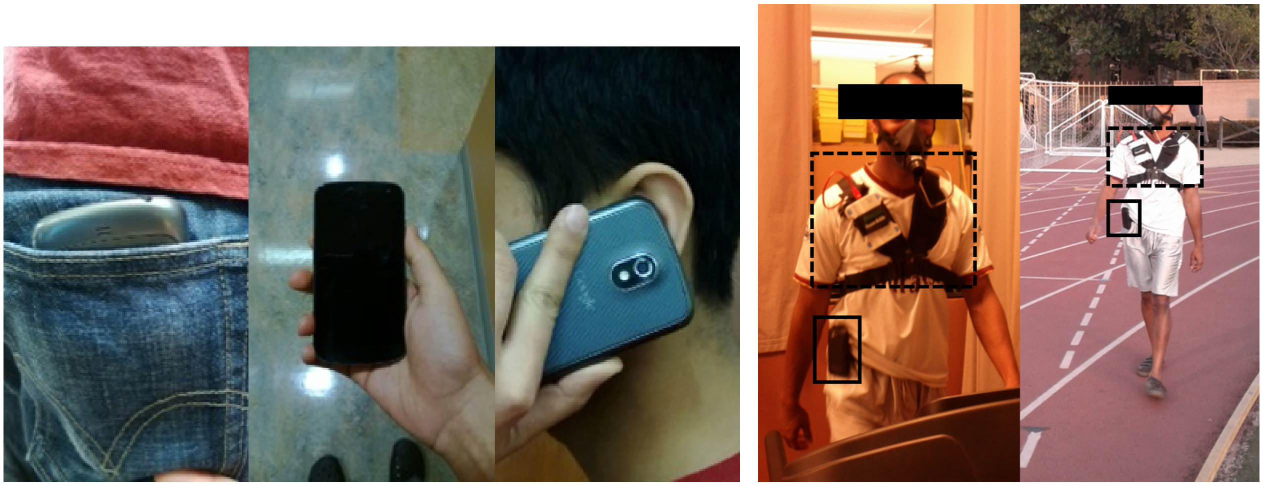
We set α_{P+1} and β_{P+1} to be the average of α_p's and β_p's over all people. It can be seen that to instantiate a model, it is enough to know the weight of a person. This model instantiation will be the result of consolidation across multiple users. The model can then be used to predict energy expenditure values given a movement descriptor $\mathbf{x}_{n_{P+1}}$

4) Determination of the Optimal Dataset: The above model relies on collecting samples of movement, weight and energy expenditure from a large number of participants to learn model parameters. One issue that arises when training such a hierarchical linear model is what is the optimal training dataset from which an accurate model can be obtained. When training regression models for walking, one can use example information from an indoor setting (using a treadmill) or an outdoor setting (overground walking). The given model was previously validated in predicting energy expenditure from treadmill walking. Our goal was to extend previous work by studying how treadmill walking-based models compare with models learned when only free living walking data are used. For this purpose, we learned separate models using treadmill data and free living data and evaluated them for accuracy.

III. Experimental Evaluation

A. Data Collection and Preprocessing

We performed two separate data collections related to validating the frequency estimation and energy expenditure estimation sections of our work. All participants signed informed



(a) Data collection for frequency detection. Three positions were measured: in back pocket, in hand, and on phone call

(b) Example of indoor and outdoor data recording sessions for energy expenditure. Phone position is shown in the solid black box, metabolic unit is shown in the dotted black box.

Figure 2: Illustration of data recording procedures for frequency detection and energy expenditure estimation

consent forms and the study was approved by the Institutional Review Board of the University of Southern California. In both data collections, accelerometer, gyroscope and rotational data were recorded with a Galaxy Nexus S or Nexus 4 smartphone. All kinematic data were collected at 50 Hz.

1) Frequency Estimation: To evaluate robustness of frequency detection to location, we collected information about participants walking at different step frequencies with the phone kept at different locations. Five participants (3 male, 2 female) participated in the study. The average age was 29.5±13.47 yrs (Max = 49.0 yr, Min = 20.0 yr), average height was 1.74±0.1 m (Max = 1.86 m, Min = 1.57 m), average weight was 62.5±4 kg (Max = 66 kg, Min = 56.7 kg).

Figure 2a illustrates the three locations for which phone data were collected. Each participant was asked to place their phone at a certain location and walk to the beats of a metronome for one minute. The purpose of a metronome was to provide a reliable ground truth for step frequency. All participants walked on a level floor, indoors. The three locations chosen were: in hand (as if using a mapping application), on phone call and in back pocket. These locations were chosen because they corresponded to the most common typical placement locations of a phone. Metronome frequencies were set at frequencies of 80, 90, 100, 110 and 120 bpm (corresponding to 1.33, 1.5, 1.67, 1.83 and 2 Hz respectively). These frequencies represented the absolute minimum and maximum step frequencies that could be considered walking across all participants. While walking, the phone collected triaxial accelerations, rotational rates and orientation information. Thus each participant generated 15 one minute samples of walking at five different step frequencies with the phones at three different locations.

Given each one minute sample, approximately 10 seconds of each sample in the beginning and end were cropped to remove transients. Each sample was then preprocessed as described in section II-B2.

2) Energy Expenditure Estimation: To evaluate robustness across people for energy prediction, we placed the phone in a belt-clip and asked participants to walking at a self-selected speeds outdoors. Data were collected from a population of 24 participants (16 male, 8 female). The average age was 25.9±4.4 yrs (Max = 33.0 yr, Min = 18.0 yr), average height was 1.74±0.07 m (Max = 1.85 m, Min = 1.60 m), average weight was 68.6±6.4 kg (Max = 81.7 kg, Min = 55.9 kg) .

Energy expenditure ground truth was measured using the Oxycon Mobile Metabolic unit from Carefusion. The cart was worn as a backpack fitted to the comfort of the participant. The metabolic unit reported participants' $\dot{V}O_2$, $\dot{V}CO_2$, and calorie data at the frequency of every breath. Calories were estimated using the Weir equation [18]. Data collection was carried out in two sessions - indoor and outdoor. In the indoor session, each participant was asked to walk on a treadmill at three speeds - 2.5, 3.0 and 3.5 mph for five minutes per speed and two minutes of settling time for each speed. In the outdoor session, each participant was asked to walk on the university athletic track at a self-selected speed for approximately 20 min. Figure 2b illustrates the data collection procedure for the energy expenditure section.

The kinematic sensor data were first preprocessed to obtain the normalized time series as described in section II-B2. At the end of this step, each participant had a time series of normalized vertical acceleration and energy expended for both indoor and outdoor walking. Each of these time series were split into ten second epochs. A 1024-point FFT and average energy expenditure were then calculated for that epoch. A peak detection algorithm was used to determine the maximum peak and thus step frequency for that epoch. For the purposes of this study, only the constant walking sections were considered. Thus for each participant, a dataset consisted of examples of step frequency and energy expenditure calculated across epochs in both treadmill and outdoor settings.

B. *Comparison Methodology for EE Estimation Algorithms*

Given a participant p, out of a population of P participants, our aim was to determine the optimal dataset to obtain accurate

Metronome Frequency (Hz)	In Back Pocket	On Phone	In Hand
1.33	4.54	14.04	7.25
1.5	1.82	4.46	1.82
1.67	50.37	6.05	7.02
1.83	49.89	2.55	6.86
2	49.26	3.46	5.33

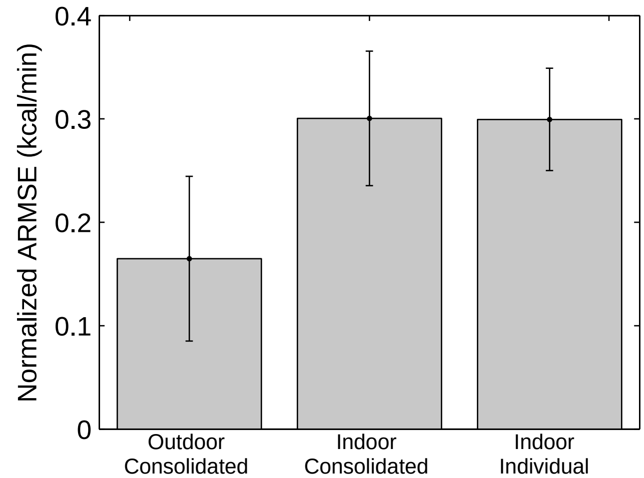
Table I: Average percentage error in frequency estimation across five participants at five metronome frequencies with the phone held in three locations.

estimates of energy expenditure from outdoor walking. For this, we considered three potential sources of data. In the first dataset, participant p's treadmill data alone was used to train a regression model. This was a special case of a hierarchical regression model with only one participant and hence no top-level dependence was required. This dataset was labeled - Indoor individual. In the second dataset, treadmill data from all P participants were used to train a hierarchical linear model. This dataset was labeled - indoor consolidated. In the third dataset, for participant p, outdoor walking information from the remaining $P-1$ participants were used to train an hierarchical linear model. This dataset was labeled - outdoor consolidated. The three models described were used to obtain energy expenditure predictions using participant p's data as test data. The normalized root mean squared error was calculated using the root mean squared error of predictions and dividing by the median value of the test data. This was done to obtain a percentage-like measure of algorithm performance. This was repeated across all participants and the errors were average across all participants.

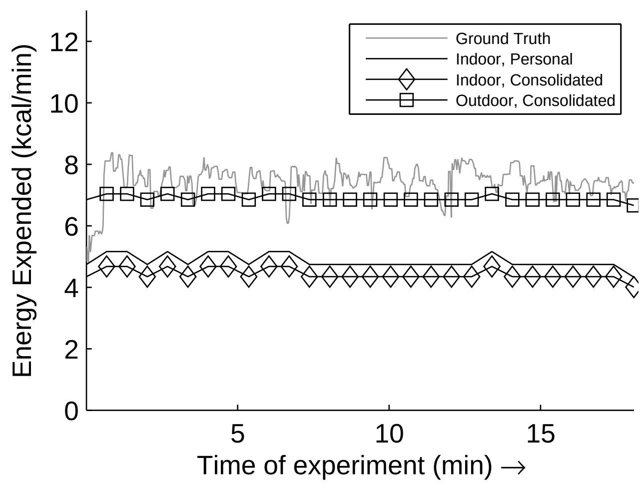
C. Results

1) Frequency Estimation: Table I shows the percentage error in prediction when walking at five different step frequencies averaged across five participants. It can be seen that in 11 out of 15 cases, the proposed algorithm has a frequency prediction error of less than 8%. We also note than in 3 out of 15 cases, the error is high as 50%. This mainly occurred at higher step frequencies in the back pocket. The main reason for this high error rate was that at these frequencies and position, for a subset of participants, the dominant peak occurred at half the step frequency instead of the actual step frequency. For these step frequencies, both the actual frequency and half of its value occur within the eligible frequency band. One reason for this could be that there exist biomechanical differences in walking at those step frequencies. Frequency-based approaches suffer from the difficulty in distinguishing harmonics from the fundamental frequency. One technique to avoid this is to use smoothing from historical data to determine a step frequency. We aim to extend this work across more participants to further examine this case.

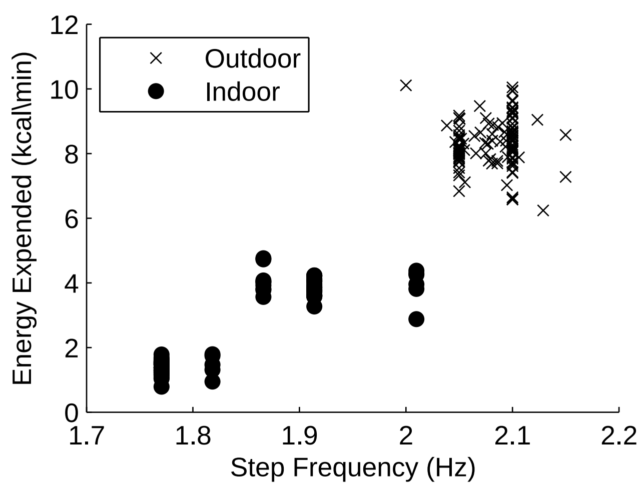
2) Energy Expenditure Prediction: Figure 3a illustrates the relative performance of different dataset. Using outdoor information from the remaining participants showed the lowest normalized root mean squared error (p<0.05 per participant). Using indoor data, whether it just from one participant or all participants resulted in higher errors. Figure 3b shows



(a) Comparison of algorithms when trained on different datasets



(b) An example trace of energy expenditure prediction for a simple participant by different algorithms



(c) Comparison of indoor versus outdoor energy expenditure for similar step frequencies in the sample individual

Figure 3: Illustration of energy expenditure prediction performance as compared across different algorithms.

an example trace for a single participant walking for approximately 20 minutes. The ground truth energy expended during this period is shown in grey. The predicted energy expenditure when using consolidated data from all participants when walking overground is shown with squares. Similar predictions when using consolidated data from the same participant and all participants walking on a treadmill are shown with the solid line and diamond lines respectively. It can be seen that the treadmill data under-predict the energy expended when walking in outdoor settings. To understand whether this was due to the algorithms or due to the data itself, we examined the frequency versus energy plot for indoor and outdoor walking. Figure 3c shows the energy expended versus step frequency plot for the same participant in both indoor (shown with circles) and outdoor scenario (shown with crosses). The graph shows that for the same or similar step frequencies, a participant expends more energy in overground walking than treadmill walking. Similar results were obtained for other participants with minor variations. This suggests that in order to use treadmill data for outdoor predictions, one has to account for this difference in energy costs between treadmill and overground walking.

Another observation that could be seen from the trace is that the energy expenditure predicted using step frequency remains fairly constant whereas the energy expenditure has a number of transients. This could be because of natural variations in the displacement of the mask, low resolution of the FFT (resulting in quantized step frequency values) or lack of modeling due to transients. We aim to explore this in future work.

IV. Conclusion and Future Work

In this paper, we presented a set of signal processing and statistical pattern recognition techniques to estimate energy expenditure from free living walking using one's mobile phone. We addressed the two issues of position independent descriptors of walking and accurately predicting energy expenditure from walking given limited training data using frequency-based descriptors and hierarchical models of energy expenditure respectively. The frequency-based features proposed were robust along a number of locations but were sensitive to harmonics. Datasets collected in outdoor settings resulted in better results than datasets from indoor settings due to differences in the energy costs of walking.

Although the algorithms proposed here have been validated on overground, level walking, we believe that that are a a number of ways to extend this work. We plan on extending the validation of the frequency-based technique on a larger population and across more locations on the body. We also aim to develop more robust algorithms to avoid false positives in frequency detection. We also plan on improving the resolution of frequency-based monitoring with higher resolution FFTs. While the current approach focused on modeling energy expenditure due to walking, we envision that the models developed could be extended to other common physical activities such as running, jogging, and walking up/downstairs as well. Our current work was limited in that it did not take into account the transient nature of energy expenditure with variation in step frequency. We plan on expanding our modeling capability to include transients. This will involve transient frequency monitoring and regression for non-stationary signals.

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