Using Wearable Physiological Sensors to Predict Energy Expenditure

Kimberly A. Ingraham[1], Daniel P. Ferris[2], and C. David Remy[1], *Member, IEEE*

***Abstract*— Lower-limb assistive robotic devices are often evaluated by measuring a reduction in the user's energy cost. Using indirect calorimetry to estimate energy cost is poorly suited for real-time estimation and long-term collection. The goal of this study was to use data from wearable sensors to predict energy cost with better temporal resolution and less variability than breath measurements. We collected physiological data (heart rate, electrodermal activity, skin temperature) and mechanical data (EMG, accelerometry) from three healthy subjects walking on a treadmill at various speeds on level ground, inclined, and backwards. Ground truth energy cost was established by averaging steady-state breath measurements. Raw physiological signals correlated well with ground truth energy cost, but raw mechanical signals did not. Correlation of mechanical signals was improved by calculating accelerometer magnitudes and linear envelope EMG signals, and further improved by averaging the signals over several seconds. A multiple linear regression including physiological and mechanical data accurately predicted ground truth energy cost across all subjects and activities tested, with less variability and better temporal resolution than breath measurements. The sensors used in this study were fully portable, and such algorithms could be used to estimate energy cost of users in the real world. This could greatly improve the design, control, and evaluation of lower-limb assistive robotic devices.**

I. INTRODUCTION

Lower-limb assistive robotic devices, such as exoskeletons and prostheses, have the potential to augment or restore locomotion in both able-bodied individuals and people with ambulatory disabilities. These devices provide net-positive power to the gait cycle, which reduces the amount of biological power the user must provide. As such, the efficacy of lower-limb assistive robotic devices is commonly evaluated by measuring the reduction in an individual's energetic cost. To date, researchers have observed reduced energy cost in individuals walking with powered prostheses [1], powered exoskeletons [2], [3], and passive exoskeletons [4]. The critical evaluation of lower-limb assistive devices therefore relies heavily on accurate, quick estimates of energetic cost. Most often, energetic cost is estimated using indirect calorimetry, in which the user wears a mask covering his or her nose and mouth, and an embedded flowmeter measures oxygen inhalation and carbon dioxide exhalation; an estimate of whole body energetic cost is then calculated from these measurements [5]. Although this technique is widely utilized, there are a number of significant challenges associated with using indirect calorimetry to estimate energetic cost. Measures of energetic cost obtained via respiratory gas analysis are dynamically delayed from the instantaneous energetic demands of the body; gas exchange kinetics have been modeled as a first-order dynamic system with a time constant between 20-60 seconds [6], [7]. Measurements are only sampled once per breath (approximately once every 3 seconds), and are inherently noisy due to high inter-breath variability. As a result, it is common practice to estimate energetic cost only during long durations of exercise, and to average several minutes of steady-state breath measurements to achieve a single estimate of energetic cost for a particular activity. In reality, humans rarely perform long bouts of continuous activity during their activities of daily living [8], and the bulky mask makes indirect calorimetry unsuitable for long-term data collection in real-world environments. As such, it would be beneficial to estimate energetic cost using less-obtrusive mobile sensors with better temporal resolution and less variability than breath-by-breath measurements.

Fortunately, the development of wearable sensing technology is rapidly expanding. Many devices are now capable of recording real-time, reliable physiological data (e.g., heart rate) and mechanical data (e.g., step counts) during both exercise and activities of daily living. Although commercial wearable sensors have quickly gained popularity among individuals interested in monitoring their personal fitness, mobile sensing also has broad applications in the fields of healthcare and rehabilitation [9]. Mobile sensing has the ability to provide quick and accurate estimates of physiological and mechanical quantities, and therefore has the potential to estimate energy cost in real time for individuals using lower-limb assistive robotic devices.

Several studies have sought to predict energetic cost based on mechanical and physiological quantities. The three main variables that have been addressed in previous efforts are the type of signal(s), the type of signal processing, and the type of prediction algorithm. Many studies have investigated the use of commercial accelerometers placed on the chest, hip, feet, and/or wrists to predict energetic cost across a wide range of activities [10]–[13]. Commercial heart rate monitors have also been used to predict energy expenditure, both individually, [14], and in combination with accelerometers [12], [15], [16], or biological parameters (e.g., gender, age, weight) [17]. Other commercial sensors incorporate autonomic nervous system parameters, such as near-skin temper-

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[1]Kimberly A. Ingraham (kaingr@umich.edu) and C. David Remy are with the Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109, USA.

[2]Daniel P. Ferris is with the School of Kinesiology, University of Michigan, Ann Arbor, MI 48109, USA.

ature and electrodermal activity (EDA), into their estimates of energetic cost, and have been independently validated by multiple research groups [18]–[20]. Electromyography (EMG) intensity has been correlated to energetic cost on a breath-by-breath basis during both steady-state [21] and non-steady-state cycling [22]. Finally, a recent study used a combination of easy-to-obtain biological parameters (e.g., sex, body mass), heart rate, and treadmill parameters (e.g., speed, incline) to predict energy cost [23].

Previous studies have utilized a variety of signal pre-processing techniques before inputtings the data into final predictive algorithms. For tri-axial accelerometers that output accelerations in the x, y, and z, axes, the vector magnitude of the acceleration often represents the total acceleration of the segment [12], [13]. Accelerometer signals are frequently processed in the time domain, and are averaged or summed over several seconds or strides [10], [11]. Other signals, such as EMG, have been processed in the frequency domain, and resolved into EMG intensities using wavelets [21], [22]. Finally, some studies have implemented more advanced feature extraction techniques, although extensive details have not been published [20].

A large portion of studies used single and multiple regression algorithms to predict energy cost from mechanical and physiological sensors [10]–[13], [17]. Linear regression algorithms are advantageous because of their simplicity and low computational requirements. In general, it has been well-demonstrated that linear regression models are able to predict energy expenditure with small errors when compared to respiratory gas analysis for moderate-intensity walking or jogging. However, these models usually result in large subject-specific errors and do not generalize well across tasks or activities. As such, other studies have opted to use more advanced algorithms such as neural networks [14], or branched equation modeling [15].

There is an extensive body of literature documenting successful prediction of energy expenditure from a variety of mechanical and physiological sensors. However, no one model has captured the intricacies of accurately predicting energy expenditure across all subjects and activities. Most studies have included one or two sensing modalities and have been unable to draw conclusions about how combinations of multiple signals (e.g., accelerometry, EMG, electrodermal activity, heart rate) can be used to improve estimates of energetic cost. The goal of this study was to systematically test a wide range of physiological and mechanical signals to determine which signals provide the most useful information to predict energetic cost across multiple activities. This study is our first step toward using wearable sensors to predict energy cost in real time. Successful completion of this research could dramatically improve the design, control, and evaluation of lower-limb assistive devices.

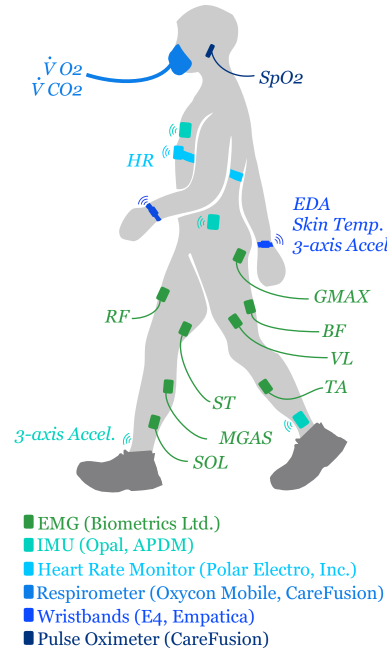

Fig. 1. Oxygen consumption ($\dot{V}_{O_2}$) and carbon dioxide production ($\dot{V}_{CO_2}$) were measured using a portable respirometer (Oxycon Mobile, CareFusion). Heart rate (HR) was measured using a wireless heart rate monitor strapped around the chest (Polar Electro, Inc.). Surface electromyography (EMG) electrodes recorded bilateral muscle activity from 8 lower limb muscles: gluteus maximus (GMAX), biceps femoris (BF), semitendinosis (ST), rectus femoris (RF), vastus lateralis (VL), medial gastrocnemius (MGAS), soleus (SOL), and tibialis anterior (TA) (Biometrics, Ltd.). Electrodermal activity (EDA), peripheral skin temperature and accelerations of the wrist were recorded using bilateral wrist sensors (E4, Empatica). Inertial measurement units (IMUs) placed on the trunk, hip, and ankles measured 3-axis limb accelerations (Opal, APDM Inc.). Blood oxygen saturation (SpO_2), was measured by a pulse oximeter secured to the subject's left earlobe (CareFusion).

II. METHODS

A. Data Collection

We collected data from three healthy subjects (2 male, 1 female, age (mean±SD): 26.3±3.2 years, height: 1.76±0.16 m, weight: 64.5±2.6 kg), who gave informed consent to a protocol approved by the University of Michigan Institutional Review Board. Each subject walked on a treadmill at various speeds in a pseudo-random order during three ambulation tasks: level walking (LW), incline walking (IW), and backwards walking (BW). During the LW task, subjects walked at 0.4, 0.8, 1.2, 1.6, and 2.0 m/s; during the IW task, subjects walked at 0.4, 0.6, 0.9, 1.2, and 1.4 m/s; during the BW task, subjects walked at 0.4, 0.6, 0.9, and 1.1 m/s. Subject 3 was unable to complete the fastest trials during all three conditions, so we did not collect these data. The treadmill belt acceleration was fast enough that changes between speeds were considered instantaneous step changes. Subjects walked at each speed for 6 minutes, enough time for respiratory measurements to reach a steady-state value. Subjects rested between ambulation tasks for 10-15 minutes. Before the ambulation tasks, subjects completed a standing trial, where they stood quietly for 6 minutes; respiratory data were collected during this trial. During data collection, subjects wore a variety of physiological and mechanical sensors, detailed in Fig. 1. All sensor signals were time-synchronized.

B. Data Processing

We calculated measured energetic cost (in Watts) from $\dot{V}_{O_2}$ and $\dot{V}_{CO_2}$ using the Brockway equation [5], subtracted off the subject's average standing energetic cost to yield net energetic cost. We normalized the data to subject body mass. The average of the final 3 minutes of measured energetic cost data at each condition established the 'ground truth' energetic cost for that condition. We interpolated all sensor data using nearest-neighbor interpolation and re-sampled at 1 kHz; we concatenated all data from level walking, incline walking, and backwards walking tasks. We calculated accelerometer magnitudes by computing the vector norm of the x, y, and z axes of each tri-axial accelerometer ($\sqrt{x^2 + y^2 + z^2}$). We generated EMG linear envelopes by band-pass filtering the raw EMG signals between 30-350 Hz, full-wave rectifying, and low-pass filtering with a cutoff frequency of 5 Hz. Each subject's EMG linear envelopes were normalized to peak activation level obtained across all ambulation tasks. Accelerometer magnitudes and EMG linear envelopes were time-averaged using a sliding window average with window lengths of 1, 3, 5, 10, 20, and 50 seconds. We calculated Pearson correlation coefficients (r) between all raw signals, accelerometer magnitudes, and linear envelopes and ground truth energetic cost. We calculated four multiple linear regression models containing different signal subsets (see Results, Part C) using MATLAB's `regress` function.

III. RESULTS

A. Correlation of Raw Signals

We calculated Pearson correlation coefficients (r) between ground truth energetic cost and 40 raw signals: Measured energetic cost (i.e., breath measurements), heart rate, electrodermal activity, skin temperature, SpO_2, treadmill speed, accelerations (x, y, and z) of the chest, hip, right/left wrists and ankles, and 16 EMG signals. We concatenated data from level walking, incline walking, and backwards walking trials before computing correlations. All significant correlations with $|r| \geq 0.20$ are shown in Table I. All raw acceleration signals had correlations $|r| < 0.20$, with the exception of Subject 2 (see Table I). All significant correlations between raw EMG signals and ground truth energetic cost were $|r| < 0.03$ for all subjects.

TABLE I

r VALUES FOR RAW SIGNALS AND GROUND TRUTH ENERGETIC COST.

Raw Signal	Subj. 1	Subj. 2	Subj. 3	Mean (SD)
Meas. Energy Cost	0.92	0.85	0.80	0.86 (0.06)
HR	0.82	0.94	0.69	0.82 (0.13)
EDA	0.59	0.66	0.62	0.62 (0.03)
Speed	0.61	0.59	0.45	0.55 (0.09)
Skin Temp.	-	-0.27	-0.46	-0.36 (0.13)
SpO_2	0.25	-	-0.67	-0.21 (0.65)
Chest Acc-Z	-	-0.61	-	-

B. Correlation of Processed Signals

We calculated Pearson correlation coefficients (r) between ground truth energetic cost and accelerometer magnitude and accelerometer magnitude processed with 1s, 3s, 5s, 10s, 20s,

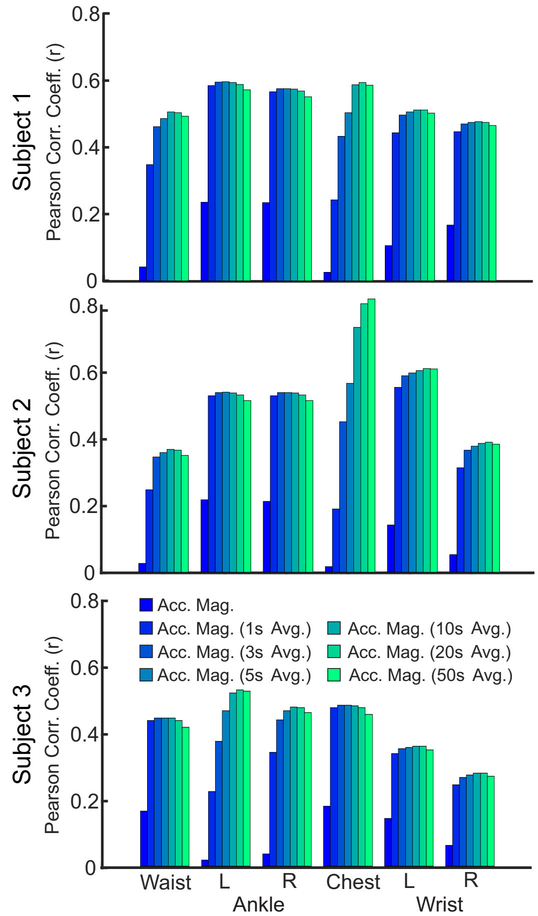

Fig. 2. Correlations between accelerometer magnitudes (Acc. Mag.) and ground truth energetic cost for accelerometers fixed to the waist, chest, and left (L) and right (R) ankles and wrists of each subject. Accelerometer magnitudes were processed using a sliding window average. The effect of different window lengths on correlation is shown. Window lengths increase from left (dark blue) to right (light green), and correspond to no average, and 1, 3, 5, 10, 20, 50 second averages, respectively.

or 50s sliding window averages (Fig. 2). Average r values (averaged across all accelerometers) for each window length are shown in Table II. We also calculated r values between ground truth energetic cost and linear envelope EMG and linear envelope EMG processed with 1s, 3s, 5s, 10s, 20s, or 50s sliding window averages (Fig. 3). Average r values (averaged across all EMG channels) for each window length are shown in Table III.

TABLE II

AVERAGE r VALUES ACROSS ACCELEROMETERS FOR DIFFERENT WINDOW LENGTHS.

Window Length	Subj.1	Subj. 2	Subj. 3	Mean (SD)
No Avg.	0.13	0.11	0.10	0.11 (0.02)
1 s.	0.43	0.39	0.34	0.34 (0.05)
3 s.	0.50	0.47	0.39	0.45 (0.06)
5 s.	0.52	0.49	0.41	0.48 (0.06)
10 s.	0.54	0.52	0.43	0.50 (0.06)
20 s.	0.54	0.53	0.42	0.50 (0.06)
50 s.	0.53	0.53	0.41	0.49 (0.06)

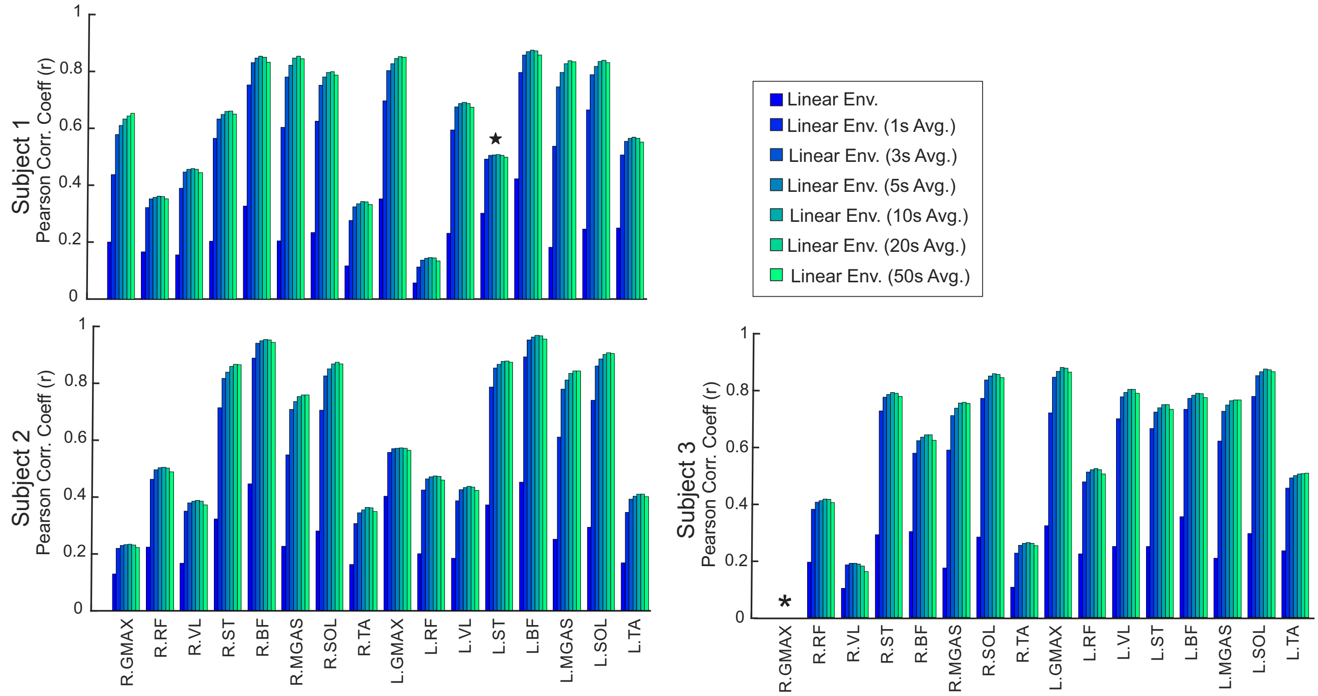

Fig. 3. Correlations between EMG linear envelopes (Linear Env.) and ground truth energetic cost for 8 left (L) and 8 right (R) EMG channels (see Fig. 1 for full EMG channel list). EMG linear envelopes were processed using a sliding window average. The effect of different window lengths on correlation is shown. Window lengths increase from left (dark blue) to right (light green), and correspond to no average, and 1, 3, 5, 10, 20, 50 second averages, respectively. ★ Due to sensor malfunction, we calculated correlations between Left ST and ground truth energetic cost for Subject 1 using only level walking and incline walking ambulation tasks. ∗ Due to sensor malfunction, we excluded Subject 3's Right GMAX data from analysis.

TABLE III

AVERAGE r VALUES ACROSS EMG CHANNELS FOR DIFFERENT WINDOW LENGTHS.

Window Length	Subj. 1	Subj. 2	Subj. 3	Mean (SD)
No Avg.	0.23	0.27	0.24	0.25 (0.02)
1 s.	0.52	0.56	0.57	0.55 (0.02)
3 s.	0.61	0.63	0.63	0.62 (0.01)
5 s.	0.63	0.64	0.64	0.64 (0.01)
10 s.	0.64	0.65	0.65	0.65 (0.01)
20 s.	0.64	0.65	0.65	0.65 (0.01)
50 s.	0.63	0.65	0.64	0.64 (0.01)

C. Linear Regressions

We trained four multiple linear regression models that predicted ground truth energetic cost from different subsets of physiological and mechanical signals (Table IV). Subset 1 included measured energetic cost. Subset 2 included mechanical signals only (EMG and accelerometry). Subset 3 included physiological signals only (heart rate, electrodermal activity, and skin temperature). Subset 4 included both mechanical and physiological signals. Based on the results from Section B, we used accelerometer magnitudes and linear envelope EMG signals processed with a 10s sliding window average in all the regressions that included accelerometry or EMG signals. Treadmill speed was not included in any of the signal subsets. The coefficient of determination (R^2) for each regression model is presented in Table IV. The Subset 4 regression, which contained mechanical and physiological signals, yielded the highest R^2 value. The relationship between ground truth energetic cost and estimated energetic cost (using Subset 4) is shown in Fig. 4. We used the Subset 4 regression model to simulate estimated energetic cost data across all subjects and all ambulation tasks (Fig. 5).

TABLE IV

SIGNAL SUBSETS USED TO TRAIN MULTIPLE LINEAR REGRESSION MODELS AND CORRESPONDING R^2 VALUES.

Subset #	Meas. Energy Cost	Acc.	EMG	HR	EDA	Skin Temp.	R^2
1	x						0.76
2		x	x				0.92
3				x	x	x	0.65
4		x	x	x	x	x	0.93

IV. DISCUSSION AND CONCLUSION

On average, across subjects and ambulation tasks, the raw signals that correlated well with energetic cost were physiological signals, such as heart rate (r=0.82) and electrodermal activity (r=0.62). Raw mechanical signals (EMG and accelerometry) did not provide useful information for predicting energetic cost. By nature, raw EMG is a highly fluctuating signal, and its sample-by-sample amplitude doesn't describe the overall level of muscle activation. Instead, by full-wave rectifying and filtering the raw EMG signal, we can generate a linear envelope, or activation profile. This type of signal processing is commonplace in rehabilitation robotics, and is often used to generate a control signal for the proportional myoelectric control of assistive robotic devices [24]. The linear envelope improved individual EMG signal correlations with steady-state energetic cost for all subjects (Fig. 3). Similarly, individual x, y, and z accelerations do not

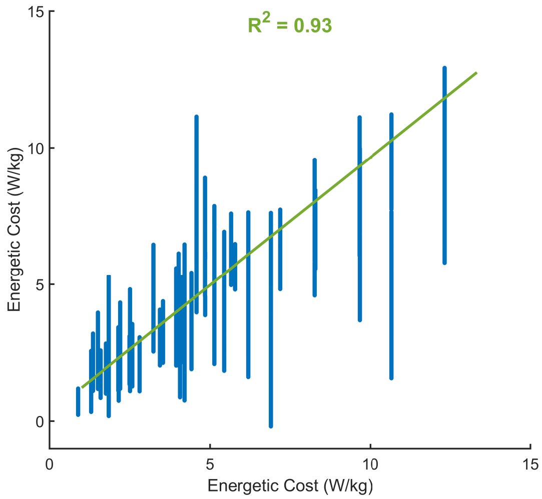

Fig. 4. Regression model containing data from all subjects and all ambulation tasks. We trained this model using both physiological signals (heart rate, electrodermal activity, and skin temperature), and mechanical signals (linear envelope EMG and accelerometer magnitudes, both processed with a 10s sliding window average). The coefficient of determination was R^2=0.93.

provide meaningful information about the overall magnitude of acceleration of each limb segment. Instead, the vector norm of the 3-axis accelerations can be used to represent this quantity, as in [12]. In this study, using accelerometer magnitudes alone did not improve accelerometer signal correlations with ground truth energetic cost (Fig. 2).

Averaging accelerometer magnitudes and EMG linear envelopes using a sliding window average dramatically improved correlation results compared to the raw signals. Increasing window lengths improved estimates of energetic cost, but with diminishing return. Tables II and III show that beyond 10 seconds, correlations do not improve appreciably with increasing window length. Stride time during walking varies with speed and ambulation task, but on average ranges between 1.5-3.5 seconds for adult walking [25]. Therefore, a sliding average window length of 10 seconds corresponds to approximately 3-6 strides. This result is somewhat surprising, as one might expect that averaging data over one stride would be sufficient to remove the periodic nature of the mechanical signals. In this analysis, we averaged the data using a time-based sliding window average with a constant window length of 10 seconds. In future analyses, we will explore averaging signals on a stride-by-stride basis, which may further reduce the number of strides required to estimate energetic cost. However, even with the current 10-second window, this approach improves the temporal resolution of estimating ground truth energetic cost over established indirect calorimetry methods, which generally requires several minutes of data to achieve a good estimate.

The results of training various multiple linear regression models using different signal subsets indicated that the physiological or mechanical sensors we used in this study were not sufficient to estimate energetic cost on their own. Rather, the combination of both mechanical and physiological signals (Subset 4), resulted in the best estimate of energetic cost. A possible explanation for this finding is rooted in the individual characteristics of the biological signals and/or the sensors themselves. Heart rate, for example, is highly affected by biological variance (e.g., fitness level, age, stress), which limits its accuracy in predicting energetic cost across different subjects and activities [26]. Accelerometers are limited in their ability to accurately predict energy cost across a wide range of activities largely due to mechanical variability during different tasks [15]. Previous studies have also noted this phenomenon, and have reported improved prediction accuracy with combined physiological and mechanical signals [12], [15], [26]. Using the regression model trained with Subset 4 to predict energetic cost resulted in estimates with less variability than measured energetic cost. The calculated root-mean-square error (RMSE) for estimated energetic cost was 0.72, and the RMSE for measured energetic cost was 1.43. The high noise levels associated with measured energetic cost make it a particularly challenging signal to work with in real time, so reducing the variability in the predicted estimate is desirable.

The sensors used in this study were fully portable, and the prediction algorithm did not use any subject-specific (e.g., weight) or task-specific (e.g., treadmill speed) information to accurately predict ground truth energetic cost across all subjects and tasks. Including biological information in the prediction may improve estimates of energetic cost on a subject-by-subject basis, and we will explore this in future work. We observed that treadmill speed was positively correlated with ground truth energetic cost (r = 0.55; Table I), and including this information would likely improve estimates of energetic cost for these tasks. But, including speed in the prediction algorithm restricts the user to the treadmill, and limits the applicability of these algorithms outside controlled laboratory settings. By using only information available from wearable sensors, we hope to develop prediction algorithms that can be used in real-world environments.

The small subject pool and number of ambulation tasks currently limits the generalizability of these results. Ideally, we want to build prediction algorithms based on a large number of individuals and across more ambulation tasks (e.g., bicycling, stair climbing, over-ground walking) to ensure the model captures the underlying physiological relationship between the sensor measurements and energetic cost. In the future, we plan to explore additional data processing algorithms to determine the most salient features of each physiological or mechanical signal. We also will explore more complex prediction algorithms (e.g., neural networks) that will be able to capture non-linearities in the data.

In this study we demonstrated that for three subjects and three ambulation tasks, a multiple linear regression model trained with physiological and mechanical signals can predict energy cost (R^2=0.93) with less variability and better temporal resolution that breath-by-breath respiratory measurements. We also showed that simple data processing, such as calculating and time-averaging EMG linear envelopes and accelerometer magnitudes can dramatically improve cor-

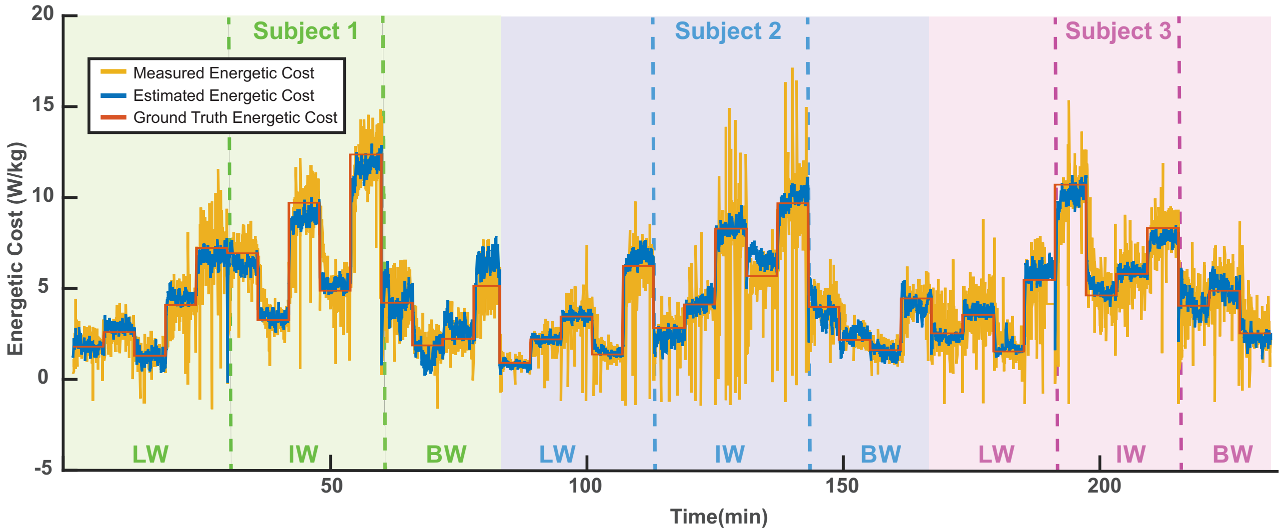

Fig. 5. Energetic cost data vs. time for all subjects and all ambulation tasks (LW = level walking, IW = incline walking, BW = backwards walking). We concatenated data from each subject and task for analysis, so data are presented continuously in time. In reality, subjects rested between each ambulation task. Measured energetic cost (from indirect calorimetry) is shown in yellow; Ground truth energetic cost is shown in red; Estimated energetic cost is shown in blue. We calculated estimated energetic cost from the regression model trained with mechanical and physiological signals (Subset 4; see Table IV).

relations with energetic cost compared to raw signals. The sensors used to predict energetic cost in this study are fully portable, and can be used in the future during over-ground or real-world experiments with individuals using lower-limb assistive robotic devices in real time.

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