Using Portable Physiological Sensors to Estimate Energy Cost for 'Body-in-the-Loop' Optimization of Assistive Robotic Devices

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***Abstract*— Lower-limb assistive robotic devices have the potential to restore ambulation in people with movement disorders. The assistance provided by these devices is governed by a large number of parameters that must be tuned on a subject-specific basis. Recently, our group developed 'body-in-the-loop' optimization algorithms, and demonstrated that they can be used to automatically determine the user's energetically optimal parameter setting. However, this algorithm relies on real-time estimates of energetic cost collected via indirect calorimetry, which is unsuited for long-term use. The purpose of this study was to estimate energy cost using data from portable, wearable sensors. We collected global signals (heart rate, electrodermal activity, skin temperature, oxygen saturation) and local signals (EMG, accelerometry) from 10 healthy subjects performing 6 different activities. We trained five multiple linear regression models with different subsets of the collected data, and concluded that the regression model trained with both global and local signals performed the best for all subjects (R^2=0.94±0.02). This work has the potential to result in translational, clinically-relevant tuning algorithms for assistive robotic devices.**

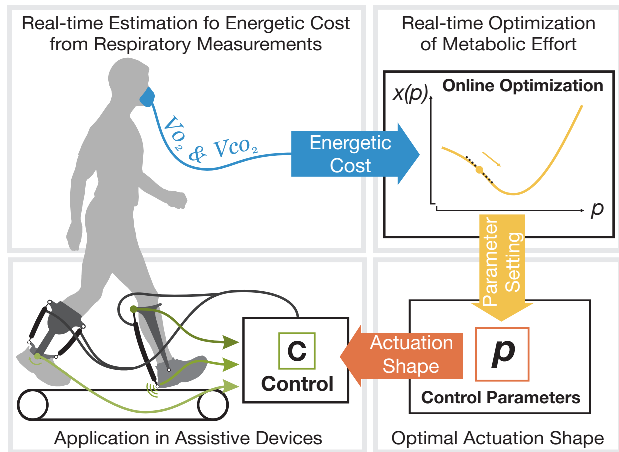

Fig. 1. 'Body-in-the-loop' optimization uses real-time respiratory measurements taken from the user to identify the energetically optimal parameter setting, and automatically updates the device controller [11].

I. INTRODUCTION

An estimated 20 million Americans are currently living with ambulatory disabilities as a result of age, neurological injury, amputation, or congenital conditions [1]. These disorders can impair an individual's ability to ambulate freely, walk long distances, climb stairs, and/or participate in independent activities of daily living. In addition, individuals with ambulatory disabilities often have a higher energetic cost of transport than healthy individuals, which can reduce their stamina [2], [3]. In recent years, major advancements in mechatronic design and control have resulted in wearable robotic lower-limb assistive devices, such as bionic prostheses (e.g., [4], [5]) and exoskeletons (e.g., [6]–[8]). The goal of such devices is to restore ambulatory function in people with movement difficulties.

The quality of assistance provided by robotic devices is governed by a large number of controller parameters. For example, the commercial BiOM powered ankle prosthesis has 11 configurable parameters that control the behavior of the device, such as the power and timing of the actuated push-off [9]. In clinical practice, these parameters are tuned empirically on a subject-specific basis, using a combination of patient feedback, clinician expertise, and visual inspection of gait characteristics. This practice is time-consuming and subjective. As the functionality of robotic assistive devices increases, so too does the number of configurable parameters, which quickly makes the empirical tuning process infeasible. Additionally, once the user leaves the clinic with their tuned device, most parameters remain static. The device therefore does not have the ability to adapt its performance to changing environmental conditions, such as walking over uneven terrain.

In the research setting, one objective metric often used to evaluate robotic assistive devices is a reduction in a user's energetic cost. Our group was the first to demonstrate an automated tuning process, which uses real-time physiological measurements to identify and prescribe optimal device parameter settings that minimize the user's energy cost [10]–[12]. In this 'body-in-the-loop' optimization scheme, we used real-time measurements of energy cost collected via indirect calorimetry (Fig. 1).

With indirect calorimetry, the user wears a mask that covers his or her nose and mouth, and an embedded flowmeter measures oxygen consumption and carbon dioxide production. Whole body energy cost is then estimated from these quantities [13]. Although this method is widely utilized, there are several challenges associated with using indirect calorimetry to estimate energy cost. Measurements are extremely noisy due to high breath-by-breath variability, and changes in the concentration of the respiratory gases

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are dynamically delayed from the instantaneous energetic demands of the body [14], [15]. As such, it is common practice to average several minutes of respiratory measurements collected during long bouts of constant-intensity exercise to obtain a single estimate of energetic cost. These challenges, plus the cumbersome and intrusive equipment required, make indirect calorimetry poorly suited for long-term, real-world applications. To improve automated tuning algorithms for assistive robotic devices, it would be beneficial to estimate energy cost using other portable physiological sensors with less variability and better temporal resolution.

Many portable, wearable sensors are now capable of monitoring and recording physiological data (e.g., heart rate) and movement data (e.g., step counts) in real time. These sensors have thus far been used in many areas of healthcare and rehabilitation, such as health and wellness monitoring, assessment of treatment efficacy, and early detection of disorders [16]. We believe using portable sensing technology to estimate energy cost can dramatically improve the automated tuning process for assistive robotic devices.

There is an extensive body of literature documenting successful prediction of energy expenditure from various physiological sensors. Some studies have used commercial accelerometers [17]–[20], heart rate monitors [21], or a combination of both [19], [22], [23] to predict energy cost. Other studies have incorporated electrodermal activity (EDA) and near-skin temperature [24]–[26], electromyography (EMG) [27], [28], or biological parameters [29], [30] into their prediction algorithms. These studies have employed of a wide variety of signal processing techniques to improve energy cost estimates. These methods include simple time-domain processing, such as calculating the vector magnitude of tri-axial accelerometers to represent the total acceleration of the segment [19], [20] or summing accelerations over several seconds or strides [17], [18]. Advanced processing techniques, including frequency-domain processing [27], [28], and feature selection using Principal Component Analysis (PCA) [26] have also been explored. Linear regression algorithms have been commonly used to predict energy cost from physiological signals due to their simplicity and low computational requirements [17]–[20], [30], but some studies have opted to use more complex algorithms such as neural networks [21], or branched equation modeling [22]. It is currently unknown what type of signal(s), processing, and prediction algorithms are best-suited for our application.

The purpose of this study was to systematically evaluate how a variety of physiological sensors affect our ability to predict energy cost. We wanted to investigate which raw signals contain salient information for this application, so we selected very simple processing and prediction algorithms. This study is the first step toward using multiple physiological sensors to predict the energy cost of individuals using robotic lower-limb assistive devices in real time.

II. METHODS

Ten healthy subjects (8 male, 2 female, age (mean±SD): 27.4±4.5 years, height: 1.76±0.09 m, weight: 69.1±9.9 kg) participated in this experiment, after giving informed consent to a University of Michigan IRB-approved protocol. Each subject completed two experimental sessions in which they performed a variety of physical activities at various speeds and/or intensities (Table I). The first experimental session consisted of sitting, standing, level walking, incline walking, and backwards walking on a treadmill (Bertec Corp., Columbus, OH); the second session consisted of sitting, standing, running on a treadmill, cycling on a stationary bike (Matrix Fitness, Cottage Grove, WI), and stair-climbing on a stairmill (Matrix Fitness, Cottage Grove, WI). Due to equipment malfunction, Subject 1 did not complete the stair-climbing activity. For each activity, subjects stood quietly for 6 minutes, performed each speed/resistance condition for 6 minutes in a random order, and then sat quietly for 6 minutes. Subjects rested for approximately 10 minutes between activities. All changes between speeds were considered instantaneous step changes. During data collection, subjects wore a variety of sensors, detailed in Fig. 2. All sensor signals were time-synchronized during collection.

TABLE I
EXPERIMENTAL ACTIVITIES.

Task	Speed	Intensity
Sitting	-	-
Standing	-	-
Level Walking	0.6 m/s	-
	0.9 m/s	-
	1.2 m/s	-
Incline Walking	0.6 m/s	4°
	1.2 m/s	4°
	0.6 m/s	9°
	1.2 m/s	9°
Backwards Walking	0.4 m/s	-
	0.7 m/s	-
Running	1.8 m/s	-
	2.2 m/s	-
	2.7 m/s	-
Cycling	70 rpm	Resistance 1
	70 rpm	Resistance 3
	70 rpm	Resistance 5
	100 rpm	Resistance 1
Stair Climbing	-	60 W
	-	75 W
	-	90 W

We calculated whole-body energetic cost (in Watts) from $\dot{V}_{O_2}$ (ml/min) and $\dot{V}_{CO_2}$ (ml/min) using the Brockway equation [13], and normalized the data to subject body mass (W/kg). The average of the final 3 minutes of breath measurements at each condition established the 'ground truth' energetic cost for that condition. For each activity, the ground truth energetic cost of the standing bout at the beginning of the trial was subtracted off to yield net energetic cost.

All sensor data were interpolated and re-sampled at 1kHz using nearest-neighbor interpolation. Signals were subsequently downsampled to 250 Hz. We calculated accelerometer magnitudes by computing the vector norm of the x, y, and z axes of each tri-axial accelerometer. We generated EMG linear envelopes by band-pass filtering the raw EMG

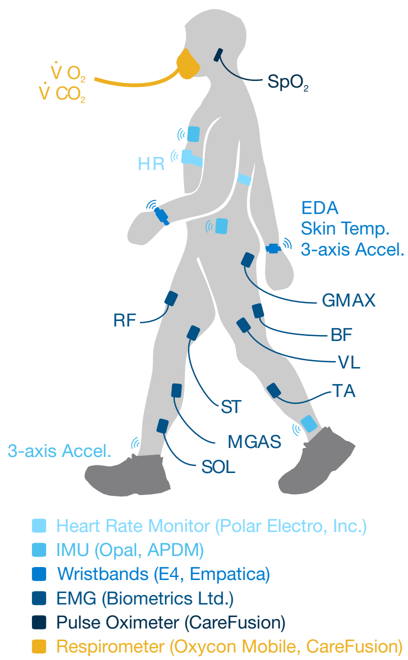

Fig. 2. Oxygen consumption ($\dot{V}_{O_2}$) and carbon dioxide production ($\dot{V}_{CO_2}$) were measured using a portable respirometer. Heart rate (HR) was measured using a wireless heart rate monitor strapped around the chest. Surface electromyography (EMG) electrodes recorded bilateral muscle activity 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). Electrodermal activity (EDA), peripheral skin temperature and accelerations of the wrist were recorded using bilateral wrist sensors. Inertial measurement units (IMUs) placed on the chest, left hip, and ankles measured 3-axis limb accelerations. Blood oxygen saturation (SpO_2), was measured by a pulse oximeter secured to the subject's left earlobe.

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 activities. Accelerometer magnitudes and EMG linear envelopes were time-averaged using a backwards-looking sliding window average with a window length of 10s. These features and window length were chosen based on previous analyses, detailed in [31].

We separated the collected signals into two categories based on their properties. Global signals (heart rate, electrodermal activity, skin temperature, and oxygen saturation) provide information about the physiology of the body as a whole, and have slower time dynamics. Local signals (accelerometry and EMG) provide information about one individual limb segment or muscle, and have fast dynamics associated with the periodicity of the gait cycle. For each subject, we calculated five multiple linear regression models that predicted ground truth energetic cost from different subsets of signals using MATLAB's `regress` function (Table II). The models were trained and tested using the data collected during all activities (excluding sitting and standing).

III. RESULTS

To evaluate the salience of each signal subset, we calculated the coefficient of determination (R^2) between estimated energetic cost and ground truth energetic cost for each subject and each signal subset. The average R^2 values across subjects are presented in Table II. We used each of the five regression models trained for each subject to simulate estimated energetic cost for all activities. We calculated the root mean squared error (RMSE) between each model's estimated energetic cost and the ground truth energetic cost. We averaged the RMSE values for Subsets 1-5 across subjects and performed a repeated-measures ANOVA analysis (α = 0.05) using SPSS Statistics 22 (IBM, Armock, NY); we conducted post hoc multiple comparison tests with a Bonferroni correction (Fig. 3). Estimated energetic cost data from a representative subject are presented in Fig. 4.

TABLE II

SIGNAL SUBSETS USED TO TRAIN MULTIPLE LINEAR REGRESSION MODELS AND AVERAGE R^2 VALUES ACROSS SUBJECTS (N=10).

#	Breath Meas.	*Local* Acc.	*Local* EMG	*Global* HR	*Global* EDA	*Global* SpO_2	*Global* Skin Temp.	R^2 Mean ±SD
1	x							0.76 ±0.05
2				x	x	x	x	0.79 ±0.09
3		x	x					0.91 ±0.04
4		x	x	x	x	x	x	0.95 ±0.02
5	x	x	x	x	x	x	x	0.95 ±0.02

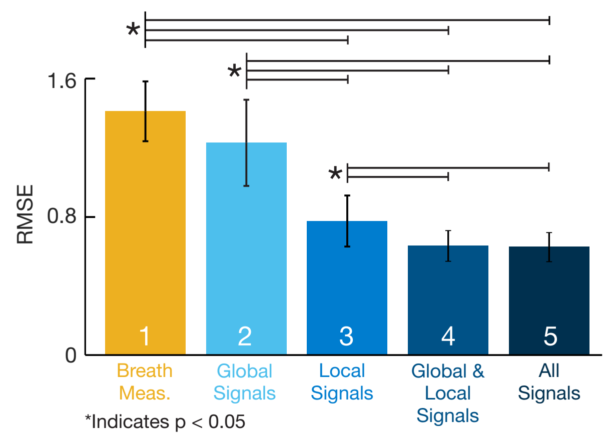

Fig. 3. Average±SD RMSE across subjects for Subsets 1-5 (see Table II). Statistically significant differences are indicated with brackets.

IV. DISCUSSION

Training various multiple linear regression models with different signal subsets allowed us to draw preliminary conclusions regarding what types of data from physiological sensors are relevant to predict energy cost across a variety of physical activities. The regression model trained with Subset 1 contained only breath measurements obtained via indirect calorimetry. Although indirect calorimetry is the 'gold-standard' method for estimating energy cost, the regression model only achieved R^2=0.76±0.05 (average±SD). Regression models trained with global signals only (Subset 2) and local signals only (Subset 3) both performed better than breath measurements. The regression model trained with Subset 4, which contained both local and global signals,

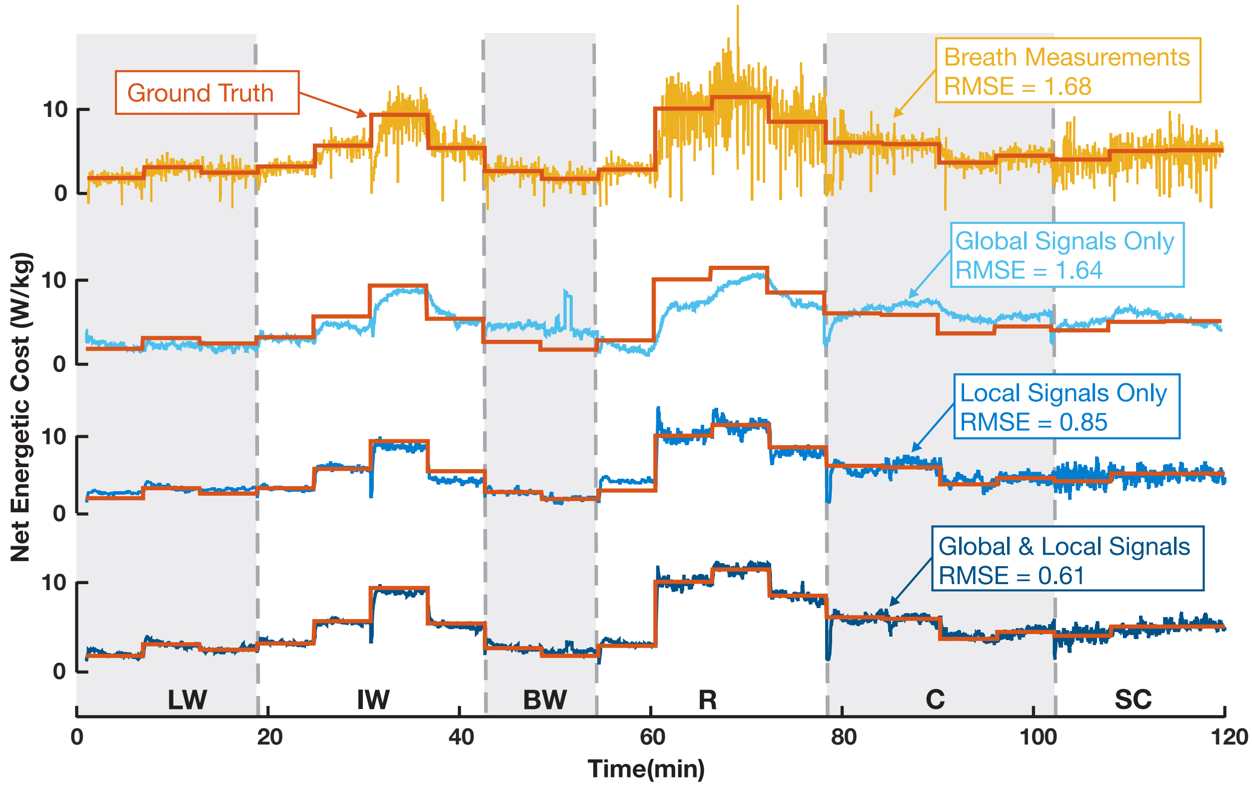

Fig. 4. Net energetic cost data vs. time for all activities are shown for one representative subject (LW=level walking, IW=incline walking, BW=backwards walking, R=running, C=cycling, SC=stair-climbing). We concatenated data from each task for analysis, so data are presented continuously in time. In reality, subjects rested between tasks. Energetic cost estimates from regression models trained with various signal subsets (see Table II) are shown in blue; ground truth energetic cost is shown in red; breath measurements (from indirect calorimetry) are shown in yellow.

achieved R^2=0.94±0.02. Adding breath measurements to the model (Subset 5) only modestly improved performance (R^2=0.95±0.02).

We used the various regression models to simulate estimated energetic cost data for each subject (one representative subject is shown in Fig. 4). There was no significant difference between the calculated RMSE of the breath measurements (Subset 1) and the estimate generated from global signals only (Subset 2) (Fig. 3). This result is likely explained by the relatively long time dynamics of the global signals, visible in Fig. 4. Using a combination of global and local signals (Subset 4) resulted in significantly lower RMSE than Subsets 1-3. In addition, there was no statistically significant difference between the RMSE of Subsets 4 and 5. Although these are preliminary findings, these results suggest that it may be possible to completely replace the mask with a combination of portable sensors, while achieving nearly the same accuracy in estimating energy cost. In this study, using a combination of global and local signals in a linear regression model reduced the variability (RMSE) in the estimated energy cost by more than two-fold, compared to indirect calorimetry (0.63±0.08 and 1.41±0.17, respectively).

There is a great deal of insight that can be gained from simple processing and prediction algorithms. By comparing different subsets of data, we were able to understand the salience of various physiological signals. Then, using a linear regression model trained with a combination of global and local signals, we successfully predicted energy cost for 10 subjects performing 6 activities with R^2 values between 0.91 and 0.96. In the future, we will use our results from the simple algorithms to explore additional data processing algorithms and more complex prediction algorithms.

This study tested only a small group of young, healthy individuals performing a small subset of physical activities. These findings may not generalize to older individuals or individuals with movement disorders, and it will be necessary to test these populations in the future. Additionally, we did not include data from any sedentary activities in our predictive algorithm. Most people spend the majority of time performing sedentary or light-intensity activities, so it will be important to incorporate these activities into future work.

V. CONCLUSION

As the development of assistive robotic devices continues to advance, the potential to restore ambulatory function to individuals with movements disorders continues to grow. However, for these devices to gain widespread clinical use, it is necessary to develop and improve automated tuning processes to relieve the burden on patients and clinicians. Current ‘body-in-the-loop’ optimization algorithms rely on respiratory measurements to quantify a user’s energetic cost, which limits their use in real-world environments. This study presents a first step toward estimating energetic cost using a variety of portable, wearable physiological sensors. This work has the potential to result in clinically-relevant tuning algorithms, as well as open the door to new physiologically-inspired control strategies for assistive robotic devices.

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