Predicting Energy Cost using Portable Physiological Sensors

Kimberly Ingraham, Daniel Ferris, and C. David Remy
University of Michigan, Ann Arbor, MI
kaingr@umich.edu

Introduction

Lower-limb robotic assistive devices, (e.g., exoskeletons and prostheses), provide net-positive power to the gait cycle, which reduces the amount of biological power the user must provide. Thus, the effectiveness of such devices is often quantified as a reduction in the individual's energetic cost [1–3]. Measures of energy cost have also been used to identify optimal parameter settings (e.g., actuation timing) for powered assistive devices in real time [4, 5]. The current 'state-of-the-art' method for estimating energetic cost during walking is 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. However, this method is unsuitable for long-term data collection due to the cumbersome equipment, and the measurements obtained breath-by-breath are sparsely sampled, noisy, and dynamically delayed from the true energetic demands of the body. Due to these challenges, it is common practice to collect 5-6 minutes of respiratory measurements per condition, and to average the last 2-3 minutes of steady-state measurements to yield one estimate of 'ground truth' energetic cost. Given that quick and accurate estimates of energetic cost are highly valuable to the design and evaluation of assistive robotic devices, it would be beneficial to estimate energy cost using other sensors with less variability and better temporal resolution.

Previous studies have attempted to predict energetic cost during walking using accelerometers [6], heart rate monitors [7], or a combination of both [8]. Other studies have correlated electromyography (EMG) intensity to energy expenditure during steady-state and non-steady state cycling [9]. Finally, one commercially available sensor incorporates autonomic nervous system parameters, such as near-skin temperature and electrodermal activity (EDA), into its estimate of energetic cost [10]. In general, it has been shown that simple linear regression algorithms can predict energy expenditure from a variety of physiological sensors (e.g., heart rate) and mechanical sensors (e.g., accelerometry). However, no one model has been able to predict energy expenditure across all subjects and activities. Most studies have only included one or two sensing modalities, and have been unable to draw conclusions about how combinations of multiple signals (e.g., accelerometry, EMG, EDA, heart rate) can be used to improve estimates of energetic cost. The goal of this study was to predict energy cost across multiple subjects and activities using a wide variety of physiological and mechanical signals.

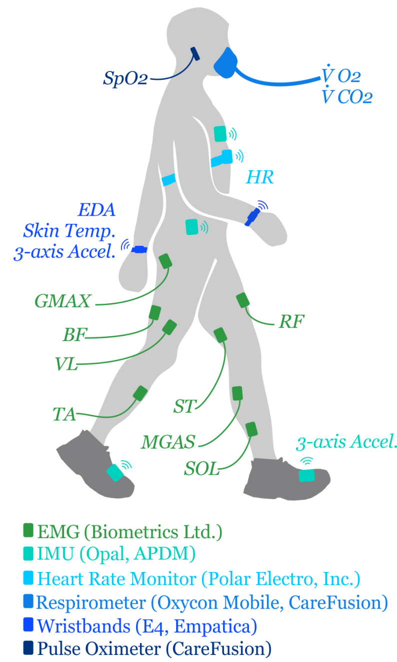

Figure 1: Oxygen consumption ($\dot{V}_{O_2}$) and carbon dioxide production ($\dot{V}_{CO_2}$) were measured using a portable respirometer. Heart rate (HR) was measured using a wireless heart rate monitor strapped around the chest. Surface electromyography (EMG) electrodes recorded bilateral muscle 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 trunk, hip, and ankles measured 3-axis limb accelerations. Blood oxygen saturation (SpO_2), was measured by a pulse oximeter secured to the subject's right earlobe.

Methods

Data Collection

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) walked on a treadmill at various speeds (0.4-2.0 m/s) during three ambulation tasks: level walking (LW), incline walking (IW), and backwards walking (BW). Subjects walked at each speed for 6 minutes. Before the walking trials, subjects stood quietly for 6 minutes while respiratory measurements were collected. Subjects wore a variety of physiological and mechanical sensors, depicted in Fig. 1.

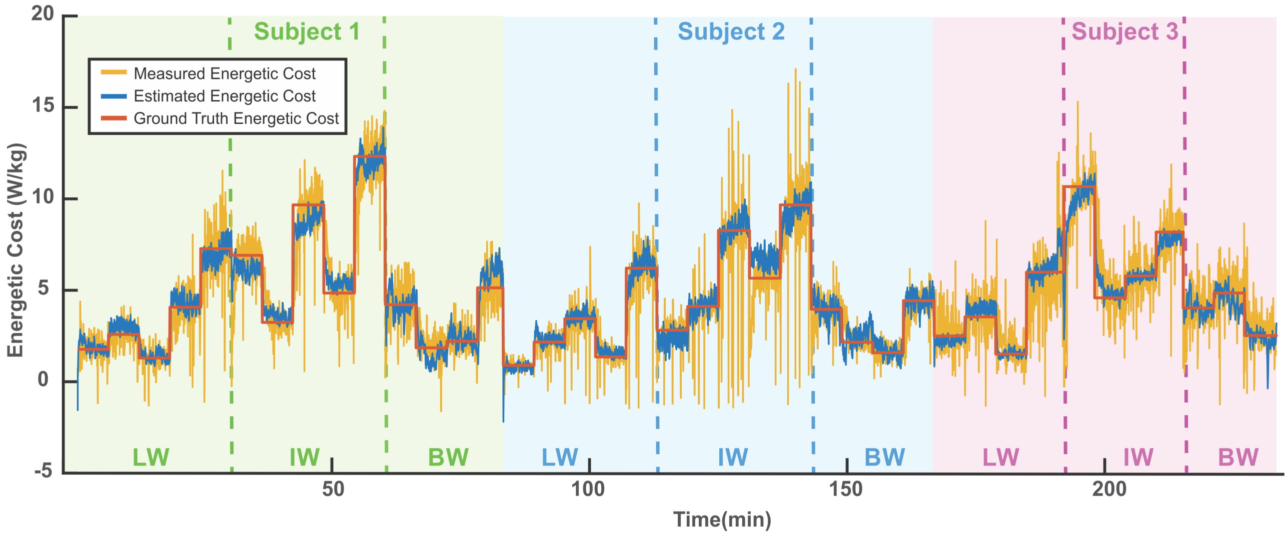

Figure 2: Concatenated energetic cost data across all subjects and all ambulation tasks (LW=level walking, IW=incline walking, BW=backwards walking). Measured energetic cost (from indirect calorimetry) is shown in yellow; Ground truth energetic cost is shown in red; Estimated energetic cost is shown in blue.

Data Processing

We calculated measured energetic cost (in Watts) from $\dot{V}_{O_2}$ and $\dot{V}_{CO_2}$ [11], and subtracted off the subject's average standing energetic cost to yield net energetic cost. The data were normalized 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. To represent the overall magnitude of acceleration of each limb segment, we computed the vector norm of the x, y, and z axes of each accelerometer. To represent the activation profile of each muscle, we generated EMG linear envelopes by full-wave rectifying and filtering the raw signals. Accelerometer magnitudes and EMG linear envelopes were time-averaged using a sliding window average with window lengths of 10 seconds [12].

Results & Discussion

We calculated four multiple linear regression models containing different processed signal subsets using MATLAB. Subset 1 included measured energetic cost (R^2=0.77). Subset 2 included mechanical signals only (EMG and accelerometry)(R^2=0.88). Subset 3 included physiological signals only (heart rate, electrodermal activity, and skin temperature)(R^2=0.65). Subset 4 included both mechanical and physiological signals (R^2=0.93). The regression model trained with Subset 4 was used to predict energy cost across all subjects and ambulation modes (Fig. 2). The estimated energetic cost had less variability than measured energetic cost; the root mean squared error (RMSE) between measured energetic cost and ground truth was 1.42; the RMSE between estimated energetic cost and ground truth was 0.74. Limitations of this work include the small sample size and limited number of activities. Future work will focus on more advanced feature extraction and prediction algorithms. The sensors used to predict energetic cost in this study are fully portable, and could be used in the future during over-ground or real-world experiments with individuals using lower-limb assistive robotic devices in real time.

References

[1] L. M. Mooney *et al.*, "Autonomous exoskeleton reduces metabolic cost of human walking," *Journal of Neuroengineering and Rehabilitation*, vol. 11, no. 1, p. 151, 2014.
[2] S. H. Collins *et al.*, "Reducing the energy cost of human walking using an unpowered exoskeleton," *Nature*, vol. 522, no. 7555, pp. 212–215, 2015.
[3] P. Malcolm *et al.*, "A simple exoskeleton that assists plantarflexion can reduce the metabolic cost of human walking," *PloS one*, vol. 8, no. 2, p. e56137, 2013.
[4] J. R. Koller *et al.*, "Confidence in the Curve: Establishing Instantaneous Cost Mapping Techniques using Bilateral Ankle Exoskeletons," *Journal of Applied Physiology*, vol. 2125, p. jap.00710.2016, 2016.
[5] W. Felt *et al.*, ""Body-In-The-Loop": Optimizing Device Parameters Using Measures of Instantaneous Energetic Cost," *PLoS One*, vol. 10, no. 8, p. e0135342, 2015.
[6] S. E. Crouter *et al.*, "Estimating energy expenditure using accelerometers," *European Journal of Applied Physiology*, vol. 98, no. 6, pp. 601–612, 2006.
[7] P. Montgomery *et al.*, "Validation of heart rate monitor-based predictions of oxygen uptake and energy expenditure," *Journal of Strength and Conditioning Research*, vol. 23, no. 5, pp. 1489–1495, 2009.
[8] S. Brage *et al.*, "Branched equation modeling of simultaneous accelerometry and heart rate monitoring improves estimate of directly measured physical activity energy expenditure," *Journal of Applied Physiology*, vol. 96, no. 1, pp. 343–351, 2004.
[9] O. M. Blake *et al.*, "Estimating changes in metabolic power from EMG," *SpringerPlus*, vol. 2, no. 1, p. 229, 2013.
[10] N. Vyas *et al.*, "Machine Learning and Sensor Fusion for Estimating Continuous Energy Expenditure," in *2011 23rd IAAI Conference on Artificial Intelligence*, vol. 33, p. 55, 2012.
[11] J. M. Brockway, "Derivation of formulae used to calculate energy expenditure in man," *Human Nutrition. Clinical Nutrition*, vol. 41, no. 6, pp. 463–71, 1987.
[12] K. A. Ingraham *et al.*, "Using Wearable Physiological Sensors to Predict Energy Expenditure," in *2017 15th IEEE/RAS-EMBS International Conference on Rehabilitation Robotics (ICORR)*, Submited, 2017.