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Lower Limb Assistive Robotic Devices

Research Prototypes

Commercial Devices
Evaluating Assistive Robotic Devices

Real-time Estimation of Energetic Cost from Respiratory Measurements

Brute-force mapping of Cost Landscape

Energetic Cost

Cost Landscape

Assistive Devices

Control

Actuation Shape

Control Parameters

[Malcolm, 2013]
Body-in-the-Loop Optimization

Real-time Estimation of Energetic Cost from Respiratory Measurements

Real-time Optimization of Metabolic Effort

Energetic Cost

[Online Optimization]

Application in Assistive Devices

Control

Actuation Shape

Control Parameters

Optimal Actuation Shape

[Koller, 2016; Felt, 2015]
Body-in-the-Loop Validation Study

- Optimize push-off timing in powered ankle exoskeletons (n=8)
- Algorithm found a minimum within 1.5% of the brute-force cost
- How can we improve this method?

[Koller, 2016]

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Challenges: Indirect Calorimetry

CHALLENGES:
- Noisy
- Sparsely sampled
- Dynamically delayed

“Breath Measurements”

“Ground Truth”

[Selinger, 2014; Lamarra, 1967]
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Challenges: Indirect Calorimetry

CHALLENGES:
- Noisy
- Sparsely sampled
- Dynamically delayed
- Bulky Equipment

[Selinger, 2014; Lamarra, 1967]
GOAL: Investigate sensor alternatives for estimating energy cost

CHALLENGES: 
- Noisy
- Sparsely sampled
- Dynamically delayed
- Bulky Equipment

Real-time Estimation of Energetic Cost from Physiological Measurements

Real-time Optimization of Energetic Cost

Application in Assistive Devices

Optimal Actuation Shape

Parameter Setting

Online Optimization

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Experimental Data Collection

10 healthy subjects (8 male, 2 female)
Experimental Data Collection

- Heart rate monitor
- 3-axis accelerometers
- Wristbands (EDA, skin temp., 3-axis accel.)
- 16 lower-limb EMG
- Pulse oximeter (O₂ saturation)
- Indirect calorimetry
Feature Extraction

**Local Signals**
- Accelerations \((x, y, z)\)
  - Vector magnitude \(= \sqrt{x^2 + y^2 + z^2}\)
  - 1-minute, 0.1 Hz Gaussian filter kernel
- EMG
  - Linear envelope = full wave rectify, low-pass filter
  - Composite sum \(= \sqrt{\sum_{i=1}^{8} LinEnv(muscle)_i^2}\)
  - 1-minute, 0.1 Hz Gaussian filter kernel

**Global Signals**
- \(\text{SpO}_2\), HR, EDA, Skin temp.
  - 1-minute sliding window average
Multiple Linear Regression Models

- Multiple linear regression models trained for each subject (concatenated all activities)

Ground Truth
Energy Cost (W/kg)

Various Combinations of Physiological Sensors

\[ R^2 \]
## Multiple Linear Regression Models

### Global Signals

<table>
<thead>
<tr>
<th>Subset #</th>
<th>Breath Meas.</th>
<th>EDA</th>
<th>Skin Temp.</th>
<th>Heart Rate</th>
<th>SpO₂</th>
<th>Acc. Mag.</th>
<th>EMG Lin. Env.</th>
<th>R² Mean±SD</th>
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<td>0.95±0.02</td>
</tr>
</tbody>
</table>

### Local Signals

Kim Ingraham – Dynamic Walking 2017
Time Series Predicted Energy Cost

- Ground Truth
- Breath Measurements RMSE = 1.68 W/kg
- Global Signals Only RMSE = 1.64 W/kg
- Local Signals Only RMSE = 0.85 W/kg
- Global & Local Signals RMSE = 0.61 W/kg
Multiple Linear Regression Models

*Indicates p < 0.05
Future Directions

Real-time Estimation of Energetic Cost from Physiological Measurements

Real-time Optimization of Energetic Cost

Application in Assistive Devices

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x(p)

p

Energetic Cost

Sensor Fusion

C

Control

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Questions?

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C. David Remy
Dan Ferris
Jeff Koller

Funding sources

Real-time Estimation of Energetic Cost from Physiological Measurements

Real-time Optimization of Energetic Cost

Sensor Fusion

Energetic Cost

$x(p)$

Online Optimization

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References


