

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

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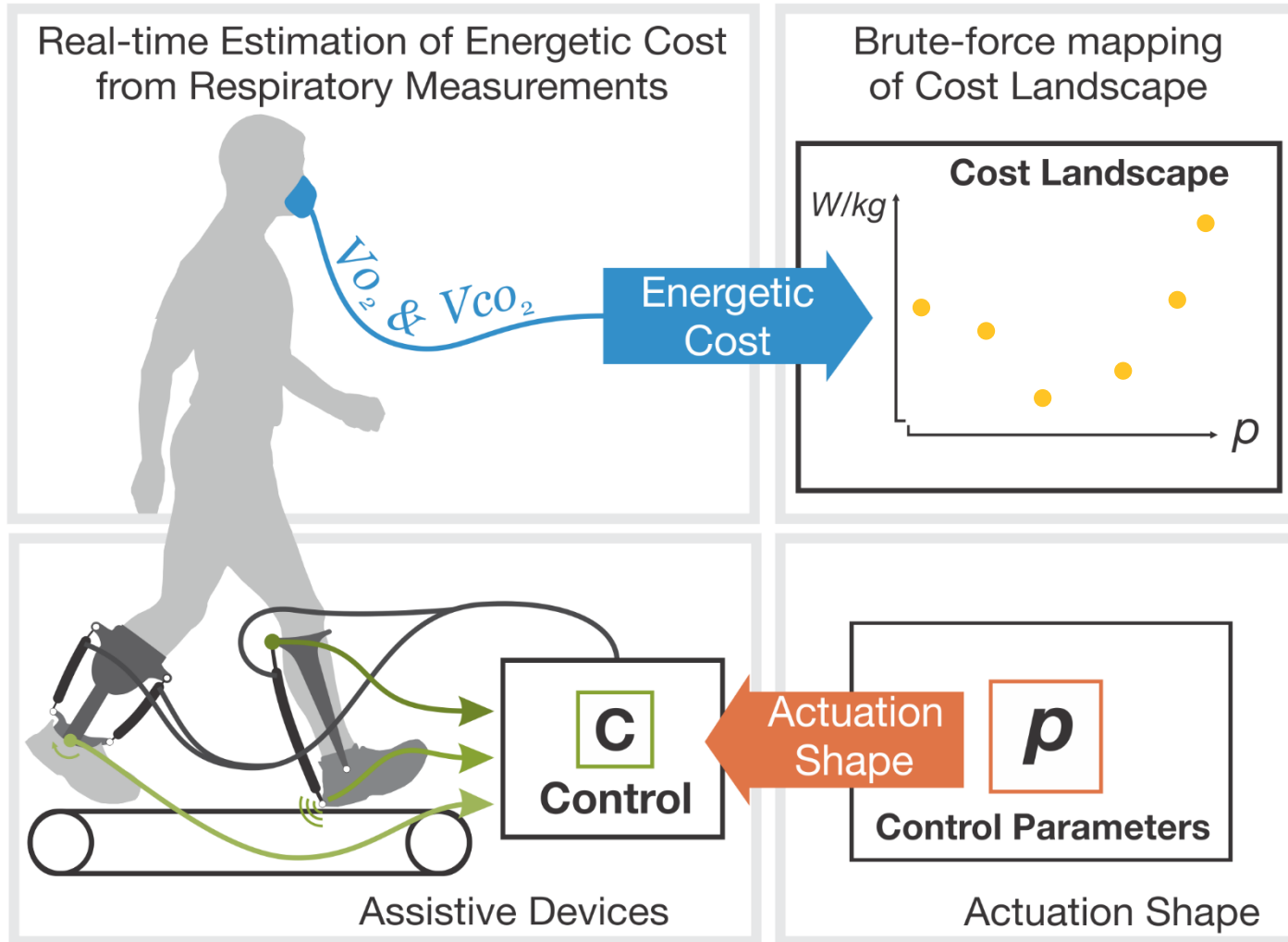
Lower Limb Assistive Robotic Devices

*Research
Prototypes*



Commercial Devices

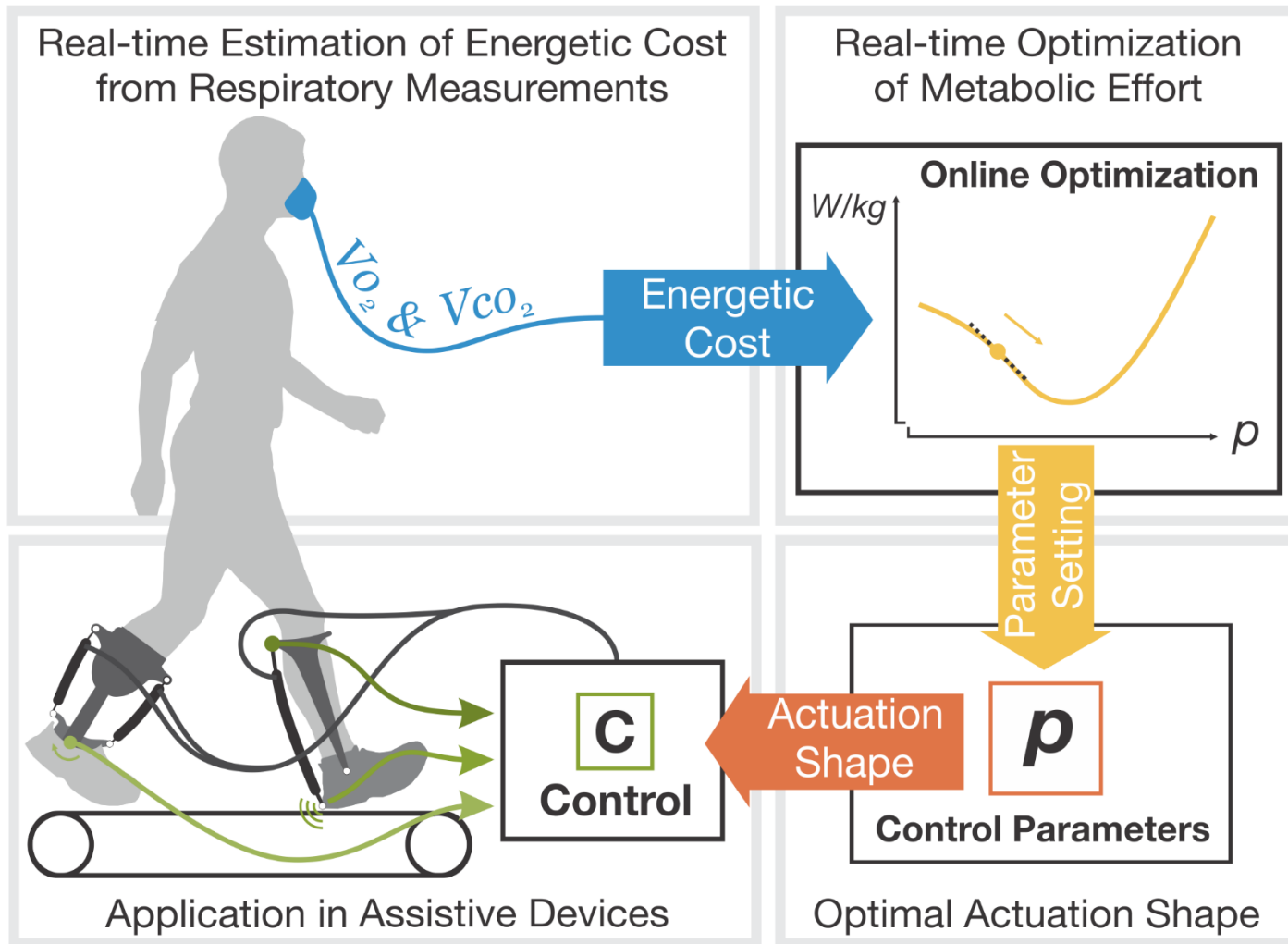
Evaluating Assistive Robotic Devices



[Malcolm, 2013]

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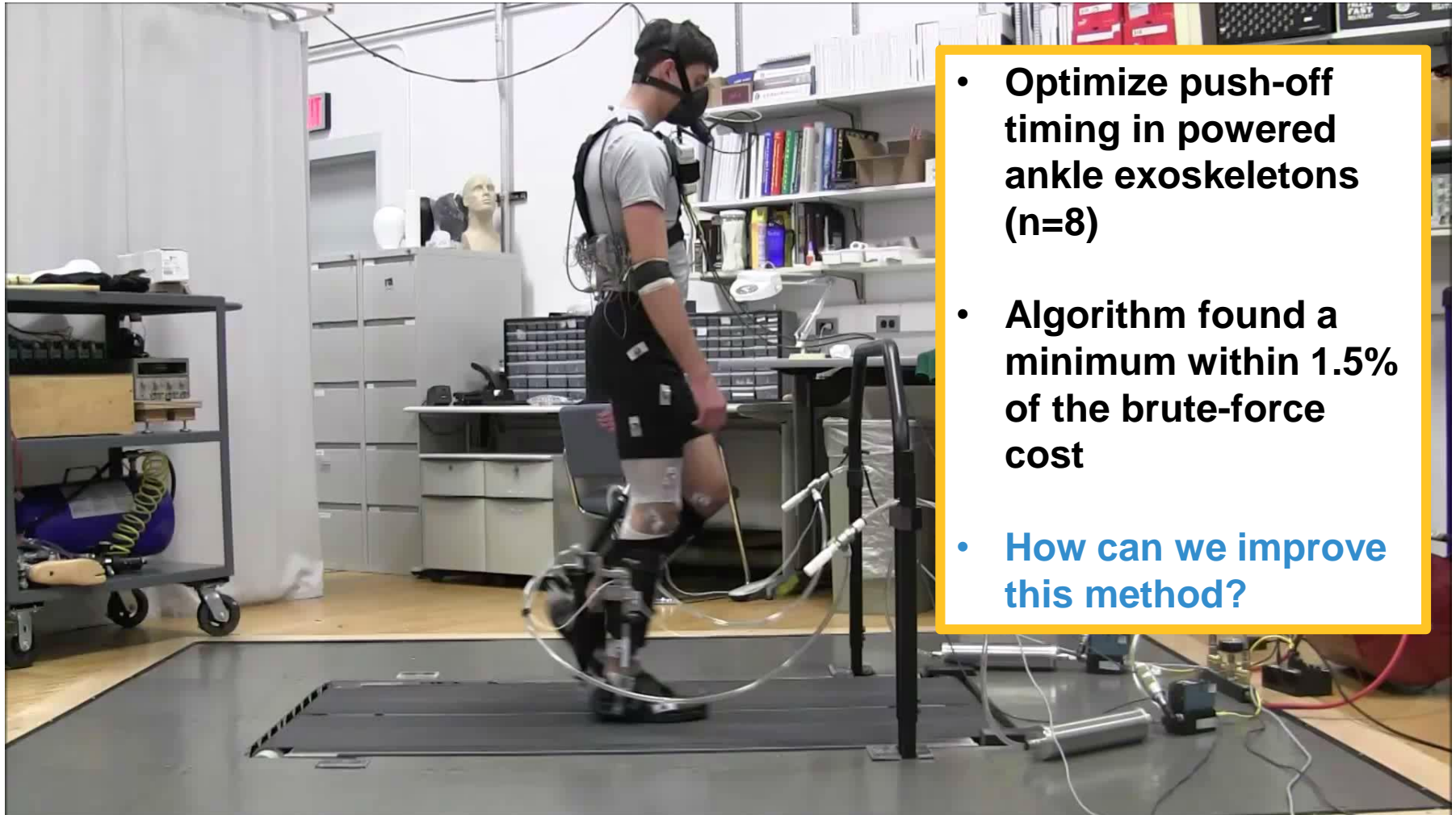
Body-in-the-Loop Optimization



[Koller, 2016; Felt, 2015]

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Body-in-the-Loop Validation Study



[Koller, 2016]

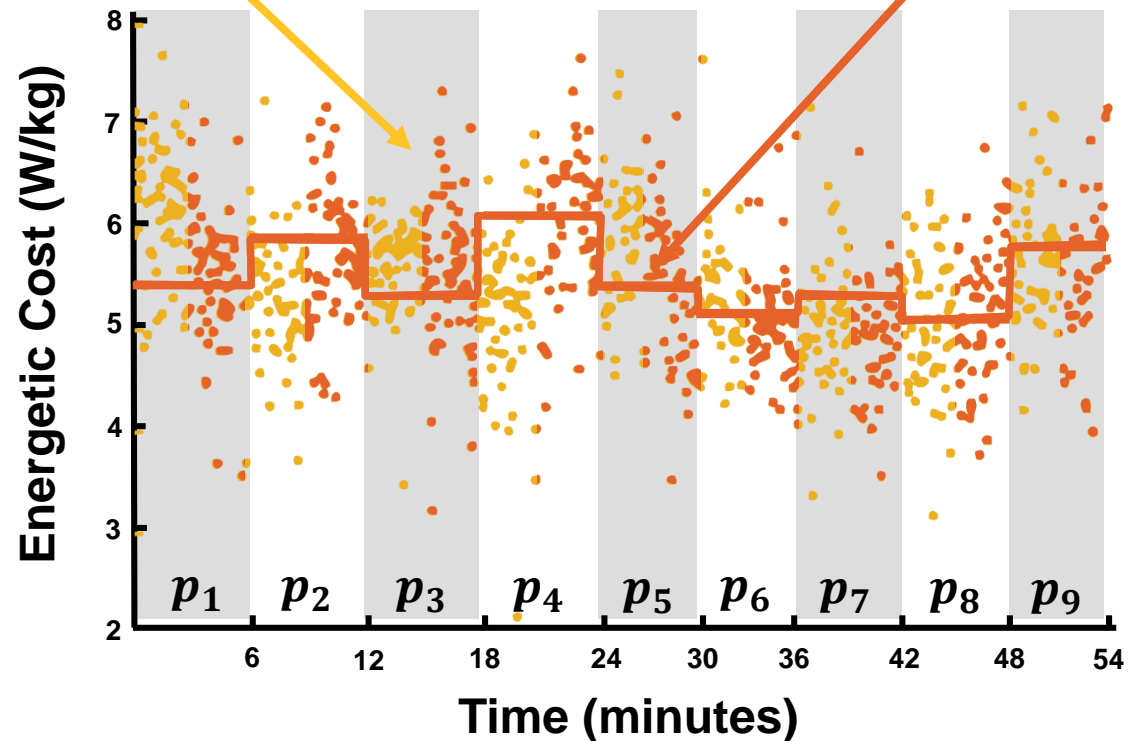
Challenges: Indirect Calorimetry

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]

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Challenges: Indirect Calorimetry

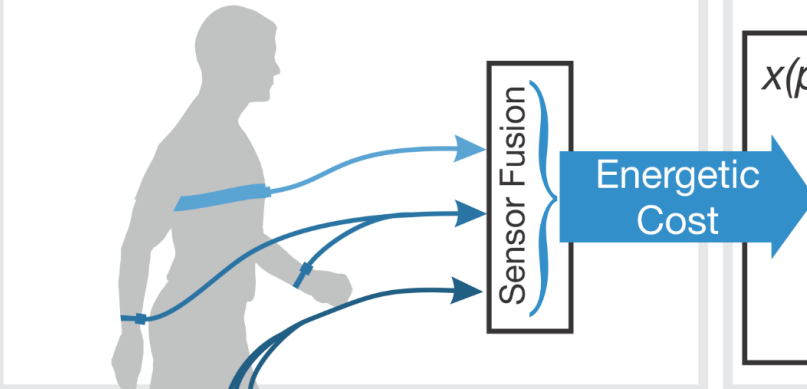
CHALLENGES:

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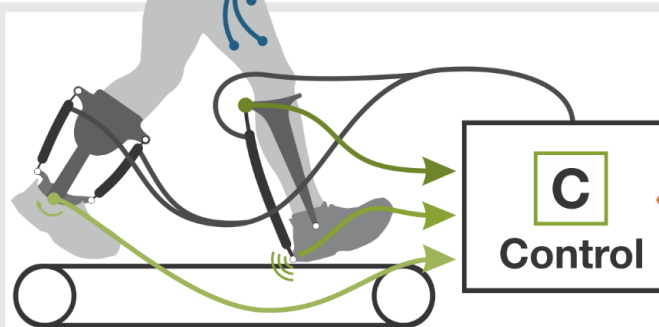
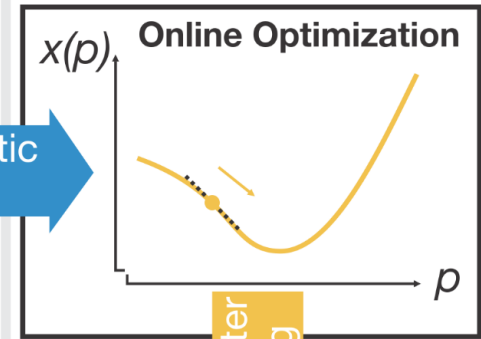
GOAL:

Investigate sensor alternatives for estimating energy cost

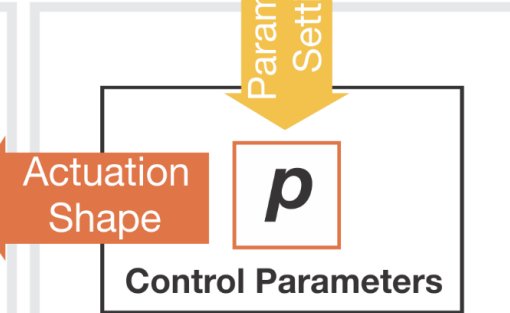
Real-time Estimation of Energetic Cost from Physiological Measurements



Real-time Optimization of Energetic Cost



Application in Assistive Devices



Optimal Actuation Shape

Experimental Data Collection

10 healthy subjects (8 male, 2 female)

walking



incline



backwards



running



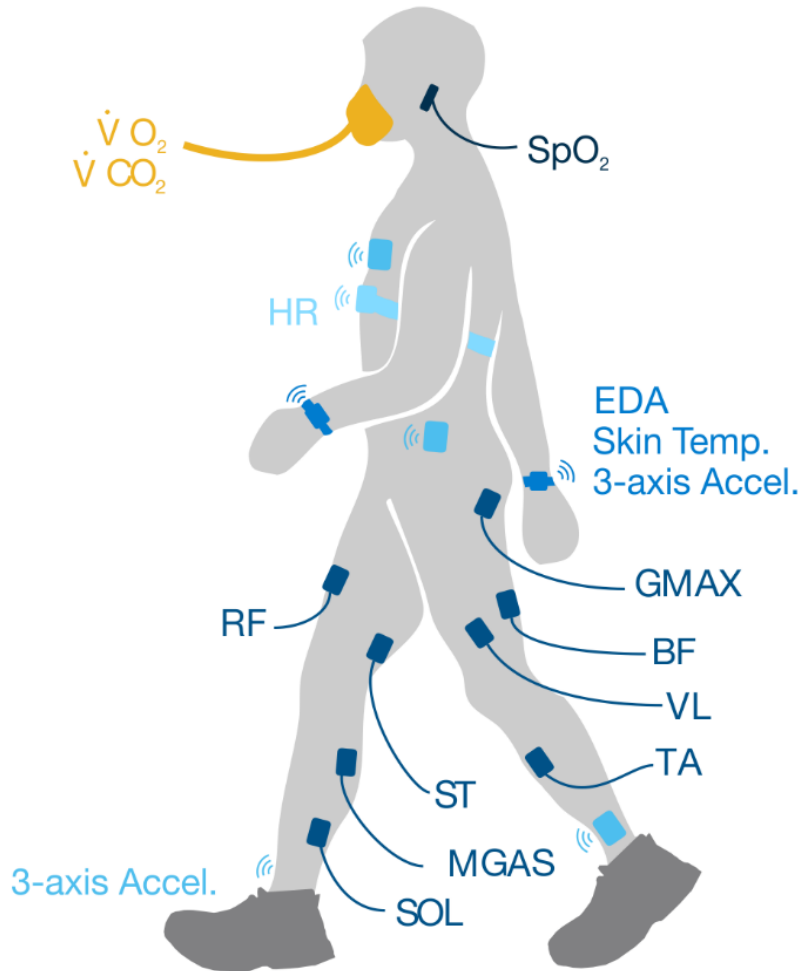
cycling



stair-climbing



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

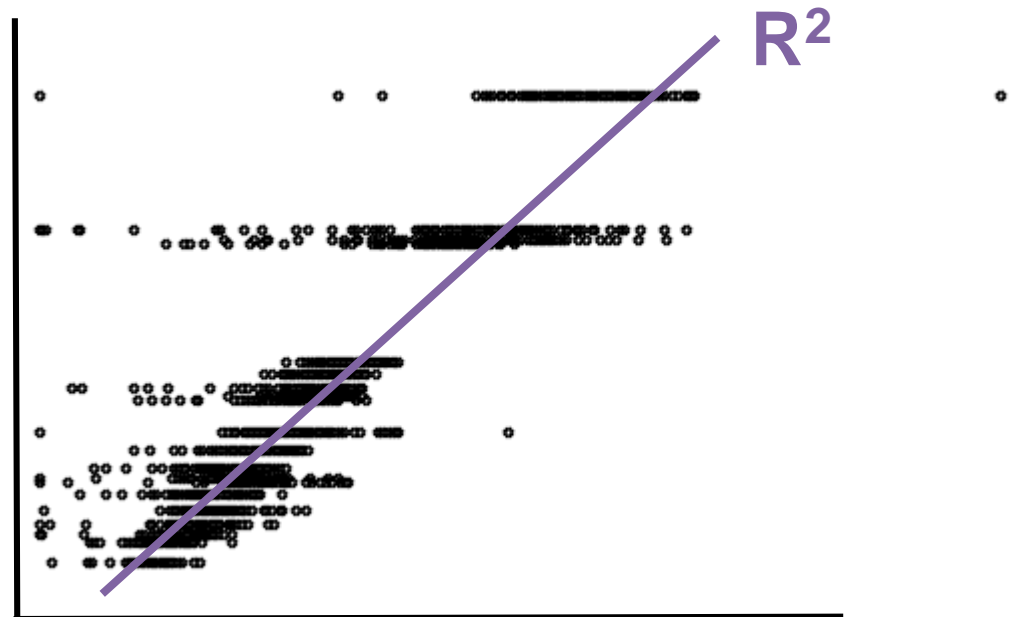
Global Signals

- SpO₂, 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)

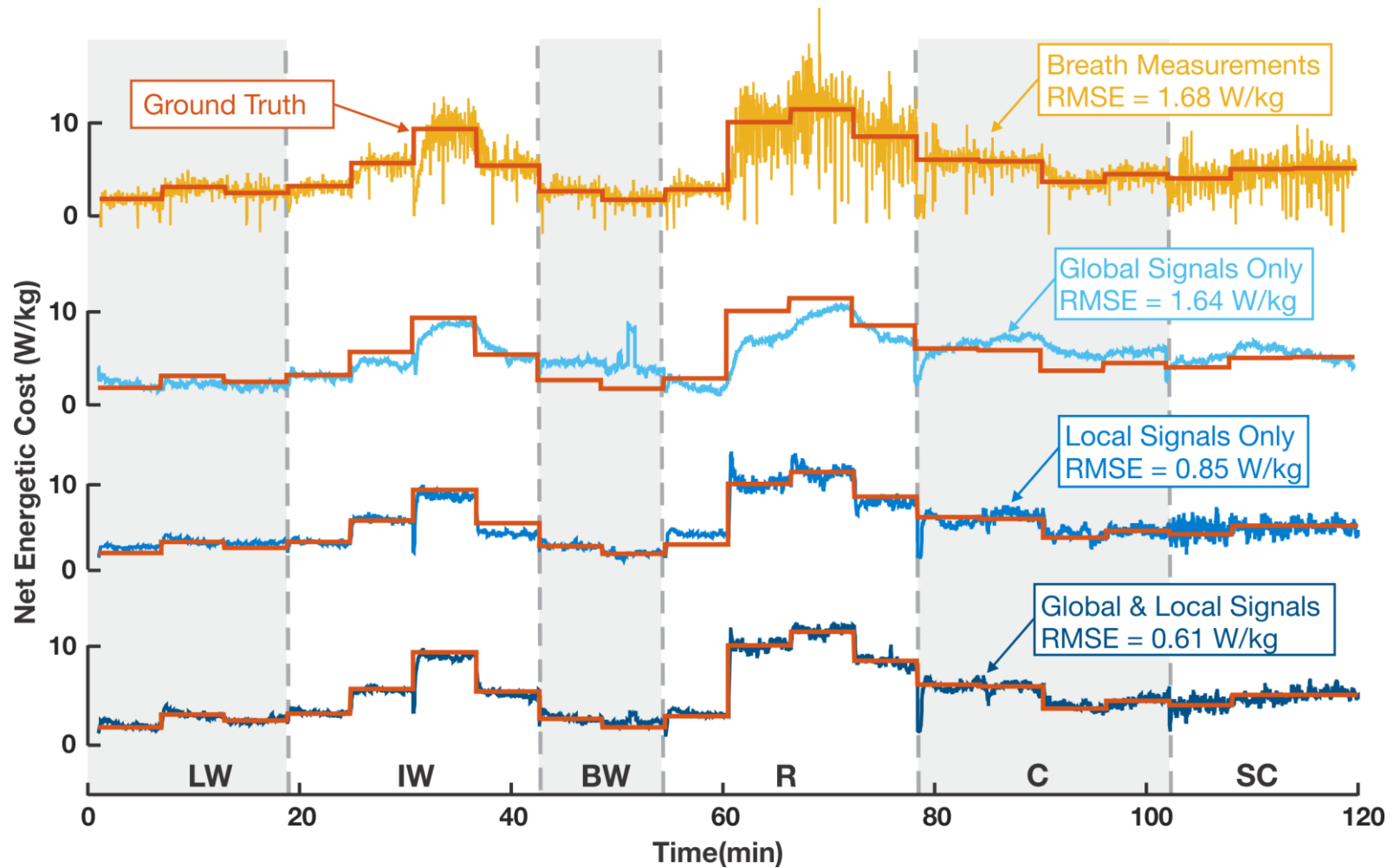


Various Combinations of
Physiological Sensors

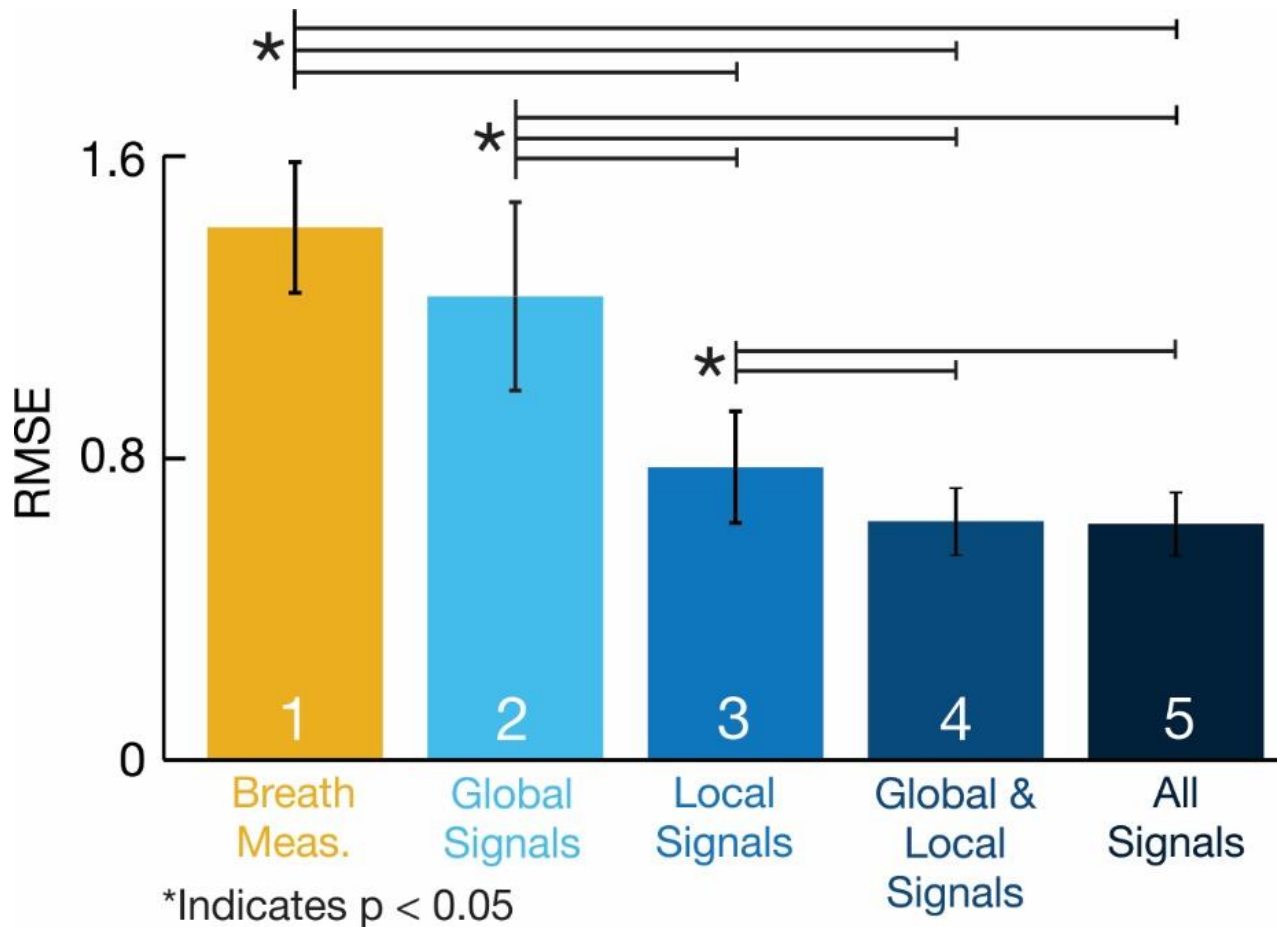
Multiple Linear Regression Models

Subset #	Breath Meas.	Global Signals				Local Signals		R ² Mean±SD
		EDA	Skin Temp.	Heart Rate	SpO ₂	Acc. Mag.	EMG Lin. Env.	
1	X							0.76±0.05
2		X	X	X	X			0.77±0.09
3						X	X	0.91±0.04
4		X	X	X	X	X	X	0.94±0.02
5	X	X	X	X	X	X	X	0.95±0.02

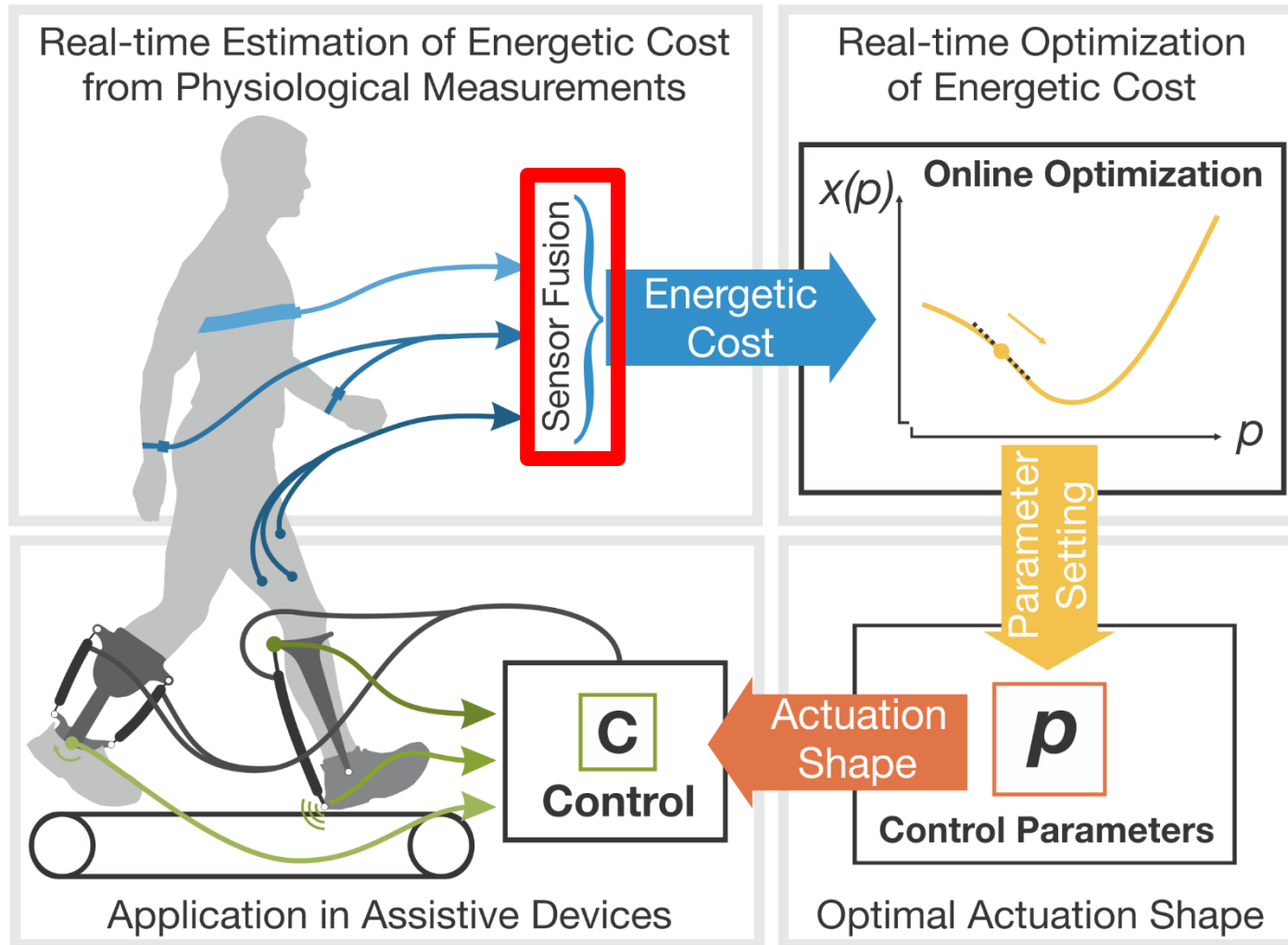
Time Series Predicted Energy Cost



Multiple Linear Regression Models



Future Directions

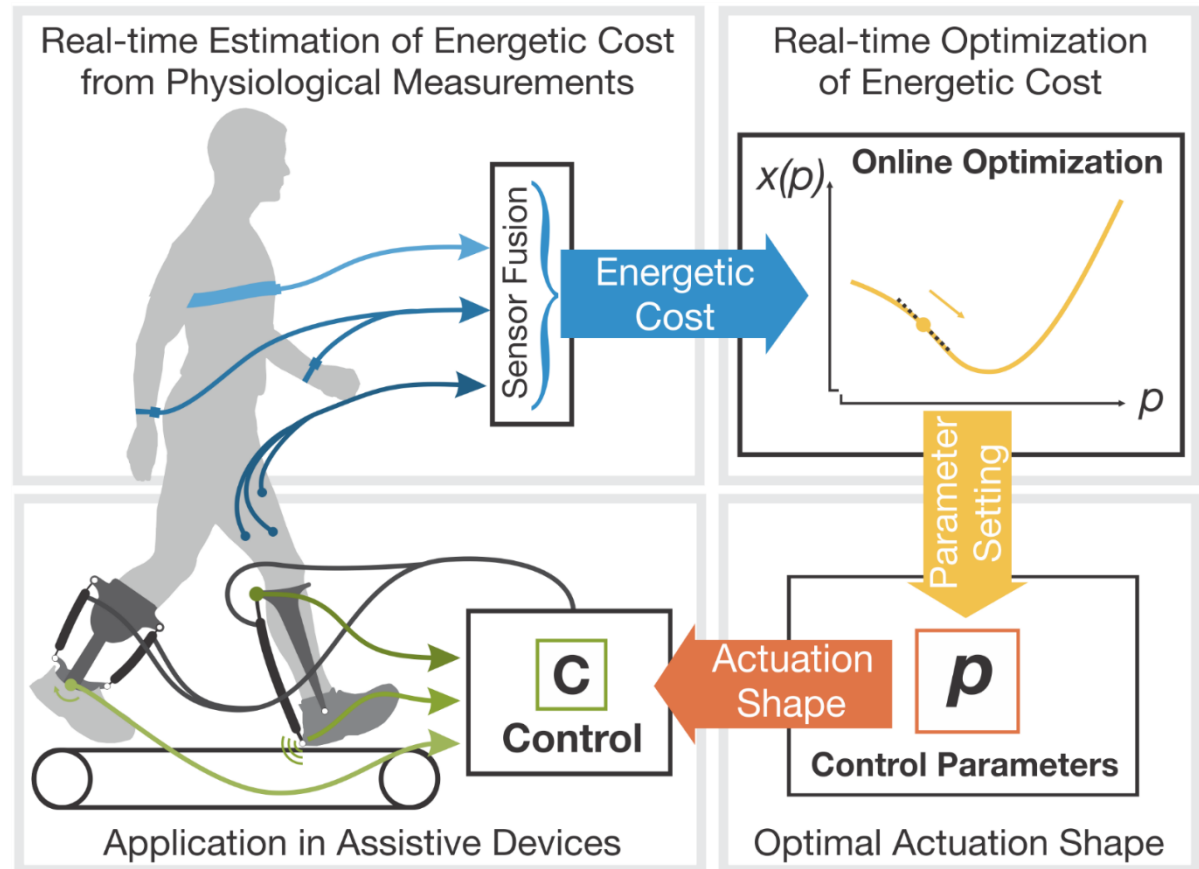


Questions?

Acknowledgements

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Jeff Koller

Funding sources



References

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