ESTIMATING METABOLIC COST DURING NON-STEADY STATE WALKING

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1. MOTIVATION

Conveniently, one can estimate energy use by muscle from measures of oxygen consumption and carbon dioxide production made at the mouth [1]. Less conveniently, these respiratory gases are delayed and noisy representations of the underlying muscle energy use. Consequently, traditional respiratory gas methods are only applied to relatively long periods of steady state walking, thereby constraining the research questions that can be effectively answered. Here, we expand on traditional methods to estimate metabolic cost during non-steady state gait by modeling the dynamic relationship between muscle energy use and metabolic cost during walking.

2. STATE OF THE ART

Whipp, Wasserman and colleagues have performed a series of insightful experiments in which they modelled ventilatory and gas exchange dynamics during non-steady state ergometer cycling [2]. However, it is unclear if these models can be directly applied to gait because walking may evoke different feedback and feedforward cardio-pulmonary responses than cycling. Furthermore, past work has been primarily concerned with understanding cardiopulmonary control mechanisms during exercise—to our knowledge, the identified dynamics have not been used to determine metabolic cost in non-steady state conditions.

3. OWN APPROACH

In order to identify the relationship between muscle energy use and metabolic cost during walking, we had subjects complete a series of enforced changes in gait. By rapidly changing treadmill speed (walking speed) and metronome frequency (step frequency) we aimed to evoke a rapid change from one preferred gait pattern to another, and thereby enforce a rapid change in muscle energy use that approximates a step function (Figure 1a). We then used optimization methods to test the ability of different models for capturing the dynamic relationship between our input (muscle energy use) and output (metabolic cost) settling (e.g. Figure 1b).

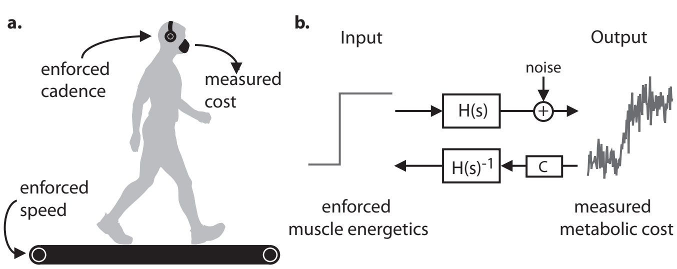

Figure 1: a. Experimental set-up. b. The relationship between input and output data can be modeled by $H(s)$. C represents our curve fitting technique, where an optimized polynomial is used to estimate profile shape less noise.

To stringently test if the inverse of our model could be used to estimate muscle energy use from the measured metabolic cost response, we enforced different muscle energy use profiles. To design these input profiles, we leveraged the relationship between step frequency and metabolic cost—where metabolic cost will increase as step frequency deviates from preferred. To quantify this relationship, our subject first walked on the treadmill at 1.25m/s at various enforced step frequencies above and below preferred. We used this data to design step frequency profiles that, at constant treadmill speed of 1.25m/s, would evoke three differing known input muscle energy use profiles, including a step, a ramp, and an exponential decay profile (Figure 2a). The subject was asked to match their steps to the changing metronome frequency while metabolic cost was measured. To estimate the shape of the underlying metabolic cost response, less noise, we fit each of the three profiles using an optimized polynomial, allowing us to fit each profile without prior knowledge of the underlying function.

4. CURRENT RESULTS

We found that the dynamic relationship between muscle energy use and measured metabolic cost could be modeled using a very simple first order linear ordinary differential equation, regardless of the magnitude or direction of the change in gait. Across all subjects, model fits yielded an average exponential time constant (τ) of 42 ± 12 s (mean $\pm$ SD). Moreover, using the inverse of our model we were able to produce estimates of muscle energy use from measured metabolic cost that closely matched the step, ramp, and exponential decay profiles, even during regions that were distinctly non-steady (Figure 2b).

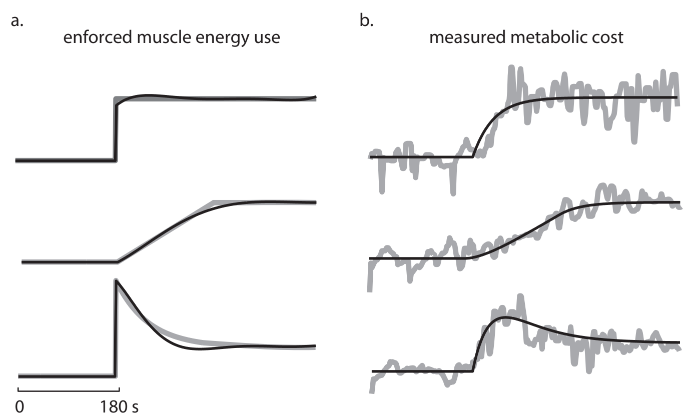

Figure 2: a. Enforced muscle energy use. b. Measured metabolic cost. All profiles have been normalized to unity. Grey lines represent actual profiles and black lines represent model estimates.

5. BEST POSSIBLE OUTCOME

Although further validation and refinement is required, our results suggest that it is indeed possible to estimate muscle energy use during non-steady state gait. Our ultimate aim is to use these techniques to study the role of metabolic cost in locomotor adaptation and learning.

REFERENCES

[1] Ferrannini. (1988) Metabolism
[2] Whipp et al. (1982) J Appl Physiol

ACKNOWLEDGMENTS

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