Estimating instantaneous energetic cost during gait adaptation

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ABSTRACT
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Estimating instantaneous energetic cost during gait adaptation

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**Abstract.** Respiratory measures of oxygen and carbon dioxide are routinely used to estimate the body’s steady-state metabolic energy use. However, slow mitochondrial dynamics, long transit times, complex respiratory control mechanisms, and high breath-by-breath variability obscure the relationship between the body’s instantaneous energy demands (instantaneous energetic cost) and that measured from respiratory gases (measured energetic cost). The purpose of this study was to expand on traditional methods of assessing metabolic cost by estimating instantaneous energetic cost during gait adaptation and other non-steady state conditions. To accomplish this goal, we first imposed known changes in energy use (input), while measuring the breath-by-breath response (output). We used these input/output relationships to model the body as a dynamic system that maps instantaneous to measured energetic cost. We found that a first-order linear differential equation well approximates transient energetic cost responses during gait. Across all subjects, model fits were parameterized by an average time constant (τ) of 42 ± 12 s with an average R² of 0.94 ± 0.05 (mean ± SD). Armed with this input/output model, we next tested whether we could use it to reliably estimate instantaneous energetic cost from breath-by-breath measures under conditions that simulated dynamically changing gait. A comparison of the imposed energetic cost profiles and our estimated instantaneous cost demonstrated a close correspondence, supporting the use our methodology to study the role of energetics during locomotor adaptation and learning.

**Key words:** energetics, gait, adaptation, indirect calorimetry, metabolic cost
1. INTRODUCTION

Steady state measurements of metabolic energetic cost have provided valuable insight into why and how we walk the way we do. Energetic cost, in this context, refers to the input energy required to power the cellular processes underlying the body’s movement. This energy is liberated from glucose, fats, and other stored foodstuffs in a reaction that requires oxygen and produces carbon dioxide (3). Consequently, energetic cost is typically measured indirectly by quantifying the oxygen and carbon dioxide in respiratory gases (2, 16). These measurements have demonstrated that we select the most fundamental characteristics of our gait—such as speed, step frequency and step width—so as to minimize energetic cost per distance travelled (4, 5, 8, 9, 17, 23, 29, 35, 36, 40). Cost measurements have also allowed the quantification of energetic penalties imposed by various gait disabilities, and the evaluation of the effectiveness of rehabilitation interventions at mitigating these added costs (5, 35, 36). Equipment and wearable devices, be it backpacks (12, 15), prosthetics (25, 41), orthoses (10, 24), or running shoes (6), have been assessed, iteratively designed, and ultimately improved based on cost measurements.

The relationship between the body’s instantaneous energy demands (instantaneous energetic cost) and that measured from respiratory gases (measured energetic cost) is complicated. Consider, for example, oxygen consumption measured at the mouth. Muscles meet their instantaneous energy demands for force generation using ATP, a form of stored energy. While ATP is immediately replenished using another form of stored energy, creatine phosphate, the mitochondrial dynamics that use oxygen and foodstuffs to replenish creatine phosphate are rather slow (1, 7, 22, 30). There are still further delays before mitochondrial oxygen consumption is reflected in respiratory gases due to blood circulation from muscle to lungs (13), oxygen exchange between the blood and the lungs, and then lung ventilation itself. The relationship between instantaneous and measured cost cannot be determined by simply adding up these component time delays because blood gases are under tight neural control (28), and
these controllers impose their own dynamics. For example, rapid increases in ventilation are often seen at the onset of exercise (28), preloading the body in anticipation of future mitochondrial oxygen requirements. Consequently, energetic cost as measured at the mouth can occur in advance of any actual energy use by muscle. An additional complicating factor is the discrete nature of breathing—while muscles may be continuously consuming the body’s oxygen, the lungs only replenish oxygen with each breath and each breath may be of drastically different volume. Irregularities in both depth and timing of breaths create noisy breath-by-breath estimates of energetic cost that do not reflect true fluctuations in muscle energy use (14, 20). In summary, the relationship between instantaneous and measured energetic cost is complicated by mitochondrial dynamics, body transit delays, and respiratory control mechanisms, and then further obscured by high breath-by-breath variability.

It is due to these complexities that energetic cost is traditionally only measured during long bouts of constant intensity conditions. By discounting non-steady state regions of cost measurements, the rate at which the oxygen is entering the body is allowed to reach equilibrium with the rate at which cellular processes are consuming it. By averaging over minutes of data, high breath-by-breath ‘noise’ is overcome and the measured energetic cost then accurately matches the instantaneous energetic cost. While these processing techniques have served us well over the past century, they restrict the research questions that can be effectively answered. Long-duration steady-state conditions, such as those experienced on a treadmill, are the exception rather than the norm during real-world walking (21). In truth, we are continually adjusting our gait to meet the demands of a changing environment and the energetic cost under these real-world conditions is essentially unknown.

Here, we expand on traditional methods of assessing energetic cost with the primary purpose of developing a technique to estimate instantaneous energetic cost during gait adaptation. We first characterized the dynamic relationship between instantaneous and measured energetic cost during walking. To accomplish this, we enforced known changes in instantaneous energy use (input)—by
prescribing changes to subjects’ walking speed and step frequency—and measured the respiratory
responses in measured energetic cost (output; Figure 1A). We then modeled the body as a dynamic
system that maps instantaneous to measured energetic cost (Figure 1B). Next, we used this model to
test two approaches for estimating instantaneous energy use from respiratory measures. The inverse
model approach is perhaps the most intuitive—the actual measured energetic cost is smoothed and then
passed through the inverse of the identified model to produce an estimate of the instantaneous energetic
cost (Figure 1C). The forward model approach estimates instantaneous energetic cost as the input that
when passed forward through the identified model produces an estimate of measured cost that best fits
the actual measured energetic cost response (Figure 1D).

2. METHODS

Ten adult subjects (body mass: 67.1 ± 6.0 kg; height: 173.7 ± 5.2 cm; mean ± SD) with no known
musculoskeletal or cardio-pulmonary impairments participated in this study. Simon Fraser University’s
Office of Research Ethics approved the protocol, and participants gave their written, informed consent
before experimentation. Experiments were performed over two or three days, with no more than two
hours of walking per day to reduce fatigue effects.

2.1 Enforcing rapid changes in instantaneous energetic cost

Subjects were instrumented with indirect calorimetry (VMax Encore Metabolic Cart, ViaSys, IL, USA)
and all walking was performed on an instrumented treadmill (FIT, Bertec Corporation, MA, USA). To
habituate subjects to the experimental set up, they walked at a range of treadmill walking speeds (0.75,
1.00, 1.25, 1.5, and 1.75 m/s) for a minimum of 10-minutes at each speed (31, 33, 34). Subjects next
completed a series of enforced rapid changes in gait. The treadmill speed (walking speed) and
metronome frequency (step frequency) were rapidly and simultaneously increased or decreased using
custom written software (Simulink Real-Time Workshop, Mathworks Inc., MA, USA), in order to
evoke a step-like change in instantaneous energetic cost (Figure 1A). We chose to not only alter speed, but also step frequency because people often take tens of seconds to adjust their step frequency to steady state following perturbations in treadmill walking speed (27, 33). Metronome frequency was set at the subjects’ preferred step frequency at each speed, defined as the average step frequency during the final 3-minutes of walking in the habituation trials. Step frequency for an individual step was calculated as the inverse of the time between foot contact events, identified from the characteristic rapid fore-aft translation in ground reaction force center of pressure (32). The treadmill speed alternated between 6-minute periods at a base speed of 1.25m/s and 6-minute periods above or below this base speed (1.5 or 1.75 m/s, and 0.75 and 1.00 m/s, respectively). This resulted in eight different changes in gait (conditions), including step-like changes up-to and down-from the non-base speeds of 0.75, 1.00, 1.5, 1.75 m/s. Speed presentation order was randomized. We designed these changes to have differing direction (increase or decrease in speed) and magnitude (absolute speed change of 0.25 or 0.50 m/s) in order to test if the identified energetic cost dynamics differed across conditions. To compensate for the variable nature of breath-by-breath measurements and to further control for order effects, we had subjects complete a second day of testing in which they repeated the enforced gait changes twice with a newly randomized order, giving us a total of three repeats for each of the eight conditions.

2.2 Modeling the relationship between instantaneous and measured energetic cost

Whipp, Wasserman and colleagues have previously modeled ventilatory gas dynamics during non-steady state cycling (37, 39). Given step changes in work rate, they found the oxygen uptake and carbon dioxide output could be well described by first-order differential equations with an accompanying time delay. Here, we use their model as a starting point for our modeling efforts while recognizing that gas kinetics during walking and cycling are not constrained to have identical dynamics. We modeled the relationship between the instantaneous energetic cost (our input) and the measured cost (our output) as a single dynamic process comprising a time-delayed first-order linear
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ordinary differential equation. The mathematical representation of this model expressed in the
frequency domain, takes the form:

\[ Y(s) = H(s)X(s), \quad (1) \]

where

\[ H(s) = \frac{A}{\tau s + 1} e^{-\delta s}, \quad (2) \]

\( X(s) \) is the input instantaneous energetic cost, and \( Y(s) \) is the output measured energetic cost. The
parameter \( \tau \) is a time constant characterizing the rate of change, \( A \) represents the amplitude of the
change, and \( \delta \) is a time delay. One may understand this model as a low-pass filter, where a rapid
change in input (instantaneous energetic cost) will result in a slow and smoothed output response
(measured energetic cost), and the amount of slowing and smoothing will increase with the magnitude
of \( \tau \). Thus, if one were to see very quick changes in measured respiratory energetic cost, it would mean
there was an exceptionally large and rapid change in the underlying instantaneous energetic cost. One
might also understand this model in terms of its response to a step input, where the produced response
would take the form of an exponential rise to steady state with a delay between the step input and the
beginning of the response.

To fit this model to our data, we analyzed three minutes of metabolic data prior to each gait change and
six minutes of data following the gait change. The magnitude of each trial was normalized to unity to
allow us to compare and average the steps of differing magnitude and direction. To accomplish this
normalization, we first subtracted the steady-state value before the gait change (the average of minutes
-3 to 0) and then divided by the amplitude of the change (the average of minutes 3 to 6). Note that this
normalization process does not affect any dynamics in the measured cost response. To solve for our
unknown model parameters (\( \tau \) and \( \delta \)), we used weighted least-squares optimization to minimize the
residuals between our model and measured data. The optimization uses the Levenberg-Marquardt
algorithm and was implemented with MATLAB’s *nlinfit* function. Due to prior normalization, best-fit amplitudes had a value of one \( (A = 1) \). In order to avoid known convergence issues with delayed dynamic models (19), we visually confirmed the accuracy of the fitted time delays. We assessed the goodness-of-fit of our estimated parameters by calculating the \( R^2 \) value between the model and our measured data. As a test of model sufficiency we also evaluated whether the addition of second process, modeled as an additional time-delayed first-order linear differential equation, produced a better fit to our data.

To test whether the same model holds regardless of magnitude or direction, we first separately fit our model to each of the eight conditions (grouped only across repeats). We then used repeated measures ANOVA to test for differences in our solved parameters between the different magnitudes and directions. If appropriate, we then grouped trials of the same direction (increase or decrease in speed) or magnitude (absolute speed change of 0.25 or 0.50 m/s) and tested for differences using a Student’s paired t-test. For all tests, we accepted \( p < 0.05 \) as statistically significant.

### 2.3 Estimating instantaneous energetic cost during dynamically changing gait

We next assessed if our solved model could be used to estimate instantaneous energetic cost from measured breath-by-breath energetic cost. To accomplish this, we had two representative subjects return for a third day of testing. Our goal was to enforce instantaneous energetic cost profiles that differed from those upon which our model was based. To design varying instantaneous energetic cost input profiles, we leveraged the fact that subject’s energetic cost will increase as their step frequency deviates from preferred (18, 29). To quantify this relationship, our test subjects first walked on the treadmill at 1.25 m/s for six minutes at nine enforced step frequencies that were at, above, and below preferred \((0, \pm 5, \pm 10, \pm 15, \pm 20 \% \text{ deviation from preferred step frequency})\). For each enforced step frequency, we took an average of the final three minutes of steady-state energetic cost data, leaving us
with nine data points that we then fit with a cubic polynomial (Figure 2B). Note that during these steady-state regions, the average measured energetic cost is equivalent to the average instantaneous energetic cost, as the gas exchange measured at the mouth has reached equilibrium with the gas exchange occurring at the muscle tissue level.

Next, the solved polynomial was used to design step frequency profiles that, at constant treadmill speed of 1.25m/s, would evoke three distinct input muscle energy use profiles—a step, a ramp, and an adaptation profile (Figure 2A). The step profile, although the same shape as the original input profile on which we based our model, imposed different physical constraints on the subject, as treadmill speed was held constant and only step frequency was rapidly increased. The ramp profile was markedly different from that of the step in that step frequency was gradually increased over the course of minutes. The adaptation profile was designed to mimic a fast adaptation, where a subject’s instantaneous energetic cost may initially step up in response to a perturbation and then rapidly decay within tens of seconds. For each trial, treadmill speed was held constant at 1.25m/s and the subject was asked to match their steps to the changing metronome frequency (Figure 2C) while we measured energetic cost. The subjects completed three repeats for each input profile shape in randomized order.

We then used two different approaches to estimate instantaneous energetic cost from measured cost, each approach having distinct strengths and drawbacks. Recall that for each subject, we have solved for an individualized model that maps instantaneous to measured energetic cost. Therefore, the inverse of this model will do the opposite: map measured to instantaneous energetic cost. This is the basis of our inverse model approach (Figure 1C). By passing a subject’s measured energetic cost data though their inverse model, we can directly compute the instantaneous energetic cost. However, it was necessary to first smooth the measured data. Passing unsmoothed data through the inverse model, which functions like a high pass filter, would effectively amplify high frequency components in the measured signal and these high frequency components tend to be dominated by the breath-by-breath noise. Although a low
pass filter could be used to first attenuate noise, it would indiscriminately attenuate all high frequency
inputs, which may include rapid changes in instantaneous energetic cost that we are seeking to identify.
Instead, to estimate the shape of the underlying energetic cost profiles, less the noise, we fit each trial
of measured data with polynomials. A constrained least squares optimization, implemented using
MATLAB’s *lsqlin* function, was used to solve for the best-fit polynomial parameters. Polynomial order
was set such that no systematic pattern was observed in the residuals. The fitted curve was required to
pass through the initial steady state value (0 after normalization) at the point of perturbation and had to
reach steady state (1 after normalization) in the last 3 minutes of the trial. These constraints are
reasonable given that the prescribed step frequencies were at steady state during these regions. We did
not constrain the initial slope of the polynomial allowing for rapid initial changes in the smoothed cost.

Our forward model approach can be used in situations where the experimenter has a good first
approximation of the shape of the instantaneous energetic cost profile (Figure 1D). This shape is
described with a set of parameters that are then optimized so that the generated input profile, when run
through the subject’s model, produces an estimate of measured cost that best fits the actual measured
energetic cost response. We used a Nelder-Mead Simplex method, implemented with MATLAB’s
*fminsearch* function, to solve for the optimal parameter values. For the step input, a single parameter
was optimized: the time of onset of the step. For the ramp input, two parameters were optimized: the
time of onset and the time of offset of the ramp, which together dictate the slope of the ramp. For the
adaptation input, three parameters were optimized: the time of onset, the amplitude of the peak, and a
decay constant. Note that the initial and final steady-state amplitudes were not optimized, as
normalization fixes them at 0 and 1, respectively.

**3.0 RESULTS**

We found that the dynamic relationship between instantaneous energetic cost and measured energetic
cost could be modeled using a first-order linear ordinary differential equation (Eq. 2). Moreover, we found that the same model appears to hold regardless of the magnitude or direction of the change in gait. We did not identify differing model parameters when each of the eight gait changes, of varying magnitude and direction, were fit separately ($p = 0.102$). When we then grouped across all trials of the same direction (increase or decrease in speed) we again found that parameters did not differ between directions ($p = 0.500$). The same was found when we grouped trials of the same magnitude (absolute speed change of 0.25 or 0.50 m/s) ($p = 0.094$). This indicates that the underlying dynamics were not significantly different irrespective of the applied magnitude or direction of the change in gait. For subsequent analyses all trials for an individual subject have been fit together.

Our model described the dynamics of respiratory metabolic cost reasonably well for most subjects. When compared to the average response, the model accounted for 82-99% of the measured variability (Figure 3). When the model was compared to individual trials, without averaging, 18-87% of the measured variability was explained. This considerably larger range in goodness-of-fit is due to the variability between breaths in measured metabolic cost, and was expected given that we did not attempt to model breath-by-breath dynamics. Adding a second dynamic process, modeled as an additional time-delayed first-order linear differential equation, did not appreciably improve our fits; visually no improvement was evident and on average only an additional 0.9% ± 1.0% of the variability was explained (mean ± SD).

Across all subjects, model fits yielded an average time constant ($\tau$) of 41.9 ± 12.0 s (mean ± SD). This means that 95% of the response to a step-like change input is completed within three time constants, or 125.6 ± 36.1 s (mean ± SD). We did not identify time delays ($\delta$) that were discernable from zero for any of the ten subjects. Due to normalization, all amplitudes ($A$) displayed in Figure 4 have a value of 1. Therefore, the mathematical representation of our model (Eq. 3) simplifies to a transfer function of the form:
This model enabled accurate estimates of instantaneous energetic cost from respiratory energetic cost measures. Using both our inverse and forward model approaches, we were able to produce estimates of instantaneous energetic cost from measured energetic cost that well matched the enforced step, ramp, and adaptation profiles (Table 1 and Figure 4). For the step and ramp input profiles, both approaches performed exceptionally well. The $R^2$ values between the enforced instantaneous energetic cost profile and the model-produced estimates of instantaneous energetic cost were between 0.87-0.99 for individual trials. As a result, averaging measured energetic cost data across the three repeats prior to applying either approach did little to improve our estimates of instantaneous energetic cost. Thus, for the step and ramp profiles, it appears possible to accurately estimate instantaneous cost from a single trial of measured energetic cost data. Single trial estimates of instantaneous energetic cost were less accurate for the adaptation profile. For subject I, individual trial $R^2$ values were as low as 0.26 and 0.38 for the inverse model approach and forward model approach, respectively. For this subject, averaging measured energetic cost data across the three repeats prior to applying the inverse model approach or forward model approach improved $R^2$ values to 0.66 and 0.75, respectively. Individual trial $R^2$ values for the adaptation trials were substantially better for Subject II (0.77-0.88).

4.0 DISCUSSION

We found that a simple first order linear differential equation can approximate transient energetic cost responses during gait. When rapid step-like changes in instantaneous energetic cost were enforced, we observed a single underlying response featuring no discernable delay. On average, subjects took two minutes to reach 95% of the steady state metabolic cost value, with all but one subject reaching 95% steady state within three minutes. These same underlying dynamics held regardless of the magnitude or direction of the change in gait. Despite the collective effect of many sources of complexity—including
mitochondrial dynamics, gas stores, transit delays, and cardio-pulmonary control—a simple model explains the transient energetic cost response during walking.

This model allowed us to produce reasonably accurate estimates of instantaneous energetic cost from respiratory cost measures. Our two approaches—the inverse model approach and forward model approach—resulted in similar estimates of instantaneous energetic cost, and when compared to our enforced cost profile, $R^2$ values were typically greater than 0.90. Both methodologies were able to capture rapid changes in instantaneous energetic cost that were prescribed during the step trials, as well as gradual changes and discontinuities that were prescribed during the ramp trials. The poorest estimates of instantaneous energetic cost were found for the adaptation trials, where fitting the rapid decay proved somewhat problematic. These sorts of transient changes in cost are more readily distorted by breath-by-breath noise because there are fewer data points available with which to fit model parameters. Our adaption trial decayed to steady state with a time constant of 60 seconds, which equates to only about 20 breaths. Better estimates may be possible with improved noise removal techniques, improved fitting techniques, or through averaging over a greater number of trial repeats.

Overall, the two approaches produced similar and seemingly accurate estimates of instantaneous energetic cost. However, each approach is subject to distinct limitations and requires different assumptions on the part of the user.

The inverse model approach requires little advance knowledge of the underlying instantaneous energetic cost profile, but is greatly complicated by breath-by-breath noise. High frequency components of breath-by-breath variability in measured energetic cost are effectively amplified when passed through the model inverse, obscuring estimated instantaneous energetic cost. To reduce their contribution, while retaining our ability to fit fast changing inputs, we first fit the noisy metabolic cost data using a polynomial. We constrained the polynomial to pass through an initial steady state value at the point of perturbation, and to reach steady state at the end of the trial. For an experimenter, these
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constraints require that the protocol be designed such that the subject begins and ends in steady state.

(These particular constraints are not universal for every experimental paradigm—researchers should identify whatever constraints on the measured data are imposed by the experimental paradigm and use them to their fitting advantage.) Although we made no assumptions about the shape of the profile between the beginning and end steady state regions, complex profiles would not be fit well by a low order polynomial. In such situations higher order polynomials, splined polynomials, or all together different functions may be necessary to accurately fit the measured energetic cost profiles. This will inevitably introduce subjectivity, as the experimenter will be required to make decisions about what profile changes are ‘true’ and what is simply ‘noise’.

Estimating instantaneous energetic cost using the forward model approach requires some advance knowledge of the profile shape. This knowledge may be based on the study design or additional measurements. For example, if the study design calls for a novel force to be rapidly applied to a limb one may reasonably assume an abrupt increase in instantaneous energy use, followed by an exponential decay as the subject adapts to the new force. One need not know the timings and magnitudes of the initial increase and subsequent decay as the forward approach employs optimization to estimate their values. Alternatively, one may deduce the profile shape from a measured physiological variable, such as the time course of adjustments to step frequency or muscle activity. It is also possible that the experimenter has a range of hypotheses about what the input profile shape may be. These hypotheses can be evaluated by optimizing each candidate input profile and testing which one provides the best fit. To illustrate this, we fit optimal step, ramp, and adaptation profiles to each of the three responses and found that each response was best fit by its respective profile shape (e.g. the enforced ramp was best fit by a ramp profile). Because the experimenter must make assumptions about the underlying profile shape, the forward approach introduces a bias based on the experimenter’s expectations. Moreover,
there may be situations where the experimenter does not have a reasonable first approximation of the
input profile shape.

In addition to the approach specific limitations described above, there are four more general limitations
to our methodology and analysis. First, we treat our enforced instantaneous energetic cost profiles as a
gold standard to which we compare our model estimates. Although we attempted to enforce a specific
cost profile by controlling walking speed and step frequency, other uncontrolled gait parameters, for
example stance time or muscle activity, may have caused instantaneous energetic cost to deviate from
our desired input profile. As a consequence, our estimates may be better or worse than presented.

Second, the identified model and its average parameters only apply to adult humans. Differences in size
and phylogenetic history are both likely to alter the dynamic relationship of other animals from that in
adult humans. Similarly, the identified model and its average parameters only apply to walking. While
we found that a single process accurately captures the identified dynamic relationship between
instantaneous and measured energetic cost, Whipp and colleagues have repeatedly found that there are
two important processes in cycling, perhaps reflecting a difference in cardio-pulmonary control
between the two tasks (37, 38). A fourth limitation of our model is that it can only be applied to
walking tasks within the tested metabolic cost range. At metabolic rates above 400W, many subjects
may breach the anaerobic threshold, causing oxygen stores to be depleted faster than they can be
replenished and rendering our measured energetic cost a poor estimate of the underlying instantaneous
energetic cost. At metabolic rates below 100W it is possible that more complex dynamics exist at the
onset of exercise, as first described by Whipp and colleagues (37). Overall, our exact model can be
used to estimate instantaneous energetic cost of walking at metabolic rates ranging from 100W to
400W. Outside of this range, care should be taken to first identify the underlying dynamic relationship
between instantaneous and measured energetic cost before applying our inverse or forward model
approach.
Our methodology may prove useful for both post-hoc and real-time estimation of energetic cost. Its accuracy benefits from a personalized model for each subject, but for some situations, it may suffice to use the average dynamic model identified in the current experiments. As an initial test of this possibility, we simulated measured energetic cost to an adaptation input profile for a subject with an exceptionally slow time constant of 60s. We then compared instantaneous cost estimates using this subject specific time constant to that obtained if we assumed our average time constant (42s). Using the average time constant still made it clear that instantaneous cost adapted by demonstrating the characteristic rapid increase followed by a slower decay. As to be expected, R² values dropped when using the average time constant, but nearly 90% of the variability was still explained. This general model is particularly useful because it allows experimenters to return to previously measured energetic cost data and estimate instantaneous energetic cost without the need for a subject specific model of cost dynamics. Another use for the identified dynamic model is real-time estimation of instantaneous cost. Kalman filters, and similar algorithms, leverage dynamic models of the system to help correct for noise and delays (11, 26). Real-time estimates of instantaneous energetics may prove useful for biofeedback, manipulating gait training based on energetic cost, or simply for online determination of when a research subject has reached steady state.

An ability to assess instantaneous energetic cost during non-steady gait could unveil new insights into walking. People rarely experience metabolic steady-state conditions; less than 1% of real-world walking bouts last the requisite five minutes (21). The fields of locomotor adaptation and learning aim to shift our scientific focus from the steady state to this real-world behaviour. Energetic concepts—such as economy, efficiency, and least effort—are often used to explain adaptations to novel environments or tasks. Yet, as researchers work to understand the neuronal circuitry involved in gait adaptation, and quantify the timescales over which adaptation occurs, they have been unable to effectively make direct comparisons to energetic cost during the adaptation itself. An understanding of
the role of energy use may help us understand how we adapt to changing environments, how we compensate for injury or motor control deficits, and how we learn new tasks. By presenting a methodology for assessing instantaneous energetic cost during adaptation and other non-steady gait conditions, we aim to provide our field with a tool with which we can investigate previously unanswerable questions.
GRANTS

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REFERENCES


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Figure 1: Experimental design. A. Experimental Set-up. To evoke known changes in instantaneous energetic cost, subjects’ walking speed (treadmill speed) and step frequency (metronome frequency) was enforced and the resulting breath-by-breath energetic cost response was measured using indirect calorimetry. B. We then modeled the relationship between instantaneous energetic cost (input) and measured energetic cost (output). Using this model we estimated instantaneous energetic cost from the
measured energetic cost response using two approaches. C. When using the inverse model approach, noisy output data was fit with a constrained polynomial, which was then passed through the inverse of our identified model to produce an estimate of instantaneous energetic cost. D. When using the forward model approach, we assumed the general shape of the input profile is known and described it by a set of parameters, which were then optimized so that the input profile, when run forward through our identified model, generated an output profile that best fit our measured output. Grey shaded boxes have been used to highlight what parameters were optimized for each processing technique.
Figure 2: A. We sought to enforce three differing but known input changes in instantaneous energetic cost. B. In order to identify what step frequency profiles would evoke these desired changes in instantaneous energetic cost, we identified each subject’s relationship between energetic cost and deviation from preferred step frequency. C. Using the solved relationship between energetic cost and step frequency, we designed step frequency profiles that would evoke our desired change in instantaneous energetic cost. The black line illustrates the step frequency commanded with a metronome and the grey line illustrates the subjects actual step frequency. All presented data is from Subject I.
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Figure 3. Modeling the measured energetic cost response. The average measured energetic cost response (black line) to 24 rapid changes in instantaneous energetic cost (grey line) is shown for each subject. The red line illustrates the model that best fits each subject’s response. Model time constants ($\tau$) and $R^2$ values for each fit are presented on the right hand side of each panel. Before we averaged the data, we normalized all instantaneous and measured energetic cost changes to unity by subtracting the initial steady-state values and dividing by the amplitude of the final steady-state values.
Figure 4: Estimating changes in instantaneous energetic cost. A. Subject I results. The enforced instantaneous energetic cost (input) and measured energetic cost response (output) are shown in black, in the left and right panels respectively for the step, ramp, and adaptation profiles. The red lines represent estimates from the inverse model approach, and the blue lines represent estimates from the forward model approach. $R^2$ values calculated between the enforced instantaneous energetic cost profiles and the inverse model approach estimates of muscle energy use are shown in red text, while that for the forward model approach estimates are shown in blue text. Data corresponding to the median trial and average trial (shaded box) have been plotted. B. Subject II results. Note that for the
Subject II, the step trials lasted only 540s as opposed to 720s due to a protocol change during data collection. Despite this change, the time given was sufficient to allow the subject to reach steady state, allowing us to process these trials in the same manner as all other trials.
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Table 1: $R^2$ values between the enforced and the model-produced estimates of instantaneous energetic cost for both the inverse model and forward model approach. We collected three repeats for each of the step, ramp, and adaptation input profiles. $R^2$ values from the three repeats have been ordered from highest to lowest. To produce the average value, we averaged the measured energetic cost data across the three repeats prior to applying the inverse model or forward model approach. Note that for each subject and each approach, we have plotted the data corresponding to the median and averaged trials in Figure 5.

<table>
<thead>
<tr>
<th>Input</th>
<th>Trial</th>
<th>Subject A</th>
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