Body-in-the-Loop – Optimizing Actual Human Walking

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1 Introduction

Decades of experimentation have shown that healthy humans walk in a way that balances the demands of stability, energy, and velocity. When walking in new settings, they are quick to adapt the parameters of their gait to once again minimize instability and energetic cost [1]. This process of gait adaptation is analogous to an *optimization* process. Humans appear to control their gait to optimize a cost function that includes energetics, arrival time, and stability. Much of this optimization occurs sub-consciously, as memory, instinct, and exploration identify an optimal gait. The question we ask is whether the same parameters that would result from a natural processes of optimization can be identified with an algorithmic process. That is, if we can measure locomotion performance and if we have control over the parameters, can we adapt the parameters to minimize the energetic cost? Can we bring the human body into a feedback loop governing a computational optimization? Whereas the body has a rich fusion of data from the nervous system, researchers are limited to what they can instrument and quantify in real-time. This makes evaluating the *cost-function* for different choices of parameters a daunting task. The most readily available measure of energetic cost comes from indirect calorimetry. These measures are notoriously noisy and time-delayed. As a consequence, subjects are typically asked to walk for 3 minutes at each parameter setting before another 2 minutes of data is averaged to obtain a single data point [2]. In this paper, we demonstrate an effective method for using the noisy, time-delayed signals inherent to physiological measures in a *body-in-the-loop* optimization process. This optimization process can be utilized to develop metabolically-optimal exoskeletons, powered prosthetics, and orthotics.

2 Methods

To evaluate our proposed method, we have chosen to optimize step frequency during treadmill walking. This makes an ideal test bed for our algorithm because, at a given walking speed, there is a clear metabolic minimum that coincides with a subjects self-selected step frequency [2]. Step frequency can be easily controlled by having subjects match their steps to a metronome beat. The preferred step frequency of the subject provides a useful reference for the results of our algorithm.

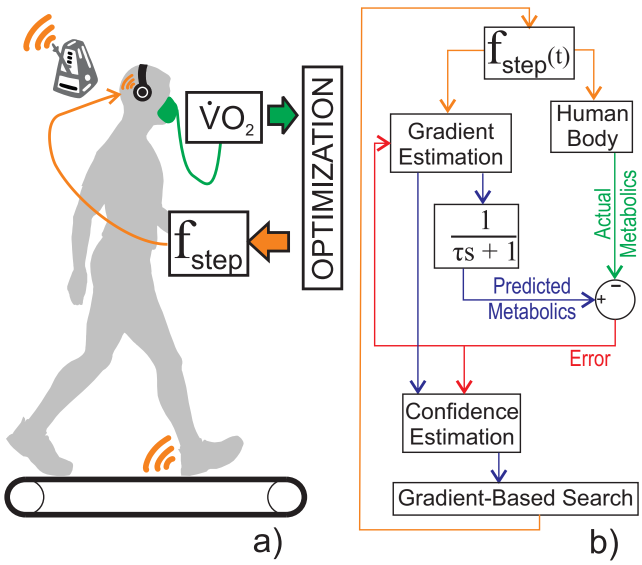

Figure 1: Using real-time measurements of energy consumption, we employ online optimization to identify optimal gait parameters (shown for step frequency in (a)). The used algorithm (shown in (b)) identifies the local gradient of the parameter space by minimizing the error between a predicted metabolic response and actual measurements. This information is used in a gradient-based optimization.

2.1 Algorithm

Optimization methods typically evaluate a function at adjacent points in the parameter space to estimate the gradient of the function and use this gradient to guide the parameter selection for subsequent iterations. Unfortunately, for metabolic energy consumption, such a direct evaluation of the cost function will take several minutes. To speed up the process, our algorithm thus uses the principles of dynamic estimation to establish gradients. This makes use of all the metabolic measurements, even those taken before steady-state is reached. The co-authors of this work have shown that the measured metabolic response of subjects undergoing dynamic changes in energy use can be approximated by a first-order system with a time constant in the order of 40 seconds [3]. By introducing a linear model that maps parameter values to metabolic effort, we can use this first order dynamic approximation to compute an expected response of the metabolic measurements to the known changes in parameters. This predicted response depends on the coefficients of the linear model, which is fitted to minimize the error between the computed dynamic response and the actual metabolic measures. Since the model is linear, the coefficients fully describe the gradient that relates parameter choices and the value of the cost function. Because of the slow metabolic dynamics and the low signal-to-noise ratios, gradient estimates obtained by this method are not always accurate. Yet, even being imprecise, the gradient can still provide useful information about the appropriate search-direction if it is of the correct sign (i.e., positive or negative). For this reason, the algorithm uses an F-test to compare the error from the gradient estimation to the error that would result from a gradient of zero. That is, the test quantifies the confidence that the current estimate of the gradient is non-zero. This confidence is then used to scale the step-size of a gradient descent method that iteratively identifies step frequencies of lower metabolic cost (Fig. 1b).

2.2 Experiment

We piloted our algorithm on one male test subject (height: 175 cm; weight: 76 kg; age: 26) that had prior experience walking to the beat of a metronome. The subject walked on a treadmill at a velocity of 1.25 m/s and step frequency was prescribed by a metronome (Fig. 1a). Metabolic power was measured in real-time using indirect calorimetry (VMax Encore Metabolic Cart, ViaSys, IL, USA) and actual step frequency was computed from the fore-aft centre of pressure of the instrumented treadmill (FIT, Bertec Corporation,MA, USA). The subject's actual step frequency and metabolic power were used as inputs to our algorithm and metronome tempo (prescribed step frequency) was our output.

Our test subject first walked on the treadmill at various prescribed step frequencies at, above, and below preferred (0, 5, 10, 15, 20 % deviation from preferred step frequency) while metabolic cost was measured. As expected, the preferred step frequency resulted in the lowest metabolic cost, and therefore provided us with a known optima to which we could compare our algorithms performance. Moreover, by evaluating the metabolic response to sudden changes in step frequency, we identified the subject's metabolic time constant (42s), which was used within our algorithm. Next, we conducted two body-in-the-loop optimization trials, beginning with a prescribed step frequency 36% above and 28% below the preferred step frequency.

3 Results

From both starting points, the algorithm converged to within 0.3 % of the subject's preferred step frequency. Our prior mapping of the relation between stride frequency and energetic cost confirmed that this preferred stride frequency corresponded to the optimal step frequency of the subject, and that the algorithm converged within one standard deviation of a natural variation. That is, our algorithm was as good in finding the minimum as the human body itself. The convergence occurred within 10 minutes of activating the optimization routine (Fig 2). In this time, only two data points of metabolic energy consumption can be obtained when using a traditional measurement protocol.

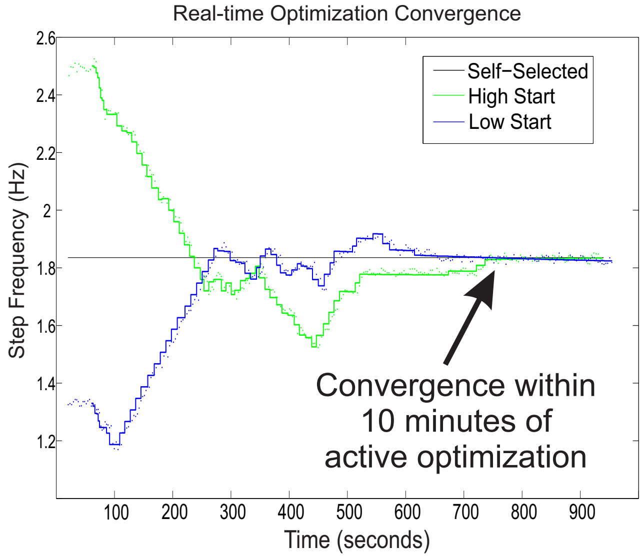

Figure 2: Our proposed algorithm was tested with the example parameter of stride frequency, which was prescribed via a metronome. The optimization process converges within 10 minutes to within 0.3 % of the subject's average preferred step frequency. Show are two trials that were initiated with the subject walking at step frequencies far from the the metabolic optimum.

4 Conclusions and Current Work

Using physiological feedback, the presented algorithm is able to identify the optimal stride frequency of actual human walking in less than 10 minutes of real-time optimization. Based on the highly encouraging results of this pilot study, we are currently conducting a larger set of experiments that we will present at Dynamic Walking. Furthermore, we are extending the proposed method to the parameter optimization of assistive devices, such as powered prosthetics and orthotics (e.g., [4]). Malcolm et al., for example, have recently quantified the relation of a timing parameter of a powered orthotic to the metabolic cost of transport of its user [5]. The relation shows a clear minimum and indicates that the correct subject-specific selection of control parameters can dramatically improve the performance of assistive devices. As part of our future work, we will automate this process to highlight one of the many possible applications of our method.

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