Confidence in the Curve

Instantaneous Cost Mapping with Ankle Exoskeletons

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Summary

Researchers and clinicians commonly try to identify parameter settings of assistive robotic devices that minimize the user's metabolic cost during use. It is standard practice to conduct a brute force parameter study to map the metabolic cost landscape in order to identify minimizing parameter configurations. However, due to the large amount of signal noise, sparse sample rate, and time delay inherent to metabolic measurements, a brute force mapping of metabolics requires long trials for each parameter setting in order to evaluate steady state values. This type of cost mapping can be a very time consuming and tedious process since many parameters must be considered to achieve an accurate mapping. We have been developing new methods for identifying optimal parameter settings in a much faster manner. By taking into consideration the underlying dynamics of the human metabolic system, the proposed methods do not have to rely on steady state metabolic measurements allowing for a rapid mapping of the landscape. In this work we show that the proposed methodology can identify optimal parameter settings of bilateral ankle exoskeletons with similar confidence to a brute force mapping in only a fraction of the time. Through this analysis, we have developed techniques to put confidence intervals on subject specific minimum locations.

Introduction

Many assistive robotic devices have complex controllers that must be tuned on a subject specific basis. Researchers and clinicians typically rely on metabolic cost as a measurement to asses device performance and conduct a brute force mapping of the parameter space to locate optimal parameter settings that minimize metabolic cost. This brute force mapping is called a *steady state cost mapping* or SSCM. A SSCM requires a significant amount of time for a number of reasons. First, metabolic measurements are extremely noisy (signal-to-noise ratio of approximately 4) and are sparsely sampled (sample rate of approximately 0.3 Hz). This means that 2-3 minutes of steady state data must be considered in order to evaluate metabolic cost at a single parameter setting. Additionally, there is an inherent time delay associated with metabolic measurements (time constant of approximately 40 seconds [4]) due to the way the human body consumes oxygen. This time delay means that it can take about 3 minutes for metabolic data to stabilize at steady state. Given the noise content, sparse sample rate, and time delay of metabolic measurements, it is common practice to take about 6-10 minutes to complete a single parameter evaluation.

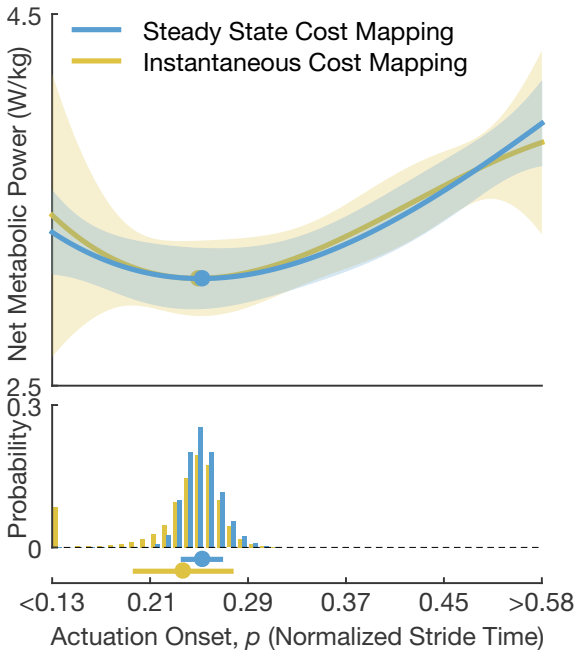

Figure 1: Analysis of a single representative subject. The top axis shows how the two polynomial fits compare given a 95% confidence interval. The bottom axis is a probability distribution of where the minimum location is assuming a Gaussian distribution of polynomials within the 95% confidence interval. Below this distribution is the mean ± s.d. of the distribution to illustrate the variability of minimum location for each protocol.

We have been working on new methods that would more quickly identify optimal parameter settings for these devices. These methods take into consideration the underlying model of the human

metabolic system which allows us to use non-steady state measurements of metabolic cost in our techniques. This is useful for real-time optimization of the metabolic cost landscape [2] or for sweeping across the parameter space in order to identify optimal parameter settings [1]. Here we focus on sweeping across a parameter space in a protocol known as an *instantaneous cost mapping* or ICM. We hypothesized that by using ICM techniques with bilateral ankle exoskeletons we could accurately identify the optimal parameter setting for actuation onset on a subject specific basis in a fraction of the time required for a SSCM. The work presented here is the first in-depth study applying ICM techniques to an assistive robotic device and the first to analyze confidence intervals of minimum locations on a subject specific basis.

Methods

We tested 8 healthy subjects with pneumatically actuated bilateral ankle exoskeletons using SSCM and ICM protocols to map their metabolic cost landscape. This landscape was estimated using a 3^{rd} order polynomial. The exoskeleton's controller was a simple on/off control scheme where actuation was turned on when subject's normalized stride time surpassed the threshold parameter p [3]. Actuation was turned off when toe off was detected. Subjects completed a training session identical to the actual data collection on a day prior to testing to allow for adaptation. During data collection, subjects completed both ICM and SSCM protocols in a pseudo-randomized order.

For the SSCM analysis, we mapped the metabolic cost landscape using 7 different parameter settings in a randomized order. We collected 6 minutes of data at each parameter setting and used the final 3 minutes of steady state data during analysis. For the ICM analysis, subjects started at one of the two extremes of the parameter space and then we ramped the parameter p across the space to the other extreme over 8 minutes. We then ramped the parameter p back for 8 minutes. The starting parameter was randomized.

We compared ICM and SSCM analyses on a subject specific basis by computing the 95% confidence interval of each estimated landscape. We assumed a Gaussian distribution within this interval to compute a probability distribution of minimum locations. Through this analysis we established confidence bounds on subject specific optimal parameter locations (Figure 1). We compared the minimums predicted by both protocols using a paired t-test ($\alpha = 0.05$).

Results & Discussion

21 minutes of data were used for the SSCM analysis while it took 54 minutes to collect. 16 minutes of data were used for the ICM analysis while it took only 20 minutes to collect. The ICM protocol identified a minimizing parameter 0.018 ± 0.103 normalized gait cycle (mean $\pm$ s.d.) away from the minimizing parameter identified using the SSCM protocol. There were no significant differences in predicted mimima between the two protocols ($p = 0.64$). Taking the landscape created with the SSCM as the ground truth, the optimal p identified by the ICM protocol would result in a average increase in metabolic cost of only 0.04 W kg^{-1} (1.3%) compared to that identified by the SSCM. These results show that an ICM protocol can accurately identify a parameter setting that minimizes metabolic effort in a fraction of the time that an SSCM protocol requires.

The confidence intervals and probability distributions of minimum locations present a new way of comparing mapping techniques on a subject specific basis. Although we show that the ICM protocol was able to identify minimizing parameter locations with similar accuracy to the SSCM protocol, our analysis shows that the standard deviation of minimum location when using the ICM protocol was on average 31.2% larger than that of the SSCM protocol. This is illustrated for a single representative subject in Figure 1 by the mean $\pm$ s.d. bars located at the bottom of the figure. We attribute this to the fact that less data were used for analysis in the ICM versus the SSCM. Simulations of the two protocols show that this confidence range should be about the same when considering the same amount of data.

References

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