Predicting Metabolic Cost Using Cumulative Muscle Activation Per unit Distance

A Thesis

by

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CHAPTER 1. INTRODUCTION

The first exoskeletons began development in the 1890s, but it's only been within the last two decades that potentially viable designs have emerged. Many studies have been conducted in order to optimize the functions of these exoskeletons in a way that generates the greatest metabolic benefit to the user. However, this research is hampered by the traditional methodology of measuring metabolic cost, indirect calorimetry. This study looks into an alternative method, based not on the overall gas exchange of the body, but rather the Cumulative Muscle Activation Per unit Distance(CMAPD).

1.1 Indirect Calorimetry

In order to calculate the metabolic cost of work being done by an individual, indirect calorimetry looks at the change in gas content between the air the user inhales, and the mixture after they exhale. This is because of the important role oxygen plays in producing cellular energy via the mitochondria. For this reason, when aerobic metabolism is occuring there will be a higher percentage of CO_2 in the exhaled air. The magnitude of this increase provides a key insight into the level of metabolic work being done in the body. As you can see in **Figure 1**, indirect calorimetry systems require tethering the participant and funneling the exhaled gasses into a system for processing. These constraints greatly limit the mobility of the participant during a trial, and largely requires them to remain in a single spot. However, the primary limitation of indirect calorimetry is the time it takes to represent changes in metabolic activity. This is due to fundamental properties of how gas composition reaches steady state slowly as a result of changes in metabolic activity. In a young healthy population it takes at least 5 min to reach steady state metabolic cost. Additionally, while indirect calorimetry is seen as the "gold standard" for measuring metabolic cost, it can only detect changes in aerobic respiration, despite the body having several pathways of anaerobic energy generation. While anaerobic processes do make up a much smaller amount of the energy being generated, depending on the specific case being studied, this distinction may be important.

The primary benefit of indirect calorimetry is the accurate and consistent comparisons it produces between activities with different levels of metabolic cost. By normalising CO_2 to the participants baseline standing condition and dividing by the speed of travel, the cost of transport(COT) for each condition can be determined. Furthermore, by dividing by each participants weight (lbs), the mass balaced COT can be found, which allows for metabolic data to be compared across the group.

Figure 1 - The PARVO system with required facemask (Left) and the associated cart (Right) responsible for processing the exhaled gasses

1.2 Cumulative Muscle Activation Per unit Distance

An action potential is the electrical discharge neurons use in order to pass information around the body. However, due to the role neurons play in exciting muscle cells, the sum of these action potentials are also able to be detected whenever a muscle is contracted. For this reason, with electromyography (EMG) it is possible to not only detect muscle contractions, but also quantify their intensity by comparing the measured voltage between multiple samples. Furthermore, by sampling a wide variety of the muscles used during a given activity and looking at changes in these values across different scenarios, it is possible to quantify changes in the degree of work being done in each condition. While this does not provide a measurement of metabolic cost compared to indirect calorimetry, there are several studies such as Blake & Wakeling (2013) which have found these two measurements to be highly correlated and suggest it could be used as a proxy.

As opposed to indirect calorimetry systems, EMG sensors are much smaller and completely mobile, as you can see in **Figure 2**. This allows for the sensors to be easily placed on the participants body at desired locations to pick up the activity of certain muscle groups. From here they’re completely free to undergo a wide variety of activities as long as they remain within a certain area.

Figure 2 - Delsys Trigno wireless EMG sensor

The size and freedom of EMG sensors opens up a wide range of options which are not possible due to the static nature of indirect calorimetry systems, but this is not the only advantage. Additionally, EMG measurements accurately reflect the intensity of each muscle contraction in real time. This means that instead of spending five or more minutes waiting for changes in gas values, the measurement reaches steady state in less than a minute, significantly cutting down on the length of data collections. Furthermore, it was mentioned as a limitation of indirect calorimetry that it can only detect changes in aerobic respiration, however since EMG values only look at the use of that energy and not the origin, they can actually represent a greater range of metabolic sources.

CHAPTER 2. METHODOLOGY

2.1 Data Collection

Three older adults(age = 69.33 ± 0.94 yr, mass = 56.15 ± 4.083 kg, height = 161.6 ± 4.26m) participated in this study. Data collection took place over multiple days per participant, with one day to get habituated to the exoskeleton, one day to record EMG, and one day to record motion capture. Several different data types were collected in the study including indirect calorimetry (Metabolics), electromyography (EMG), ultrasound, force measurements, and motion capture data (MOCAP). However, metabolics & EMG are the primary modalities collected for this data analysis.

2.2 Data Processing

Walking data was collected on participants both without the exoskeleton as well as with exoskeleton support at varying spring stiffness levels. In order to analyze the data collected, each step had to be distinguished. This is done using the data from force sensors embedded in the floor of the treadmill. By distinguishing each stride and then averaging across the trial, the typical activity of each muscle can be found. This is important due to the variability in EMG activity, after this step the activation levels become fairly consistent as seen in **Figure 3**. From here the data is integrated so that a single value for each muscle and condition can be reached. These values are then divided by the movement speed and normalized to the no exo condition. Once this step has been reached the different muscle values can be summed in order to reach the Cumulative Muscle Activation Per unit Distance (CMAPD).

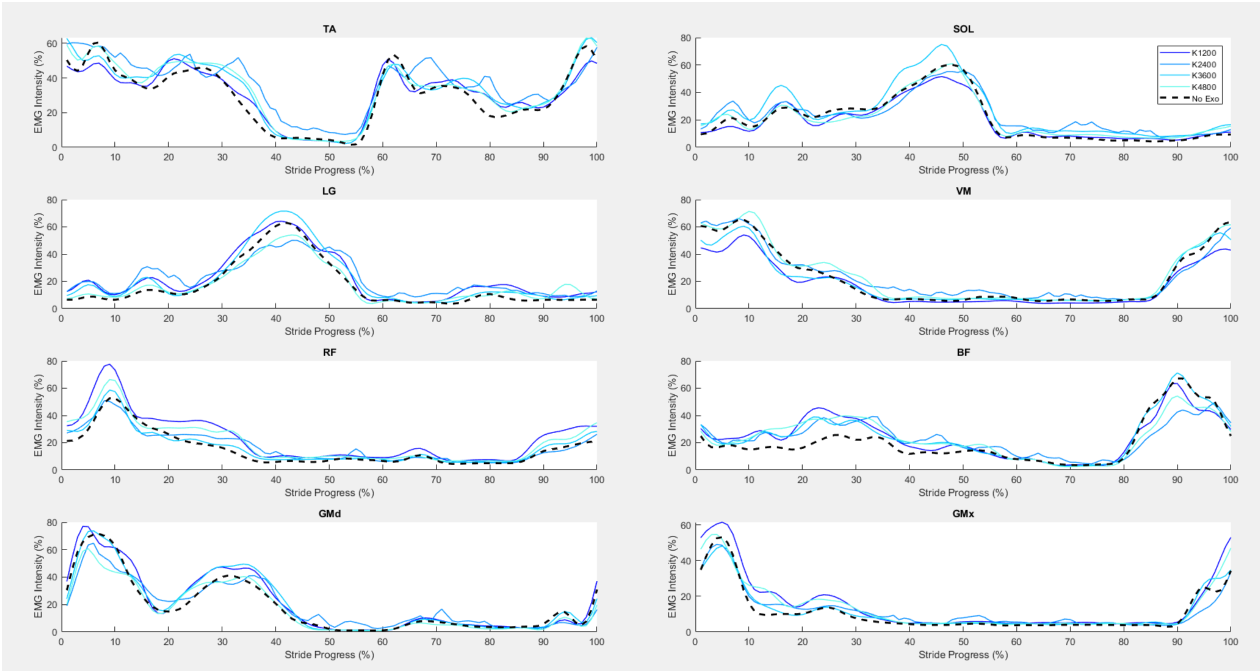

Figure 3. Average muscle activation of a stride across eight of the primary leg muscle groups.

To find the metabolic cost of transport for each condition, indirect calorimetry data was collected during every trial using the COSMED metabolic system. By first calculating the metabolic power using Brockways' equation(Brockway 1987), dividing by the movement speed(1.225 m/s) and then normalizing the values to each participant's resting baseline (found during the 2nd data collection session) the cost of transport can be reached (seen in **Figure 4**).

CHAPTER 3. RESULTS

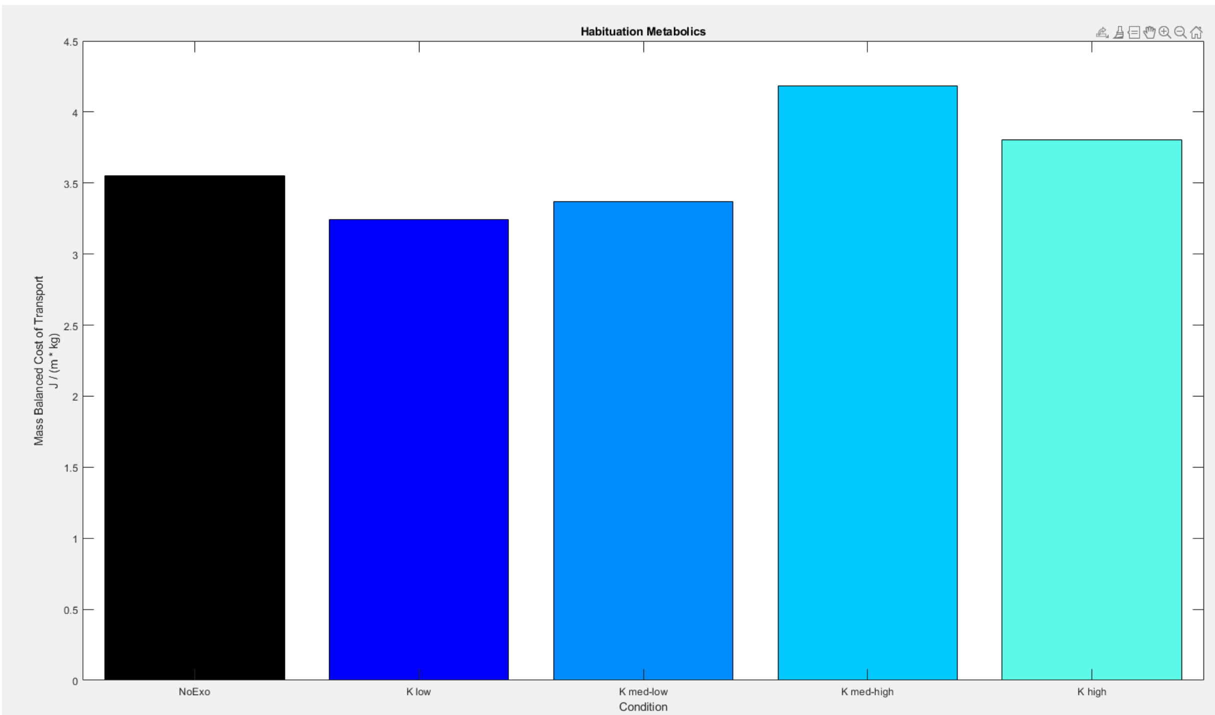

Figure 4. Metabolic cost of transport for unassisted walking as well as with increasing levels of exo spring assistance.

3.1 Statistical Analysis

Following data processing, the metabolic cost of transport from the indirect calorimetry data as well as the cumulative muscle activation per unit distance from the EMG sensors has been calculated. In order to evaluate the relationship between these two measurements, we chose to use regression analysis. However, when this test was done, no statistically significant correlation was able to be found. Originally blaming the test methodology, we looked at a number of alternative calculations. The first of which was the difference between using the integral of the stride data versus the peak in order to calculate CMAPD. As shown in **Figure 5** depending on the method used we do see fairly sizable differences in both individual values and overall trends, but we were still unable to find any significant correlation.

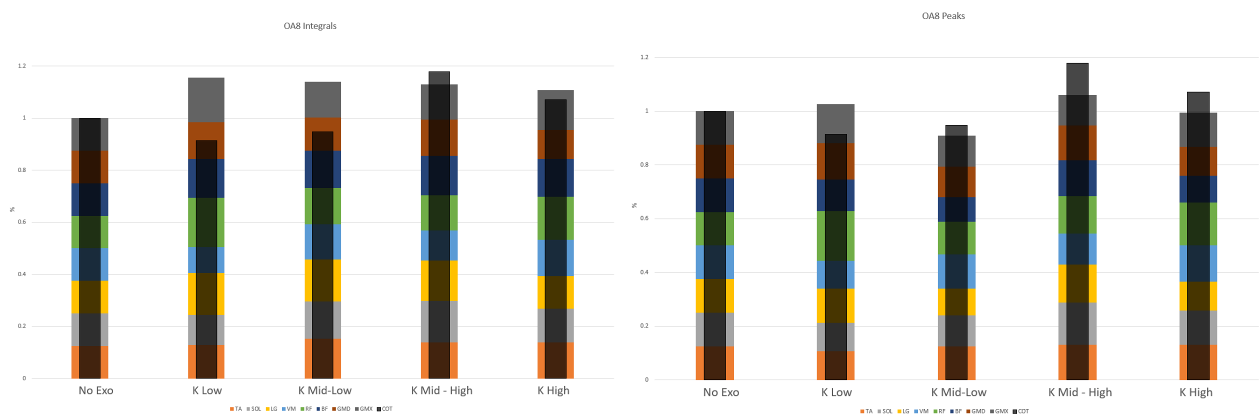

Figure 5. Individual participant data for the integral method (left) vs peak method (right). CMAPD - multicolored stacked bars each related to one of the measured muscle groups. COT - semi translucent black bar

Next we considered the weight each individual muscle should have. Originally each muscle had an equal contribution to the total CMAPD value, but this does not accurately represent the biological system as each muscle varies greatly. In order to include this aspect into our data analysis, we assigned a weight to each muscle group according to the physiological cross sectional area (PCSA) found in Fukunaga et al. (1992). The PCSA is "proportional to the maximum strength of the muscle" and is valuable for comparing the properties of each muscle (An et al. 1991). As seen in **Figure 6**, including the weight of each muscle group does lead to changes in CMAPD values & trends, but still there was no statistically significant correlation between CMAPD & COT.

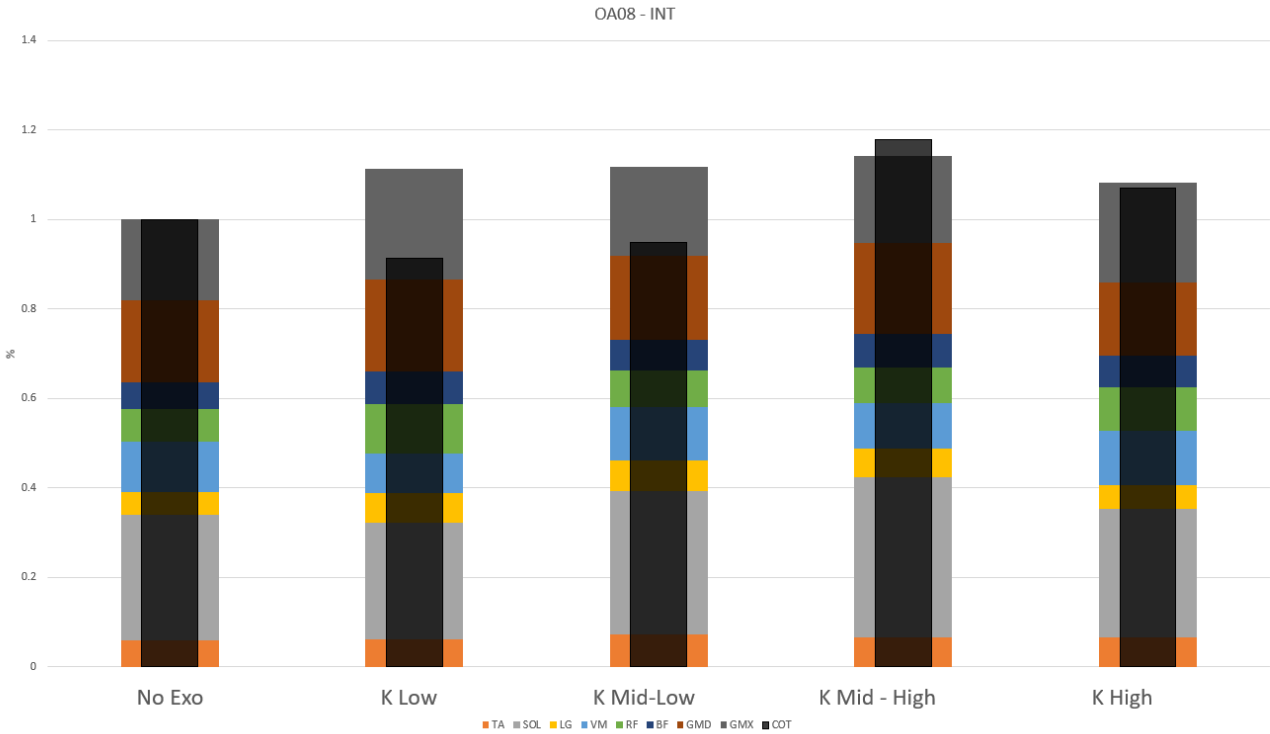

Figure 6. PCSA adjusted CMAPD vs COT, Integral Method

Running out of alternatives, the final calculation we analyzed was the CMAPD of the soleus muscleand how that related to the cost of transport because the exoskeleton primarily influences the soleus muscle. This method had the lowest P value out of any of the sets listed previously with P = .0685 for the soleus muscle (seen in **Figure 7**). Though this value still is not significant it does help point out a potential explanation for the results we've found.

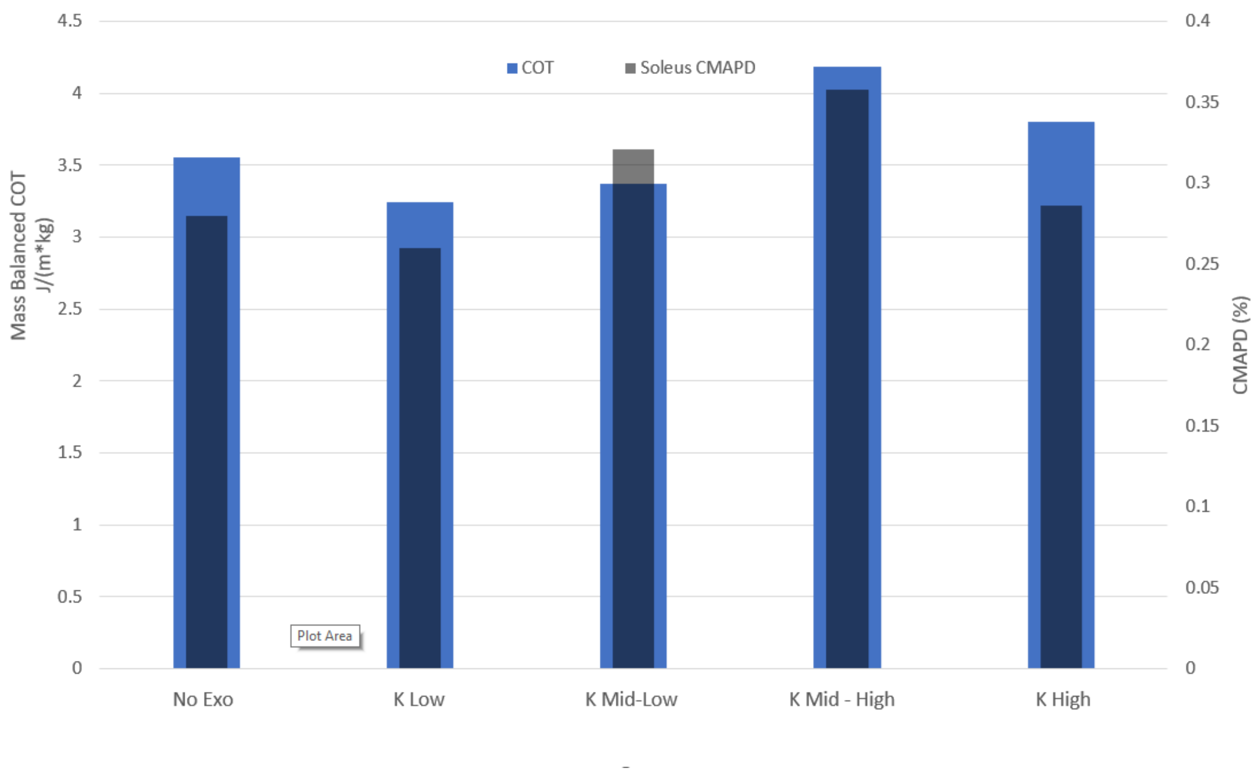

Figure 7. Soleus CMAPD vs Mass Balanced COT,

3.2 Discussion

While being unable to find any statistically significant correlations does greatly limit any conclusions this study can make, there's still much that can be learned from it. The first limitation is the small sample size. Due to issues with equipment, data from only 3 participants were used. Second, this data was only collected in older adults. Due to muscle changes with age, this could explain why we aren't seeing correlations like those in literature.

Since our study sought to find a relationship between CMAPD and COT as had been seen in a number of other papers, the particular failure of this situation actually tells us a lot about the benefits and limitations of CMAPD. In other studies, where a correlation was found the activity was consistent across the different conditions only with variations in intensity. In our study we had expected to mirror this trend, but what we failed to consider was the fundamental ways that the different exo conditions affected muscle activity. As the exo interacted with the participant some muscles would be assisted and not have to work as hard, but others may compensate or resist and actually have to do more work compared to the unassisted walking. This means that depending on which muscles we were measuring, our CMAPD values may not have been representative of the activity being conducted. This is further supported by the results we saw when looking at individual muscles. Some closely follow the trends seen in the cost of transport values, but others differ greatly. This is why our overall values weren't significant. Without adequately including all muscles being affected, and appropriately valuing their contributions, there's no way the summative value could be accurate. Before going into the takeaways of this paper, its important to note the small sample size of this experiment and make clear that future studies following the same methodology, but with more participants could reach very different conclusions.

3.3 Conclusion

With the data available to us, we've actually shown the necessity of indirect calorimetry over alternative estimations based on electromyography. While EMG may be a proxyt in some activities, this study should warrant that sufficient validation be taken before any conclusions about equivalence can be reached.

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