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Experimental Characterization of Multi-objective Optimization in Human Walking

Jean Starr
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Reviewed and approved* by the following:

Joseph P. Cusumano
Professor of Engineering Science and Mechanics
Thesis Supervisor

Gary L. Gray
Associate Professor of Engineering Science and Mechanics
Honors Advisor

Vincent F. Meunier
P.B. Breneman Chair and Professor
of Engineering Science and Mechanics
Department Head

* Signatures are on file in the Schreyer Honors College

ABSTRACT

Humans walk every single day, yet few understand how human locomotion is achieved. Walking can be broken down into two main objectives: to avoid falls and to change positions while following some path. This means that walking is multi-objective, that is, there can be a range of walking parameters that contribute in harmony to the overall task. These parameters can be analyzed using cost functions which contribute to the study of multi-objective walking. The cost functions show that walking parameters receive a specific weight distribution to maintain locomotion. We hypothesize that maintaining step width, and therefore balance, is more important in locomotion than maintaining lateral body position. Furthermore, we hypothesize that the weight of each cost changes when faced with different walking conditions. This paper explores the importance of step width and lateral body position in human locomotion to determine the cost weights given to these walking parameters and their changing magnitudes to counteract perturbations. Linear regression and significance testing will be used to extract and analyze cost weights in optimal regulation models.

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Chapter 1

Introduction

Most people know how to walk, but few understand how walking is achieved. Walking is achieved through motor regulation. Motor regulation is an important topic of study that aims to understand how people achieve desired movements. The big picture for walking is to avoid falls and achieve a goal. This goal can range from something as simple as walking down a sidewalk to something more complicated like maneuvering through a crowded room.

Walking involves complex biomechanics. The neuromuscular system helps manage forces and maintain balance during locomotion. Two important parameters that heavily affect balance are the position of the body's center of mass (CoM) and step width. To avoid falls, the body's CoM must be controlled so that it stays within the bounds defined by each foot placement. This illustrates the multi-objective nature of human walking; in general, multiple parameters are relevant to achieving different goals while walking, but trade-offs must be made to optimize locomotion. It is important to understand not only how humans maintain balance during a step, but also how locomotion is maintained from one step to the next while accomplishing other task goals. Furthermore, it is important to consider how locomotion is achieved when faced with external disturbances, i.e., physical obstacles or uneven terrain.

Walking is a skill that humans learn at an early age. This learning process is so common that people tend to overlook the details involved. When looking deeper, the neural processes and biomechanics behind human walking are rather complex. Walking involves the transfer of body weight achieved through the neuromuscular system, which manages any external forces to remain balanced while the body is displaced. This process can be broken down into four stages: maintain upright posture, control leg trajectory to ensure gentle ground contact, produce mechanical energy for speed control, and absorb forces to maintain balance [10]. All four of these stages are achieved during every step taken while walking.

A major requirement of the walking process is maintaining balance from step to step. To remain balanced, the body's CoM should not exceed the position of either stance foot in any direction [17]. Research has shown that the CoM position and step width are key factors to remain balanced while walking [1,12,17]. What remains unclear is how the body reacts to different environmental conditions, such as uneven terrain or physical obstacles, to achieve the same goal. This thesis presents a method for analyzing walking data that allows researchers to reverse engineer the control system used to achieve steady walking.

Motor regulation is the collaboration of the body's systems, like muscles and neural circuitry, to achieve a desired movement [2]. The neural processes underlying motor regulation can be thought of as the body's software and are a key to human walking. The study of motor regulation has been used to improve the quality of life in a variety of areas, such as sports, medicine, and standard day-to-day activities [3]. In response to changing surroundings, the body can change speed, direction, or elevation to keep moving [4]. The efficiency with which the body can handle these changes is extraordinary, yet we complete these movements effortlessly. Motor regulation is accompanied by abundant variability. That is, the body will never complete a task in the exact same way twice. This variability is due to physiological noise present in the nervous system, which arises from the body's abundant lines of communication working to achieve multiple tasks simultaneously [1,5].

It is important to realize that, as with the walking task itself, motor regulation is multi-objective [1,17]. The body can focus on more than one goal at a time, and these goals can provide competing "costs" that need to be minimized. While walking, the body works to hold the CoM between the stance feet while, at the same time, trying to maintain position relative to a given path [17]. Thus, maintaining and balancing the lateral CoM position and step width allows the body to remain stable and achieve the walking goal of staying on a path.

Lateral movements are particularly important because failing to manage them can lead to falls. Specifically, maintaining proper step width while walking is critical for fall avoidance [7, 11, 12]. At the same time, lateral accelerations of the CoM must act in the opposite direction of any external disturbances. The body achieves this by strategically placing the foot at the next step. However, there are an infinite number of options for such a foot placement. Such kinematic redundancy is referred to as equifinality: i.e., there are infinitely many ways to achieve the same task goal [6,18].

Human gait changes depending on the terrain. When the walking path is smooth and external forces are not a factor, identical steps would be followed by identical results. Therefore, the interaction between the body and the contact surface becomes predictable [16]. However, perfectly smooth walking terrain is not realistic. On uneven surfaces, the reaction forces between the foot and the surface vary in magnitude and direction from step to step, directly impacting dynamic balance [16]. In such conditions, identical steps are not followed by identical results. Remaining balanced in these conditions becomes heavily dependent on the relationship between CoM and step width [17].

Studies have shown that the CoM position during a step, while one leg is swinging forward, predicts the placement of the following step [9, 13]. However, it is important to consider how the body adjusts from one step to the next. Humans use visual input to help determine the next step [4, 8, 14, 19]. When vision is hindered, humans adapt to more cautious walking, for example, by using slower speeds and shorter stride lengths, to counter any lack of confidence or efficiency even on smooth terrain [14, 15]. On smooth terrain, visual input is not completely necessary for foot placement. Visual input becomes drastically more important when the walking path is not smooth. On uneven terrain, including obstacles, humans must find a balance between their gait cycle and the desirable locations for foot placement to remain on balance and maintain locomotion [20]. When humans perceive obstacles in upcoming terrain, changes to walking parameters can be seen as soon as three to four steps before reaching the obstacle. Humans are also capable of quickly changing the trajectory of their feet when an obstacle is moved to another position than it was initially perceived to be in [19]. Visual input is crucial while walking, but it remains unclear exactly how human gait changes in different environmental conditions to remain on balance and maintain locomotion.

In this thesis, I will present a method for analyzing data obtained from human walking on a treadmill under three different walking conditions: no perturbations (NOP), platform perturbations (PLA), and visual perturbations (VIS). This analysis, carried out using linear regression on an optimal regulation stepping model, provides an objective means for extracting weights associated with different costs hypothesized to play a role in maintaining balance during locomotion. This analysis will allow us to not only determine which costs are given more emphasis or weight but also allow us to observe how humans adapt to counter perturbations.

The next chapter discusses the basic theory behind the calculations used for my research. This includes an explanation of how the data was collected, the derivation of a multi-objective optimal stepping model, and a discussion of how regression can be applied to estimate a mixture parameter quantifying the relative weights of the step width and position costs. Chapter three discusses the results showing the value of the mixture parameter and how it varies with different walking conditions. Chapter four is the conclusion of this thesis which includes a summary of the results, ethical issues present in this work, and future applications for the results.

Chapter 2

Experimental Methods

Data Collection

Ethics Statement

Prior to participating, all participants signed informed consent statements approved by the Institutional Review Board at The Pennsylvania State University, and both Brooke Army Medical Center and The University of Texas at Austin [21, 22].

Participants

The data analyzed here were collected as part of a previous experiment involving thirteen able-bodied (AB) adults and eight trans-tibial amputees (TT) [21, 22]. All participants were screened by a physical therapist for orthopedic or neurological impairments that would impact their gait. Participant characteristics can be found in Table 1 of [21].

Experimental System and Procedure

The experimental procedure can be found in the study from which the stepping data originates [21]. To summarize the procedure, participants walked on a 2 x 3m treadmill in a Computer Aided Rehabilitation Environment (CAREN) (Motek, Amsterdam, Netherlands). Each participant walked on a treadmill at a fixed speed scaled to their leg length under three walking conditions: no perturbations (NOP), platform perturbations

(PLA), and visual perturbations (VIS). For the VIS condition, the treadmill was surrounded by a 7m diameter dome to create a virtual environment.

Linear Regression Derivations

The human gait data we are analyzing is a time series of the left (z_L) and right (z_R) foot positions. From these, the width (w) and lateral body position (z_B) can be derived. These parameters are the basis for our analysis of lateral stepping data and are illustrated in figure 1-1. They are utilized in the form of task-level observables to begin estimating multi-objective cost weights. The cost weights provide a measure of how much focus each parameter receives. Reiterating the multi-objective nature of human walking, different parameters are given a different amount of focus, or weight, to remain on balance and achieve a desired goal.

The analysis starts with a set of observables that define the position of the left and right foot in terms of the lateral body position and step width. These observables are expressed in terms of the next step (k+1), but they are applicable at any step.

$$z_R(\mathrm{k}+1) = z_B(\mathrm{k}+1) + \frac{1}{2}\, w(\mathrm{k}+1) \tag{1a}$$

$$z_L(\mathrm{k}+1) = z_B(\mathrm{k}+1) - \frac{1}{2} w(\mathrm{k}+1) \tag{1b}$$

Eqs. (1) show that the position of the left and right foot can be determined by the lateral body position and step width and vice versa. These observables will be utilized in later calculations.

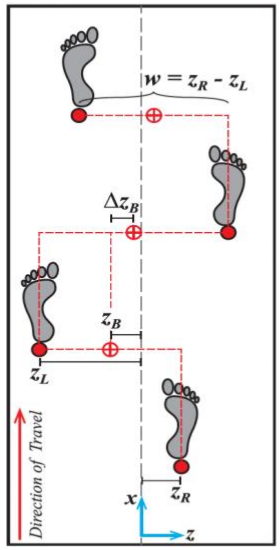

Figure 1-1. Illustration of the step width (w), lateral body position (z_B), left foot position (z_L), and right foot position (z_R) as viewed from above. Change in lateral body position (Δz_B) does not apply to my analysis [1].

Multiple linear regression is used to determine relationships between parameters in human gait. However, this can be implemented in two ways: either using an *a posteriori* mixture approach, in which each cost is computed separately and combined after the fact, or using an *a priori* cost approach, which makes use of a multi-objective cost function. To start, we use an *a posteriori* mixture to determine cost updates for the left and right steps. We start with quadratic costs for the step width and step position. The variables w^* and $z_B{}^*$ represent target values obtained from previous experiments to be approximately equal to the sample means.

$$C_w = (w(\mathrm{k}+1) - w^*)^2 \tag{2a}$$

$$C_{zB} = (z_B(\mathrm{k}+1) - z_B{}^*)^2 \tag{2b}$$

The task variables w and z_B are regulated by the following update equations.

$$w(\mathrm{k}+1) = w(\mathrm{k}) + \Delta w + \sigma_w \eta_w(\mathrm{k}) \tag{3a}$$

$$z_B(\mathrm{k}+1) = z_B(\mathrm{k}) + \Delta z_B + \sigma_{zB} \eta_{zB}(\mathrm{k}) \tag{3b}$$

The quantities Δw and Δz_B are optimal regulators to be determined and η_w and η_{zB} are independent Gaussian random variables with zero mean and unit variance of :

$$\mathbb{E}[\eta_w \eta_{zB}] = 0;\ \mathbb{E}[\eta_w] = \mathbb{E}[\eta_{zB}] = 0;\ \mathbb{E}[{\eta_w}^2] = \mathbb{E}\ [{\eta_{zB}}^2] = 1. \tag{4}$$

The last product in Eqs. (3) represent the noise of the regulators. By substituting Eqs. (3) into Eqs. (2) and taking the expected value, the following optimal regulators are found.

$$\Delta w = -\left(w(\mathrm{k}) - w^*\right) \tag{5a}$$

$$\Delta z_B = -\left(z_B(\mathrm{k}) - z_B{}^*\right) \tag{5b}$$

Notice that the expression within the parenthesis is the difference between the current value and the target value, i.e., the deviation from the target value. The optimal regulator is found by negating this deviation. If Eqs. (5) are plugged into Eqs. (3), we find that $w(\mathrm{k+1})$ and $z_B(\mathrm{k+1})$ are equal to the target value plus noise. This means that the value of each observable at each step is equal to the target value, *on average*.

For this *a posteriori* approach, the above costs for C_W and C_{ZB} are treated as independent functions. However, in human locomotion it is evident that both costs need to be considered simultaneously; whereas each cost independently predicts a different “best” foot placement, there can only be one new foot position for each step. To determine the respective weights assigned to step width and lateral body position, we start by considering a right step during which the position of the left foot does not change, that is $z_L(\mathrm{k+1}) = z_L(\mathrm{k})$. Recall that the regulators for $w(\mathrm{k+1})$ and $z_B(\mathrm{k+1})$ are equal to the target value plus noise. To consider both costs, we apply the regulators one at a time into the update Eq. (1a) for a right step. This is done by first plugging in the regulator for

w(k+1) into the update equation for z_R(k+1). We then repeat this calculation by plugging in the regulator for z_B (k+1), instead of w(k+1), to obtain the following.

$$z_R(\mathrm{k+1}) = z_L(\mathrm{k}) + w^* + \sigma_w \eta_w(\mathrm{k}) \tag{6a}$$

$$z_R(\mathrm{k+1}) = -z_L(\mathrm{k}) + 2z_B^* + \sigma_{zB}\, \eta_{zB}(\mathrm{k}) \tag{6b}$$

This now yields two update equations for z_R(k+1) in terms of w and z_B respectively. To combine them, we apply a mixture parameter ρ, where $0 \leq \rho \leq 1$, representing the weights associated with each cost for a right step, as follows:

$$z_R(\mathrm{k+1}) = \rho\,[z_L(\mathrm{k}) + w^* + \sigma_w \eta_w(\mathrm{k})] + (1-\rho)\,[-z_L(\mathrm{k}) + 2z_B^* + 2\sigma_{zB}\, \eta_{zB}(\mathrm{k})] \tag{7}$$

When $\rho = 1$, there is 100% regulation of w. When $\rho = 0$, there is 100% regulation of z_B. The above procedure can be repeated for Eq. (1b) to determine the mixture model for z_L(k+1) where z_R(k+1) = z_R(k).

Instead of considering C_W and C_{ZB} separately, a multi-objective cost can be defined as *a priori* as:

$$C = \alpha C_W + \beta C_{ZB} \tag{8}$$

C_W and C_{ZB} are defined in Eqs. (2). The parameters α and β represent positive weights for the w and z_B costs respectively. Eqs. (1) can be inverted to obtain expressions for w(k+1) and z_B(k+1). These expressions can then be substituted into Eqs. (2) to obtain the multi-objective cost in terms of the left and right step positions.

$$C = \alpha\,(z_R(\mathrm{k+1}) - z_L(\mathrm{k+1}) - w^*)^2 + \beta\,(\tfrac{1}{2}\,[z_R(\mathrm{k+1}) + z_L(\mathrm{k+1})] - z^*)^2 \tag{9}$$

Utilizing this method for the cost function, the update equations for the right and left step respectively are shown below, where $\Delta\, z_R$ and $\Delta\, z_L$ are the optimal regulator inputs that we desire. The variables η_R and η_L are once again assumed to be independent Gaussian random variables with mean of zero and unit variance of:

$$\mathbb{E}[\eta_R \eta_L] = 0;\ \mathbb{E}[\eta_R] = \mathbb{E}[\eta_L] = 0;\ \mathbb{E}[\eta_R{}^2] = \mathbb{E}\ [\eta_L{}^2] = 1. \tag{10}$$

$$z_R\,(\mathrm{k{+}1}) = z_R(\mathrm{k}) + \Delta z_R + \sigma_R\,\eta_R\,(\mathrm{k}) \tag{11a}$$

$$z_L(\mathrm{k{+}1}) = z_L(\mathrm{k}) \tag{11b}$$

$$z_L\,(\mathrm{k{+}1}) = z_L\,(\mathrm{k}) + \Delta z_L + \sigma_L\,\eta_L(\mathrm{k}) \tag{12a}$$

$$z_R\,(\mathrm{k{+}1}) = z_R\,(\mathrm{k})\ (12\mathrm{b}) \tag{12b}$$

Eqs. (11, 12) can now be plugged into Eq. (9) giving the multi-objective cost in terms of both foot positions and the optimal regulators. Taking the expected value yields optimal regulators for $\Delta\, z_R$ and $\Delta\, z_L$. Substituting the resulting regulators into Eqs. (11, 12) yields the desired stepping updates for z_R (k+1) and z_L (k+1).

$$z_R\,(\mathrm{k{+}1}) = \frac{4\alpha-\beta}{4\alpha+\beta}\,z_L\,(\mathrm{k}) + \frac{2(\beta z_{B*} + 2\alpha w*)}{4\alpha+\beta} + \sigma_R\,\eta_R(\mathrm{k}) \tag{13a}$$

$$z_L\,(\mathrm{k{+}1}) = z_L\,(\mathrm{k}) \tag{13b}$$

$$z_L\,(\mathrm{k{+}1}) = \frac{4\alpha-\beta}{4\alpha+\beta}\,z_R(\mathrm{k}) + \frac{2(\beta z_{B*} - 2\alpha w*)}{4\alpha+\beta} + \sigma_L\,\eta_L\,(\mathrm{k}) \tag{14a}$$

$$z_R\,(\mathrm{k{+}1}) = z_R(\mathrm{k}) \tag{14b}$$

Looking at Eq. (13a), the coefficient of z_L(k) and the second term are both constants. The final term is noise and the same goes for Eq. (14a). That is, the update equations have the final form:

$$z_R\,(\mathrm{k{+}1}) = Az_L\,(\mathrm{k}) + B + \mathrm{noise} \tag{15a}$$

$$z_L\,(\mathrm{k{+}1}) = Az_R\,(\mathrm{k}) + B + \mathrm{noise} \tag{15b}$$

Thus, for the left and right step, we can estimate the constants *A* and *B*. These values can be obtained accurately through a multiple linear regression analysis. However, we can improve the calculation further before starting regression. We begin by setting Eq. (7) equal to Eq. (13a) because they are both equal to $z_R(\mathrm{k}+1)$.

$$(2\rho - 1)\, z_L(\mathrm{k}) + 2(1-\rho) z_B{}^{*} + \rho w^{*} + 2(1-\rho)\, \sigma_{zB}\, \eta_{zB}(\mathrm{k}) + \rho\sigma_w\, \eta_w(\mathrm{k})$$

$$= \frac{4\alpha - \beta}{4\alpha + \beta}\, z_L(\mathrm{k}) + \frac{2(\beta z_{B^*} + 2\alpha w_*)}{4\alpha + \beta} + \sigma_R\, \eta_R(\mathrm{k}) \qquad (16)$$

By equating the coefficients for $z_L(\mathrm{k})$, we obtain an expression for ρ in terms of α and β. Because ρ is a function of α and β, we are only concerned with determining the values of ρ for this research.

$$\rho = \frac{4\alpha}{4\alpha + \beta} \qquad (17a)$$

Further equating coefficients gives:

$$2(1-\rho) z_B{}^{*} + \rho w^{*} = \frac{2(\beta z_{B^*} + 2\alpha w_*)}{4\alpha + \beta} \qquad (17b)$$

By substituting Eq. (17a) in for ρ, the left side of Eq. (17b) is identical to the right side. Therefore, the constant and $z_L(\mathrm{k})$ terms cancel out leaving the following relationship between the noise.

$$2(1-\rho)\, \sigma_{zB}\, \eta_{zB}(\mathrm{k}) + \rho\sigma_w\, \eta_w(\mathrm{k}) = \sigma_R\, \eta_R(\mathrm{k}) \qquad (18)$$

If we use the same relationships defined in Eqs. (4, 10), both sides of Eq. (18) have zero mean. We also see the following relationships by taking the expected value of Eq. (18).

$$\mathbb{E}[\, (\sigma_R\, \eta_R(\mathrm{k})\,)^2\,] = \sigma_R{}^2 \qquad (19a)$$

$$\mathbb{E}[\, (\, 2(1-\rho)\, \sigma_{zB}\, \eta_{zB}(\mathrm{k}) + \rho\sigma_w\, \eta_w(\mathrm{k})\,)^2\,] = \rho^2\sigma_w{}^2 + 4(1-\rho)^2\sigma_{zB}{}^2 \qquad (19b)$$

Therefore,

$$\sigma_R{}^2 = \rho^2\sigma_w{}^2 + 4(1-\rho)^2\sigma_{zB}{}^2 \qquad (19c)$$

Repeating the above calculations starting with Eq. (16), where we now use the corresponding equations for $z_L(\mathrm{k}+1)$, yields:

$$\sigma_L{}^2 = \rho^2\sigma_w{}^2 + 4(1-\rho)^2\sigma_{zB}{}^2 \tag{19d}$$

We have now shown that an *a priori* and an *a posteriori* formulations are equivalent under the parameter change in Eq. (17a) given that the noise parameters have the same relationships seen in Eqs. (19c, 19d).

To obtain accurate measures, it is good practice to utilize mean subtracted data for regression. If we take the expected value of Eqs. (13a, 14a) we find:

$$\bar{z}_R = \frac{4\alpha-\beta}{4\alpha+\beta}\bar{z}_L + \frac{2(\beta z_{B*} + 2\alpha w*)}{4\alpha+\beta} \tag{20a}$$

$$\bar{z}_L = \frac{4\alpha-\beta}{4\alpha+\beta}\bar{z}_R + \frac{2(\beta z_{B*} - 2\alpha w*)}{4\alpha+\beta} \tag{20b}$$

We then solve for the target values to obtain:

$$w^* = \bar{z}_R - \bar{z}_L \equiv \overline{w} \tag{21a}$$

$$z_B{}^* = \frac{1}{2}(\bar{z}_R + \bar{z}_L) \equiv \bar{z}_B \tag{21b}$$

We expect this for optimal regulators because they achieve task goals with zero *average* error. We now subtract $\bar{z}_R$ and $\bar{z}_L$ from their respective step update equations to give updates in terms of fluctuations δ_s (k) $\triangleq$ z_s (k) – $\bar{z}_s$ ($s = L$, R):

$$\delta_R(\mathrm{k+1}) = \frac{4\alpha-\beta}{4\alpha+\beta}\delta_L(\mathrm{k}) + \sigma_R\eta_R(\mathrm{k}) \tag{22a}$$

$$\delta_L(\mathrm{k+1}) = \frac{4\alpha-\beta}{4\alpha+\beta}\delta_R(\mathrm{k}) + \sigma_L\eta_L(\mathrm{k}) \tag{22b}$$

We can further simplify Eqs. (22) into the following form showing that now, we only need to estimate one constant, *D*.

$$\delta_R(\mathrm{k+1}) = D\,\delta_L(\mathrm{k}) + \sigma_R\eta_R(\mathrm{k}) \tag{23a}$$

$$\delta_L(\mathrm{k+1}) = D\,\delta_R(\mathrm{k}) + \sigma_L\eta_L(\mathrm{k}) \tag{23b}$$

Using the Eq. (17a), we obtain the following:

$$D = 2\rho - 1 \tag{24a}$$

This constant can be easily calculated from the stepping time series through linear regression. Once we find the estimated constant D, we can determine ρ from the following relation.

$$\rho = \frac{1 + D}{2} \tag{24b}$$

To summarize, determining the cost weights is our main goal. This is because the value of cost weights shows which walking parameters, w or z_B, receive more weight. Therefore, the cost weights allow us to determine the role that position and balance play in walking. Through a series of derivations, from Eqs. (1) to Eqs. (15), we were able to derive stepping updates for z_R (k+1) and z_L (k+1) with two unknown constants. While the cost weights could have been determined from this point, we were able to simplify the stepping updates even further. By using the mean subtracted data, we obtained Eqs. (23) to determine that we only need to estimate one constant, D. Using this constant, we can then find the mixture parameter, ρ, to ultimately determine how much lateral body position and step width contribute to human locomotion. In the next chapter, Eqs. (23, 24) will be used for a regression analysis to determine the value of ρ and how that value changes across the walking conditions (NOP, PLA, VIS) and the participant groups (AB, TT).

Chapter 3

Results

In the last chapter, we obtained fluctuation updates for the left and right step in Eqs. (22). The fluctuation updates use deviations from the mean for the stepping time series data, which is good practice for regression. This form of the updates requires that only one constant, *D*, be determined. These fluctuation updates will be used in linear regression to determine the mixture parameter, ρ which can be calculated from *D*. Once ρ is determined, we will be able to conclude the cost weights applied to both *w* and z_B to determine which parameter is more important in walking with no perturbations (NOP), platform perturbations (PLA), and visual perturbations (VIS).

Coefficients for Stepping Observables

To begin, we need to determine the value of constant *D*. We start by calculating the mean position for both z_L and z_R from the stepping data. We then subtract the mean step position from each z_L and z_R position to obtain the deviations from the mean. Next, we conduct regression with the current step deviation as the response variable and the previous contralateral step deviation as the predictor. The resulting regression coefficient is our desired constant *D* from Eqs. (23). Utilizing Eq. (24b), we calculate ρ.

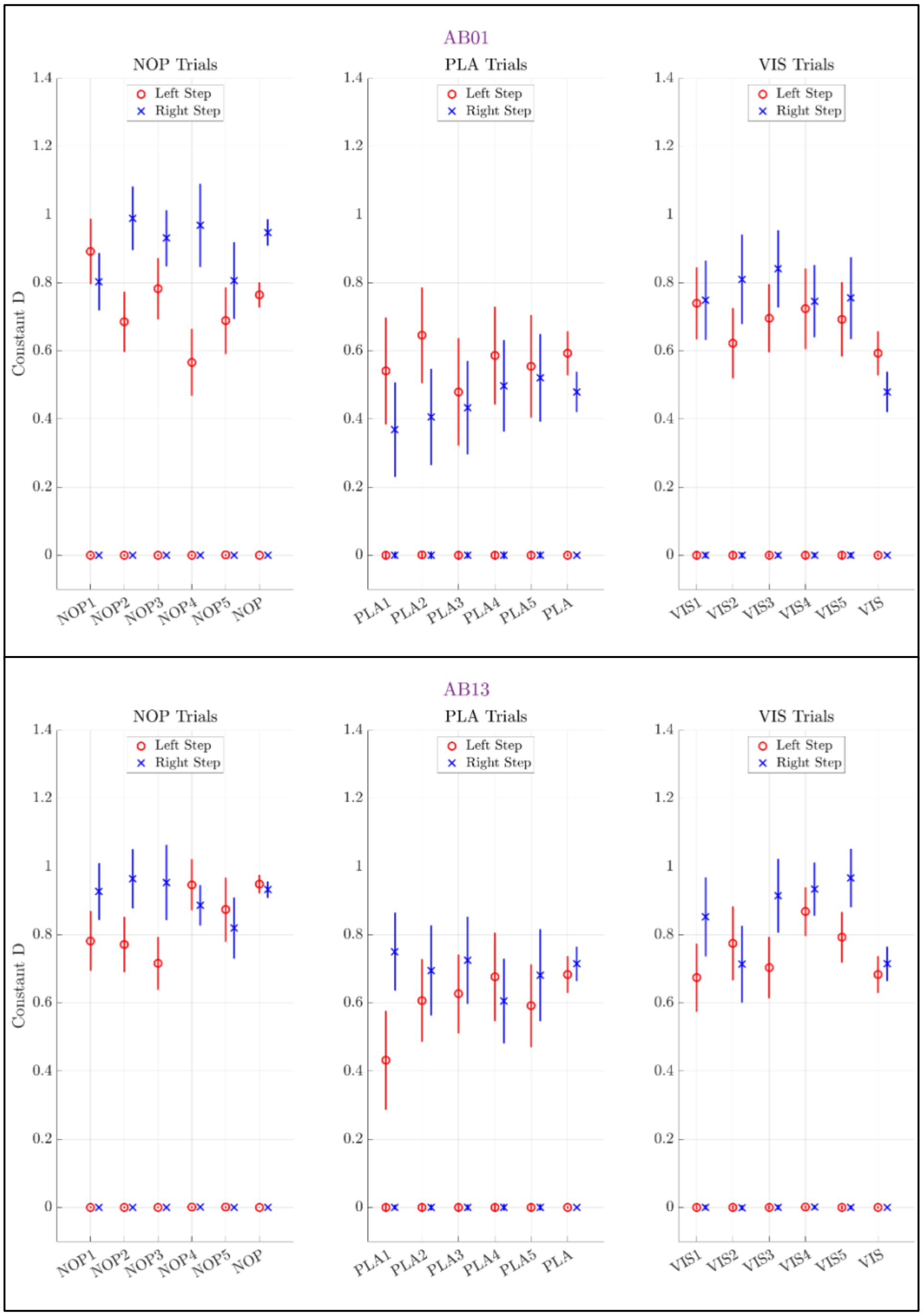

Figure 3-1. Typical coefficient estimates for constant *D* from fluctuation update equations (Eqs. 23 in Ch. 2) for the first and last AB participants. Coefficient estimates were plotted for the five walking trials corresponding to each walking condition. Data from the five walking trials were then combined and plotted as the last column for each walking condition. The vertical line passing through each data point is the 95% confidence interval for the coefficient estimate. These data were used to estimate the mixture parameter (ρ) using Eq. (24b).

Fig. (3-1) shows the estimated data for constant D from Eqs. (23). All 13 able-bodied (AB) participants were analyzed, but AB01 and AB13 are shown as examples. From Eq. (24b), D and ρ are directly proportional. While these are not ρ plots, we expect the ρ values to have a similar distribution.

Mixture Parameter

The mixture parameter ρ allows us to determine the weight associated with the costs for w and z_B for each step. We want to determine not only the value of the mixture parameter but how that value changes across the three walking conditions. The walking data is organized to determine ρ for the right foot, left foot, and combined foot data for each condition.

Referring to Eq. (7), ρ is the multiplier for the w cost and $(1 - \rho)$ is the multiplier for the z_B cost. This means a $\rho > 0.5$ corresponds to more weight on maintaining step width and less weight on maintaining lateral body position. From Fig. (3-2), the median mixture parameter is greater than 0.5 for all three walking conditions for both the AB and TT data. When looking at the individual walking conditions, the mixture parameter is not only greater than 0.5, but it appears to be roughly 0.9 for the NOP and VIS conditions and roughly 0.8 for the PLA condition. This means that during human locomotion, step width is a significantly more important predictor for the position of the next step than lateral body position. The PLA and VIS conditions have lower values of ρ as compared to the NOP condition. As physical and visual perturbations are applied, the lateral body position becomes a slightly more important predictor and the weight applied to z_B

increases, however, *w* is still the abundant predictor. The PLA condition has a noticeably lower value of ρ than the NOP and VIS conditions. This means when the platform is physically shaken, maintaining lateral body position becomes considerably more important to maintain locomotion. The differences in the walking conditions show how multi-objective human walking is.

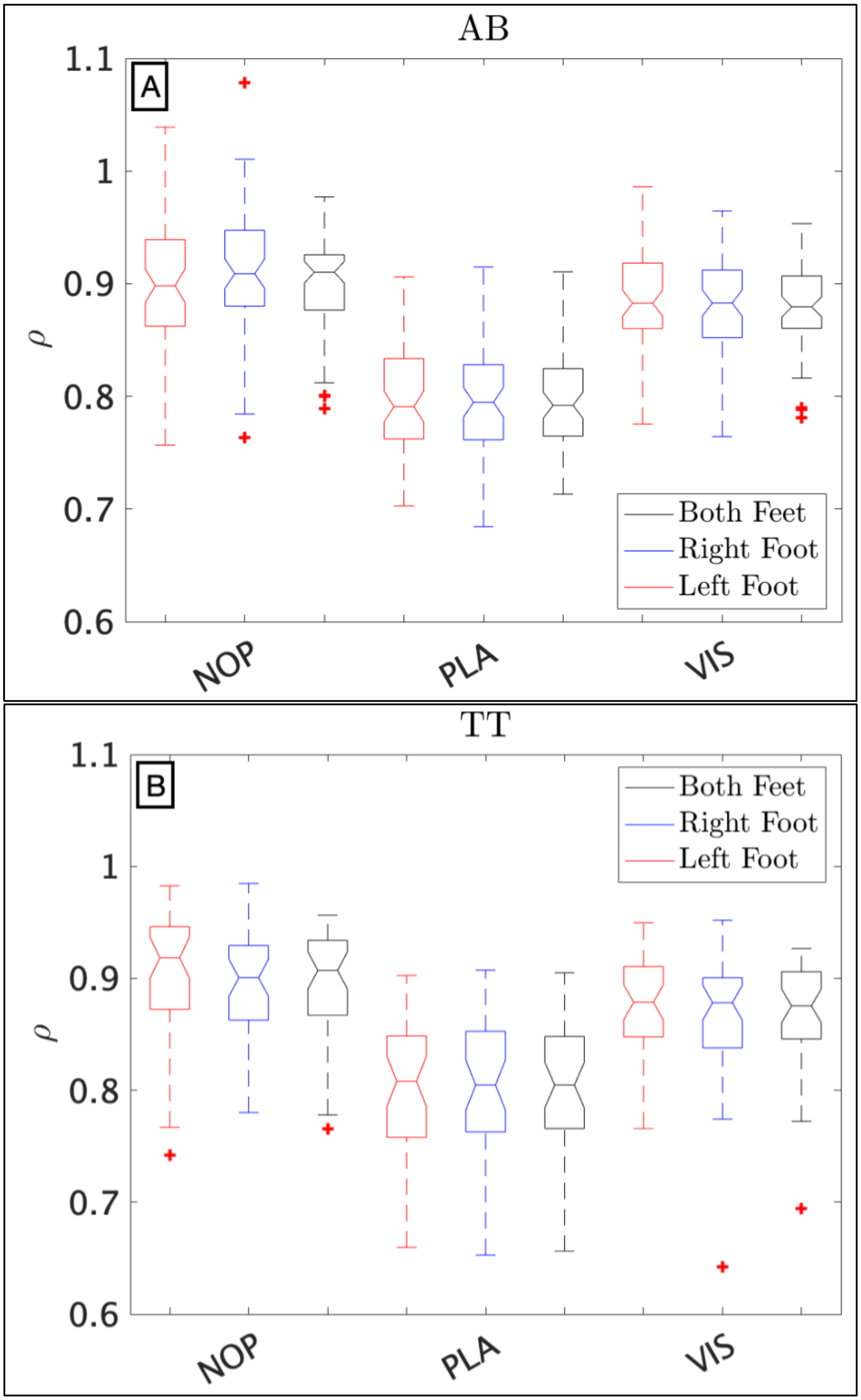

Figure 3-2. Box plots of the estimated mixture parameter (ρ) values for the AB individuals and TT amputees. A) AB participants data. B) TT participants data. This figure shows that every single estimate of ρ, for both walking group and walking condition is substantially greater than 0.5. This means the majority of the cost is given to maintaining step width, w. This suggests that stepping regulation heavily emphasizes maintaining balance over maintaining position.

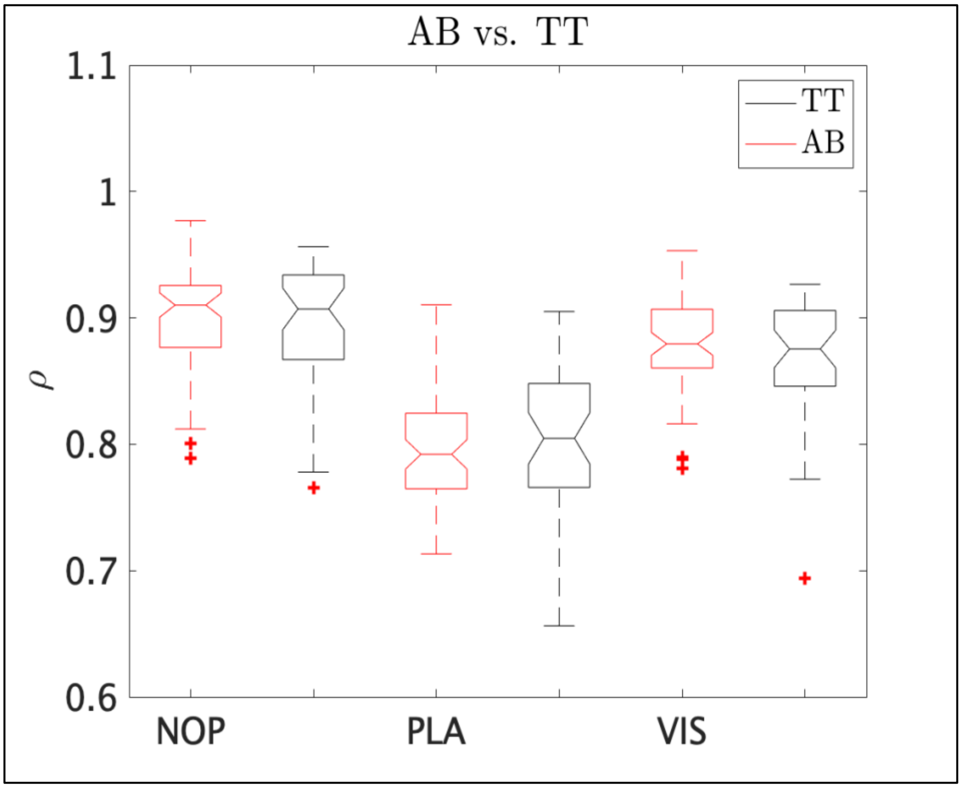

Figure 3-3. Box plots of estimated mixture parameter (ρ) values for the AB individuals and TT amputees for combined left and right foot data. To allow for direct comparison, we replotted the third boxplot of each condition from Fig. 3-2, corresponding to the combined foot data, to better visualize the comparison between the AB and TT participants.

When comparing the AB and TT data, there is not a substantial difference between the two groups. The combined foot walking data for AB and TT can be seen in Fig. (3-3). The ρ data appears to be very similar between the two groups. The medians and interquartile ranges both appear to be roughly equal for each walking condition. However, we need to complete a more objective analysis to determine the numerical differences between the AB and TT groups.

Significance Testing for AB and TT Participant Groups

The AB and TT data sets appear to be similar according to the mixture parameter estimates. However, it is important to conduct significance testing to determine if the observed differences are likely to have occurred merely as a result of chance. This analysis begins by treating the data as a mixed-effects model. This model type is used when two or more variables are being used to predict a single outcome variable. A mixed-effects model is also used to determine the relationship between variables [23]. In this case, we are seeking to determine if there is a relationship between the participant groups (AB and TT) and the walking conditions (NOP, PLA, and VIS).

We first need to determine if a mixed-effects model is an appropriate way to analyze the data. We want the data to have a normal distribution. This can be determined by looking at the residuals for ρ. The residual is the difference between the observed value and the predicted value. Looking at the normal probability plot in Fig. (3-4A), the data points should be strongly aligned to the red diagonal line, which they appear to be. We also want the histogram in Fig. (3-4C) to appear as a bell curve. While this histogram is not a perfect bell curve, it is approximately bell-shaped to indicate a normal distribution. Figs. (3-4B, 3-4D) show if the residuals have any noticeable patterns when plotted by order or value. There are not any discernable patterns in either plot. Therefore, all four plots show that the mixed-effects model is a good fit for the data.

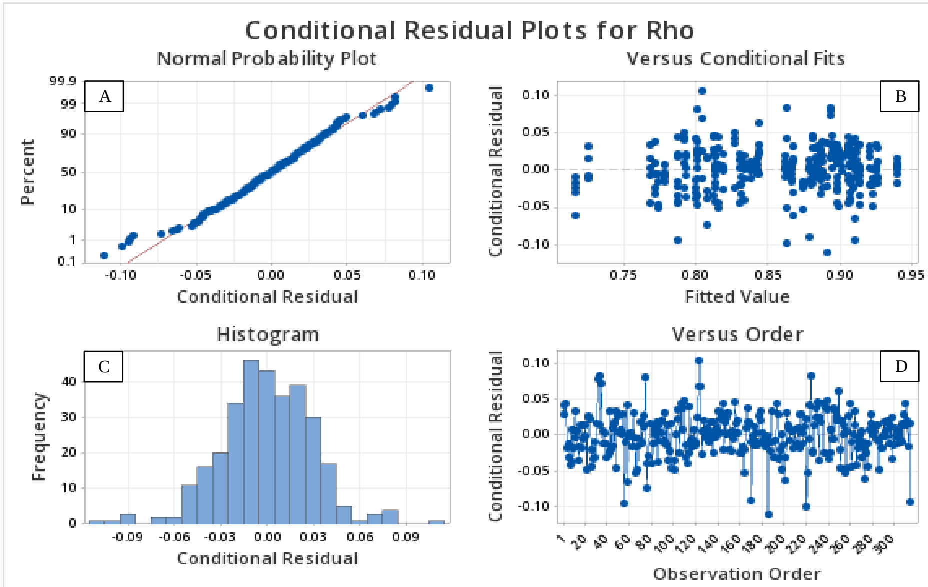

Figure 3-4. Conditional residual plots for estimating the mixture parameter (ρ). A) Normal probability plot displaying residual deviations. The residuals are aligned very well along the diagonal indicating a good fit. B) Histogram displaying data distribution. While the histogram is not a perfect bell curve, it is close enough to indicate a normal distribution. C) Residuals versus conditional fit plot for pattern observation. D) Residuals versus order plot for pattern observation. There are no discernable patterns in plots B or D; this indicates a good fit.

We can now perform the significance tests. The level of significance for these results is p = 0.05, meaning any p ≤ 0.05 is statistically significant. The first results to check are from the test of fixed effects seen in Table (3-1). This compares the data from the participant groups, walking conditions, and the interaction between the groups and conditions. The first result we care about is the p-value for the group*condition interaction. This result compares the participant groups responses to the different walking conditions. The p-value of this interaction (p = 0.183) is not statistically significant, which means there is no real difference between the AB and TT walking data. Because this interaction is not significant, we now look at the p-values for the groups and conditions separately. The p-value of the group term (p = 0.792) is not statistically significant. Therefore, there are no differences between the AB and TT groups.

The p-value of the condition comparison came out to be 0.000, which is just an artifact of the software used: it is not exactly zero. However, it indicates that this p-value is highly statistically significant ($p < 0.001$). This means that there is at least one difference between the NOP, PLA, and VIS conditions. However, this specific test does not allow us to determine which conditions differ from one another.

To determine the specific differences between the walking conditions, we need to do a post hoc analysis of this model. This analysis determines the significance level of each condition comparison. All three condition comparisons have p-values less than 0.001 as seen in Table (3-2). These results show that all three walking conditions are significantly different. Therefore, no perturbations, platform perturbations, and visual perturbations all require a different weight distribution for the w and z_B costs to maintain locomotion.

Table 3-1. Test of fixed effects results for the mixture parameter (ρ). The AB and TT groups are not statistically significant from each other ($p > 0.05$). The conditions are highly statistically significant ($p < 0.001$); all three walking conditions require a different weight distribution for the w and z_B costs. The interaction between group and condition is not statistically significant; the AB and TT groups respond to the walking conditions in a similar manner.

Term	P-Value
Group	0.792
Condition	0.000
Group*Condition	0.183

Table 3-2. The p-value data for the mixture parameter (ρ) comparison between all three walking conditions. The individual confidence level is 98.09%. We see that in all cases the differences between the walking conditions are highly statistically significant ($p < 0.001$).

Condition Comparison	Adjusted P-Value
NOP - PLA	0.000
NOP - VIS	0.000
PLA - VIS	0.000

To summarize, the data showed that the walking participants heavily emphasized the regulation of step width over the regulation of lateral body position. This indicates balance is a more important factor during locomotion than body position is. These results will be discussed further in the next chapter.

Chapter 4

Discussion and Conclusions

This thesis began by analyzing human gait under three different walking conditions. We hypothesized that cost functions associated with different parameters played an important role in regulating stepping during locomotion. These cost functions, corresponding to step width, *w*, and lateral body position, z_B, were derived and then their relative weights were estimated using linear regression. We sought to determine how the weights were distributed between the *w* and z_B costs, as well as how the weights changed when experiencing different walking conditions.

The first result we obtained was the extracted coefficient data (Fig. 3-1) from the updated stepping observables. This result allowed us to view the differences between the three walking conditions. Walking with no perturbations (NOP) and walking with visual perturbations (VIS) produced a similar gait response when viewing the extracted coefficient data from the updated stepping observables. However, platform perturbations (PLA) produced a noticeably different walking response. When the platform was physically shaken, both the AB and TT participant data had significantly lower values of coefficient *D*. This meant that there was a considerably different weight distribution between the walking parameters during the PLA condition than the other two conditions.

To further study our hypothesized importance of *w* and z_B for stepping regulation, we analyzed the mixture parameter. We determined that more weight is applied to the step width cost than the lateral body position cost (Fig. 3-2, 3-3) across all three walking conditions for both the AB and TT groups. While both parameters are important, step width is a more important predictor for the position of the next step than the lateral body position. When the platform was shaken, the lateral body position became more important. However, across all three walking conditions, we can conclude maintaining step width is significantly more important.

While the coefficient and mixture parameter plots provided important results on the weights applied to w and z_B, we could still not draw confident conclusions on the differences between the walking conditions and the participant groups. While there seemed to be a small difference between the AB and TT walking groups visually, significance testing proved that the two groups are not significantly different from each other in a statistical sense. This result means able-bodied individuals and transtibial amputees achieve walking in the same way, i.e., there is no discernable difference between the two groups during locomotion. Furthermore, it was clear that the mixture parameter for the PLA walking condition was substantially lower as compared to NOP and VIS. However, results showed that, for both groups, all three of these walking conditions are significantly different from each other. During these three walking conditions, step width and lateral body position receive a different amount of weight to maintain locomotion.

Future Applications

This work is based on the general hypothesis that human motor regulation is multi-objective in nature and is based on different costs that can depend on physical ability and environmental conditions. In the work done for this thesis, we showed that it is possible to estimate cost weights from stepping data using linear regression. Furthermore, we determined that the differences in cost weights are all statistically significant during the three different walking conditions. The data we used for this analysis was collected only for walking in a straight line, which is just a small piece of real-life walking. Thus, it would be good to conduct similar data analyses with data from different walking tasks including, for example, maneuvers required to change direction or avoid obstacles. This analysis could be utilized to determine how stepping costs are adjusted to trade off stability and maneuverability.

The participants in both groups were less than about 32 years of age. While participants in this group were healthy individuals, this work could be applied to populations of younger and older ages to determine how the walking system develops and declines through aging. The methods developed in this work can also be utilized to diagnose neuromotor disorders as well as to monitor the progress of rehabilitation from injury or disease. While these results give us a reasonable picture of how walking is regulated in healthy individuals, the distribution of weights between different costs pertaining to balance and maneuverability, or other costs such as energy or risk, may be drastically different for different age groups or in cases where neuromotor disorders are present.

Ethical Considerations

The data analyzed in this thesis were collected as part of a previous experiment involving thirteen able-bodied adults and eight trans-tibial amputees. These participants volunteered for the data collection process and all their information was kept anonymous. It is important to realize that data can become exploited when conducting research with anonymous volunteers. While efforts have been made to keep this data anonymous, there is always a chance that it does not remain that way. This is one issue pertaining to research with human volunteers.

The walking data used in this thesis was collected in Penn State's Locomotor Control Laboratory. This is a full gait lab that requires expensive equipment to collect data. Human locomotion is an important topic of study, but unfortunately, these experiments cannot be run without large financial investments. In the future, it is worth considering how these experiments can be run more affordably.

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ACADEMIC VITA

Jean Starr

150 Johnson Road Leechburg PA, 15656

Jean.starr21@gmail.com

Education

The Pennsylvania State University, Schreyer Honors College
Bachelor of Science in Engineering Science, May 2023
Minor in Engineering Mechanics

Work Experience

May 2016 – Present
Farm Worker, Starr Valley Farm

- Supervise farm workers in hazardous environments
- Ensure 60 cattle have food, water, and secure perimeters
- Maintain and repair 5 miles of cattle fence
- Operate farm equipment to produce hay, spread fertilizer, mow fields
- Tag and document 15 newborn calves annually for organic certification records
- Provide customer service during sales process

Involvement

August 2019-Present
Student-Athlete, Penn State Track and Field

- Collaborate with more than 100 teammates, coaches, and staff
- Commit 30 hours weekly between practices and competitions
- Participate in weekly team meetings to review performance and discuss goals

January 2020
Volunteer, Penn State Athlete Hour

- Supported Penn State’s annual student-run philanthropy, THON