Broadening the Capability of Kinetics Analysis in Biomechanics

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Abstract
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Broadening the Capability of Kinetics Analysis in Biomechanics

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Nicholas Nelson

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Advisor: Dr. Bradley Davidson
Abstract

Two studies are discussed in this manuscript each preceded by a literature review of the topic. The first review and study explore agility movements and the effect that alternative upper designs in shoes might have on ground reaction force measures of performance. The second review and study evaluate methods of predicting ground reaction forces without the use of a force platform. A method of using effective forces and ways of improving its accuracy are evaluated in depth.
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Chapter One: Aims

The ability to conduct biomechanical analyses of human movement is restricted. The simplest methods for collecting data about athletic performances or altered gaits can only tell a bulk story of the movement while more specific external or internal methods require expensive instruments that collect data in complicated networks that are only seen in state-of-the-art biomechanics laboratories. Further, even those high-end networks of the best technologies are restricted within small, calibrated laboratory environments with stationary equipment which requires subjects to alter their movements to accommodate the collection.

These restrictions do not mean that useful information cannot be obtained in these labs. External mechanics collected by single force platforms or other single-instrument setups can still yield information that can help to describe phenomena like changes in performance due to footwear or fatigue. Standardized movements across the field of biomechanics research, like sagittal walking or countermovement jumps, also allows for communication of results regardless of what level of mechanisms, whether bulk, external or internal, between laboratories.

However, the broadening of the accessibility of this information, by exploring new methods or creating new devices, would definitely improve what biomechanics studies could learn. Laboratories or clinics that could not afford the full network of devices required to do inverse dynamics calculations could take advantage of what knowledge
they could learn from the joint mechanics of their patients and the development of athletic footwear could take their analyses onto the trail or court.

This manuscript explores the possibilities of broadening the capabilities of kinetics analysis in biomechanics. A traditional agility performance study of the design of alternative closure systems for trail shoes was conducted. This study on endurance and trail running athletes prompted questions of what it would take to get a real *in situ* collection of data on a trail. These inquiries lead to the second part of this thesis: exploring potential methods for predicting ground reaction forces without the use of a force platform, diving particularly into the use of effective forces as a physics-based method of doing so.

Predicting ground reaction forces (GRFs) using kinematics would not only expand what movements could be analyzed to those that could not be performed in the tight calibrated spaces of a biomechanics lab, but the opportunity to do inverse dynamics calculations without the need for stationary networks of devices. This broadening of capability would make these analyses more accessible to labs and clinics that could not afford high-end instruments. Instead, they may only need to buy a set of seven inertial measuring units.

**Overview:**

Chapter two covers a general review of how agility should be defined in biomechanical studies, how performance is measured, and what interventions might improve performance. A definition of agility is adopted which categorizes a network of factors both cognitive and physical that contribute to a person’s agility. We discuss three different levels of performance measures which describe overall, external, and then
internal biomechanical measures, what they mean, and how they are collected. Finally, a summary of major performance interventions focusing on footwear is presented ending with a note on the developing understanding of the upper closure design of shoes and its effects on athletic performance.

Chapter three describes an experimental study evaluating the effects of alternative closure systems for trail shoes on athlete performance under fatigue. Three different configurations are tested including a standard lacing system. External measures of performance calculated from ground reaction forces for countermovement jump repetitions are analyzed for each subject with each configuration before and after an endurance run. Results suggest that alternative configurations might improve performance, but assessments of alternative configurations on fatigue are inconclusive.

In the course of conducting the second study, many subjects noted how different treadmill running felt from overground running on trails or on the road. This prompted inquiries into what methods would be required to take biomechanical data collections out of the lab, leading to the work discussed in the second half of this thesis.

The fourth chapter explores methods of predicting ground reaction forces without the use of a force platform, which would in part enable biomechanics analysis to take place outside of a laboratory setting. Physics based models of human movement are explored including mass spring-damper-models of the lower legs as well as link-segment models of the human body as potential methods. Mass-spring-damper models are dismissed and a method that utilizes effective forces is chosen for further exploration.

Chapter five takes the effective force method of predicting ground reaction forces and attempts to apply it to the collection of agility performance measures. Effective force
models tracking 13-7- and 1-segment models are compared to ground reaction force profiles measured directly. Methods for selecting cutoff frequencies for lowpass filtering segment kinematics are also compared in an attempt to capture high frequency impacts in the predictions. Four different activities are analyzed for both their time-series accuracy to true ground reaction force profiles as well as point estimate comparisons for measures of agility performance. The accuracy of this method is found to be potentially inadequate for full scale studies as a replacement for force platforms, but insights into routes for improvement are suggested.

Chapter six concludes with suggestions for future work in both studies discussed in this thesis.
Chapter Two: A Review of Biomechanics Methodology for Agility and Performance Interventions

Defining Agility

Studies of performance in agility seek to better understand the neuromuscular mechanics underpinning these motions and to use these measures to evaluate or develop interventions to improve athlete performance or protect them from injury. However, developing meaningful studies to evaluate athletic agility requires a strong definition to guide the design of the study.

In current literature, no single definition of agility is used from study to study. Barnes (2007) describes agility motions as changes of direction with minimal loss of control or speed. This definition uses a broad understanding of agility without any preconceived ideas of what contributes to the motion biomechanically. Spiteri (2015) provides a more specific set of potential factors that might define agility from context to context. These factors include multi-direction movements, specific coordination of movement toward a direction or target, or movement in response to changing external stimuli. This definition is more useful than Barnes’ definition as it lists specific qualities that might have measurable outcomes that could be related to biomechanical variables like directional ground reaction forces or joint ranges of motion.

Spiteri’s definition follows after Young (2002), who adds a few more layers of specificity and categorization in a definition that splits contributions to agility between
“perceptual and decision making factors” and “change of direction speed”. Young’s Deterministic Model of Agility (Figure 1) is a definition that could be extremely helpful in planning a study around biomechanical factors in agility. For example, Young’s inclusion of “body lean and posture” as a contributor to technique within change of direction speed could prompt a study on body length and mass parameters’ contribution to agility movements.

![Figure 1. Young’s (2002) Deterministic Model of Agility Movements](image)

Sheppard (2006) in a review on definitions and evaluations of agility movements rejects Young’s model for defining agility with too broad a definition of what could be categorized as agility movements. He questions that if one researcher defines both a preplanned obstacle course and a reactive evasion drill as agility motions, how can the two movements be compared? For Sheppard the definition for agility must be narrow and uniform in order to establish a basis for comparison from movement to movement. Sheppard proposes agility be defined as “a rapid whole-body movement with change of velocity or direction in response to a stimulus”. Any definition without one of those
components, particularly the stimulus response, does not count as an agility motion in this definition.

The flexibility of Young’s definition allows for the components of agility to be observed both in isolation and in their interactions. While Sheppard is right to assert that strict definitions are useful for unilateral comparison, this narrow definition would not allow for the decomposition of agility motions to evaluate where interventions, like training or sportswear, might affect outcomes. For instance, a study observing the involvement of shoes in the mechanics of agility would likely want an isolated, preplanned change of direction movement without the inclusion of stimulus. Simulating stimulus would be important in a study evaluating an intervention in an accurate context of the motion, but it is a stretch of the imagination to think that shoes would affect the cognitive ability of an athlete’s reaction time rather than just the fundamental ground-shoe or ankle mechanics of a movement. Reaction time might be confounding in such a narrow observation like this. This thesis uses Young’s tiered Deterministic Model of Agility from here out.

**Measuring the Mechanics of Agility**

For the works presented in this thesis, we are interested mostly in the “change of direction and speed” categories of Young’s model. In general biomechanical studies, the depth that change of direction and control of acceleration can be analyzed depends on the tools used to collect information. The modes and methods of collection decide what performance variables one can evaluate. This section describes three levels of specificity that researchers can attain for agility movements based on the tools at their disposal. The first level utilizes simple, inexpensive tools to get an understanding of bulk movement.
The second level requires one primary instrument to describe deeper details of movement, in this case force platforms for measuring ground reaction forces. The third level uses networks of instruments in order to do analyses that attempt to estimate the internal dynamics of human movement.

At the first level, simple tools of data collection, like stop watches and measurements of distance, can provide the most surface-level observations of performance. Temporal variables like time to complete a course or cover a certain distance tells a bulk story of speed or acceleration. Heights jumped and distances covered in a period of time are similarly easy to collect. These measures are useful in their simplicity of collection and their direct relation to races or competitive sports. This level’s limitations lie in the lack of specificity in its measures. Time to complete a course might speak generally to an athlete’s speed and control of motion but does not inform what attributes of their motions contribute to the higher completion time, like their ability to change direction or reach top speeds. The generality of the measurements put these tools as the first level of data collection.

This level provides measures that are most common from a coaching and training standpoint. Well established activities like the 505-test, the T-test, and the Illinois test (Figure 2) are agility trials that use measures like time to complete to compare athletic ability. In biomechanics studies, changes in these bulk measures are typically described in comparison to changes in higher level variables.
Figure 2. Diagrams of the Illinois test (left) and the 505 test (right) from (Sheppard, 2006). The Illinois test involves consecutive changes of direction around multiple obstacles before and after sprinting from the start and to the finish. The 505 test is a down and back sprinting and change of direction activity.

The next level of data collection should take another step toward specificity in its measurements. Direct measurements can take place with a single type of instrument. For our purposes, we will consider the use of a force platform (FP) independently to collect GRFs. Force platforms provide more specific variables during ground contact like contact time, peak force, and rate of force development that can relate to the bulk variables of average speed or jump height by measuring ground reaction forces (GRFs) directly. FPs are more commonly found in laboratory or clinical environments studying biomechanics.

Studies like (McLellan, 2011) have demonstrated that the dependent variables calculated from FP data are well correlated with the bulk measures of surface level biomechanics. Figure 3 shows a typical vertical ground reaction force profile for a countermovement jump with common measures labelled on it. Peak force measures the maximum force the athlete is putting out to continue the jumping sequence for this
exercise. Rates of force development measures both the absorption of impact and the development of force output as the athlete lands and prepares to jump again. The peak force and peak rate of force development were both shown by McLellan to be highly correlated with vertical jump distance.

Figure 3. An example of a countermovement jump vertical force profile with GRF measures of peak force (red star) and rate of force development (green line).

The FP level of measurement, while more informative, can be more restrictive in its application because of the need to have the FP in a fixed location connected to a data acquisition device. Athletes must also perform the agility motions being analyzed in such a way that makes solid contact with the FP, which can force a subject to alter their movement to accommodate, potentially changing outcomes like range of motion or contact time. The increased specificity, allowing for the observation of ground-foot
interactions, puts single instrument collections, like those done with FPs, at the second level of collection. GRFs, however, are still only an external measure of performance and only result due to the internal mechanisms of human movement.

The third level of biomechanical data collection is defined by its ability to understand internal mechanisms of movement. This level usually requires networks of instruments and methods to provide insights of what happens within the dynamic system of the human body. Optical or inertial motion capture in tandem with FPs can allow for the calculations of inverse dynamics for estimating joint moments and forces. Kinematic and joint force and moment data can also estimate joint power and work to evaluate the energy that is lost or produced in a joint during a motion. The addition of kinematics can also help to identify eccentric and concentric phases of motion within a force profile based on center of mass power, the vector product of force and velocity, as the body changes direction in an agility motion (Figure 4).
Additional devices like electromyography (EMG) can be included to provide input to musculoskeletal models to predict muscle forces and skeletal loads and pressure socks might be included to get a refined pressure mapping during contact within a shoe. Utilizing networks of biomechanical instruments can be incredibly informative but are only typically used in state-of-the-art biomechanics research labs due to the restrictive costs of these tools.

**Interventions to Improve Performance**

Now that we have defined agility in a way that subdivides its contributing pieces and established the methods and levels of specificity that can be used to analyze those pieces, we can discuss the interventions that might improve an athlete’s agility and how those improvements are compared in literature. Two avenues for improving agility are
prevalent in literature. The first, which we will discuss briefly, are training interventions. The second is the inclusion of athleticwear in which footwear dominates the conversation for agility and running.

Training and treatment regimens have been evaluated time and again using standard agility based measures. Training interventions can improve agility biomechanics by refining technique, enhancing the strength or flexibility of key muscle groups, or focusing on strengthening parts of the body that are prone to injury. Two examples include Standing and Maulder (2017), who compared the technique of a standing start versus block start in initial accelerations during a sprint by looking at kinematic variables. A second example is the work of Lephart et al. (2005) who compared the effect of different strength conditioning regimens, plyometric and resistance, on changes in athlete performance, showing similar increases in peak vertical ground reaction force in jumping activities for both methods.

Changes to external interactions (e.g. footwear) offer an alternative to the training regimens for conditioning or movement technique which affect an athlete’s physical or cognitive approaches to agility movements. Footwear is ubiquitous in all athletic endeavors and different designs are prescribed for all different activities. In their review on shoe design, Reinschmidt and Nigg (2000) claim that the three most important functional design factors of athletic shoes are injury prevention, performance, and comfort. The changes to agility motions that shoes provide can be applied immediately, so testing their influence on biomechanics allows for quick iteration of design.

A large breadth of studies focuses on design as it relates to health. For sports such as running where continual repeated motions cause cyclical loading in the legs, loading rate
is a serious concern for musculoskeletal health. Concerning athlete health, the design of a shoe’s lower is usually the focus. Rice et al. (2016) performed a study observing the difference in ‘minimal’ and standard designs of shoe lowers as it pertains to loading rates during running. They found that the benefits of minimal or standard shoes depends on a runner’s foot strike pattern. Hamill and Bates (1988) similarly looked at how the shock attenuation of running shoes can degrade over long terms of use. Another study of note, conducted by Nigg et al. (2017), evaluated the effect of running shoe style on joint kinematics which they suggested changed based on paths of minimal energy.

While performance on its own is less represented in athletics and footwear research, the topic still spans a wide breadth of shoe components. Farina et al. (2019) investigated the integration of a curved carbon fiber plate to the shoe’s lower as a method of energy return for increased running economy. In a different vein, Chanda et al. (2018) evaluated shoe-floor interaction through the lens of traction. Brizuela et al. (1997) performed an investigation on the effect of high-top ankle support in basketball performance and shock attenuation, noting the reduction in performance and range of motion as a cost to the benefit of reduced ankle injuries during cutting maneuvers.

It is worth noting that these studies often limit their evaluation to a change in the shoe lower design on runners. Nigg’s (2017) work specifically differentiated the shoes by 5 design parameters: midsole hardness, outer sole hardness, heel cushioning, heel outer sole groove width, and heel outer sole groove distance from heel edge. Rice’s (2016) distinction of minimal and standard also pertained solely to the thickness of the shoe’s cushioning. When it comes to loading rates and peak forces, this line of thinking makes sense. The shoe’s lower is the primary shield between an athlete’s foot and the rigid
ground. That interaction can be tuned to either enhance performance through reduced cushioning, allowing for direct power transfer, or to attenuate shock by adding cushioning.

Reinschmidt and Nigg (2000) deigned that “the most important factors influencing court performance” are traction, dynamic stability, and muscle fatigue. They mostly evaluate the design of shoe lowers, but the design of shoe uppers is only mentioned in passing. Shoe upper design has only recently become a topic of interest in sports biomechanics. Pryhoda et al. (2020), and Subramanium et al. (2021) have each investigated the effect of alternative shoe upper designs on performance and health. Pryhoda demonstrated improved ground reaction force measures in field and court sport athletes during agility activities with alternative upper designs. Subramanium showed that a reinforced upper designed to better contain the foot decreased ankle work during cutting movements, which could be a performance benefit for agility athletes. Based on Reinschmidt and Nigg’s (2000) claims, the findings that a better fit of a shoe’s upper may improve performance appear sound by allowing the foot and shoe to move in better solidarity.

The rationale that shoe upper designs can affect athlete performance will be the focus of the next chapter of this thes
Chapter Three: Alternative Shoe Upper Designs Affect GRF Measures of Performance in Countermovement Jumps

Introduction:

In comparing the methods of performance evaluations for agility and endurance activities, trail running finds an interesting middle ground between the two definitions. A runner’s endurance is tested over the course of many miles of running, but the ability to make quick adjustments while running up or down inclines and across uneven terrain is just as important to maintain.

Past studies have related the effects of fatigue to diminishing abilities to change directions or stop in athletes. Cortes (2012) noted increased rotation and decreased flexion in knee joint angles during side shuffle activities pre and post fatigue which are associated with injury. Shultz (2015) similarly found stiffening of leg joint kinematics post fatigue and Quammen (2012) associated the same finding of reduced knee flexion angles post fatigue with higher peak GRFs during a stop-jump task. These studies were motivated by concerns for athlete musculoskeletal health. We found no references discussing fatigue’s effects on agility performance, especially in regard to shoe design.

Reinschmidt and Nigg (2000) claimed that an ideal shoe would aid in the preferred musculoskeletal motion of a given activity, be that running or changing direction, and result in more efficient biomechanics. Pryhoda et al. (2020) demonstrated in a study on court and field athletes that alternative upper designs in shoes meant to enhance fit do
significantly improve the GRF measures of agility performance. Nigg’s later study with Subramanium (2021) also demonstrated a decrease in ankle work during shuffling movements with a reinforced upper. If Reinschmidt and Nigg’s (2000) original claim is correct, then improved fit might help long term endurance as well. This outcome would be beneficial for long distance runners, court athletes, or trail runners exercising a combination of endurance and agility.

The purpose of this study is to evaluate the claim that improved fit configurations in trail shoe upper designs mitigates factors that cause fatigue which negatively impact agility performance. We test two main hypotheses. First, we hypothesized that alternative fit configurations would perform better overall in agility performance measures than a standard upper design. Second, we hypothesized that the magnitude of change in performance due to fatigue would be smaller in runners while wearing alternative fit configurations than while wearing standard configurations due to effects on overall endurance. Answering these hypotheses will bolster our understanding of the effects of shoe upper design in general and potentially support future results relating shoe fit to fatigue.

**Methods:**

The agility performance of high-performing recreational distance runners was analyzed to compare the effect of shoe closure configurations on performance both before and after an endurance run. Six ground reaction force measures of agility performance before and after fatigue were compared across standard and alternative configurations provided by BOA Technology inc. The University of Denver Institutional Review Board approved this investigation.
**Participants:**

Thirty-two recreational distance runners were recruited for this study. Inclusion criteria required participants to regularly run more than 30 miles per week, hold 5K race times under 20 minutes for men and under 22 minutes for women, or 10K times under 42 minutes for men and under 46 minutes for women. Each participant was also required to fit into either a size 10.5 or 11.5 shoe for men or a size 7.5 or 9.5 shoe for women. All athletes reported no injuries within 6 months prior to participating in the study. The demographic parameters of all participants are summarized in Table 1 below.

**Table 1. Participant demographics (Presented as Mean (± Standard Deviation))**

<table>
<thead>
<tr>
<th></th>
<th>Male (n = 16)</th>
<th>Female (n = 16)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>34 (10)</td>
<td>30 (6)</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>177.8 (4.8)</td>
<td>168.5 (5.2)</td>
</tr>
<tr>
<td>Mass (kg)</td>
<td>72.2 (7.6)</td>
<td>60.0 (6.8)</td>
</tr>
</tbody>
</table>

**Instrumentation:**

Kinematics were recorded in an overground optical motion capture space outfitted with 12 Vicon cameras. Retroreflective marker clusters were affixed to 7 lower body segments (foot, lower leg, upper leg, and pelvis) to track the motion of these segments in the space at 100 Hz. Ground reaction kinetics were measured with a sampling rate of 1000 Hz via 4 AMTI force platforms level with the floor in the center of the overground space. Kinematic and kinetic data were streamed through the Vicon Nexus program to The Motion Monitor (TMM) for preprocessing. Kinematic and kinetic data were both filtered using a 4th order zero-phase lag Butterworth lowpass filter with a cutoff frequency of 15 Hz.
Protocol and Activities:

This protocol was conducted at BOA Technology Inc.’s Performance Fit Lab. Participants were asked to attend three different sessions separated by at least two days. Upon arrival, participants were provided with one of the three shoe configurations in an order determined by a counterbalanced randomization of conditions. Participants were given 10 minutes for self-prescribed warmups for agility and distance running activities.

The kinematics and ground kinetics of agility movements were collected before and after a 45 minute treadmill run at submaximal paces averaging 3.18 ± 0.26 m/s. Two trials of 8 repetitions of agility movements were collected in both pre and post run agility sessions.

This work focuses on the Countermovement Jump (CMJ) agility motion as an activity commonplace in conditioning settings. CMJ is also prevalent in athletics research with well documented relationships between GRF measures and athletic performance (McLellan, 2011). Before and after the run, participants performed two trials of eight continuous countermovement jumps. Participants were asked to jump powerfully and as continually as possible during each collection. The CMJs took place in the center of the overground lab with each foot landing in a separate force platform.

Across 32 subjects, 2304 jumps were analyzed. In each trial of 8 repetitions, the first and last repetitions were removed to guarantee recordings of continuous movement. Repetitions landing outside of the force platforms were also removed.

Shoes:

Participants wore their own athletic clothing and were provided with New Balance Hierro trail running shoes designed with three different upper tightening configurations
The standard lacing (SL) configuration utilized laces common to most running shoes. The alternative configurations, provided by BOA Technology Inc, included the single dial (SD) configuration and the dual dial (DD) configuration. Both dial configurations tighten three straps along the medial aspect of the shoe via BOA L6 eyestay mounted dials pulling low-friction TX4 laces. The SD configuration adjusted all three straps with just one dial while the DD configuration adjusts the most proximal strap with one dial and the two distal straps with a separate dial, allowing for more customization of the shoe’s fit. During warmups, athletes were given the opportunity to familiarize themselves with the BOA dials and adjust the tension in the shoes as they saw fit.

Figure 5. New Balance Hierro trail running shoes with BOA Dual Dial (left), BOA Single Dial (middle), and Standard Lacing (right) upper tightening configurations

Agility performance variables of Contact Time, Peak Eccentric Rate of Force Development (RFD), Peak Concentric GRF, Eccentric Work, and Concentric work were calculated from the vertical GRF profile. All performance variables were calculated using TMM pipelines and MATLAB scripts.

**Statistical Analysis:**

Calculated performance variables in SD and DD configurations were compared to the SL configuration as a standard both overall and in changes before and after the endurance run. A linear mixed-effects model with the fixed effect of configuration condition and the
random effect of subject and subject mass interaction was used to quantify changes. Mass was also included as a covariate to the model. The SL configuration was parameterized as a fixed intercept with the SD and DD configurations modelled as slope coefficients. The model produced $p$-values for changes in performance variables. The rate of Type 1 errors was set to 0.05 for the analysis. Statistical analyses were performed using the JMP software.

**Results:**

Overall, the Dual Dial Configuration generally yielded improvements in certain performance measures over the Standard Lace Configuration. However, comparisons of measures only after the 45-minute endurance run demonstrated no statistically significant differences between the configurations. This leveling of performance after the endurance also yielded a higher decrease in negative eccentric work for Dual Dials, considering they performed better than laces before the run. Each of the five performance measures were compared in the pre and post trials, as well as all together, and in difference.

No differences were found in contact time for any scenario of comparison. Eccentric rate of force development also demonstrated no difference between configurations in all comparisons.

The Dual Dial Configuration saw increases compared to the Standard Lace Configuration in the peak concentric GRF for both pre-run and overall comparisons. The pre-run comparison saw an almost significant increase in peak concentric force of 30.7 N (4.81%) at $p = 0.0584$. For both pre and post trials, the increase was significant at 25.2 N (3.94%) at a $p$ value of 0.025. No significant differences were calculated for post only and differences between pre and post.
The eccentric work similarly saw improvements in pre only and overall comparisons for DD. Pre only comparisons showed 12.3 J (6.1%) less negative work than SL and a reduction of 7.3 J (3.63%) for comparison across pre and post data. In this case, no differences were found for post only, but the change from pre to post run saw a steeper increase in negative work for DD compared to SL at 8.9 J greater change in negative work than the change observed for laces.

For concentric work, DD performed consistently higher than the SL Configuration both pre and post run at 10.3 J (7.13%) and 10.4 J (7.55%) higher, respectively. As a result, DD also performed better than the SL Configuration overall with 10.3 J (7.28%) more work. No significant differences in the changes pre and post run were detected for DD.

No differences were observed in the performance measures for the Single Dial Configuration compared to the Standard Lace Configuration except for a 5.7 J (3.96%) decrease in concentric work in the overall comparison.

Discussion:

This study’s findings that GRF measures of athletic performance in CMJ are improved overall with the Dual Dial Configuration of shoe uppers are in line with Pryhoda (2020). They found that the Tri-Panel configuration, which most resembles the Dual Dial Configuration, decreased ground contact time and increased concentric COM power. These changes were determined for subjects involved in court and field based athletics, which differs from the high-performing endurance runners recruited for this study. The improvement for both populations implies that the benefits of alternative
upper configurations might apply to more general populations rather than just agility trained athletes.

The similar shoes between this study and (Pryhoda, 2020) provided benefits to both groups, but in different measures which is likely related to the populations recruited for each study. The improvements in GRF performance measures observed by Pryhoda (2020) in countermovement jumps for their tri-panel configuration was a 3.3% improvement in ground contact time and a 2.8% improvement in peak concentric mass power. We did not see a change in ground contact time for the runners involved in this study. Conversely, measures of eccentric and concentric work both improved as well as measures of peak concentric force in this study for the DD Configuration, which was not observed in Pryhoda’s (2020) results. McLellan (2011) noted that measures like rate of force development or contact time in countermovement jumps were better correlated to overall performance in explosively trained athletes versus the rest of their subjects. The endurance runners recruited for this study were not well trained in jumping and change of direction movements compared to the subjects recruited for Pryhoda’s (2020) agility study. The difference in training and the outcomes observed in the performance metrics suggests that differently trained populations of athletes, depending on sports, may gain different benefits from alternative upper closure designs. Changes in peak concentric mass power were not analyzed in these results, so we cannot make that comparison.

The lack of change between the SD and SL Configurations in all overall measures except concentric work, for which SL was better, suggests that the greater number of adjustment points on the DD Configurations might have led to the measured improvements. The SD and DD Configurations have similar constructions except that the
DD configuration has two points of tensioning, controlling the upper strap and lower straps separately, where the SD and SL Configurations both only have one point of controlling tension. Pryhoda (2020) claimed that the improved ability of a shoe’s closure system to conform to different foot morphologies could better secure the foot to the lower of the shoe creating a more dynamic fit and potentially improving performance. The two points of adjustment for the DD Configuration allows for a more customizable fit and the improvement in performance measures that result would seem to support Pryhoda’s (2020) claim.

Observations of external mechanics do not allow us to draw any definitive conclusions about the effects of alternative upper designs on resistance to fatigue. Previous studies on fatigue and agility observed changes in GRF measures as well as joint ranges of motion, force, and moments (Cortes 2012, Shultz 2015, Quammen 2012). Evaluations of internal mechanics and ranges of motion might present a more nuanced understanding of how the endurance protocol in this study affected performance in the CMJ activity. These data were collected, and that analysis is ongoing.

**Limitations:**

The population of subjects recruited for this study were endurance runners and not specifically trained for explosive change of direction agility movements like countermovement jumps. The lack of familiarity with the movements may have contributed to changes in their movement approaches both before and after the endurance run in a particular session or between sessions which were separated by multiple days. Pre and post run, a well-trained field or court based athlete might have been able to maintain a consistent technique, allowing for a more direct comparison to be made before
and after the endurance run. Participants in this study on occasion changed their movement technique noticeably pre and post run. The lack of familiarity with the movement might have made their technique more sensitive to their relative fatigue, potentially contributing to why most of the measures were not different between configurations post run. Recruiting subjects who participate in highly fatiguing sports that require proficiency in agility movements, like soccer, might have provided a better comparison for pre and post run measures.

A second limitation was the endurance protocol which had every runner complete a 45-minute run between the agility sessions. Runners recruited for this study, while all relatively high caliber, differed in fitness. A 45-minute run might have completely exhausted one participant and not another. This change in fitness for a 45-minute run may also have been affected by the protocol taking place for each condition separated by at least 2 days. Factors like water consumption, diet in the days preceding, time of day and other variables that affect levels of fatigue post run were not controlled for. Again, this may have led to the 45-minute run having a different impact for the one participant on different days. This fatiguability from athlete to athlete and from collection to collection were not controlled for in the endurance protocol and may have potentially affected pre and post run comparisons. Somehow standardizing fatigue across athletes may have improved our observations.

One more consideration lies with the uncontrolled tensioning of the BOA dials. Dial torques, the measure of the tightness the athletes adjusted the DD and SD shoes to, were recorded before the first agility session, but not before the second. Subjects were required to remove their shoes after the 45-minute run and often readjusted their shoes after the
first agility session. This may have contributed to a difference in fit pre and post run as well as in between sessions in comparisons between SD and DD Configurations.

**Conclusion:**

In summary, a study of 32 endurance runners found that the dual dial alternative fit configuration improved three GRF measures of performance overall. The overall improvement in performance aligns with (Pryhoda et al., 2020), who saw improvements in a court and field-based athletes, indicating that alternative fits might benefit wider populations of athletes. Generally, no differences were detected from agility performance measures that would indicate that alternative fits helped these athletes resist fatigue more than the standard lacing configuration.
Chapter Four: Predicting Ground Reaction Forces with Physics-Based Models of Human Movement

Introduction:

Representations of overall health or physical ability manifest in the biomechanics of human movement. Problems with the central nervous system due to stroke or cerebral palsy result in altered gait. Athletic training also has the ability to encourage more efficient or powerful movements in an athlete. Researchers are often interested in assessing the physics of these motions in order to better understand the pathologies that underlie an issue or to try to find avenues toward enhancing performance. The development of research methods toward these ends would be beneficial.

A complete understanding of the mechanisms of human motion is seldom possible to achieve. Simplified models are used in order to estimate the true nature of what is a vastly complex physical system. Muscle models approximating force generation on the cellular level or multi-segment models of the foot estimating the deformable structural kinematics of the foot are two methods of simplification used in biomechanics. Simplified models and methods of observing the mechanics of motion are employed so that researchers and clinicians may attempt to understand how all of the systems involved in human motion interact while maintaining practical approaches.

Ground reaction forces (GRFs) are one such observation that is key to understanding human motion. GRFs are a necessity in calculations such as those done in inverse
dynamics which allow researchers to estimate forces that are difficult to directly observe like skeletal loads, joint reaction forces, and muscle tensions. The observations of GRFs are often limited, however. The collection of GRFs is typically restricted to laboratory environments with expensive force platforms. The need to collect data in a lab, often in tandem with optical motion capture systems, limits the kinds of movements that can be observed as well as how naturally they can be performed.

A solution to this limitation is to find effective ways to record or estimate GRFs without static force platforms. Solutions in the form of wearable force transducers embedded in shoes or in socks are in development and use in some labs. The extra subject instrumentation involved in these solutions contributes to some similar problems of unnatural or limited movement as with force platforms. Another alternative is to use kinematics and an understanding of the mechanics of human locomotion to estimate GRFs. Simplified mass-spring-damper (MSD) models of the human body have been employed in attempts to quantify parameters involved in human locomotion, including GRFs. The use of inertial measurement units (IMUs) to freely track the kinematics of body segments and center of masses (COM) have also been employed to varying degrees of success. These physics-based methods have the benefit of being derivable from measurable and physically meaningful quantities like position and mass or spring and damping constants. This paper explores the use of physics-based models of human locomotion and dynamics to estimate GRFs in human movement.
**Background:**

It has been argued that simplified models of human motion, despite not representing the full complexity of the system, can be useful in representing components of human motion, like stride length or cyclical motion. Alexander provides perhaps the simplest model of human walking in (Alexander, 1995). Alexander’s example of human walking as a point mass riding alternating pendulums (Figure 6) provides an intuitive insight into the transition point between walking and running, as well as a simple explanation for why astronauts did not walk with a normal gait on the moon.

![Figure 6. Alexander's simplest model of walking: a point mass on an inverted rigid pendulum (Alexander, 1995)](image)

Blickhan (1989) adds to this understanding of walking by including a spring between the mass and the ground to better model the bouncing gait of walking (Blickhan, 1989). With this mass-spring-pendulum model of walking, Blickhan claims that aspects of gait including portions of the GRF can be estimated.
From there, MSD models have been expanded upon in numerous ways to attempt to predict or understand parameters involved in locomotion. (Nikooyan and Zadpoor, 2011) provides a review of MSD models which attempt to quantify the contributions of foot-ground interactions, foot-shoe interactions, and the “wobbling masses” of the body in motion.

Another camp of researchers eschews the use of simplified mechanical models for straightforward dynamics by observing the kinematics of motion. Ancillao et al., 2018, provides a review of attempts to estimate GRFs using different analyses of a variety of configurations of IMUs. These analyses include methods as simple as observing only COM acceleration with a trunk mounted IMU and determining GRFs using Newton’s second law to more complex models using 17 IMUs and a full link-segment model of the body to accurately predict GRFs in all 3 directions during walking. IMUs are advantageous toward the goal of finding GRFs without force platforms as they provide a form of motion capture that can also be taken out of laboratory settings to observe segment kinematics.

Between these two camps some success has been achieved in estimating GRFs, but a reliable and robust solution has yet to be reached.

**Previous Investigations:**

**Mass Spring Damper Models of Gait:**

MSD models have been explored since the late 1980’s, starting with the works of Alexander, Blickhan, and McMahon. Research in this area has iterated on MSD models to explore a variety of physical parameters in gait. What has not been fully evaluated,
however, is whether or not these models act as true representations of lower body mechanics, or if the results are merely coincidental. This distinction would identify whether or not these models would be the best candidate for predicting GRFs outside of the lab.

Blickhan’s mass-spring pendulum model (Figure 7) was presented in 1989, but the work of Bullimore et al. (2007) sought to validate it as a predictive tool. This study investigated the feasibility for Blickhan’s model to predict 10 kinetic and kinematic parameters, including stride length, peak force, and impulse, and to validate previous theoretical work which concluded that the MSD model would over predict horizontal GRFs. The kinetics, kinematics, and mass of 10 runners from a previous study were used as input parameters for initial velocity and angle. These data were also used to evaluate the agreement of the predictions.

Figure 7. Blickhan's mass-spring pendulum model as represented in (Bullimore and Burn, 2007). \( l_0 \) represents the neutral length of the spring, \( \theta_0 \) is the landing angle, \( x_c \) is the horizontal contact distance, \( \Delta y \) is the distance the point mass, \( k \) is the spring stiffness, and \( m \) is the point mass. Notations 1, 2, and 3 show the landing, midstance, and takeoff phases of gait respectively.
The predicted values were compared with the same experimental values from collected kinematic data and an instrumented force treadmill (Figure 8). Of the parameters observed, 6 of 10 of the calculated parameters were predicted well by the model. Stance time, vertical impulse, contact length, duty factor, relative stride length, and relative peak force were within 20% of the experimental values. The authors claim that this implies that the simplified model must account for the biomechanical features that play a role in these parameters.

The authors noted features missing from the model as reasons for poorly predicted parameters. The ideal pendulum model did not account for movement of the center of pressure along the foot which affected predicted horizontal GRFs. Additionally, aerial time was overestimated due to the symmetry of the model’s landing and takeoff heights, which is not characteristic of human locomotion.

Figure 8. An example of a vertical GRF profile predicted by Blickhan's model (SM) compared to experimental data (exp) (Bullimore and Burn, 2007)
This work acts as one piece of evidence which supports the use of MSD models as a predictive tool. Bullimore et al. provide reliability to the developments and iterations attempting to account for the limitations of Blickhan’s model.

The authors conclude with a major question for MSD models. How is the behavior of the body which resembles that of an MSD system implemented? In other words, does the anatomy of the lower body act as an MSD system during running, or is it coincidental that the behaviors match? Studies on the elastic and passive properties of musculoskeletal tissues support the notion that the body stores and releases energy elastically during running (Alexander, 1984), but MSD models are often entirely passive where the human body locomotes actively.

Following Bullimore’s suggestion that missing features account for MSD model prediction inaccuracies, more complex MSD models might come closer to reliable estimations. The MSD model developed by Liu and Nigg (Liu and Nigg, 2000) accounted for yet another biomechanical factor that previous models had not accounted for. This model included both rigid and ‘wobbling’ masses simulating soft tissues (Figure 9). The masses of this model were also distributed to represent the upper and lower body. The objective of this study was to determine how the mass distribution represented on an MSD model would affect running. Using a model was advantageous for this study because human body mass distribution is a challenging independent variable to control.
The study ran several simulations to account for varying speeds of impact, foot-ground stiffnesses, and various distributions of mass. They were successful in recreating the passive and beginning of the active peaks of the vertical GRF profile (Figure 10). The authors avoided the latter half of the force, saying that their model would not accurately represent that and were able to evaluate the effects of each mass and stiffness variable of interest. Their finding aligned with previous research on the topic.

The authors acknowledged in the discussion that their model was only able to predict some of the parameters of human running by its nature, echoing the sentiment of Bullimore that adding more physical features might step estimations closer to full reliability. They cited a lack of neuromuscular control implemented to change stiffness and damping coefficients actively during impact as one major shortcoming of a passive model. This also explains why they only observed the initial passive peak of the GRF profile, ignoring the active peak.
Figure 10. Examples of predicted vertical GRF profiles from (Liu and Nigg, 2000). The left shows the effect of shoe hardness on the passive peak of the early waveform. The right shows the effect of landing velocity on the early peak of the waveform.

While this study was successful at describing the effect of certain input parameters on the outcome of a GRF profile, a pattern begins to emerge. Despite the high level of complexity compared to previous models, this MSD model was still incomplete. It served the purposes of the study, but the authors still recommended further improvements. The usefulness of this model outside of its intended purpose is limited. 14 mechanical parameters are required to calculate the equations of motion which have also been abstracted from specific physical meaning. Based on this study, it is difficult to see how a model like this could be used on an individual subject level in a clinical or training setting.

For the models discussed here, empirical kinematic data only served as initial conditions to the system dynamics. One might expect that if an MSD model could represent lower body mechanics that inputting time-series kinematics into the system would output accurate parameters as a result. Nedergaarde et al. (2018) attempts this, motivated by the possibility of measuring GRFs outside of the lab.
Using a simple MSD model, the measured resultant accelerations of the trunk segment from 20 runners were inputted as the acceleration of the representative upper body mass. The authors created an optimization procedure to fit the mechanical parameters of the model to the recorded acceleration and then calculated and compared resultant GRFs to measured GRFs. For comparison, the same procedure was done in reverse: using the resultant GRF profile from a force platform to calculate an estimated trunk acceleration. Their results (Figure 11) showed poor relationships between predicted GRFs and measured GRFs. The root mean square error (RMSE) of the predicted GRFs increased with the experimental running speeds, starting at 6.68 N/kg at 2 m/s to 12.77 N/kg at 5 m/s. The authors concluded by saying that they would not recommend using accelerometry as an input to an MSD model.

Figure 11. Examples of the outcome of fitting measured trunk acceleration to Nedergaarde's MSD model. The top row (A) shows the measured acceleration (black line) and the matched model acceleration (dotted red line). The second row (B) shows the model's GRF output (dotted red line) overlayed on the measured resultant GRF profile
Their conclusion seems counterintuitive. Newton’s laws would have us believe that there is a direct relationship between forces and acceleration. During running, if drag is neglected, the only external forces that act on the runner are gravitational forces and GRFs. The acceleration of the body’s segments should be directly related to the GRFs which occur during contact. Nedergaarde’s results more support the notion that MSD models do not represent the dynamics of biomechanical systems. These models can be designed to align with certain principals of human mechanics, but these studies do not show that they model the real dynamics of the human body.

**Dynamics Based Predictions of Ground Reaction Forces:**

The work of Clark et al. (2014) specifically eschews the predictions of MSD systems, citing limitations due to numerous input variables, post hoc analyses, and the inability to analyze both running and sprinting gait without changes. The authors instead propose a method of vertical GRF estimation using curve fits derived from the impulse of two anatomical masses: the lower leg and the rest of the body. The only other inputs included were contact and aerial times of the foot during different running speeds.

The raised cosine bell curve predictions (Figure 12) fitted to data collected from 42 subjects running at a range of speeds showed good fits between predicted and measured vertical wave forms with R2 values of 0.96±0.03. This goodness of fit was consistent among speeds ranging from jogging to sprinting and runners with fore and rear foot striking; a range which the authors note most MSD models cannot predict. They conclude
that this model shows vertical force waveforms are largely governed by the motion of only two major masses of the human body.

Figure 12. Clark and Weyand's model to predict vertical GRF profiles. Graph A shows experimental force data from 5 steps at 3 m/s. Plot B shows the 2 RCB curve functions individual and combined fitted from the average data of steps 1, 3, and 5 from plot A. Plot C compares the real and modeled GRF profile (Clark et al., 2017)

This method is limited in its scope. They claim it could be used as a tool for analyzing gait in clinical settings or for wearable force prediction. However, the fundamental element of their prediction, the raised cosine bell curve functions, seem as if they could only predict the ideal vertical running waveform. They do not show that the forces for individuals with altered gait or motions outside of running might be predicted by their method. Similar to MSD models, the curves fit to match the vertical running GRF might only align with specific biomechanics, not represent them.
Instead of using kinematics to fit curves, using the kinematics of the entire system might prove more realistic. In an iteration of the work of Ren et al. (2008), Karatsidis et al. (2017) tracked the kinematics of walking using 17 IMUs and a link-segment model of the entire body, seeking to predict GRFs and ground reaction moments. The authors also tried to solve the dynamic indeterminacy problem of calculating GRFs during the double support phase of walking.

![Figure 13. The Xsens MVN link-segment model used by (Karatsidis et al., 2017).](image)

The walking kinematics of 11 subjects were recorded with both inertial and optical motion capture and a set of force platforms. A ‘smooth transition assumption’ was implemented during the double support phase to assist in predicting the transition in load from foot to foot. The predicted GRFs from both motion capture systems proved to be similar. High correlation coefficients and low root mean square errors were recorded for
the inertial system in for all walking speeds in the single stance phase for the sagittal and transverse planes of force when compared to the force platform ($\rho = 0.749 – 0.940$, $\text{RMSE} = 0.004 – 0.020$). The frontal forces yielded worse correlations.

![Figure 14](image)

**Figure 14.** Comparisons between measured and optical motion capture predicted GRFs in anterior, lateral, and vertical directions normalized to body weight (BW). The thin gray line and shaded area shows predicted values ± 1 standard deviation. The thick black line and thin black lines show force platform values ± 1 standard deviation (Karatsidis et al., 2017).

This study demonstrated a remarkable ability to predict GRFs using a full body set of IMUs. The authors did note a number of limitations. The largest were related to many of the drawbacks that are inherent and well documented in IMU systems including noisy
data, interruptible heading and reference systems, and the number of transformations the
data underwent to represent COM accelerations. Some of the deviations from the
measured force platform values were also attributed to relatively low forces and
movement speeds in walking. A sensitivity analysis performed in this study suggested
that mass and inertial estimations play a major factor in the accuracy of the predictions.

In their conclusion, the authors suggest a system requiring fewer IMUs, simplifying
the system for ease of use. Other studies have attempted to drop the number of IMUs
involved down to just 1 using only dynamics (Wundersitz et al., 2013) or aiding the data
with machine learning (Mohamed Refai et al., 2020). The literature does not appear to
have many attempts at intermediate steps such as reducing the number of segments to 7,
representing the lower body and HAT segments, which aim to take GRF measurements
out of the lab.
Chapter Five: Ground Reaction Force Predictions during Agility Movements using Effective Force

Introduction:

Motivation:

Collecting reliable biomechanical data during human movement requires a network of instruments confined within a laboratory environment. Biomechanics labs often restrict movement to calibrated motion capture spaces or require movements to take place while contacting small force platforms embedded in the ground. The size of these spaces also lacks the flexibility to be moved with almost all standard tools built for a stationary laboratory. Moreover, these tools are prohibitively expensive with costs well over $10,000 for a small optical motion capture setup.

Fortunately, advancements in inertial measuring unit (IMU) technology have allowed for the portability of kinematic data collections, prompting the notion of a ‘portable biomechanics lab’. Given reasonable ranges of data streaming from IMU devices, or onboard memory in an IMU, the opportunity to collect kinematic data in the true context of a motion, like on a running trail or on a crowded basketball court, becomes a possibility where optical motion capture (OMC) would be impossible to practice. IMU systems will still require some development in order to match the quality of data provided by OMC due to noisy measurements from accelerometers, problematic drift in gyroscopes, and the overall challenges of tracking position in a global reference frame.
Unfortunately, kinematic data on their own do not provide as much insight into the mechanics of movement compared to just ground reaction forces or the combination of the two. Ground reaction forces (GRFs) measured on their own can provide specific mechanical insight on ground-foot interactions and are also necessary for inverse dynamics calculations when combined with kinematic data. Kinematics on their own can provide useful information on joint ranges of motion or speed, but the single type of data restricts analysis to just a surface level understanding of movement.

One alternative to measuring GRFs directly is to utilize the effective force of movement which results from GRFs. Effective force, sometimes referred to as inertial force, is the force resulting from the net applied force on an object which is equal to the mass times the acceleration. Ground reaction forces are one of the few external forces involved in movement, so a knowledge of a body’s kinematics through the lens of “force equals mass times acceleration” might yield GRFs. The ability to predict GRFs with portable motion capture tracking the effective force of a body may potentially allow for full inverse dynamics analysis to be possible outside of the lab with only a few, relatively inexpensive, IMUs.

**Previous Work:**

*Effective Forces in Movement Analysis:*

Effective forces have been explored in biomechanics literature in the past, though not for the purpose of replacing a force platform. The work of Thornton et al. (1975) used the relationship between GRFs and effective force to evaluate the sensitivity of inverse dynamics calculations to mass and length parameters estimated for body segments.
Bobbert et al. (1991) used effective force calculations to characterize the different frequency contributions of body segments to a typical running GRF profile. Additionally, Koopman (1995) used effective forces to estimate unmeasured segment kinematics with a combination of optimization and inverse dynamics calculations.

**Effective Forces in Force Prediction and Inverse Dynamics:**

Effective forces have been explored in biomechanics literature in the past, though not for the purpose of replacing a force platform. The work of Thornton et al. (1975) used the relationship between GRFs and effective force to evaluate the sensitivity of inverse dynamics calculations to mass and length parameters estimated for body segments. Bobbert et al. (1991) used effective force calculations to characterize the different frequency contributions of body segments to a typical running GRF profile. Additionally, Koopman (1995) used effective forces to estimate unmeasured segment kinematics with a combination of optimization and inverse dynamics calculations.

Methods utilizing effective forces have been explored for inverse dynamic calculations for walking gait with the express purpose of forgoing force platforms. Hardt (1980) demonstrates potentially the earliest attempt to perform inverse dynamics calculations using effective force, but their method was not validated against a force platform’s measures. More recently, Ren (2007) and Karatsidis (2016) attempted inverse dynamics calculations with the effective forces of walking gait, using optical and inertial motion capture, respectively. Ren measured the effective forces of a 13-segment model and Karatsidis used Xsens IMUs to construct a 17-segment effective force model. Both
studies found some reasonable accuracy in inverse dynamics calculations for walking gait that matched well with the data calculated with measured GRFs.

Both studies had some notable shortcomings in their approach that would likely restrict the methods’ use in analyses for general movements. First, the kinematics were lowpass filtered at extremely low cutoff frequencies of 4.5 Hz and 6 Hz. This might be sufficient to capture the frequency of limb movement during walking, which is a slow and low-impact movement, but agility and higher speed motions would almost certainly lose meaningful kinematic information at such a low cutoff. To contrast, many agility studies (see chapter 2) filter OMC marker kinematics between 10 and 20 Hz to account for the speed and frequency of agility motions.

Second, both Ren and Karatsidis attempted to apply a smooth transition assumption in order to solve the indeterminacy problem that results during the double stance phase of walking. The effective force method cannot resolve multiple GRF vectors in a double stance movement, so they applied the assumption that typical walking gait smoothly shifts the body’s weight from one foot to the other. While this worked well for them, this kind of assumption cannot necessarily be used for all human movement and restricts their methods’ use to only typical gait.

Third, these studies spent little time evaluating the accuracy of predicted GRF profiles in comparison to the results of their inverse dynamics calculations. The potential for this method to replace force platforms opens it up to both external and internal evaluations of movement mechanics. Thus, it is essential that a strong understanding of what aspects of effective force contributes to the force profiles typically seen in force
platform data. Effective forces need to be shown that they can reliably predict this external level of information before they can be applied to internal levels.

It is worth noting the interesting implications that could come with using EFs as the basis for inverse dynamics calculations instead of traditional FP input. Bisseling (2006) and Edwards (2011) have both attempted to address the problem of impact artifacts appearing in joint moment and force calculations when following traditional inverse dynamics by suggesting either filtering both marker kinematic data and FP data at the same cutoff frequencies or filtering joint mechanics data only after all of the calculations have been completed. Fluit (2014) pointed out that the apparent artifacts might be due to a redundancy and contradiction between the effective force of each segment and the input of FP data for GRFs. Fluit argued that calculating GRFs using effective forces would remove that redundancy and avoid the artifacts.

**Limited Kinematics for Force Prediction with Machine Learning:**

In their conclusion, Karatsidis et al. called for further investigation into the method, noting the potential for an effective force method which tracks fewer segments of the body: a reduced segment model. Kinematic predictions of GRFs with less than full body kinematics have been explored, but overwhelmingly with the assistance of machine learning. Single- and reduced-segment models have been explored. Wouda (2018) used 3 IMUs attached to the lower legs and pelvis with an artificial neural network (ANN) to predict both knee joint angles and vertical GRFs during running with high correlation coefficients between 0.96 and 0.99 and low RMSE values ranging from 0.09 to 0.25 Newtons. Refai (2020) used a single IMU affixed to the pelvis to attempt to predict both
shear and vertical forces during different walking tasks. Their predictions yielded middling correlation coefficients ranging from 0.29 to 0.81 depending on the GRF direction and normalized RMSEs were found from 4.4 to 7.0%. Johnson (2018) trained a machine learning algorithm by data mining optical motion capture data tracking 5 segments, getting correlation coefficient values for GRF predictions ranging from 0.88 to 0.99 during running.

These explorations of both walking and agility movements use motion capture including OMC, IMUs and even computer vision (Zell, 2019). Machine learning methods have the major downside, however, of needing to be trained by data covering a large and spanning state space that encompasses all needed kinematics for a desired movement. This lends these methods to the problem of overfitting, or accuracy in only what they have been trained for, which does not lend itself to a flexible method of predicting forces for general movements of all kinds.

**Our Approach:**

This work seeks to expand our understanding of what may contribute to the reliability of a pure physics-based method for predicting ground reaction forces. The effective force method of predicting ground reaction force profiles presented here is a proof of concept for more general methods for GRF prediction which may predict a range of high speed and impact motions. We also explore how reducing the number of segments observed in a given motion from a 13-segment, full body set to a 7-segment lower body model or a 1-segment model might affect force predictions. Finally, this paper explores how GRF predictions might be improved by filtering the kinematics of different segments of the
body at different cutoff frequencies, taking inspiration from the work of Bobbert (1991) and also Clark and Weyand (2016).

Three main hypotheses are considered in this manuscript. First, we hypothesize that a full 13-segment effective force model will be able to accurately predict GRF profiles for a variety of agility movements in all 3 directions of motion. Second, we hypothesize that a reduced 7-segment, lower body effective force model will be able to predict GRF profiles with only a small reduction in accuracy compared to the 13-segment model and that a 1-segment model might be able to predict some features of force profiles well. Last, we expect differing lowpass cutoff frequencies by segment will help to improve the method’s prediction of force profiles.

Methods:

Data Processing:

Ground Reaction Forces:

GRFs were collected at 1000 Hz from a set of four AMTI force platforms (FP). The data were decimated to 100 Hz to match the sampling rate of the kinematic data. Once decimated, these data were filtered with a zero-phase lag Butterworth filter with a 45 Hz lowpass cutoff frequency to remove any high frequency noise resulting from the analog to digital conversion in the signal. Initial ground contacts during motion were identified when the vertical force measured over 20 N and were ended when the force decreased passed that value.
**Effective Force Method:**

*Calculating Effective Force:*

The method for predicting ground reaction forces is derived in the manner of Ren et al. (2007). The effective force (EF) of a rigid body is defined as the body’s mass multiplied by the linear acceleration of the body’s center of mass (COM) relative to a Newtonian reference frame, $N$. For a rigid link-segment model $B$ with $n$ rigid segments, the EF of the system can be calculated by the sum of the EFs of each of $B$’s segments set equal to the sum of $m$ external forces on the system (Equation 1).

$$
\sum_{i=1}^{m} \mathbf{\hat{F}}_{i,ext}^B = \sum_{j=1}^{n} \left( m_j \times N\mathbf{\hat{a}}_{COM}^B \right) \quad (1)
$$

When drag is assumed to be negligible, the only external forces involved in agility motions are ground reaction forces and gravitational forces. Most of this information can be known. Gravity is a known quantity and the kinematics of the body as a link-segment model collected from motion capture techniques provides COM accelerations. Some assumptions about mass and length properties derived from sources like (de Leva, 1996) provide us with all of the quantities needed to solve for GRFs. Thus, subtracting the gravitational force on each segment from the effective force of each segment results in a formula which solves for unknown ground reaction forces (Equation 2).

$$
\mathbf{\hat{F}}_{GRF}^B = \sum_{j=1}^{n} \left( m_j \times \left( N\mathbf{\hat{a}}_{COM}^B - N\mathbf{\hat{g}}^B \right) \right) \quad (2)
$$

This formula can identify a GRF vector during a single contact, however during motions involving double stance (standing, walking, countermovement jumps), it would
be impossible to quantify different GRF vectors applied at the left foot or the right foot without additional information.

*Link-Segment Model:*

13-segment, 7-segment, and 1-segment EF models were developed to predict GRFs (Figure 15). The mass proportions and COM locations for each segment were determined using fits from (de Leva, 1996). The 13-segment model includes feet, lower leg, upper leg, pelvis, thorax, upper arm, forearm, and head segments. The trunk is modeled as 2-segments, the pelvis and thorax, and the mass of the hands are lumped in with the forearms. COM location calculations from de Leva were adjusted for the lumped segments in this model.

The 7-segment model includes feet, lower leg, upper leg, and pelvis segments. The mass of the upper body was lumped into the mass of the pelvis segment. The location of the center of mass was not adjusted for the lumped upper body masses in this model.

The 1-segment model estimates the whole body COM as the pelvis COM used in the previous models. The entire body’s mass is lumped into this single segment.
Figure 15. Illustration of the multi-segment model including feet, lower legs, upper legs, pelvis, thorax, upper arms, lower arms, and head segments. The three reduced segment models are highlighted.

**Kinematic Lowpass Cutoff Frequency Choice Methods:**

We hypothesized that filtering the kinematics of each segment differently according to the motion might improve the EF prediction’s accuracy. A standard, power spectrum density, and optimization methods of choosing cutoff frequencies for each segment were employed for each activity. Each set was compared using the variations of cutoff values within an activity and the accuracy of the resulting prediction.

*Standard Filtering Frequency Selection Method (10 Hz):*

As a standard, the first method filtered all of the segment position kinematics with a lowpass cutoff frequency of 10 Hz. This value was chosen to be higher than the 6 Hz and 4.5 Hz used by Karatsidis and Ren, respectively, to accommodate for the faster movements and to match more closely with other agility studies which tend to use lowpass cutoffs between 10 and 20 Hz in traditional kinematic analyses.
Cumulative Power Spectrum Density Frequency Selection Method (PSD):

This frequency choice method uses the calculated frequency content of the measured kinematics for each segment to determine a cutoff frequency unique to that segment. Each cutoff is determined in the manner of (Sinclair, 2013). The Fast Fourier Transform is applied to unfiltered position data for each segment and the cumulative power spectrum density (PSD) is calculated using the cumulative numerical integration of that data. Setting the maximum value of the PSD to 100%, corresponding frequencies can be determined at different levels using assumptions of what percent of the power contributes to noise or signal (Figure 16). We evaluated three levels in this work: 90% PSD, 95% PSD, and 97.5% PSD.

![Cumulative Power Spectrum Density: Right Foot Vertical Kinematics](image)

**Figure 16.** Selection of a right foot segment cutoff frequency at 95% PSD

Optimization Cutoff Frequency Selection Method:

This frequency choice method optimized segment cutoff frequencies to directly reduce error in the EF prediction. Interior-point optimization was used a systematic
method of reducing error by altering the cutoff frequencies of each segment during each contact of each activity. During the optimization, the lowpass cutoff frequencies of each segment were varied as input parameters with the minimization of vertical RMSE values between EF and FP measures of force for a given contact set as the cost function. The optimization was run for the 13, 7, and 1 segment EF models separately.

**Comparisons:**

Predicted GRF outcomes were compared to the measured GRFs by both the time series profiles and dependent variable point estimates used in agility based investigations depending on the activity observed.

*Time-Series Comparisons: RMSE and rRMSE*

The time series comparisons were made from the beginning to end of each contact using RMSE and relative RMSE (rRMSE) similar to Karatsidis et al. (2018). The rRMSE describes the time-series root mean square error as a value relative to the average range of the two signals. These measures provided some insight to the overall accuracy of a given contact in the prediction. The relative measures were also used for comparison across movements with greater or lesser peak forces. The use of rRMSE by Karatsidis served as a basis for comparison of the efficacy of their gait study and this study on agility.

*Point Estimate Comparisons: Dependent Variables used in Agility Investigations*

Peak force was defined as the maximum value in the force profile and was calculated for each prediction and for the measured force profile in a direction of interest. Rate of force development was defined as the average slope of the force profile from contact to
the instance of the peak force calculated using a 5-point numerical derivative along a
direction of interest.

*Point Estimate Comparisons: Bland-Altman Limits of Agreement*

Bland-Altman Limits of Agreement (LoA) (Bland and Altman, 1986) were employed
to evaluate the accuracy and precision of point estimates for peak force and average rate
of force development in the direction of interest for certain activities. Bland-Altman plots
provide insight as to how a prediction might over or underestimate a point estimate
compared to another standard over a range of measurements. An ideal Bland-Altman plot
would cluster predicted data horizontally along a negligible bias above or below 0. A
flawed prediction might show data in a consistent horizontal bias parallel to 0 or begin to
show either positive or negative bias as the magnitude of the measure changes.

The LoA were used to compare the range one might expect a prediction to calculate a
value relative to the true value. The LoA plots show vertical bars which represent a range
of plus or minus two standard deviations calculated from the variation of the predicted
values. Particularly wide LoA show an unreliable method which may vary greatly from
the true value where smaller ranges show a more precise prediction method.

*Frequency Selection Method Comparisons:*

Means and standard deviations of cutoff frequencies for each frequency choice
method were calculated and depicted in heat maps on link segment model illustrations.
The means of each frequency choice compared with the evaluated accuracy of each
 corresponding activity provided insight to which segments must be filtered at certain
rates either to reduce error from soft tissue noise or other sources or increase accuracy by avoiding the attenuation of predicted force profile features.

**Data Collection:**

**Participants:**

Three participants were recruited to participate in this study. Each subject wore their own athletic wear and were provided with shoes of an appropriate size that were fitted with Velcro straps to affix motion capture equipment to.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Subject 2</th>
<th>Subject 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex:</td>
<td>Male</td>
<td>Female</td>
</tr>
<tr>
<td>Age (years):</td>
<td>24</td>
<td>23</td>
</tr>
<tr>
<td>Height (cm):</td>
<td>182.9</td>
<td>165.2</td>
</tr>
<tr>
<td>Mass (kg):</td>
<td>78.93</td>
<td>55.5</td>
</tr>
</tbody>
</table>

**Experimental Setup:**

Participants were outfitted with 13 rigid retroreflective marker clusters affixed to 13 body segments (Figure 15). Each activity was performed at BOA Technology Inc.’s Performance Fit Laboratory. The overground space is equipped with four AMTI force platforms and 12 Vicon cameras. Kinematic and kinetic data were streamed at 100 Hz and 1000 Hz, respectively, through the Vicon Nexus software into The Motion Monitor software for pre-processing.
**Activities:**

The ground reaction forces and kinematics for Drop-Landing (DL), Jogging (JG), Lateral Skater (LS) and Simulated Trail (ST) movements were collected. Each activity was selected for increasing complexity of motion in order to assess the EF method’s predictions in different scenarios. Examples of each observed GRF profile are shown below in Figure 17.

![Comparison of Measured Force Profiles From Each Activity](image)

**Figure 17.** Force platform measures of the vertical (v), lateral (l), or horizontal (h) forces from each activity

**Drop Landing (DL):**

Participants stood on a box 7 inches above the force platform, stepping off to land on their right leg in the force platform (Figure 18). The duration of the contact was calculated from when the measured vertical GRF exceeded 20 N to half a second later
after the participant had steadied their motion. The EF prediction was evaluated using Bland-Altman limits of agreement for the peak vertical GRF value.

This activity was included for the distinct impact peak in the vertical GRF profile which typical filtering parameters might attenuate in a pure kinematic prediction of force. In the usual vertical GRF profile, this peak occurred within the first 50 ms of contact. The magnitude of the peak also tended to be higher than the vertical GRF magnitudes in the other activities discussed below.

![TMM animation output of the drop landing exercise before (left) and after (right) dropping.](image)

**Figure 18.** TMM animation output of the drop landing exercise before (left) and after (right) dropping.

*Jogging (JG):*

Participants were instructed to jog across the force platforms at a slow self-selected pace. During each trial, 2 right foot contacts were collected across three consecutive force platforms. The subject performed this activity using a rearfoot striking pattern. The EF
prediction was evaluated using rRMSE, RMSE, and Bland-Altman LoA for peak vertical GRF and vertical RFD.

This activity was included due to the well documented vertical force profile in jogging. Where the drop landing had the impact peak as a single feature of interest, the vertical GRF profile for rear-foot strike jogging has a notable impact peak as well as an overall propulsive peak in its profile.

*Lateral Skater Jump (LS):*

Participants began this activity standing 1 meter to the left of a force platform. When instructed, the participant jumped from left to right, switching directions to jump back as quickly as possible while making contact with the force platform. The activity was analyzed with RMSE and rRMSE in the lateral direction as well as Bland-Altman LoA for peak lateral GRF and lateral RFD.

This activity features a more complex range of motion than jogging or drop landing as there are significant changes in direction both in the vertical and the lateral planes of motion.
Figure 19. TMM animation output of the lateral skater jump

*Simulated Trail Motion (ST)*:

Subjects ran across the overground lab leaping laterally on and off the force platforms as they continued forward (Figure 20). The EF prediction was assessed using RMSE and rRMSE for each direction of motion.

This activity includes motion in all three planes. The force profiles for this motion have the greatest magnitude in the vertical direction, followed by the lateral direction, then the least horizontally. The relative accuracy of the EF prediction in each direction may provide insight into the ability for EF to predict more ‘improvisational’ movements that might feature in a trail run or in sudden, small corrections on uneven terrain.
Figure 20. The simulated trail motion progression in TMM’s animation output

Results:

Drop Landing:

Each EF model and frequency choice method consistently underestimated the true peak force in DL (Figure 21) in six repetitions of this activity. The Bland-Altman plots developed for the predicted impact peak force demonstrated negative biases in all models and frequency choice methods except for the single segment model with 10 Hz cutoffs (Figure 22). There was less bias with higher cutoff frequencies in the pelvis and thorax segments demonstrated by the 10 Hz and 97.5% PSD frequency choice methods (Figure 23).
Figure 21. One representative contact of predicted vertical GRF profiles for DL using each model and frequency choice method.
Jogging:

The EF method predicted the overall vertical GRF profile as well as its point estimates with reasonable accuracy. 31 repetitions of this motion were collected. The 13 and 7-segment EF models with PSD frequency choice methods had similar rRMSE and RMSE values to the 13 and 7-segment 10 Hz method outcomes, with the exception of the 7-segment 97.5% PSD, at close to 10% rRMSE (Figure 25). The single segment for the 90% PSD method yielded a lower rRMSE than the single-segment 10 Hz model by almost 4%. Overall, the optimized frequency method held the lowest RMSE values for all 3 EF models at close to 8% or 0.15 BWs for the 13 and 7-segment models. Qualitatively, the optimized vertical GRF profile was also capable of showing the rear-foot strike.
impact inflection 12 of the 19 times it was apparent in the measured force profile (Figure 24).

![Vertical GRF Predictions during Contact: Jogging](image1)

**Figure 24.** A contact of the vertical ground reaction force profile for jogging.

![Comparison of Vertical GRF Predictions: Jogging](image2)

**Figure 25.** RMSE (left) and relative RMSE (right) comparing predicted and measured vertical force profiles in jogging.
The Bland-Altman plots for peak vertical GRF and RFD maintained small biases without any consistent under or over estimation across frequency choice methods (Figure 26, Figure 28). The 97.5% PSD frequency choice method in the 1-segment model showed the worst agreement, including a skewed distribution in the rate of force development.

The LoA were similar to the 10 Hz method for the 90% PSD, 95% PSD and Optimized frequency choice methods between each segment model, ranging across less than 2 BW for peak vertical GRF measures (Figure 27) and less than 15 BW/s in vertical RFD (Figure 29).

Figure 26. Peak vertical GRF Bland-Altman plots for Jogging across each model and frequency choice method.
Figure 27. Limits of Agreement for peak vertical GRF across EF models and frequency choice methods.

Figure 28. Bland-Altman plots for vertical RFD in jogging for each EF model and frequency choice method.
Figure 29. Limits of Agreement for vertical RFD across EF models and frequency choice methods.

In the frequency layout (Figure 30), the optimized frequency choice method, which maintained strongest agreement in all measures, had frequencies of 31.90 Hz and 20.29 Hz for the right and left feet in the 13-segment model, respectively. Similarly, the 7-segment model’s feet were optimized to an average 29.33 Hz and 20.97 Hz for the right and left feet. The rest of the lower body segments were all above 10 Hz with the upper body holding below 10 Hz with the exception of the arms.
Lateral Skater:

The lateral skater activity, which involves significant motion in both vertical and lateral directions, performed slightly worse in the lateral direction than was observed for the vertical profile in jogging, but maintains strong agreement in its point estimates.

Thirty repetitions were collected for this activity. In direct comparison to the absolute RMSE for the vertical profile in jogging, the lateral skater’s lateral forces had smaller absolute RMSE values, ranging from less than 0.1 to less than 0.15 BWs in all but the 97.5% PSD frequency choice method, but somewhat higher rRMSE values, ranging from 10 to 15% in 13 and 7-segment EF models with all FCMs except 97.5% PSD, due to the lower magnitude of force applied laterally.

Figure 30. Chosen cutoff frequencies by frequency choice method for each EF model.
Figure 31. A representative contact for the lateral GRF of the lateral skater activity.

Figure 32. RMSE and rRMSE values for the lateral GRF profile in the lateral skater activity.
Bland-Altman plots for both peak lateral GRF and lateral RFD showed no consistent under or over estimation in calculated average biases for both measures. The 97.5% PSD method showed a skewed distribution for all three EF models for calculations of peak lateral GRF. Bland-Altman plots for RFD showed slightly skewed distributions for 7 and 1-segment EF models in all frequency choice methods except in 90% PSD.

LoA for peak lateral GRF maintained similar ranges compared to the vertical peak GRF LoA in jogging. The 97.5% PSD frequency choice method was the exception with wider ranges from plus or minus 0.3 to 0.6 BWs, increasing with reducing segment numbers. Lateral RFD had improved LoA compared to vertical RFD in jogging with a minimum range of plus or minus 2.57 BW/s for the optimized 13-segment model and a max range of plus or minus 6.97 BW/s for the 97.5% PSD 7-segment model.

<table>
<thead>
<tr>
<th>Biases</th>
<th>13</th>
<th>7</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>90% PSD</td>
<td>-0.060</td>
<td>-0.095</td>
<td>-0.177</td>
</tr>
<tr>
<td>95% PSD</td>
<td>0.024</td>
<td>-0.027</td>
<td>-0.054</td>
</tr>
<tr>
<td>97.5% PSD</td>
<td>0.057</td>
<td>0.020</td>
<td>0.059</td>
</tr>
<tr>
<td>10 Hz</td>
<td>0.111</td>
<td>0.050</td>
<td>0.044</td>
</tr>
<tr>
<td>Optimized</td>
<td>0.041</td>
<td>0.014</td>
<td>-0.212</td>
</tr>
</tbody>
</table>
Figure 33. Bland-Altman plots for lateral GRF measures in the lateral skater activity.

Figure 34. Limits of Agreement for peak lateral GRF in the lateral skater activity.

Figure 35. Bland-Altman plots for lateral RFD measures in the lateral skater activity.

70
Figure 36. Limits of Agreement for lateral RFD measures in the lateral skater activity.

**Simulated Trail Motion:**

All EF models and frequency choice methods poorly estimated all three directions of force simultaneously during the transverse jog activity. 12 repetitions were collected for this activity. Predicted vertical GRFs held the strongest alignment with the measured force profile with a minimum average rRMSE value of 12.12% for the optimized 7-segment model and all other 13 and 7-segment EF models near 15% rRMSE with the exception of the 97.5% PSD frequency choice method. The 13-segment model at 97.5% PSD had its smallest average rRMSE at 22.5%. The horizontal and lateral RMSE and rRMSE values were all higher than the vertical RMSE values. The optimized 13-segment model had an average rRMSE value of 26.65% as one specific example of the lack of alignment in the shear forces.
Figure 37. A representative horizontal GRF profile from the simulated trail motion.

Figure 38. A representative lateral GRF profile from the simulated trail motion.
Figure 39. A representative vertical GRF profile from the simulated trail motion.

Comparison of Horizontal GRF Predictions: Simulated Trail Motion

Figure 40. RMSE and rRMSE values for the horizontal GRF profile in the simulated trail motion.
Figure 41. RMSE and rRMSE values for the lateral GRF profile in the simulated trail motion.

Figure 42. RMSE and rRMSE values for the vertical GRF profile in the simulated trail motion.
Discussion:

Ground reaction forces were predicted using the effective forces calculated for all three link segment models using the five different cutoff frequency choice methods. Each predicted GRF was compared over the contact time determined from the measured GRFs. The 13-segment EF model with the 10 Hz frequency choice method was used as the baseline to compare all other models and methods to.

Our three hypotheses were evaluated by the exploration of this proof of concept method. The first was that the full 13-segment model would be able to accurately predict ground reaction force profiles in all three planes of movement for agility activities. The second hypothesis stated that the 7-segment model would be negligibly less accurate than the 13-segment model, potentially validating its use as a less expensive alternative. The last hypothesis was that adjusting the lowpass cutoff frequencies segment by segment to favor the contribution of specific effective forces in GRF profiles would improve the accuracy of EF predictions.

**Hypothesis 1: General Accuracy**

From the limited sample size this study presents, the conclusion for the first hypothesis is mixed. The EF model predicts GRF profiles with a slight decrease in accuracy relative to the findings of Karatsidis in the best cases. However, the accuracy of the EF models on whole decreased with more complex motions for different directions in the LS and ST motions. For the simulated trail movement in particular, estimates for all three directions of motion were poor. For point estimates, the 13-segment EF model did
maintain strong agreements, but potentially not to a resolution necessary for implementation in a full scale study.

Time-Series Predictions:

The overall accuracy judged by rRMSE values compared to Karatsidis is only slightly worse based on a comparison to the vertical jogging GRF profiles collected in this study. Table 2 shows the direct comparison between this study and theirs. The rRMSE values are higher, closer to 10%, but with narrower standard deviation values, less than 1%, for each frequency choice method. This was to be expected. We used higher cutoff frequencies in this study in general than in Karatsidis’ work which filtered all kinematics at 4.5 Hz. The higher rates probably allowed more soft tissue and clothing artifacts into the prediction signal than Karatsidis’ method would allow. In the same vein, the higher speed motions as well as the cluster based method of optical motion capture likely yielded more of these artifacts than would be present in walking movements.

Table 3. Comparison to (Karatsidis, 2017) rRMSE values for vertical GRF profiles at 3 different speeds of walking compared to rRMSEs reported for jogging in this study with 10 Hz, 95% PSD, and Optimized frequency choice methods.

<table>
<thead>
<tr>
<th>vGRF</th>
<th>Walking (Karatsidis, 2016)</th>
<th>Jogging (~2 m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>rRMSE (%)</td>
<td>Slow (~0.86 m/s)</td>
<td>Normal (~1.28 m/s)</td>
</tr>
<tr>
<td></td>
<td>5.5 (2.2)</td>
<td>4.8 (2.7)</td>
</tr>
</tbody>
</table>

Based on the works of Ren and Karatsidis, there was reason to believe a 13-segment EF model would accurately predict GRF profiles for agility motions. They claimed that the predicted GRF profiles they found for walking were most accurate in the vertical
direction due to the relative signal to noise ratio in other directions of motion being much higher for walking. Following that logic, we analyzed jogging, lateral skater, and the simulated trail motion as 1, 2, and 3 direction movements, respectively, attempting to expand into motions with significant forces in all three directions.

We found a general decrease in accuracy as the motions became more complicated. Jogging provided the best alignment to the true forces with our observations only in the vertical direction of force. However, while the lateral skater and simulated trail motions still maintained vertical forces as the direction of highest magnitude, the vertical forces did not maintain the same level of alignment as they did with jogging.

The decrease in accuracy with complexity does not bode well for the hope of a generalizable method of predicting forces. Factors that may have contributed to this decline in accuracy could be related to the higher speed of the motion or potentially more soft tissue and clothing artifacts resulting from the complexity of the motion. The decrease in accuracy signals that more nuanced motions, like those we would hope to see in situ on the trail, field, or court, would not be predicted well. Naturally, this study only sought to explore this method and where its shortcomings lie, so the data for this claim is limited, and a more in depth study would be needed to determine to what degree nuanced, multiplanar motion can or cannot be predicted.

*Point Estimate Predictions of GRF Measures:*

The conclusion for the point estimate accuracy is also mixed and may need a deeper investigation to validate just how accurate or inaccurate it might be. For 13 and 7-segment models in the Bland-Altman and LoA analyses of point estimates for peak GRF
and RFD in jogging and lateral skater activities performed reasonably well, with small positive or negative biases in the best frequency choice methods and tight corresponding limits of agreement. The concern comes when comparing this data to published studies in agility.

Pryhoda et al. (2020) found a statistically significant change in RFD and peak force during a lateral skater jump activity due to a change in footwear closure configurations. The change in peak force was significant at 0.056 BW difference and the change in RFD was significant at 2.92 BW/s difference. Considering limits of agreement as a resolution of average data, the best predictions in this study for peak force was a range of plus or minus 0.081 BW in the 7-segment 90% PSD model and the best LoAs for RFD were 2.57 BW/s in the optimized 13-segment EF model. The nuanced changes found by Pryhoda would probably not get picked up by this method because the changes fall too close to the resolution of the LoAs.

Conversely, a less nuanced statistically significant change might be found using this method. Rice et al. (2016), in a study on the differences in forefoot and rearfoot strikers in minimal and standard shoe designs, found statistical significance in instantaneous loading rate (RFD) at 16 BW/s, which is much larger than the LoA found in this study for vertical and lateral RFD measures. A comparison during a full scale study attempting to find changes in agility due to an intervention would present an opportunity to demonstrate an EF model’s true capability in this regard.
Reduced Segment EF Models:

The 13 and 7 segment models did not perform dramatically different for all comparisons in this study. Calculated LoAs for peak forces and RFDs in jogging and lateral skater movements did not widen notably across most frequency choice methods. Further, it can be seen that, with the exception of the 97.5% PSD method in jogging, the RMSE and rRMSE values of the 7-segment model never differed more than one standard deviation from the 13-segment model’s values.

Given that all of these movements involve impacts in the lower body, it follows that a 7-segment model would feasibly represent most of the GRF profiles involved. This finding supports the argument made by Clark and Weyand’s (2016) model for predicting ground reaction forces discussed earlier in this thesis. The rationale that the vertical force profile of jogging is decided largely by the impulse of two lumped masses, the lower leg, and the rest of the body, aligns with the accuracy of the 7-segment model relative to the 13-segment model. The EF models also have the benefit of all calculations being based on the physics of measured movement rather than an arbitrary curve fit based on physical parameters. The outcomes of the frequency choice methods also support this with higher lower-leg frequency cutoffs representing impact peaks better in vertical GRF profiles.

The single segment model performed worst in most movements and comparisons, but the drop landing and jogging data suggest that single segment models might be useful in predicting impact peaks. In the drop landing activity with higher cutoff frequencies from the 97.5% PSD method (9.57 Hz) and the 10 Hz method, the single segment model had the least bias. This pattern again emerges in the LoA for vertical peak force in jogging
where the single segment has ranges as good if not better than the 13-segment model
does for most of the frequency choice methods. This outcome implies that the kinematics
and mass of the trunk segments play a major role in impact forces, which makes sense
considering their masses relative to other body segments.

Frequency Choice Methods:

This study shows that filtering different segments at different cutoff frequencies can
improve GRF predictions relative to a standard 10 Hz for all segments. The optimized
frequency choice method always had similar or better RMSE values than the 10 Hz
method. Additionally, the 10 Hz method always had wider ranges in the LoA than either
90%, 95%, or optimized frequency choice methods. Plainly, varied cutoff frequencies
improved accuracy by all measures in this study.

The differing cutoff frequencies found for both the PSD methods and the optimized
method can be interpreted in multiple ways. First, higher frequencies might indicate more
contribution from the ground reaction force to the motion of that segment. This is
supported by the frequency layouts generated for jogging. As Clark and Weyand’s (2016)
work suggests, the impact of the lower leg contributes notably to the vertical GRF profile.
In the frequency choice methods, the feet, particularly the right foot, have higher cutoff
frequencies chosen than the rest of the body. In the optimized method, where the feet
were on average filtered at 31 and 29 Hz for the right and left, respectively, the predicted
GRF profile was able to replicate the impact inflection characteristic of a rearfoot striking
runner where no other method could. In the 19 GRF profiles where this inflection
occurred, the optimized 13 and 7 segment models replicated 12 of them. The contribution
of the trunk mass to peak impact force discussed in the previous section also supports this interpretation.

The second interpretation of differing cutoff frequencies in this study might also suggest the models’ sensitivity to the segment’s mass. This observation comes almost exclusively from the optimized frequency choice method. In the optimized 13-segment models, the arms tend to optimize for higher cutoff frequencies. It may be appropriate for the lower segments to have higher frequencies due to their contribution to impacts, but this does not follow for the arms. The optimization method possibly optimized for higher values in the arms because of their low mass relative to the rest of the body which would not weight their accelerations high in the net effective force model. This is supported by the relatively low values chosen for the trunk masses in the optimization method. The single segment performed best in the drop landing when it was cutoff at higher frequencies, like the 10 Hz and 97.5% PSD methods, but the optimization did not perform as well. If the optimization chose for model sensitivity, the large masses of the trunk would weight the accelerations of those two segments very high and be a potential source of error by amplifying the same soft tissue artifacts present in all of the segments. That concern becomes apparent in other activities where the 97.5% PSD method performs the worst in almost all cases.

The third interpretation comes from an understanding that lower frequencies are associated with high inertia or damping in mechanical systems. Differing cutoff frequencies might be a way to model damping throughout the system. The human body is not an ideal link-segment model so segment interactions do not conserve energy.
Considering GRFs as the input force to the system, we expect the effects of the input to dissipate as it travels away from the source through soft tissues, bone impedance, and the imperfect rotation about the joints (links) of the segments.

**Limitations:**

The most notable limitation of this study is the number of subjects recruited for the collection of data and the relatively small number of repetitions for each activity that were observed. These small sample sizes make claims made from statistical measures like the limits of agreement less reliable for some of these activities. The trends observed here might be followed up by larger scale studies with narrower scopes aimed to continue to validate the EF method of predicting GRFs.

For limitations within the collection of data, a cluster based motion capture method was used, which may have contributed to more soft tissue and clothing artifacts in the data. The clusters of markers defined segments on their own, so any weaknesses in their fixtures resulting in shaking during the agility activities would result in the kinematics for that whole segment being affected. Optical motion capture where individual points are placed on bony landmarks of the body may not have been as affected. Given that the PSD frequency choice methods were reliant on the frequency content of each segment, this method may have been affected significantly by worsened clothing artifact.

A limitation in the application of frequency choice methods comes with the choice to optimize and choose frequencies based only on vertical force profiles. We focused our analyses for the lateral skater and simulated trail motions on lateral and horizontal motions, not just the vertical. There is a possibility that had we optimized or chosen
frequencies from the frequency content of those shear motions then there would have been more agreement in those directions. We did a cursory observation and noticed a general decrease in performance overall when optimizing a lateral skater activity for lateral forces instead of vertical forces, but observations across the whole data set might have shown improvements. This is another avenue that could be explored in a future study.

**Conclusion:**

The accuracy of the effective force method of predicting ground reaction forces should be improved before the method can be considered as a viable replacement to force platform measurements. We presented concerns that the accuracy of this method decreases with faster and more complex motions and that the point estimates for GRF measures of accuracy might not have a refined enough resolution to detect nuanced differences in a full scale agility study.

Despite concerns of accuracy overall, reducing the number of segments included in kinematic observations to represent only the lower body does not reduce the accuracy of GRF predictions drastically in comparison to a full body model. Additionally, differing lowpass cutoff frequencies for position data on a segment by segment basis can improve the accuracy of predictions.
Chapter 6: Future Work

For both studies presented in this manuscript, there is potential future work to be done. Studying the effect of alternative shoe upper design on long distance runner agility will require comparing the internal mechanisms of their movements between shoe configurations and pre and post running. This evaluation could also include a parallel exploration of how their biomechanics change over the course of the long distance run. Ground reaction force data and the kinematics of the participant’s left leg were collected during the 45-minute running protocol and the information therein might prove insightful both in exploring the effect of fatigue on running and agility, but also how footwear might help runners resist fatigue.

The ultimate purpose of the effective force method’s exploration was to find avenues of interest that would be worth exploring as future work. Primarily, the efficacy of the method for predicting both directional forces and GRF measures of performance was brought into question due to the accuracy we observed. The experimental data from (Pryhoda et al., 2020), which we referenced as an example of where the method might fail to detect changes in performance, is available at the University of Denver. The kinematic data collected for that study could retroactively be explored using the effective force method to see if the same conclusions might be drawn for the GRF measures of performance.
The retroactive study evaluation could be taken a step further if the EF method is proven accurate with GRFs, at the external level. (Harrison et al. 2021) followed the GRF measures study with a second part analysis on the joint mechanics involved in court athletes given different shoe closure systems. The EF method could again be used retroactively to do inverse dynamics calculations to assess its ability to detect changes on an internal mechanics level.

Another exploration that we chose to forgo in this manuscript is the use of IMUs for the effective force method. IMUs were used to collect kinematic data in parallel with the OMC system described in the study. However, the data that the Xsens system yields goes through black-box method that is not accessible due to the algorithms’ proprietary nature. The data processing used in the study to smooth the data based on measured kinematics would not have been applicable to that kinematic information. Additionally, the effective force method via IMUs requires both the acceleration and angular velocity signals provided by the sensor to calculate effective force. The requirement for these second and first order data would make the application of the frequency selection method much different had those raw signals been accessible.

Following further investigations into the accuracy of the EF method and its application with IMUs, more studies based on environment would be required to validate the method for general usage in predicting forces. Predictions of forces on non-rigid terrain or on an incline would be a step forward in stretching the limits of analysis with this method.
References


Brizuela, G., Llana, S., Ferrandis, R. and Garcia-Belenguer, A.C., 1997. The influence of basketball shoes with increased ankle support on shock attenuation and


Appendix A: Auxiliary Effective Force Method Analyses

Correlation Coefficients:

Both Ren (2007) and Karatsidis (2018) included the calculation of average Pearson’s correlation coefficients for their GRF predictions. To assist in the convergent validation we calculated these coefficients in the same manner. The figures were ultimately excluded from the main body of this work because the coefficients were all generally very high, even for the effective force models and frequency choice methods yielded the worst alignments in agreement and RMSE values. These did not meaningfully add to the discussion on accuracy, so they were omitted.

![Correlation Coefficient of Vertical GRF Prediction by Frequency Method: Drop Landing](image)

Figure 43. Average Pearson's correlation coefficients for vertical GRF profile predictions in drop landing.
Figure 44. Average Pearson's correlation coefficients for vertical GRF profile predictions in jogging.

Figure 45. Average Pearson's correlation coefficients for lateral GRF profile predictions in lateral skater.
Figure 46. Average Pearson's correlation coefficients for horizontal GRF profile predictions in the simulated trail motion.

Figure 47. Average Pearson's correlation coefficients for lateral GRF profile predictions in the simulated trail motion.
Figure 48. Average Pearson's correlation coefficients for vertical GRF profile predictions in the simulated trail motion.