Agility Quantification using Body Worn Inertial Sensors

by

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B.S., University of Portland **(2015)**

Submitted to the Department of Mechanical Engineering in partial fulfillment of the requirements for the degree of

Master of Science in Mechanical Engineering

at the

MASSACHUSETTS INSTITUTE OF **TECHNOLOGY**

June **2017**

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Abstract

Agility is defined as the ability to quickly change speed or direction. Planned agility refers to the physical act of changing direction and reactive agility addresses the additional cognitive responses needed to react quickly to an external cue. This work specifically considers reactive agility. Agility performance is often evaluated using time-based metrics, which provide little information about which factors aid or limit success. Two studies were completed to identify key factors contributing to agility performance. The objective of the first study was to determine how novices and experts working in athletic, clinical, and military environments qualitatively and quantitatively evaluate agility performance. Thirty-three participants completed a survey which involved scoring **16** athletes on a **7** point Likert scale of not agile to agile. The spread of the scores indicated that even within groups, participants had different opinions about which aspects of technique contributed to high performance. Participant responses were used to link several terms to agility technique.

The objective of the second study was to apply these terms to the development of objective biomechanical metrics. An array of body-worn inertial sensors was used to calculate metrics that were sensitive to performance speed. Five metrics were defined (normalized number of foot contacts, stride length variance, arm swing variance, mean normalized stride frequency, and number of body rotations). Eighteen participants donned **13** sensors to complete a reactive agility task, which involved navigating a set of cones in response to a vocal cue. Participants were grouped into fast, medium, and slow performance based on their completion time. Participants in the fast group had the smallest number of foot contacts after normalizing **by** height, highest stride length variance, highest forearm angular velocity variance, and highest stride frequency after normalizing **by** height.These metric values translate to an efficient strategy for making turns **by** minimizing path length between cues and cones, effectively adjusting stride in reaction to turn points, and using tight pumping arm motions to aid in accelerating out of endpoint cones.The results of this study have the potential to inform the development of a composite agility score constructed from the list of significant metrics.

Study **1** informed the quantification of qualitative agility terminology and Study 2 mapped these terms to speed of performance. The outcomes from these studies can assist in strategy development for training and rehabilitation across athletic, clinical, and military domains.

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Acknowledgments

I would like to thank Professor Leia Stirling, without whom, this thesis would not have been possible. I am grateful for all of the time she has spent meeting with me, teaching and mentoring me, as well as creating opportunities that have allowed me to develop as both an an engineer and a person. Her passion, enthusiasm, and general wealth of knowledge has been invaluable throughout my **SM** experience.

I want to deeply thank our collaborators at the University of Michigan not only for providing the videos of the athletes on the obstacle course and performing the data collection, but also for their feedback on methodology and hypotheses during weekly meetings throughout the past year and a half. In particular **I** would like to thank Prof. Noel Perkins, Dr. Stephen Cain, Dr. Antonia Zaferiou, Mr. Steven Davidson, Dr. Lauro Ojeda, Ms. Rachel Vitali, Mr. Jon Mendicelli, Mr. Nathan Kossey, and Mr. Cody McKay.

I would also like to thank Professor Neville Hogan and the rest of the Newman Lab for welcoming me into the group, providing insights during weekly lab meetings, and providing exposure to other biomechanics applications that have helped me to develop as an engineering student.

Thank you to the members of the Man Vehicle Lab, for their ideas, friendship, and support. I would especially like to thank: Alan Natapoff for discussions on the statistical analysis; **My** UROPs Aaron Huang, Solan Megerssa, and Alexander Danielsen-Haces for their work on data synchronization and **GUI** development for an additional project; Liz Zotos and Sally Chapman for providing advice and help throughout my stay at MIT; and my officemates Alison Gibson and Raquel Galvan-Garza for making our office a fun place to work.

The research presented in this thesis was supported **by** the **US** Army Natick Soldier Research, Development and Engineering Center **(W911QY-13-C- 0011)** and a National Science Foundation Graduate Research Fellowship under Grant No. 1122374. Any opinions, findings, and conclusions or recommendations expressed in this material are my own and do not necessarily reflect the views of the sponsors.

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Chapter 1

Introduction

1.1 Motivation

Agility, the ability to quickly change speed or direction **[1],** is a common consideration for success in athletic settings and has been anecdotally described as characteristic of the world's best team sport athletes **[1,2].** Agility is also important in military domains, where warfighters need to make quick evasive maneuvers, and in clinical domains where patients traverse crowded environments $[3, 4]$. Two types of agility are discussed in literature $$ planned agility and reactive agility. Planned agility includes a course that requires the physical act of changing direction, where the person knows the course a priori and navigates a predefined path. Reactive, or unplanned agility, incorporates a cognitive component **by** involving perception and reaction to an external cue **[5].** For reactive agility, the course is not pre-planned and direction changes are signaled during the navigation of the course.

Planned and reactive agility tests typically quantify agility performance using timebased metrics-primarily the time elapsed between crossing the start and finish line. While speed is important for agility, the parameter does not provide insights about strategy or technique, which enable identification of injury risk and areas of improvement. An athlete may traverse a course at high speed while putting himself or herself at risk for an Anterior Cruciate Ligament **(ACL)** injury. Additionally, without any feedback other than time

taken to complete a course, an individual may find it difficult to target specific aspects of their movement pattern that restrict them from reaching their full performance potential or progressing in a rehabilitation program. It is unclear from the literature whether additional measures should **be** considered beyond speed for assessing agility performance and which measures would be most appropriate. Insights about agility strategy and technique made in athletic, clinical, and military environments are typically obtained from experts that visually assess agility tasks qualitatively. This thesis explores the potential to quantify agility using biomechanical metrics so that performance can be clearly monitored and the success of training methods can be determined.

1.2 Literature Review and Background

1.2.1 Agility Tasks

Multiple planned agility tests have been implemented for evaluation purposes. Three of the most commonly used tests are the T-Test, Illinois Agility Test, and **505** Test (Figure **1.1).** The T-Test, named for the shape of the associated course, requires 4 directional changes. The athlete runs from the start line to a cone **5** meters ahead, side steps to a cone **5** meters to the left of the center cone, side steps in the opposite direction to a cone **5** meters to right of the center cone, sidesteps from the right cone to the center once again, and backpedals to the start line [2]. The Illinois Agility Test is a timed task involving straight sprinting and weaving through 4 cones. The movement patterns resemble those applied to dodge opponents in soccer and rugby **[6].** To complete the **505** test, which was originally designed for cricket players, athletes sprint forward from a start line, pivot **180** degrees and return to the start line [4].

Figure **1.1** Planned Agility Courses **[6]. A,** T-Test. B, Illinois Agility Test. **C, 505** Agility Test

Although these tests accurately replicate the sharp direction changes required in multiple athletic environments, they do not address the cognitive processes involved. Other tests have been developed that consider the reactive aspects of agility. Spasic et al. **[71** designed a course, similar to the T-Test, for handball players that required participants to react to visual cues (Figure 1.2a). Light-emitting diodes (LEDs) placed within one of two cones lit up in a randomized order each time the participant crossed an infrared beam during the straight sprint. Athletes had to assess which cone was illuminated and shuffle to that cone as quickly as possible. Additional reactive agility tests have assessed anticipation skills and

decision time using stimuli provided in real-time **by** another person or through a video clip of an athlete performing a set of sport-specific movements **[5,8].** Sekulic et al. **[9]** developed a reactive agility course that permitted evaluation of variation in cutting angle, while enabling flexibility in running technique (side stepping not required), and was distinct from other courses **by** requiring athletes to come to an abrupt stop and accelerate out of breakpoints (Figure **1.2b).**

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Figure 1.2 Reactive Agility Courses **[7, 9].A,** Reactive test developed **by** Spasic et al. B, Reactive test developed **by** Sekulic et al. Both courses included visual cues in the form of LEDs within cones, triggered once an infrared sensor detected motion **(MC -** microcontroller, JR **-** infrared sensor).

1.2.2 Measures of Agility

A majority of the literature discussing agility tasks has relied on time through an agility course as the agility measure. Sekulic et al. **[9]** found that the performance times for their reactive agility course differentiated college-aged athletes involved in agility-saturated sports (soccer, basketball, handball, volleyball) from those not involved in agility-saturated sports (gymnastics, dance). Spasic et al. **[7]** used performance time to create a perceptual-reactive-

capacity index (the ratio of completion time for the reactive version of the course divided **by** completion time of the planned version of the course). This index was examined with the hypothesis that it would distinguish defensive handball players from offensive handball players. The results of the study supported the hypothesis that defensive players, who regularly react to opponents' actions, have a better perceptual-reactive-capacity index than offensive players, who primarily perform planned changes in direction.

Previous studies have also explored particular components of technique (e.g., straight sprinting performance, leg strength, and power qualities) and their correlations with planned agility course time **[10-13].** Tsitkaris et al. **[10]** designed a study to investigate the influences of balance, speed, and power on agility performance for male and female college students. Power was measured using a squat jump test. Balance scores were recorded after participants completed a dynamic balance assessment during which they viewed a moving cursor and adjusted their center of mass in response while standing on a moveable platform. Speed was captured during a **10** meter and 20 meter straight sprint. The investigators calculated correlation coefficients between speed, balance, and power test scores and the time to complete five planned agility tasks. Their findings indicated that female participants had power values that were associated with time to complete two of the five agility tasks. They found that the agility performance of male participants was significantly related to their dynamic balance test scores.

In an examination of agility in college-aged male physical education students, Markovic et al. [12] selected leg extensor strength qualities as predictors. These qualities consisted of: explosive strength (vertical jump and countermovement jump tests), elastic strength (drop jumps), and maximal strength (squat jumps). The course time for three agility tests formed the agility performance metric. After completing a regression with three strength factors as predictors and an agility factor as the criterion, the researchers concluded that leg extensor strength qualities are poor predictors of agility performance in physically active men.

In addition to power and strength, muscle activity has been explored as a predictive measure for agility performance. Spiteri et al. **[5]** compared the differences in muscle activation strategy employed when performing two consecutive agility movements. Electromyography **(EMG)** of six muscles in the dominant leg was recorded using wireless surface electrodes. Participants completed sharp cuts over force plates to the left or right of a projection screen presenting a visual stimulus. Decision time was quantified during agility trials as the time between the presentation of a video clip alerting a participant to change direction and the participant's first foot strike initiating a change of direction. The investigators concluded that faster agility performance was associated with more pre-heel strike activity and greater anterior activation during stance phase for the rectus femoris, vastus medialis, and biceps femoris muscles. This muscle activity increased hip and knee extension, leading to a greater propulsive impulse. They also observed that longer decision times during one of the directional changes led to greater activation of the anterior muscles and body deceleration while movement direction was determined.

Some studies have analyzed the mechanics of movement when reacting to a cue for slow direction changes [14-16]. These studies were reviewed for their potential to provide insight into biomechanical measures that may set planned and reactive agility performance apart. Ashburn et al. [14] compared the ability of adults with and without Parkinson's disease to complete **180** degree turning-on-the spot when cued and found both groups had initial head movement followed **by** eyes, head, shoulders, feet. Patla et al. **[15]** examined whole body turning kinematics while walking at a self-selected pace with visually cued turns and found that two mechanisms were used to move the center of mass in a new direction: **(1)** foot placement (more common for planned movements) and (2) trunk roll about the hip joint in the frontal plane. Houck et al. **[16]** evaluated frontal plane trunk and lower extremity adjustments during anticipated and unanticipated walking to detect **ACL** injury risk. Anticipation affected participant hip and knee adduction, which was speculated to increase the likelihood for the knee to enter the injury prone valgus position. These studies were performed at lower speeds than the quick cuts exercised in athletic and military settings, but highlight that reactive tasks can drive differences in how one performs the motion.

Additional studies have attempted to define biomechanical measures to investigate the

change of direction ability of athletes and soldiers performing in higher speed environments. In an evaluation of male collegiate soccer players, Sasaki et al. **[17]** discovered that forward angular displacement of the trunk was positively correlated with a cutting task similar to the **505** agility test. It was proposed that optimal inclination angles may exist that directly affect change of direction performance. Marshall et al **[18]** recruited gaelic hurling players to complete a **75** degree cut over a force plate. Biomechanical factors including peak ankle power, range of pelvis lateral tilt, peak ankle plantar flexor moment, and ground contact time were associated with cutting time. Kim et al. **[19]** studied the biomechanical factors contributing to anticipated and unanticipated side cutting maneuvers in middle school male soccer players. The findings of this study revealed that knee flexion and time to peak ground reaction force were greater for the unanticipated condition. Failure to anticipate alters the external moments applied to the knee due to the reduced time to implement postural adjustment strategies. McGinnis et al. [20] evaluated sacrum kinematics for a slalom run course completed using a belt-worn inertial measurement unit **(IMU).** Two groups were identified that demonstrated unique movement patterns to negotiate the turns. One group was characterized **by** greater forward tilt of the pelvis, as well as alignment between the anterior direction of the pelvis and the instantaneous direction of travel. These technique differences did not result in significantly different course completion times, indicating that multiple techniques could contribute to high agility performance.

A summary of the measures that have been shown to be correlated with planned and reactive changes in direction is given in Table **1.1.** The findings of these studies highlight potential differences in planned and reactive agility tasks. These studies also confirm the feasibility of defining kinematic measures for agility performance and provide a range of current measures that may inform additional metrics that capture agility technique.

Table **1.1** Metrics associated with planned and reactive change of direction **(COD)**

1.2.3 Methods of Biomechanics Measurement

Human biomechanics is often quantified using **3D** motion capture systems (mocap), which typically incorporate reflective markers tracked **by** infrared cameras. The advantages of mocap are that it allows researchers to analyze kinematics in a relatively standardized manner for a variety of applications. However, mocap involves extensive processing time, requires data collection to take place in a fixed volume, and can have marker occlusions limiting potential analyses. Another method for quantifying human biomechanics is the use of IMUs, which extend the tasks and environments that may be assessed. IMUs are particularly useful for agility evaluation which can benefit from taking place outdoors for military training and field sports. **A** limitation of IMUs is the drift error that occurs as a result of integrating raw acceleration or angular velocity values over time. Accelerometer data can be fused with angular velocity data in Kalman filters to help address this problem [21]. Other methods used for drift correction are zero velocity updates or updates at times within a course when position is known if trajectories are being estimated. An alternative approach

to preventing drift error is to avoid integration altogether and create metrics that use raw sensor data.

1.3 Research Objectives

1.3.1 Overview

This thesis addresses two aspects of reactive agility performance evaluation. It first explores the effect of different user groups on qualitative and quantitative agility assessment. As discussed in Section **1.1,** insights about agility strategy and technique made in athletic, clinical, and military environments are typically obtained from experts that visually assess agility tasks. The large range of measures that have been explored experimentally (Section 1.2.2) emphasize that different experts may assess agility differently. Determining the key terms experts use to define athlete agility level may identify new parameters for assessing agility technique. The new parameters may be more aligned with operational interpretation of agility than the measures already examined in the literature. Formalizing expert terms may also extend previous studies that have found weak correlations when comparing agility performance to course time, enabling the identification of performance strengths and weaknesses.

This thesis also discusses the application of expert terms to the development of biomechanical metrics that are sensitive to the speed of agility task performance. **All** of the metrics we propose map to common terms highlighted **by** athletic, clinical, and military experts while evaluating videos of agility performance. These metrics are applicable for training across these domains and may provide improved understanding of technique and in the future could be related to injury risk mechanisms.

1.3.2 Specific Aims

Aim **1:** Determine how experts evaluate agility and identify key terms defining optimal agility technique.

Aim 2: Derive biomechanical metrics to quantify reactive agility technique using an array of body-worn **IMU** sensors.

1.4 Thesis Outline

These specific aims are addressed with the following structure:

Chapter **I.** Introduction **-** This chapter presents the motivation, literature review, research objectives, and specific aims of the thesis.

Chapter **II.** Study **1:** User Study **-** This chapter explains the methods, results, and discussion for the study of clinical, military, and athletic evaluations of agility performance.

Chapter III. Study 2: Metric Development **-** This chapter explains the methods, results, and discussion related to the derivation of biomechanical metrics using IMUs.

Chapter IV. Conclusion **-** Concluding remarks on the research and its contributions are made in this chapter, and suggestions for future research beyond the scope of this thesis are offered.

Chapter 2

Study 1: User Study

2.1 Background

It is unclear from the literature whether additional measures should **be** considered beyond speed for assessing agility performance. Insights about agility strategy and technique made in athletic, clinical, and military environments are typically obtained from experts that visually assess agility tasks. The objective of this study was to determine how experts evaluate agility and to identify key terms defining agility performance. The metrics identified may enable a focused examination of new parameters for assessing agility technique and extend previous studies that have found weak correlations when comparing to solely course time, enabling the identification of performance strengths and weaknesses.

2.2 Methods

2.2.1 Participants

The study was completed **by 33** adults (mean age **30** years, **SD=9** years; **16** female). Participants were recruited within an expert group- athletic $(n=8)$, clinical $(n=7)$, military $(n=8)$ - or novice group $(n=10)$ based on their experience evaluating human performance. Expert groups were familiar with formal training and evaluation guidelines within their **field.** The novice group had no previous knowledge of formal guidelines. The athletic group consisted of coaches specializing in football, rugby, soccer, **field** hockey, tennis, and track. The clinical group consisted of physical therapists. The military group included experienced members of Air Force and Army Reserve Officers' Training Corps (ROTC).

2.2.2 Athlete Videos

Expert and novice participants were asked to analyze videos of athletes completing a reactive agility obstacle. These videos were obtained from a previously collected data set. The reactive agility obstacle (Figure 2.1) was a sub-set of the obstacles performed **by** the athletes (see Appendix B for full course). To complete the obstacle, athletes $(n=16)$ ran from the start line to an endpoint, touched the top of the endpoint cone, ran back to the start line, and turned around to repeat these actions for three more endpoints as quickly as possible. Endpoints were vocally announced each time the athletes crossed the cue line. Athletes were not provided a strategy on how to complete the task. Half of the athletes completed the reactive agility obstacle **6** times, while the other half completed this obstacle **3** times. The same **3** obstacle paths were traversed **by** all athletes. Written consent was provided **by** each athlete and procedures were approved **by** the University of Michigan IRB and the MIT Committee on the Use of Humans as Experimental Subjects **(COUHES).** Athletes were compensated up to **\$50** for their participation. The videos were parsed and the reactive agility videos of the athletes on their second and third runs through the obstacle were used within the user study. Videos were de-identified **by** blurring participant faces using Adobe After Effects software. Athlete videos were categorized as slow, medium, or fast based on the time it took them to complete the course. Videos were shown at real-speed and not normalized for time.

Figure 2.1 Reactive agility course adapted from Sekulic et al **[9].** Athletes received verbal cues at the location notated and touched 4 endpoint cones **(30** cm tall) per trial.

2.2.3 User Study Experimental Protocol

Procedures for the user study were approved **by** the MIT **COUHES** and all participants provided written consent. Participants received up to \$20 in compensation. Participants completed an online agility evaluation survey consisting of 4 parts (Appendix **D).** Part **1** was a short answer question asking for any terms or definitions that the participant associated with agility performance. Part 2 presented the videos showing the **16** athletes completing their second time through the reactive agility course. Participants were asked to score each athlete's video on a Likert scale ranging from **1** (not agile) to **7** (very agile). Each video was approximately 45 seconds long and was presented on a new page of the form in a randomized order. Participants took a **10** minute break after the first **16** videos. The second set of **16** videos showed the athletes completing their third time through the reactive agility course and were presented in mirrored order, without informing participants of the repetition of athletes. There was an option to take a **5** minute break before beginning Part **3** of the survey, which requested a ranking of agility performance. Two sub-sets of **5** videos from the group of **16** athletes were arranged on the same page and participants ranked each set of videos from most agile to least agile. Both sub-sets contained a mixture of videos

from the first and second set of athlete videos. The first sub-set of **5** videos included the performance of 1 fast and 4 medium speed athletes. The second sub-set contained 1 fast, **¹**medium, and **3** slow athletes. The sub-sets grouped athletes with similar performance times together, placing predominantly fast and medium speed athletes in the first group and predominantly slow and medium speed athletes in the second group. The grouping was done this way to encourage participants to think about factors other than time when determining rankings. Participants were not asked to rank all videos because the representative selections in the sub-sets met the goal of identifying whether technique was being used to differentiate athletes with similar performance times. Both the scoring and ranking sections of the survey prompted participants to provide explanations for their selections. Part 4 of the survey provided space for further explanation if the participant's definition of agility had changed based on watching the videos. Survey completion time ranged from 1 to 2 hours.

2.2.4 Data Analysis

A Wilcoxon Signed Rank test was used to evaluate difference in rater score between first and second videos for the athletes. **A** paired t-test was used to assess difference in course completion time between the first and second videos for the athletes. **A** Kruskal-Wallis test was used to evaluate differences in score between groups. Differences between rankings as determined through scores and explicit ranks were determined with a Chi-squared test. The fourth spread of the scores was calculated for each video to quantify variability. This calculation involved ordering the observations of data from smallest to largest and subtracting the median of the lower half of the data from the median of the upper half of the data. The fourth spread was chosen as an alternative to standard deviation because of its use of median values instead of mean values, which is more appropriate for Likert scale data [22].

A qualitative analysis was performed to identify the most common descriptors for agility performance. An initial list of terms to describe commonly used phrases in the survey explanations was developed **by** a first pass through of the qualitative data. Subsequent passes through all terms were made to assess if a phrase **by** a rater aligned with a term, or if a new term needed to be generated. Similar terms or phrases were combined and the coding scheme was refined upon follow-on passes through the terms. Frequencies for each term were assessed as the number of participants who used it.

2.3 Hypotheses

In this thesis, we consider how agility is characterized **by** athletic, clinical, and military experts when viewing the same task and group of participants. Variations in environment and performance expectations for each area of expertise may drive differences in qualitative assessment. For example, a physical therapist may place less emphasis on speed than a soccer coach, given a desire for patients to develop healthy movement patterns rather than react quickly to an external cue. Further, we anticipate that even though all experts were trained in their discipline, there may be variability within as well as across disciplines based on different specialties or sub-specialties.

To extend the understanding of agility performance beyond speed-based measures, this study investigated how videos of athletes with comparable speeds were ranked. Rankings using internal reference frames (a Likert score) and forced reference frames (explicit ranks) were considered. Maio et al. **[23** discussed the potential differences between the two, highlighting that rankings of ethical acceptability of behaviors using scores were more correlated with a priori predictions than explicit ranks. The investigators argued that explicit rankings may cause participants to make unimportant distinctions that would not have been made otherwise. However, the additional distinctions explicit rankings may generate **by** forcing participants to be more detail-oriented may be particularly useful for assessing human performance. We included both ranking methods in order to further evaluate these relationships.

In this study, we hypothesize that **(1)** agility scores are consistent between viewings of the same athlete; (2) the definition of agility differs **by** expert background; **(3)** assessments within group are similar; (4) the rankings assessed through a forced reference frame differ from an internal reference frame.

2.4 Results and Discussion

2.4.1 Analysis of Qualitative Descriptions

The survey responses (Tables 2.1 and **2.2,** Appendix **E)** demonstrated that participants evaluated agility most frequently using terms related to athlete speed and ability to change direction, which aligns with the definition of agility found in literature **[1].** Examples of phrases coded as speed and change of direction were "time through the course" and "sharp movements when cutting and turning". The next frequently used term, "efficient path" is closely tied to the ability to change direction. Several raters commented that an athletes ability to cut his or her body "quickly in the given direction without requiring any arcing paths to get there" was important. The efficient path term is distinct from the change of direction term as it highlights a particular strategy for making the turn, specifically the ability make precise turns towards the desired endpoint **by** minimizing path length. The high frequency of performance speed was supplemented **by** the term "reaction time," which is a focus on the response time after cue calls. Experts repeatedly mentioned decision-making in their responses, which highlights the importance of cognitive performance in the agility task. Their comments align with the agility definition provided **by** researchers such as Spiteri et al. **[5],** which discuss the correct identification and rapid interpretation of environmental cues in addition to changing direction. Another term that emerged from the survey responses was "body alignment," which included comments such as lowering the center of mass while bending at the knee and hip joints. Participants suggested that a proper body alignment enabled athletes to make sharp changes in direction, burst out of the course's breakpoints, and decelerate with full control. While related to speed and direction change, acceleration was categorized as a separate term as locations within the course could be performed using a constant speed direction change. Expert comments related to acceleration during the course provided additional information on strategy. Foot contacts provide additional information on athlete technique, with a given body speed having the potential for few or many contacts. Experts noted that athletes with good footwork minimized the amount of steps taken to make a turn and used "short, quick steps" or "good stutter stepping". They also mentioned that tight pumping arm motions aided athletes in changing direction and maintaining stability. Those that did not adequately pump their arms appeared to be less energetic. **A** smaller frequency of participants mentioned the value of making smooth movements, which may contradict with the stutter stepping strategy, efficient path, and abrupt body movements contributing to quick changes in direction.

In the last section of the survey, participants were asked to discuss whether the definition they provided for agility at the beginning of the survey had changed after viewing the videos. While many novices explicitly noted they adapted their definition (n=8 of **10),** fewer participants made this explicit assessment in the expert groups (n=3 out of **8** athletic experts, n=3 out of **7** clinical experts, and n=2 out of **8** military experts). It was expected that novice definitions would experience the most change given their lack of exposure to formal agility evaluation methods. Some experts commented that while their general view of agility remained the same, the factors they considered to contribute to this view were dependent on the selected drill and were easier to articulate after reviewing the videos. For example, one expert in the athletic group expanded on his initial listing of speed and body control at the start of the survey to include "sharp, quick turns with the subject accelerating out of the turn using their arms". Other experts mentioned a new consideration of "bend in the knee and hip to allow twist and drive" to quantify readiness as well as the "accuracy of movement pathway".

	Athletic	Clinical	Military	Novice
speed	7	6	7	10
change direction	7	6	6	5
efficient path	5	6	6	6
reaction time	4	3	5	9
body alignment	7	6	5	2
acceleration	4	3	4	$\overline{2}$
foot contacts	4	$\overline{2}$	$\overline{2}$	5
arm motion	3	3		4
smooth	1	3	2	
coordination	$\overline{2}$		2	
stride	$\bf{0}$	4	$\bf{0}$	2

Table 2.2 Agility Term Frequencies Broken Down **by** Group

2.4.2 Effect of Viewing Number on the Agility Score

Higher scores were provided by the clinical $(Z = 2.603, p < 0.01)$, military $(Z = 3.229,$ $p<.01$,), and novice $(Z = 1.961, p<.05)$ groups for the second set of videos than for the first set (Figure 2.2). This result does not support Hypothesis **1,** that scores would remain consistent during both evaluations of the same athlete. There was no significant difference in athlete time through the course for the two videos shown in the survey $(t = 1.103, p = .282)$. Differences in scoring may be due to participants having been unable to gauge the range of athletic skillset in performance before beginning the survey and therefore they relied on an internal representation of performance. Clinical, military, and novice groups may have adjusted their internal reference after the first set of viewings. The updated clarity in

definition mentioned **by** participants at the end of the survey (Section 2.4.1) aligns with the difference in Score 2 observed for some groups. As the selected reactive agility task was from the athletic literature, there is a possibility that the athletic group was more familiar with assessing agility with similar tasks, creating a more informed initial representation that was not adjusted to a significant level. This difference in scoring for some groups informed the decision to assess within and across group differences using Score 2 for further analysis.

Figure 2.2 Average group scores for first and second video evaluation. Scores ranged from **¹**(low agility) to **7** (high agility). The asterisks **(*)** represent Wilcoxon Signed Rank test results with p-values below **.05**

2.4.3 Effect of Expertise on the Agility Score

Score 2 was only significantly different between groups for one video (Video 2, X^2 = **10.055, p < .05)** (Figure **2.3).** This outcome does not support Hypothesis 2, which states that the definition of agility differs **by** expert background. What was observed was variability even within groups. The scoring disagreement between groups for Video 2 stemmed from the athletes good technique but slow pace, according to the scoring explanations provided **by** the participants. While speed was one of the most popular metrics considered to contribute to agility (see Table 2.1), some groups gave more weight to metrics related to strategy. The explanations provided **by** the clinical group for Video 2 as well as the trend of higher scores from this group despite the athlete's slow pace, indicated that clinicians prioritized metrics that were independent of speed such as efficient turns and skillful footwork (foot contacts and stride) to cut in the proper direction. Conversely, the trend of low scores for Video 2 from athletic group evaluators can be interpreted as heavier penalties for the low speed of the performance.

Trends from Figure **2.3** indicate that videos **6, 10,** and 12 received the highest median scores from each group. The comments made **by** participants for these videos were in agreement about fast pace and good technique contributing to high performance. Participants specifically mentioned that these **3** athletes had fast reaction times, made quick turns, and lowered their center of gravity to touch the cones.

Score 2 distribution between groups. Scores ranged from **¹**(low agility) to **7** (high agility). The asterisks **(*)** represent Kruskal-Wallis test results with **p**values below **.05** Figure **2.3**

The spread of responses within groups fluctuated **by** video presented and was largest for the athletic and novice groups (Figure 2.4). The spread in novice users is likely a result of individuals without basic training with which to guide their evaluations. However, the results for the athletic group do not support Hypothesis **3** which states that assessments within group are similar. While athletic-driven agility courses are used across multiple sports, individual sports may still value different components of agility performance. The variation in athletic group scoring may arise from our inclusion of a variety of sports. For example, the athletic group consisted of coaches from sports such as such as soccer and tennis, which differ in required skillset. Large fourth spreads were observed across most groups for the evaluation of videos 4 and **11.** Participants commented that the athletes in these videos were fast but had poor technique. There were disagreements within groups about what constituted poor technique, with some evaluators mentioning poor posture, while others discussed slow decision making and a lack of coordination. This variability in responses implies that even within groups, participants had different opinions about which aspects of technique contributed to high performance. Additionally, the variability in the rating of a fast athlete indicates that speed alone does not make an individual agile.

Figure 2.4 Fourth spread of Score 2 within groups for each observed video.

2.4.4 Comparison of Agility Scores with Forced Rankings

Hypothesis 4 examined if the ranking created **by** pooling scores for each athlete was different from the explicit ranking completed in Part **3** of the survey. The Chi-squared test results revealed that significantly different **(p <.05)** rankings were provided for 4 out of the **¹⁰** athletes evaluated using both methods (Table **2.3).** It is important to note that participants were forced to give different explicit ranks for each athlete while the scoring section of the survey permitted ties. The difference in ranking procedure is one possible source of variability in these two ordering methods. It was also observed that the 4 athletes with different rankings were either classified as medium speed out of the possible fast, medium, and slow categories or had speeds that were approximately equal to other athletes with which they were ranked. In these cases, the difficulty in discerning performance **by** speed alone likely drove participants to consider technique in ways that may not have been considered when scoring athletes individually. The forced rankings provide additional support that participants had varying internal valuations on the metrics for evaluating athletes.

2.5 Limitations

A larger sample size may have aided in accommodating subgroups within the expert groups. Subgroups would have prevented the pooling of sub-specializations, which may look for different skillsets, and may have reduced the variability observed within groups. Another limitation of the survey was the use of videos filmed from inconsistent angles, which some participants stated made athletes appear faster or slower. While a forced ranking across all videos would have been interesting to examine, sub-set rankings with representative selections met the goal of identifying whether participants used technique to differentiate athletes with similar performance times.

2.6 Hypothesis Review

In this study, we hypothesized that **(1)** agility scores are consistent between viewings of the same athlete; (2) the definition of agility differs **by** expert background; **(3)** assessments within group are similar; (4) the rankings assessed through a forced reference frame differ from an internal reference frame.

Our findings did not support Hypothesis **1.** Clinical, military, and novice groups provided higher scores for the second set of videos. The second score provided for the videos was only significantly different between groups for one athlete. This result did not support Hypothesis 2, which expected a much greater difference in score values for evaluators in separate fields. Large fourth spreads in Score 2 for multiple videos as well disagreements in evaluator comments within groups for the same videos, did not provide the consistency expected for Hypothesis **3.** Hypothesis 4 was partially supported **by** chi-squared results. These results revealed that significantly different rankings were provided for 4 out of the **10** athletes evaluated using both forced ranks and explicit ranks.

2.7 Summary

The objective of this study was to determine how experts evaluate agility and to identify key terms defining agility performance. The metrics identified have potential to aid in quantifying agility for training and rehabilitation in clinical, military, and athletic environments. The survey analysis found that expert decision-making is guided **by** technique-based metrics in addition to speed-based metrics. These findings are based on qualitative analysis of the participant-provided descriptions and quantitative analysis of the scores and ranks. The value placed on certain strategies was not dependent on area of expertise as scoring was variable within and across groups for several athletes scored.

The qualitative analysis summarizing the agility techniques noted **by** the participants can be used to define quantitative biomechanical metrics. There is opportunity to select metrics that are possible to robustly estimate using mocap, as well as defining measures that map to these terms using data from wearable sensors. The use of wearable sensing enables data collection in a natural setting, which extends the tasks and environments that may be assessed. The definitions of quantitative metrics that map to the qualitative terms provide a means to examine the multiple components that combine to enable an interpretation of agility. Similar to a decision-maker, these component metrics could be combined to construct a composite agility score. For example, the composite could be defined as a weighted average, with the frequency with which terms occurred in the survey used to define the weights. However, the variability in responses for individuals within and between groups highlights that such a composite may need to be tuned to address the strategies desired **by** a particular user or have weightings shown explicitly so that it can be interpreted **by** users who prioritize different techniques. The development of quantitative scores will enable a better understanding of a persons strategy and can aid in detecting areas for performance training beyond the time-based methods currently used. These methods will also be valuable in assessing operational decisions for military environments, or rehabilitation needs in a clinical environment. For example, quantitative scores could inform how selected military gear affects agility and could aid clinicians in selecting a plan of care using metric-based patient progress.

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Chapter 3

Study 2: Metric Development

3.1 Background

Both planned and reactive agility drills use time-based metrics to evaluate agility performance. While speed is important for agility, the parameter does not provide insights about which aspects of performance contribute to or limit success. Human biomechanics is often quantified using mocap, which typically requires data collection to take place in a lab setting. IMUs are an alternative to mocap that extend the tasks and environments that may be assessed. The objective of this study was to derive biomechanical metrics to quantify reactive agility technique using an array of body-worn IMUs and extend previous studies that have found weak correlations when comparing to solely course time. **All** of the metrics we propose map to common terms highlighted **by** athletic, clinical, and military experts while evaluating videos of agility performance. These metrics are applicable for training across these domains, may provide improved understanding of technique, and in the future could **be** related to injury risk mechanisms.
3.2 Methods

3.2.1 Participants

This study was completed by 18 recreational athletes (9 female, mean age: 20 ± 2 years, height: 68 ± 4 inches, weight: 152 ± 30 pounds; mean \pm standard deviation), recruited from the University of Michigan for participation. Two additional athletes completed the agility task but were excluded from the analysis as a result of missing data for a foot **IMU** and helmet **IMU.** Participants were eligible if they **(1)** were between the ages of **18-26,** (2) were physically active, **(3)** had not had a recent hip, knee, or ankle surgery, and (4) were not experiencing lower limb joint pain. **All** athletes provided written consent. The experimental protocol was approved **by** the University of Michigan IRB and the MIT Committee on the Use of Humans as Experimental Subjects **(COUHES).**

3.2.2 Experimental Protocol

Participants completed a reactive agility course (Figure 2.1), which was part of a larger obstacle course (Appendix B). Cones **30** cm high marked the path. Participants wore **13** wireless Inertial Measurement Units (APDM Opal IMUs, with a 3-axis accelerometer **(6g** range), angular rate gyro (2000 deg/s range), and magnetometer **(6** Gauss)). Additional technical specifications are listed in Appendix **C.** The IMUs (sampled at **128** Hz) were placed on the feet, shanks, thighs, sacrum, torso, forearms, biceps, and head. Each **IMU** was secured with velcro straps and athletic tape (Figure **3.1).** Trials consisted of four endpoints traversed in a randomized sequence. To complete an endpoint sequence, participants began at the start line, ran across a cue line where they received a vocal cue, touched the prescribed cone, returned to and touched the start line, and repeated the process for **3** more cues. **All** athletes had identical endpoint sequences defined **by** cone number: 4-3-4-1, 2-4-3-4, and **3-** 4-1-2. An investigator captured completion time for each trial **by** pressing the button on a trigger-enabled **IMU** when the participant crossed the start and finish lines.

=4

Figure **3.1** Placement of IMUs on the subject [20].Boxes illustrate the locations of the torso **IMU** (box **A),** the sacrum **IMU** (box B), and the lower extremity IMUs (box **C).** IMUs are held in place using a combination of elastic straps and athletic tape, as depicted in box **C.**

3.2.3 Metric Selection

A total of **10** agility metrics were calculated. Five of these metrics were not included beyond the initial definition stage because they had confounds or were **highly** correlated with another metric. The **5** metrics discussed in this chapter (Table **3.1)** were associated with terms used **by** military, clinical, and athletic experts to evaluate agility technique in Study **1. All** of these metrics are unique from those previously described in literature (Section 1.2.2). Experts used the terms "foot contacts" and noted that athletes with good footwork minimized the number of steps taken to turn. Additionally, these athletes used "short, quick

steps" within a turn region and long strides at high speed on the course straightaways. Experts also discussed "efficient path", which highlighted the ability to make precise turns towards the desired endpoint **by** minimizing path length. From these terms, we defined number of foot contacts (normalized **by** athlete height), which mapped to the "foot contacts" term. Although it is possible to calculate path trajectory with the **IMU** data, this metric is obtained through the double integral of the acceleration data and its calculation is limited **by** the **IMU** acceleration range. Saturation of the **IMU** accelerometers has been observed when participants are running at high speeds. Anytime the accelerometer is saturated, there is missing area under the acceleration curve that should be integrated and which may lead to underestimated distances. There is no current method in place to quantitatively describe this underestimating effect. The number of foot contacts is a possible surrogate for path efficiency that is a more robust calculation. We hypothesized that the normalized number of foot contacts contributed to agility technique and affected performance speed. This metric was normalized **by** participant height to remove the confound caused **by** the observed trend of fewer foot contacts for taller subjects. The second metric was stride length variance, which maps to the "stride" and "foot contacts" terms. We hypothesized that high-speed performers had a better ability to respond to the different stride requirements of the course (during straight regions and turn regions), resulting in greater stride length variance.

Experts discussed the need for athletes to use their arms to change direction **by** pumping them while accelerating away from endpoint cones. The "arm motion" expert term was mapped to arm swing variance. Our hypothesis was that high performers would use a baseline pumping motion when sprinting on straightaways and pump their arms with greater intensity when changing direction, resulting in a greater arm swing variance.

While our metrics looked to extend agility quantification beyond course speed, it should be noted that "speed" is a critical feature of high performers and was the most frequently used term **by** experts evaluating athlete performance. Instead of requiring a known start and stop location, we defined normalized stride frequency as a metric of speed. We hypothesized that the fastest performers had the greatest average stride frequencies.

While not explicitly mentioned **by** the experts, the fifth metric presented here was defined as the effective body rotations, and was an inferred interpretation of expert comments on "inefficient movements to change direction" or "executed turns efficiently in terms of energy usage". The metric captures the number of full body rotations made while navigating the agility course. Athletes who consistently rotated in the same direction at the start line and endpoint cones had a maximum number of body rotations. We hypothesized that completing rotations in a consistent direction at the cones, rather than rotating one way to touch the cone and re-adjusting the body to rotate another way to return to the start line, may contribute to path efficiency **by** reducing the time and energy needed to navigate the course.

Metric Name	Equation/Variable	Description	Expert Term
Normalized number of foot contacts	$n_{contacts}$ height	Number of heel-strikes and toe-offs detected from acceleration, angular velocity, and time from a foot-mounted IMU. Normalized by participant height.	Foot contacts, efficient path
Stride length variance	σ^2_{SL}	Variance in stride lengths defined by distance between consecutive heel-strikes	Stride, foot contacts
Arm swing variance	$\overline{\sigma^2}_{AS}$	Variance in raw angular velocity magnitude obtained from forearm IMU. IMU worn like wrist watch	Arm motion
Mean normalized stride frequency	$NSD = \frac{SD}{\sqrt{\frac{height}{9.81}}}$ $NSF = \frac{1}{NSD}$	Unit-less quantity calculated for each stride using stride duration normalized (NSD) by participant height.	Speed
Effective body rotations	′ (∠ heading _{start} ₎ 、 —∠ heading _{end}) 360	Difference between torso heading angle at the start and end of the trial. Result divided by 360 to convert from degrees to number of rotations.	Change direction, efficient path

Table **3.1** Agility Metric Details

3.2.4 Hypotheses

In this study, we hypothesize that: **(1)** The normalized number of foot contacts contributed to agility technique and affected performance speed; (2) High performers had greater stride length variance than low performers; **(3)** High performers had the greatest arm swing variance; (4) The fastest performers had the greatest average stride frequencies; **(5)** Completing rotations in a consistent direction at the cones may be a pattern adapted **by** high performers that contributes to path efficiency.

3.2.5 Data Processing and Metric Calculation

One limitation of using IMUs for data collection is that estimates of translational velocity and displacement are corrupted **by** drift error, which results from numerical integration of small errors in acceleration. The majority of our metrics addressed this limitation **by** using raw data from the sensors or incorporating zero velocity updates. Acceleration, angular velocity, and orientation data from the IMUs were used to derive the selected metrics (Table **3.1).** Arm swing variance was calculated from the raw forearm angular velocities **by** low pass filtering (4th order, cutoff frequency of **15** Hz) for the whole trial with data from both forearms. Some metrics required identifying foot contacts, which were detected using a wavelet analysis to determine when foot acceleration reached a threshold level for high frequency [24]. The foot contact detection algorithm used zero velocity updates for drift correction (Appendix F). The number of heel-strikes was divided **by** participant height to estimate normalized number of foot contacts. Stride lengths were calculated from the distance between consecutive heel-strikes for the left and right foot of each participant. Stride length variance included lengths from both feet for the duration of the course. Stride frequency was determined for the whole course using stride durations (time between consecutive heel-strikes) from both feet, normalized **by** participant height.

The APDM quaternion orientation estimate from the torso IMU was used to determine the torso heading angle, which was calculated **by (1)** converting the quaternion to a direction cosine matrix **(DCM),** (2) extracting the second column of the **DCM** as the sensor y-axis

(Figure 3.2a) direction in the world frame, and **(3)** selecting the first two components of the y-axis direction as the horizontal projection. **A** quantitative representation of these steps is given below.

The equations for each of the terms used in the quaternion:

$$
q_0 = e_x \sin\left(\frac{\vartheta}{2}\right)
$$

$$
q_1 = e_y \sin\left(\frac{\vartheta}{2}\right)
$$

$$
q_2 = e_z \sin\left(\frac{\vartheta}{2}\right)
$$

$$
q_3 = \cos\left(\frac{\vartheta}{2}\right)
$$

Where $e = \begin{cases} e_x \\ e_y \\ e_z \end{cases}$ is the principal axis and ϑ is the principal angle.

The quaternion was converted to a **DCM** using the following formula:

Horizontal projection

 \sim

$$
[C] = \begin{bmatrix} q_3^2 + q_0^2 - q_1^2 - q_2^2 & \sqrt{2(q_0q_1 + q_3q_2)} & 2(q_0q_2 - q_3q_1) \\ 2(q_0q_1 - q_3q_2) & q_3^2 - q_0^2 + q_1^2 - q_2^2 \\ 2(q_0q_2 + q_3q_1) & 2(q_1q_2 - q_3q_0) & q_3^2 - q_0^2 - q_1^2 + q_2^2 \end{bmatrix}
$$

Sensor y-axis

The **DCM** can be expressed in terms of Euler angles:

$$
\varphi = yaw \quad \theta = pitch \quad \phi = roll
$$

$$
[C] = \begin{bmatrix} \cos \theta \cos \varphi & -\cos \phi \sin \varphi + \sin \phi \sin \theta \cos \varphi \\ \cos \theta \sin \varphi & \cos \phi \cos \varphi + \sin \phi \sin \theta \sin \varphi \\ -\sin \theta & \sin \phi \cos \theta \end{bmatrix} \begin{array}{l} \sin \phi \sin \varphi + \cos \varphi \sin \theta \cos \varphi \\ -\sin \phi \cos \varphi + \cos \phi \sin \theta \sin \varphi \\ \cos \phi \cos \theta \end{array}
$$

 $\sin \phi \sin \varphi + \cos \varphi \sin \theta \cos \varphi$ $\cos \phi \cos \theta$

A small angle approximation for pitch and roll that assumes both angles are negligible results in this simplified **DCM:**

$$
[C] = \begin{bmatrix} \cos \varphi & -\sin \varphi & 0 \\ \sin \varphi & \cos \varphi & 0 \\ 0 & 0 & 1 \end{bmatrix}
$$

When a participant's torso is upright, the projection of the sensor y-axis on the horizontal plane in the inertial frame is equivalent to the torso yaw angle in an Euler angle expression of orientation. We assumed that the torso was close to upright for the majority of the agility trials and this approximation of torso yaw angle was used to define heading angle. **A** sample torso heading angle profile is shown in Figure **3.2b,** with left rotations represented as increased positive heading angle values and right rotations represented as negative values. Effective body rotations was then defined as the difference between the initial and final heading angles, normalized **by 360** (the number of degrees in a full rotation). The correlation between metrics was examined, with high correlations defined **by** coefficients greater than or equal to **0.7 [25].** The metrics presented here exclude metrics that were **highly** correlated with another metric. An evaluation of hand and foot dominance was performed after reviewing videos of the three agility trials. Fourteen participants had videos available with planting and touching preferences in full view.

t;..

Figure **3.2** Torso heading angle. **A,** Orientation of the Torso **IMU** strapped to the sternum of each participant. B, Heading angle for the 4 endpoint agility course. Left torso rotations are positive and right rotations are negative. The dashed lines represent each cue call.

3.2.6 Statistical Analysis

Participants were stratified into equally-sized high, medium, and low performing groups based on the average time it took them to complete three reactive agility trials. Participants were unique to the speed groups, however, three of the analyzed trials would have been categorized differently if stratification had been performed **by** trial. **A** Shapiro-Wilk test was performed to check for normal distribution of these groups. While there were groups that had normally distributed metrics, not all groups were normally distributed $(p<0.05)$. Therefore, the Kruskal-Wallis test was used to evaluate a difference in the agility metric values across speed groups. The False Detection Rate procedure **[26]** was implemented to address the multiple omnibus tests performed, with $p_i < \frac{m_0}{m} * 0.05$, where m is the total number of tests performed and *mo* is the number of false null hypotheses prior to the correction. Metrics with

significant Kruskal-Wallis results were further analyzed using the Dwass-Steel-Chritchlow-Fligner test for pairwise comparisons.

3.3 Results

The averages and ranges in course completion time for each speed group are given in Table **3.2.** The Kruskal Wallis tests (Table **3.3)** showed that there was a statistically significant $(p < .04)$ difference in metric values between different speed groups for 4 metrics: normalized number of foot contacts, stride length variance, arm swing variance, and mean normalized stride frequency (Figure **3.3).** No significant results were observed for effective body rotations. Trends for the number of normalized foot contacts indicated that slow participants had more foot contacts than medium and fast speed participants, although no significant pairwise comparisons were found between individual speed groups. Arm swing variance was greater for fast participants than slow participants $(p < .01)$. Significant pairwise comparisons were found between the fast and slow group $(p < .01)$ as well as the fast and medium speed group ($p < .05$) for the stride length variance metric. Values for this metric decreased with speed. Mean normalized stride frequency was found to be higher for the fast speed group when compared to both the medium $(p < .01)$ and slow speed $(p < .01)$ groups. Counts of the number of times dominant hands and feet were used at each endpoint cone are shown in Table 3.4.

Figure **3.3** Distribution of metric values for speed groups. The asterisks **(*)** represent pairwise comparison results with $p < .05$. The effect size between fast and slow groups for **A,** B, **C, D, E** is: 0.47, **0.63,** 0.47, **0.57, 0.17.**

Table **3.3** Agility Metric Statistical Results. The plus signs **(+)** highlight Kruskal-Wallis results with **p<** 0.04 and the asterisks **(*)** highlight Dwass-Steel-Chritchlow-Fligner pairwise comparison results with **p< 0.05.** For

pairwise comparisons, $FM = Fast v$. Medium, $FS = Fast v$. Slow, and $MS =$ Medium vs. Slow speed groups

** The effect size calculation $\left(r = \frac{z \text{ score}}{\sqrt{\text{sample size}}} \right)$ was between fast and slow groups only.

Table 3.4 Dominant Hand and Foot Count for **All** Participants. The endpoint sequences for the agility trials were: $4-3-4-1$, $2-4-3-4$, and $3-4-1-2$. When considering 14 participants for the three trials, Endpoints **1** and 2 were approached **28** times, Endpoint **3** was approached 42 times and Endpoint 4 was approached **70** times.

3.4 Discussion

In this study, we defined biomechanical features of a reactive agility task to gain insight on the techniques that **led** to improved speed on the course. We hypothesized that the following uncorrelated biomechanical metrics were sensitive to the speed of the agility task: normalized number of foot contacts, stride length variance, arm swing variance, mean normalized stride frequency, and effective body rotations. The results of this study indicate that participants who took fewer steps (normalized **by** their body height) throughout the agility course were better performers. This finding aligns with the "foot contacts" term prioritized **by** athletic, clinical, and military experts evaluating agility technique. Experts connected a large number of foot contacts to unnecessary steps, including before breakpoints and double footed turns, both limiting the ability to make sharp changes in direction [Chapter 2]. **Al**though they also commented on the use of quick stutter steps to effectively change direction. While the value placed on stutter stepping seems to contradict comments about unnecessary steps at turns, taking **2-3** stutter steps at the center breakpoint may have aided in pivoting quickly and preventing additional steps to complete the full turn. Participants using fewer foot contacts may have utilized a more efficient strategy for making turns **by** minimizing path length, which may have been accompanied **by** stutter steps at the turn region. Athletes who did not stutter step continued with the stride length used on the straightaway of the course and tended to take more arcing paths in order to adjust to the direction change. These observations from video indicate that well-placed stutter stepping aided in minimizing foot contacts while traversing the agility course.

The increase in stride length variance **by** speed group implies that agility performance is dependent on the ability to adjust stride in reaction to turn points and cue calls. Experts valued long strides at high speed on the straightaways of the course as well as short quick strides when changing direction [Chapter 2]. Our results are consistent with Sayers et al. **[27],** which suggests that rapid direction changes are aided **by** lowering center of gravity and shortening stride lengths. Mean normalized stride frequency was sensitive to the speed of agility performance as well, supporting the selection of this metric as an overall speed parameter.

Variance in forearm angular velocity was greater for fast participants than slow participants. This result aligns with multiple experts who mentioned that the use of arms to change direction affected their evaluations of agility [Chapter 2]. Tight pumping motions to accelerate out of endpoint cones appears to play an important role in fast performance times. Additional support is provided **by** Arellano et al. **[28],** who found that participants running on a treadmill while swinging their arms had improved lateral balance and minimized energetic cost when compared to participants running with their arms crossed in front of their chest. The ability to effectively accelerate in a new direction may have been a result of the added stability provided **by** increased arm swing. Additionally, experts mentioned that athletes who were using their arms fully appeared more energetic, which likely contributed to these athletes receiving higher scores when evaluating videos of their performances.

No significant results were found for the effect of rotation strategy (effective body rotations) on participant speed. This metric captured the number of times a participant made **360** degree turns when navigating the course, with participants who consistently rotated their body in the same direction after touching cones having a maximum metric value. The data did not support that effective rotations were different across speed of performance.

Further observations of video performances of participants in the fast group revealed that various rotation strategies contributed to high performance. The number of body rotations of each participant was likely more dependent on hand and foot dominance than agility level. There were multiple cases in which participants chose to turn in a manner that allowed them to consistently plant with the same foot or touch a cone with the same hand. It may be more appropriate to quantify path efficiency **by** calculating path curvature from cue call to endpoint cone instead of effective body rotations, but this is limited **by** the range of accelerometers used in the present study. Stride length is less affected **by** accelerometer range than path curvature, since its calculation is not purely dependent on an integration of acceleration. The foot detection algorithm which contributes to stride length calculation involves a continuous wavelet analysis of foot acceleration and angular velocity (Appendix F).

3.5 Limitations

A limitation in metric interpretation was verification **by** their sensitivity to speed alone. Future work should investigate the sensitivity of biomechanical metrics to other factors contributing to agility performance, such as technique and injury-risk. It may also **be** that when a participant is carrying additional mass (e.g. a backpack or body armor), other metrics may be sensitive to the change in weight that were not apparent when only examining speed. Another limitation is the use of research staff to vocally announce cues and press the trigger button when participants crossed the cue line. This methodology adds variance in the timing and pitch of the announcements as well as slight delays in button pushes. Additionally, this study used surrogate measures for change of direction ability instead of calculating a metric from raw acceleration or angular velocity data. There were several confounding factors identified in an attempt to work with these data to directly investigate a "quick change". One factor was the coupling of the underlying noise from the IMUs with the natural body oscillations during the task, limiting detection of abrupt body segment reactions. Another factor was the variation in turning techniques within speed groups based on foot placement, which could increase or decrease torso heading angle depending on foot placement prior to the cone. While an initial change in heading angle post cue could potentially inform on agility, stutter stepping (as seen in Figure **3.2b** at the cues) would affect these initial slope calculations. Averaging torso angular velocity, another direct measure of orientation change, between the cue and cone becomes confounded because similar results would be obtained for fast performers with large initial peaks in the data and slow performers with lower data magnitudes maintained for a longer period of time. However, if the window is decreased and only the first step or a percentage of the path is considered, the turning technique may affect the interpretation of the window selected. **A** schematic detailing this confound for a similar metric is included in Appendix **A.**

3.6 Hypothesis Review

In this study, we hypothesized that: **(1)** The normalized number of foot contacts contributed to agility technique and affected performance speed; (2) High performers had greater stride length variance than low performers; **(3)** High performers had the greatest arm swing variance; (4) The fastest performers had the greatest average stride frequencies; **(5)** Completing rotations in a consistent direction at the cones may be a pattern adapted **by** high performers that contributes to path efficiency. The results supported Hypotheses $(1)-(4)$. Our findings did not support Hypothesis **5;** the effective body rotations metric did not significantly differentiate high and low performers.

3.7 Summary

Kinematic data from multiple body-worn IMUs can be used to quantify performance in a natural setting and extend previous agility-related studies, which used mocap or fewer body-worn sensors. The results of this study revealed that fast agility performance was distinguished from slower performance **by: (1)** fewer normalized foot contacts, (2) higher stride length variance, **(3)** higher arm swing variance, and (4) higher mean normalized stride frequency. These component metrics mapped to terms previously identified **by** athletic, clinical, and military experts as important for evaluating agility performance. The metrics could be combined to construct a composite agility score, which could aid in identifying performance weaknesses and tailoring performance training in these three environments. Additionally, the development of a quantitative agility score has the potential to aid military personnel in identifying the effect of load configurations on agility and clinicians in monitoring patient rehabilitation progress.

Chapter 4

Conclusion

4.1 Research Summary

The studies included in this thesis address two aspects of reactive agility performance evaluation. The first study explores the effect of different user groups on qualitative and quantitative agility assessment. The aim of this study was to determine how experts evaluate agility and identify key terms defining optimal agility technique. Thirty-three participants completed a survey which involved scoring **16** athletes twice on a **7** point Likert scale of not agile to agile and ranking two subsets of **5** athletes. Their responses were analyzed within and between groups. The results of Study 1 revealed that expert evaluators made decisions that were guided **by** technique-based metrics in addition to speed-based metrics. The value placed on certain strategies was not dependent on area of expertise as scoring was variable within and across groups for several athletes scored. Participant responses were used to link several terms to agility technique with the objective of quantifying these terms in Study 2.

Study 2 discusses the application of expert terms to the development of biomechanical metrics that are sensitive to the speed of agility task performance. The aim of this study was to derive biomechanical metrics to quantify reactive agility technique using an array of body-worn **IMU** sensors. Five metrics were defined (normalized number of foot contacts, stride length variance, arm swing variance, mean normalized stride frequency, and number

of body rotations). Eighteen participants donned **13** IMUs to complete a reactive agility task, which involved navigating a set of cones in response to a vocal cue. Participants were grouped into fast, medium, and slow performance based on their completion time. Metric values were analyzed to detect any differences between speed groups. The results of this study supported the hypothesis that biomechanical metrics can be derived from body-worn IMUs to quantify multiple aspects of reactive agility technique. The selection of IMUs over the more commonly applied method of mocap for the evaluation of movement mechanics has the advantage of allowing data collection in a natural setting. Additionally, the metrics introduced in this study are unique to the metrics previously defined in literature and increase the understanding of human agility beyond the time-based methods currently used. The results of Study 2 revealed that fast agility performance was distinguished from slower performance **by: (1)** fewer normalized foot contacts, (2) higher stride length variance, **(3)** higher arm swing variance, and (4) higher mean normalized stride frequency. These component metrics mapped to terms identified **by** athletic, clinical, and military experts in Study **1** as important for evaluating agility performance. The development of a quantitative score from a combination of the metrics will aid in revealing areas for improvement for training as well as rehabilitation purposes.

4.2 Contributions

- * Extended the evaluation of reactive agility beyond time-based measures **by** analyzing the biomechanics of performance.
- **"** Defined and compared agility terms used **by** athletic, clinical, and military experts.
- Defined IMU-based agility metrics with the ability to differentiate between high and low speed performers.
- **"** Examined agility metrics for confounds and investigated how technique could the affect interpretation of metric values.

4.3 Future Work

The current list of biomechanical metrics addresses **6** out of the **11** terms defined **by** expert evaluators. Future work includes exploring methods for quantifying the remaining terms. Additionally, significant metrics can be combined to construct a composite agility score to assist in identifying performance weaknesses. The benefits of a composite score are that it defines the cumulative effect of several aspects of agility performance. While an athlete may be weak in an area defined **by** one metric, the athlete may be stronger in areas more critical for the agility task in question. This information is valuable to athletic or military evaluators who often aim to compare performance of several athletes, as well as clinicians who aim to identify appropriate rehabilitation plans based on weaknesses. One important consideration for the composite score is selecting the appropriate method for normalizing the metrics. **A** future task will involve determining whether metric normalization should take place between: **(1)** multiple individuals that have completed the agility course **by** calculating percentiles (defined **by** dividing the performance of all individuals into **100** groups and establishing which group a certain individual falls into), or (2) within each individual **by** determining this individual's expected range of performance and how their current performance falls within this range. Another topic of interest is the correlation of expert balance scores with agility scores. Experts were asked to rate balance as well as agility during Study 1 and a subset reported that they perceived a relationship between the two aspects of performance. This thesis discusses the quantification of reactive agility but there is also a possibility to use expert scores to inform the quantification of balance. Quantifying the relationship between agility and balance could inform the format of a composite performance score. It may be appropriate to make one of the aspects of performance (agility or balance) a factor in the score of the other aspect of performance, rather than creating separate agility and balance scores. Future agility studies may also benefit from considering different course geometries and determining the effect of these geometries on selected metrics. There could be a robust methodology for normalizing metrics **by** the cutting angle attempted or other required movement patterns of an agility task. Another future task is to develop improved IMU-based algorithms for estimating path trajectories.

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Appendix A

Additional Metrics Considered

A.1 Overview

A total of **10** agility metrics were calculated. Chapter **3** discussed **5** metrics that were associated with terms used **by** military, clinical, and athletic experts. The remaining **5** metrics had confounds or were **highly** correlated with another metric. The details of the metrics that were not selected for further analysis are discussed in Section **A.2.**

Many of the metrics relied on the knowledge of cone and cue locations for the reactive agility task. Cues were identified using data from a trigger-enabled **IMU** which was pressed each time a participant crossed the cue line. Cone locations were approximated **by** identifying the 4 points of maximum anterior posterior (AP) torso lean during each trial. Figure **A.1** shows the cone locations as detected from sample AP lean data.

Figure **A.1** Cue and cone locations for a sample trial.

A.2 Metric Details

Change in Torso heading angle post cue: Change in torso heading angle was calculated **by** subtracting the angle at the time of each cue call from the angle at the end of the stride following each cue call. The final metric was a sum of heading angle changes for all cues crossed. This metric was created in response to expert feedback about the importance of reaction time and quick direction changes. It was expected that the change in torso heading angle would be largest for fast participants as a result of a quicker rotation from the straightaway of the course to the endpoint-facing direction after a cue was given.

The results of this metric were difficult to interpret given the variation in turning strategy used **by** participants, which often included side stepping instead of body rotations immediately post cue (Figure **A.2).** It was also observed that stutter step strategy confounded the change in angle calculation. Some athletes took quick stutter steps following the cue call and had a smaller reported change in heading angle compared to others who took longer strides. **A** similar confound of technique is still observed if change in heading angle is defined **by** a percentage of course time instead of stride.

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Figure **A.2** Sample heading angle profiles for the 4 endpoint agility course. **A:** Profile for a participant that primarily side steps toward endpoints. B: Profile for a participant that primarily rotates torso toward endpoints.

Path Jerk: Path jerk was calculated using all torso heading angle values between the start and end of the agility course. The algorithm takes the first derivative of these heading angles to determine angular velocity, the second derivative to obtain angular acceleration, and the third derivative to provide the jerk value. Two hypotheses were considered for this metric. The first was that path jerk would be at a maximum value for athletes with poor running technique who may have displayed oscillatory yaw rotations of their torso, instead of a smooth torso heading profile with all energy consistently directed in the instantaneous direction of travel. The other hypothesis was that path jerk would be higher for a fast performer that has a quick turn with increased change in heading, where the slower performer has wider arcing turns. This metric was excluded because of the complexities of referring to heading angle as discussed in the previous section as well as its dependency on the endpoint sequence observed. The variations in path required for the agility task would create a different jerk independent of the strategy selected. Endpoint turn angles were either 45 or **90** degrees and path jerk was expected to be higher for the **90** degree turns than the 45 degree turns. Future work involves investigating how to normalize metrics so that they are independent of course endpoint.

Percent Angular Velocity Direction: We hypothesized that high performers would be aligned with the direction of the destination endpoint for **a** greater percentage of time than low performers (e.g. higher percent right angular velocity direction for right endpoints), and interpreted this direction alignment as meaning the high performers completed quicker turns. To calculate percent angular velocity direction, the angular velocity of a sternum **IMU** was low pass filtered with a cutoff frequency of **15** Hz. Nominal angular velocity spanned a range of **0.5** rad/sec **(0.07** turns/sec). The nominal range was selected after reviewing angular velocity values during the first few seconds of agility trials for several participants. Left, right, and nominal angular velocity directions were calculated for each time step and percentages of each direction were determined per trial. This metric was evaluated from the stride pre cue call to the cone for each endpoint. Percent right angular velocity directions were averaged for all right facing endpoints (endpoints **3** and 4) and left directions were averaged for left facing endpoints **(1** and 2). The formulas used for these calculations are listed below, with angular velocity direction abbreviated as **AVD:**

% Right *AVD per trial* =
$$
\left(\frac{\text{number of serum angular velocities } > 0.5}{\text{number of samples from stride pre cue to cone}}\right) \times 100
$$

% Left *AVD per trial* = $\left(\frac{\text{number of serum angular velocities } < -0.5}{\text{number of samples from stride pre cue to cone}}\right) \times 100$

The calculation below shows the steps for determining total right and left percent angular velocity directions for reactive agility course **1. The endpoint** sequence was 4-3-4-1. The first **3** endpoints were on the right of the course and the last endpoint was on the left.

Total % *Right AVD* = $mean$ % *Right AVD*_{trial1}, % *Right AVD*_{trial2}, % *Right AVD*_{trial3}) *Total* % *Left AVD* = % *Left AVD_{trial4}*

The angular velocity direction metric was originally defined for a smaller version of the reactive agility course, which was used in a pilot study with **3** participants (original dimensions shown in Figure 1.2B; final dimensions shown in Figure 2.1). This metric was excluded from Study 2 because our hypothesis did not match the technique observed for the larger course. The extra space between cue line and cone for the final course provided the opportunity for sternum angular velocity to come down from a peak value during direction change post cue call to a nominal value as the sternum straightened out during the approach to a cone. The tighter dimensions of the original course had little room for participants to return to a straight path and was more likely to result in sternum angular velocity values above the nominal band between cue and cone.

Turn **time at cones:** Calculations for turn time at the cones involved identifying the time of the last heel strike pre cone and the first heel strike post cone. Turn time was the difference between the two values. The resulting metric was the sum of four turn times evaluated for the course. We hypothesized that high performers would spend less time turning than low performers. The turn time metric was confounded **by** depending on foot contacts to define the turning period. Variation in stepping technique (e.g. stutter stepping) affected the accurate capture of when definite movements for a turn were beginning and ending. We also considered looking at the change in angular velocity for a certain percentage of the course between the start line and cue line. The issue with this method was that any chosen percentages were arbitrary and still confounded technique without providing input on technique. Unfortunately, no button presses were made when participants crossed the start line, so this information was not available to help define a more definite time period for turning evaluation.

Mean Sacrum Acceleration from cue to cone:

The magnitude of sacrum acceleration in the world frame was averaged for the time

period between cue and cone. This average was divided **by** the number of foot contacts between cue and cone to calculate mean sacrum acceleration per step. The resulting metric is the sum of the absolute value of four mean sacrum acceleration values evaluated for the course. Given that agility is defined as the ability to change speed and direction quickly, we chose to explore an acceleration metric at stop-and-go points in the course. We hypothesized that high performers would have greater metric values than slow performers as a result of more acceleration after cue calls and deceleration during the approach to the cones. We normalized the metric **by** the number of foot contacts in order to prevent the confound created **by** the varying number of steps taken **by** athletes with different leg lengths. Mean sacrum acceleration was excluded from the final metric list because the averaging of acceleration between cue and cone was confounded. Similar results would be obtained for fast performers with large initial and final peaks in the data and slow performers with lower magnitudes maintained for a longer period of time (Figures **A.3** and A.4). Similar to the foot contacts confound discussed for the turn time metric, mean sacrum acceleration would be confounded if we looked at values for the step prior to the cone or the step after the cue.

Figure **A.3** Sample sacrum acceleration magnitude plots for **1** endpoint. Sacrum acceleration is low pass filtered (4th order, cut off frequency $= 2$ Hz). A: Plot for a fast participant (final metric value = $0.92 \frac{m}{s^2}$ /step). B: Plot for a slow participant (final metric value = $0.93 \frac{m}{s^2}$ /step).

Figure A.4 Representation of observed sacrum acceleration patterns for fast and slow performers

Appendix B

Full Obstacle Course

Obstacles:

- **1 -** Sprint
- 2 **-** Med Ball Toss
- **3 -** Strength Test
- 4 **-** Vertical Jumps
- **5 -** Casualty Drag
- **6 -** Reactive Agility
- **7 -** Wall
- **8 -** Jump Landing
- **9 -** Balance Beam
- **10-** Window
- **11 -** Agility Run
- **12 -** Bounding Rush
- **13 -** High Crawl
- 14 **-** Vertical Transfer
- **15 -** Stairs
- **16 -** 400m Run

Appendix C

Sensor Characteristics

Appendix **D**

Survey Setup

Video **1**

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Appendix E

Extended Survey Responses

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Appendix F

Foot Contact Detection

A wavelet analysis was completed **by** our collaborators at the University of Michigan [24] to detect foot contacts. IMU data was used to identify foot strikes and push-offs **by** locating times in which the acceleration and angular velocity measured **by** the **IMU** contained significant high frequency content; this is based on the idea that there are sudden changes in the force acting on the foot when the foot hits or leaves the ground, and that the sudden changes will cause rapid (high frequency) changes in the acceleration and angular velocity signals. The following steps are a high level overview of the foot contact detection methods.

- **"** Time points with high frequency content were identified **by** performing a continuous wavelet transform (CWT) using FFT (cwtft, MATLAB, MathWorks) on each measured signal of acceleration and angular velocity (six total).
- **"** For each signal, the percentage of total energy above 20 Hz at each time point was calculated. The percentage of energy above 20 Hz for all **6** signals was summed, giving an estimate of signal energy above 20 Hz for all signals versus time. This estimate is referred to as "Percentage normalized frequency content" in Figure F.1. Peaks in this signal indicate either terminal contact (push-off) or initial contact (foot strike).
- **"** Acceleration of each foot **IMU** was resolved in the inertial frame and integrated to obtain velocity.
- Velocity was drift corrected using zero velocity updates.
- **"** Local maxima in the horizontal velocity magnitude were detected and used to define peak swing phase.
- **"** An algorithm checked to see if two contact points **(1** foot-strike and 1 push-off) were located between each velocity peak. **If** so, an additional zero-velocity point was found in between the two contact points using angular velocity magnitude.
- The user could view plots of horizontal velocity magnitude and normalized frequency content through a graphical user interface **(GUI)** with the automatically detected foot contacts labeled. This **GUI** popped up if the algorithm detected an incorrect pattern in foot-strikes, push offs, and peak swing phases. The user would then use their cursor to manually correct errors in foot contact detection (e.g. only **1** contact shown between 2 velocity peaks) **by** adding or removing contacts. **If** no peak in normalized frequency content was available for guidance, the user made an assumption about where a missing contact should be added based on the distance between foot contacts and velocity magnitude peaks before or after the error (all contact locations could be viewed **by** scrolling through the GUI). An example of a situation in which a missing contact would **be** added is indicated with an arrow in Figure F.1. The average percentage of manual corrections needed for a participant was approximately **6%** when considering the total number of steps taken per reactive agility trial.

Figure F.1 Foot contact detection

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