THE APPLICATION OF PCA AS A MOVEMENT PATTERN RECOGNITION
TECHNIQUE: A PROOF OF PRINCIPLE

by

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Abstract

Quantitative methods can help us understand how underlying attributes contribute to movement patterns. Applying principal components analysis (PCA) to whole-body motion data may provide an objective data-driven method to identify unique and statistically important movement patterns. Therefore, the primary purpose of this study was to determine if athletes’ movement patterns can be differentiated based on skill level or sport played using PCA.

Motion capture data from 542 athletes performing three sport-screening movements (i.e. bird-dog, drop jump, T-balance) were analyzed. A PCA-based pattern recognition technique was used to analyze the data. Prior to analyzing the effects of skill level or sport on movement patterns, methodological considerations related to motion analysis reference coordinate system were assessed. All analyses were addressed as case-studies.

For the first case study, referencing motion data to a global (lab-based) coordinate system compared to a local (segment-based) coordinate system affected the ability to interpret important movement features. Furthermore, for the second case study, where the interpretability of PCs was assessed when data were referenced to a stationary versus a moving segment-based coordinate system, PCs were more interpretable when data were referenced to a stationary coordinate system for both the bird-dog and T-balance task.

As a result of the findings from case study 1 and 2, only stationary segment-based coordinate systems were used in cases 3 and 4. During the bird-dog task, elite athletes had significantly lower scores compared to recreational athletes for principal component (PC) 1. For the T-balance movement, elite athletes had significantly lower scores compared to recreational athletes for PC 2. In both analyses the lower scores in elite athletes represented a greater range of
motion. Finally, case study 4 reported differences in athletes’ movement patterns who competed in different sports, and significant differences in technique were detected during the bird-dog task.

Through these case studies, this thesis highlights the feasibility of applying PCA as a movement pattern recognition technique in athletes. Future research can build on this proof-of-principle work to develop robust quantitative methods to help us better understand how underlying attributes (e.g. height, sex, ability, injury history, training type) contribute to performance.
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Chapter 1

Introduction

Movement screens are often used to identify aberrant movement patterns that are believed to increase risk of injury and/or impede performance. This is accomplished by examining individuals’ kinetics and kinematics data to evaluate the correctness and proficiency of their movement (Donà et al., 2009). However, movement screening remains primarily qualitative, meaning they are based on the visual appraisal of movement. Quantitative methods can help us understand how underlying attributes contribute to movement quality and patterns. Quantitative methods could enhance movement screening, by increasing objectivity, while creating the potential to detect new and important movement features that may not be easily visible to the human eye. This work explores the viability of a principal component analysis-based movement pattern recognition technique to permit an objective characterization of movement within a movement screening paradigm.

Movement screens are growing in popularity amongst coaches and athletes to exploit aberrant movements. A commonly used quantitative movement screen is the functional movement screen (FMS™) (Functional Movement Systems, Chatham, VA, USA). The FMS™ is a quantitative, subjective movement screen, meaning that athletes receive a numerical score, however that score is based on subjective observations. The screen is comprised of mobility and stability tasks that are designed to put the participant in extreme positions where, if present, weaknesses and imbalances can be detected. Each test is given a score by a rater, who rates each task based on certain grading criteria that can be seen by the human eye. However, it was recently found that if the participants were made aware of the grading criteria, within minutes they were able to significantly improve their FMS™ score (Frost et al., 2015). This leads to the question of
how much the FMS™ score is reflective of “dysfunction” and how much is reflective of external factors, such as knowledge of grading criteria. Another limitation of currently used quantitative, subjective movement screens is that differences between scores need to be large enough for the human eye to detect. Motion capture systems are able to detect differences in movements much smaller than can be seen and processed by a human observer and give measures that can provide athletes and coaches with quantitative, objective feedback.

Quantifying movement patterns requires motion capture data. Motion capture systems are able to track the 3D motions of reflective markers carefully placed on the body to comprehensively describe the human motion. However, the comprehensive motion data are difficult to interpret on their own. As such, they may be reduced by characterizing the motions of specific joints of interest, or by applying other data reduction methods, such as principal component analysis (PCA). The use of PCA for motion analysis, enabling the extraction of fundamental patterns of coordination of complex movements, has dramatically increased.

PCA is a multivariate statistical technique, which aims to reduce high-dimensional data sets. The PCA process identifies principal components (PCs), with the first component accounting for the largest possible variance and each following component descending in variance under the constraints of the preceding components (Abdi and Williams, 2010). If there are redundancies in the data, a subset of the data will explain the majority of the variance (Troje, 2002); for example, the first four principal components may account for 98% of the variance. Using PCA to examine the entire movement (i.e. all marker trajectories) can help accurately identify embedded patterns of complex movements.
PCA-based movement pattern recognition technique used in this thesis is an extension of traditional PCA. For the technique used in this thesis, PCA is applied twice to subject data to reduce the dimensionality of motion. An initial PCA is performed to find redundant features of motion in order to reduce the number of parameters to be analyzed. The second PCA is performed to allow for comparisons to be made between athletes. The second PCA outputs principal components, scores, and a mean movement, in order to allow for the data to be reconstructed to identify the differences in movement patterns. The technique has previously been effectively used to detect and explain differences in gait patterns based on the participants age, sex, and feelings (happy/sad, nevous/relaxed) (Troje, 2002); to objectively analyze skiing technique (Federolf et al., 2014), and to develop an objective judging tool for competitive diving (Young and Reinkensmeyer, 2014). The PCA-based movement pattern recognition technique was the first data-driven method to decompose and analyze the complex, whole-body movement of a skier (Federolf et al., 2014). An obvious benefit of this technique, is it is able to provide objective biomechanical feedback to coaches and athletes to use when planning the training of athletes (Federolf et al., 2014). However, a less obvious, secondary benefit of the technique is that it can be used to support the development of instructors’ or coaches’ skills to assess an athlete’s movements (Federolf et al., 2014). The PCA-based movement pattern recognition technique also allowed researchers to characterize movement features during diving, where dive scores could be calculated based on how a given feature pattern related to the mean (Young and Reinkensmeyer, 2014). The technique has been able to provide researchers, coaches, and judges a method to objectively assess and score movement patterns of athletes performing different movement skills.

The technique is able to objectively detect differences in movement patterns, however, certain considerations need to be taken into account when using the technique. A possible concern
outlined by Federolf et al. (2014) was possible differences in results when relating data to different coordinate systems. Federolf et al. (2014) predicted that changing the reference system may result in changing what each PC represents. In addition, PCA is able to detect differences based on how the athlete is positioned relative to the global space, which is not always beneficial information. Therefore, which coordinate system the data should be referenced to needs to be explored. Another prospective concern is whether or not the technique is able to distinguish differences in athletes in non-cyclical, constrained movements. For the purpose of this thesis, a constrained movement is defined as movement that has set beginning, middle and end tasks that need to be accomplished. Therefore, the purposes of the current study were: 1) to address methodological considerations by determining differences in results when data are referenced to different reference systems when using PCA, and 2) to use what was learned in purpose 1 to assess the application of pattern recognition for differentiating whole-body movement patterns in athletes of different skill level and sport during non-cyclical, constrained movements using PCA.
Chapter 2
Overview of Literature

The principal component analysis (PCA)-based movement pattern recognition technique used in this thesis approaches movement variability from the perspective of the whole-body. The technique allows for movement variance to be examined as a whole system, rather than as individual parts.

2.1 Variability in Motion

Human movement variability is the normal variation that occurs in motor performance between individuals (inter-individual variability) or across multiple repetitions within an individual (intra-individual variability). Traditional perspectives believe that intra-individual variability can be attributed to random error or noise. However, more recent perspectives believe that movement variability is not random, but in fact is functional and the study of the variability can provide meaningful insight regarding human movement. Variability in movement is thought to be functional in three different ways by affecting: 1) compensatory movements, 2) ability to adjust to the environment, and 3) risk of injury during repetitive movements (Bartlett et al., 2007). Moreover, variability can also be influenced by experience, and can reflect personal differences in technique.

Studies targeting sporting movements provide evidence that compensatory patterns may emerge between athletes. In a study looking at movement variability in female basketball players varying in skill level from national team players to players with very little experience, skilled players had less variability at the elbow and wrist joints. However, there were no significant differences in the amount of variability in the elbow trajectory between the two groups (Button et al., 2003). It is believed that the variability in the elbow trajectory is a compensatory technique to
reduce the variability of the ball’s trajectory. Similar findings have been found by researchers looking at target throwing of balls and darts, tasks that require accuracy (Kudo et al., 2000; Muller and Loosch, 1999). When studying variability as a contributor to compensatory techniques, it has been found that variability in the shoulder, elbow, and wrist joints did not affect the height, angle or speed of release of the ball. This suggests that compensatory mechanisms were occurring at the shoulder, elbow and wrist in order to minimize variability of the release parameters (height, angle or speed of release) (Davids and Glazier, 2010).

Compensatory patterns may also emerge within individuals’ when moving in different performance environments. Researchers looking at treadmill running versus over-ground running have found that runners have greater amounts of variability during over-ground running compared to treadmill running (Wheat et al., 2005). Further research investigated running on a self-propelled treadmill (the treadmill changes speed as the runner changes speed). Again, the runners during over-ground running had greater variability than when running on the self-propelled treadmill. This suggests that runners have greater variability while running over-ground to adjust to environmental factors such as uneven ground, wind and obstacles (Bartlett et al., 2007; Wheat et al., 2005). Therefore, it is thought that variability contributes to the functionality of being able to react and adjust to environmental factors.

Coordinative variability within a repetitive movement task may decrease the risk of an over-use injury. Previous research has found that increased coordinative variability is associated with a healthy state, whereas low coordinative variability is associated with an unhealthy state when looking at overuse injuries (Hamill et al., 2012). It is hypothesized that an increase in variability diffuses the strain on tissues, joints and bones during repetitive movements. Although, it is important to note that the decrease in variability cannot be assumed to be cause of the injury,
as it may be a result of the injury. There may be differences in movement variance during specific movement tasks between sports that require the movement in the sport compared to sports that do not require the movement. For example, basketball players may have greater variance during a drop jump compared to golfers, because basketball requires jumping whereas golf does not. Basketball players may adopt a more variable movement pattern compared to golfers in order to decrease the risk of over-use injuries.

Expertise can also influence variability within a movement. Variability in human motion is due to the complex nature and large amount of redundancy within the neuro-musculo-skeletal system. Due to these redundancies, movement tasks can be completed in a multitude of different combinations. In sport, compensatory variability can be seen in elite athletes who are able to exploit the many degrees of freedom to their advantage (Davids et al., 2003). On the contrary, less skilled athletes tend to firmly fix the degrees of freedom and will show as much or more variability than the elites. The variability seen by less skilled athletes is not functional and is due to weak adaptations to task constraints (Davids et al., 2003).

Exploring movement pattern variability can also discover unique, individualistic differences in movement technique. When looking at javelin throwers at the World Athletic Championships, it was seen that each finalist adopted a unique technique to throw the javelin (Morriss et al., 1997). It is thought that the differences in individuals’ technique are due to individual-specific self-organization processes. Due the differences in technique, it is thought that individual training programs should be performed in a way that replicates the individual’s technique (Morriss et al., 1997).

Using movement pattern recognition techniques, individual, customized training programs can be developed to build better training programs by replicating the individual’s technique.
Whole-body pattern recognition techniques could also help researchers to better understand the compensatory mechanisms used by athletes and to detect if there are differences in movement patterns between athletes of different skill levels and sports.

2.2 Movement Screens

Movement screens are used to assess athletes’ movement patterns during specific tasks. They can be used to help determine deficiencies in stability, power, and flexibility. Three common movement screens are the functional movement screen, the vertical drop jump, and single-leg balance tasks. However, these three movement screens are subjective tests. Clinicians or raters give a quantitative score based on subjective grading criteria. There are no quantitative measures or cut offs used to assess the motion, raters follow subjective guidelines, but are free to perceive motions on their own. In addition, the differences in movement patterns need to be large enough to be detected by the human eye.

2.2.1 Functional Movement Screen

The functional movement screen (FMS™) (Functional Movement Systems, Chatham, VA, USA) is a subjective screening tool that is used to evaluate movement quality. The screen is comprised of seven tests that test both mobility and stability, with one of the tests being the bird-dog test. The tests are designed to put the participant in extreme positions where, if present, weaknesses and imbalances can be detected. Each test is scored based by the rater on a four-point scale (0-3), providing a final score out of 21. Although the scoring system is based on subjective measures, previous research has found that there is high intra- and inter- repeatability amongst both novice and expert level raters (Minick et al., 2010; Teyhen et al., 2012).

Within the literature, there are conflicting reports on the effectiveness of the FMS™ to predict injury. Some researchers found that athletes and military cadets who receive ≥14 are at a
significantly higher risk of injury than those who score >14 (Chorba et al., 2010; Kiesel et al., 2007; Sorenson, 2009). However, other researchers have shown that there is no significant relationship between FMS™ scores and risk of injury (McGill et al., 2012; Sorenson, 2009). One study found that if females scored ≤14 on the FMS, they were at a significantly increased risk of injury, but males who scored ≤14 were not (Knapik et al., 2015).

One concerning factor, however, is that it was recently found that if the participants were made aware of the grading criteria, within minutes they were able to significantly improve their FMS™ score (Frost et al., 2015). This leads to the question of how much the FMS™ score is reflective of “dysfunction” and how much is reflective of external factors, such as grading criteria.

2.2.2 Drop Jump Tests

The drop jump test consists of an athlete jumping down from a box onto the floor and then immediately transitioning into a maximum vertical jump. At the first landing of the jump, the athlete has to absorb the impact of the drop in order to transition into the jump. The test is often used to identify deficiencies in knee stability. Clinicians and researchers focus on abduction and flexion of the knees, internal rotation and flexion of the hips and the kinetic motion patterns throughout the jump (Griffin, 2006; Hewett, 2005). Differences in kinetics during a vertical jumping task have also been examined between sports. Volleyball players had slower time profiles and lower jump heights compared to baseball players, where football and basketball player’s profiles and jump heights were in-between (Guillaume et al., 2014). This is thought to be due to the nature of the sports. Although football and baseball do not require a lot of jumping during play, they require short, explosive muscular actions such as pitching, sprinting, or tackling. On the other hand, volleyball and basketball have to require more time optimization of their jumps during play.
in order to be at the highest point to attack the ball (Guillaume et al., 2014). On this basis, the drop jump could be expected to reveal movement pattern differences on the basis of an athlete’s sport.

2.2.3 Single-Leg Balance Tests

Performance on single-leg balance tests, like the T-balance, may exploit experience related differences. A previous study looking at single-leg balance of national and regional level soccer players, found that the national level soccer players had a smaller centre of pressure surface area and centre of pressure velocity (increase postural control) compared to the regional players (Paillard et al., 2006). Similarly, elite golfers had superior balance with both eyes open and eyes closed compared to their less proficient counterparts (Sell et al., 2007). It is suggested that the superior postural control of elite athletes is due to repetitive training that influences motor responses and improves the athlete’s ability to attend to proprioceptive and visual cues, neuromuscular coordination, strength, and range of motion (Bressel et al., 2007; Glofcheskie, 2015; Hrysomallis, 2010).

Performance on single leg balance tasks may also exploit sport-related differences between athletes. When looking at balance between athletes who compete in different sports, previous research found that soccer players had superior postural control during single-leg dynamic balance tasks compared to basketball players (Bressel et al., 2007; Hrysomallis, 2010). This is thought to be due to the fact that soccer players often support their body mass on one foot while kicking the ball (Hrysomallis, 2010). The T-balance task may help demonstrate differences in whole-body motion variability between elite and recreational athletes, as well as difference between athletes competing in different sports.
2.3 Movement Pattern Recognition Techniques

Quantitative methods may provide coaches and athletes with better ways to objectively characterize motion patterns. With advancement in motion capture technology, increased access to motion capture laboratories, and the reduction in costs of motion capture systems, motion capture has become a viable method to collect data. Motion capture systems are able to provide 3D motion trajectories for the entire body, although, in order to capture the whole-body movement, outputs are generally quite large. Therefore, analytical techniques need to incorporate data reduction as part of the analysis. However, in order to get meaningful results, the data need to be able to be interpreted after they have been reduced.

2.3.1 Principle Component Analysis (PCA)

The use of PCA for motion analysis, enabling the extraction of fundamental patterns of coordination of complex movement, has dramatically increased. (Abdi and Williams, 2010). PCA is a multivariate statistical technique, which aims to reduce high-dimensional data sets. The goal of PCA is to provide an objective tool to identify and rank differences based on amount of variance explained within a data set, thus is able to reduce data. The PCA process identifies principal components, with the first component accounting for the largest possible variance and each following component descending in variance under the constraints of the preceding components (Abdi and Williams, 2010). If there are redundancies in the data, a subset of the data will explain the majority of the variance (Troje, 2002); for example, the first four principal components may account for 98% of the variance.

Each principal component is also associated with a score; the score is a weighting factor for the principal component. The motion data can be modeled with fewer parameters based on the following equation:
\[ P_j(t) = p_{j,0} + p_{j,1}c_{j,1} + p_{j,2}c_{j,2} + \ldots + p_{j,n}c_{j,n} \]

where \( P_j(t) \) is the modeled motion, \( p_{j,0} \) is the time-series mean posture, \( p_{j,n} \) is the \( n^{th} \) principal component, and \( c_{j,n} \) is the score associated to the principal component (Troje, 2002). The higher the sum of the explained variance, the more accurate the replicated data will be.

2.3.1.1 PCA-Based Movement Pattern Recognition Technique

It is thought that complex movements can likely be characterized by a subset of pattern dynamics that emerge. Due to the complexity of sport movements, previous research has used PCA to identify movement features that contribute the greatest amount of variance to specific movements (Federolf et al., 2014; Troje, 2002; Young and Reinkensmeyer, 2014). A PCA-driven movement recognition technique has been used to recreate movement patterns during walking (Troje, 2002), diving (Young and Reinkensmeyer, 2014) and skiing (Federolf et al., 2014).

The technique has been effectively used to detect and explain differences in gait patterns based on the participants age, sex, and feelings (happy/sad, nervous/relaxed) (Troje, 2002); to objectively analyze skiing technique (Federolf et al., 2014), and to develop an objective judging tool for competitive diving (Young and Reinkensmeyer, 2014). The PCA-based movement pattern recognition technique was the first data-driven method to decompose and analyze the complex, whole-body movement of a skier (Federolf et al., 2014). An obvious benefit of this technique, is its ability to provide objective biomechanical feedback to coaches and athletes to use when planning the training of athletes (Federolf et al., 2014). However, a less obvious, secondary benefit of the technique is that it can be used to support the development of instructors’ or coaches’ skills to assess an athlete’s movements (Federolf et al., 2014). The PCA-based movement pattern recognition technique also allowed researchers to characterize movement features during diving, where dive scores could be calculated based on how a given feature pattern related to the mean
The technique has been able to provide researchers, coaches, and judges a method to objectively assess and score movement patterns of athletes performing different movement skills.

The technique is able to detect objective differences in movement patterns, however, certain considerations need to be taken into account when using the technique. A possible concern outlined by Federolf et al. (2014) was possible differences in results when expressing data to different reference systems. Federolf et al. (2014) predicted that changing the reference system may result in changing what each PC represents. Therefore, which coordinate system the data should be referenced to needs to be further examined. In addition, PCA is able to detect differences based on how the athlete is positioned relative to the global space, which is not always beneficial information. Another prospective concern is whether or not the technique is able to distinguish differences in athletes in non-cyclical, constrained movements. For the purpose of this thesis, a constrained movement is defined as movement that has set beginning, middle and end tasks that need to be accomplished.

2.5 Purpose

Currently, movement screens are used as a method to detect aberrant movement patterns. A major limitation with the three aforementioned movement screens is that they are commonly evaluated subjectively, where the score is in the “eye of the beholder”. Since there are no quantitative measures or cut offs used to assess the motion, raters follow subjective guidelines, but are free to perceive motions on their own. One way to objectively quantify movement is through the use of motion capture. Motion capture systems can record whole-body motion at a much finer level of detail and accuracy than done by a human observer (Federolf et al., 2014). However, the comprehensive motion data are usually quite large and difficult to interpret on their own. As such,
they may be reduced by characterizing the motions of specific joints of interest, or by applying other data reduction methods, such as PCA.

PCA exists as a viable method that could permit more objective assessments for movement screens. However, based on noted challenges in previous research, adopting this methodology to movement screening requires exploration into certain methodological factors. In addition, consistent with dynamic systems theory, unique patterns of movement emerge due to sport, environment, and experience. However, to the best of the authors’ knowledge, there has been no previous research that examines objective differences in whole-body movement patterns during movement screens between athletes of different skill levels and sport. Therefore, this study will explore the feasibility of adopting this method to movement screening through a series of case studies.

The purpose of case 1 is to assess the influence of a global versus local coordinate system on the interpretability of movement patterns characterized using PCA. As noted by Federolf et al. (2014), if an appropriate reference system is not chosen, then the principal components may be harder to analyze and interpret than principal components from a more appropriate reference frame. By exploring this effect, we will generate evidence to help determine which reference system is most appropriate for a given situation.

The purpose of case 2 is to assess the influence of a moving versus a stationary local coordinate system. Global coordinate systems cannot always be used; therefore, this case will explore whether a moving or a stationary local reference system is more intuitively interpretable. By exploring this effect, we will generate evidence to help determine whether a moving or a stationary reference system is more appropriate for given situations.
The purpose of case 3 is to assess whether PCA can detect differences in movement patterns between athletes of varying skill level during non-cyclical, constrained tasks. It was hypothesized, based on previous research, that there would be differences in movement patterns between recreational and elite athletes (Glofcheskie, 2015; Hrysomallis, 2010; Paillard and Noé, 2006).

The purpose of case 4 is to assess whether PCA could detect differences in movement patterns between athletes competing in different sports during non-cyclical, constrained tasks. It was hypothesized that there would be differences between athletes of different sports. It was hypothesized that golfers would have superior postural control of the trunk during the bird-dog task (Glofcheskie, 2015) and soccer players would have superior postural control during the T-balance (Bressel et al., 2007).
Chapter 3
General Methodology

This thesis, reporting on a secondary data analysis was made possible by Motus Global, LLC (Massapequa, NY, USA). Motus Global uses motion capture technology and analytical techniques to provide biomechanical-based feedback to athletes and coaches in order to guide improvements in performance and injury reduction. Motion capture data analyzed in this thesis were obtained by Motus Global as they conducted their proprietary screening process on 542 athletes. Prior to obtaining these data, a non-disclosure agreement (Appendix A) was signed by all participating persons, ensuring that they do not disclose proprietary protocols, client information, or raw data from their athletes.

3.1 Participants

Motion capture data were obtained from 542 athletes (Table 1). This sample included athletes competing in baseball, basketball, soccer, golf, tennis, track and field, squash, cricket, lacrosse, football or volleyball. Prior to data collection, each participant read and signed an informed consent form (Appendix B) permitting Motus Global to use the data for future research.

<table>
<thead>
<tr>
<th>Sex</th>
<th>n</th>
<th>Age</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>479</td>
<td>20.3 (4.50)</td>
<td>185.29 (19.39)</td>
<td>86.08 (22.25)</td>
</tr>
<tr>
<td>Female</td>
<td>63</td>
<td>18.97 (5.68)</td>
<td>167.96 (8.86)</td>
<td>61.14 (13.30)</td>
</tr>
<tr>
<td>Total</td>
<td>542</td>
<td>20.2 (4.67)</td>
<td>183.3 (19.28)</td>
<td>83.1 (22.85)</td>
</tr>
</tbody>
</table>

3.2 How the Data were Generated

To provide context for how the motion capture data were collected, the following section summarizes the standard protocol implemented by Motus Global. Upon arrival at the Motus
laboratory, participants read and signed the consent form. Once the consent form was signed, the participants had their height (with shoes on) and weight measured and then described all previous injuries that caused missed playing time (missed playing time considered as two or more missed training days) in the past 10 years (Appendix C). The collected information included: place of injury, diagnosis of injury, date of injury, surgical or non-surgical, and amount of time missed before returning to play.

The participants were then outfitted with 45 passive, reflective markers (B&L Engineering, Santa Ana, CA, USA) to capture whole-body kinematic data. 37 markers were placed on anatomical landmarks to define the head, trunk, upper arms, forearms, pelvis, thighs, shanks and feet (Appendix D). Eight markers were used as tracking markers (one marker placed on each thigh, each forearm, each bicep, the right shank, and the right scapula) to assist with tracking the segments and also to identify the left limbs from the right. After the athlete was outfitted with all of the markers, (s)he performed a calibration trial (Figure 1) in order to zero movement to the standing position. During the calibration trial, the athlete stood with their feet shoulder width apart and toes pointing straight forward. The arms were abducted 90°, with a 90° bend in the elbow. The athlete then rotated his or her arms 90° both internally and externally.

The athlete then completed a proprietary movement screening battery. The drop-jump, bird-dog and T-balance tests were included in that battery, where motion data from those three activities were analyzed in this thesis. The selected tests were chosen in order to maximize examination of motion and stability at the shoulder, spine, hip, knee, and ankle. Full-body motion data were captured using an 8-camera Raptor-E (Motion Analysis, Santa Rosa, CA, USA) motion capture system.
3.2.1 Bird-Dog Test

The bird-dog test (also known as rotary stability) is a common spine stabilizing exercise used in yoga and rehabilitation therapy that emphasizes core strength, trunk stability and balance (McGill and Karpowicz, 2009). The athlete begins in a crawling position with one arm and the contralateral leg (e.g. left arm and right leg) extended until they are parallel with the floor at their trunk height (Figure 2A). The athlete then draws the elbow and knee of those respective limbs in towards the transverse midline so that they are touching (Figure 2B) and then returns back to the extended position (Figure 2C). The test is performed on both sides.
3.2.2 \textit{T-Balance Test}

The T-balance test challenges knee, hip, trunk stability, and postural control. Athlete’s begin by standing on one leg with the opposite hip and knee flexed to 90° and the hands in a prayer position at nipple line (Figure 3A). This position is held for three seconds. In one fluid motion, the athlete hinges at the hip, extending the hip and knee, bringing the trunk parallel to the floor, while extending both of arms out to 90° of abduction at the shoulder, creating a T-shape with the arms and the trunk. The athlete rotates forward as far as possible, while maintaining balance. Once reaching the T-position (Figure 3B), the athlete then returns to the starting position (Figure 3C). The test is performed on both the left and right foot.

![Figure 3. T-Balance Test.](image)

![Figure 4. Drop Jump Test](image)
3.2.3 Drop Jump

The drop jump test is commonly used in research and clinical settings to detect deficiencies in knee stability (Hewett, 2005). The athlete begins by standing on a box 30 cm tall (Figure 4A). The participant then drops down off of the box onto the floor (Figure 4B) then immediately jumps upwards, aiming for maximum vertical height (Figure 4C).

3.3 Data Analysis

3.3.1 Pre-Processing

Prior to implementing the PCA-based method, motion data were inspected, labeled, used to model joint centres, and clipped to respective trial start and end features. Motion capture data were collected and labelled using Cortex (Motion Analysis, Santa Rosa, CA, USA). Data from the anatomical landmarks and the tracking markers during the calibration trial were used to develop a 3D, whole-body kinematic model in Visual3D (C-Motion, Inc., Germantown, MD, USA) (Figure 5; Appendix E). The model was then applied to all motion trials outputting joint centre positional data bilaterally for the wrist, elbow, shoulder, foot, ankle, knee, and hip; in addition, centre of gravity positional data were outputted for the trunk, head, and pelvis. Lastly, marker positional raw data for the left and right heel, T2, T8, sternum, and the back, front and sides of the head were extracted to model the feet, trunk and head more robustly (Figure 5). Data were then exported to Matlab (The MathWorks, Natick, MA, USA). All trials were clipped to specific start and end-point criteria (Appendix F) and time normalized to 100 frames to control for differences in the absolute time taken to complete each movement.
3.3.2 Application of PCA as a Movement Pattern Recognition Technique

A principal component analysis (PCA)-based movement pattern recognition technique, as done by Troje (2002) was used to analyze the data. The technique consisted of running two PCAs. The first PCA was within the subject and outputted the principal components and corresponding scores for the variability within the movement. The second PCA compared variability across subjects.
3.3.2.1 First Principal Component Analysis

A 78 x 101 matrix was created for each athlete for each task. The x,y and z positions for each calculated joint centre, centre of gravity, and marker position data (26 location x 3 axes) comprised the 78 variables. Each variable was time-normalized to 100, resulting in 101 points.

A principal component analysis was applied to the movement data corresponding to each individual movement performance and a trace criterion of 90% was applied (i.e. the sum of the explained variance of the retained eigenpostures had to be greater than 90%). As a result, the PCA generated four eigenvectors, herein referred to as eigenpostures (Figure 6) (matrix was a [4 x 78]), the reference posture (the average posture throughout the movement) (matrix was a [1 x 78]) and the scores (one for each time point) associated with each eigenposture (matrix was a [4 x 101]) (Figure 7) were extracted for each athlete. The eigenpostures are the principal component postures (eigenvectors), which are arranged in their order of explained variance (eigenvalues). The principal component scores (PC scores), explain how each eigenposture varies over the course of the movement. The movement was then able to be recreated using:

\[ M_{\text{recreated}} = \sum P_{\text{reference}} + (P_1S_1) + (P_2S_2) + (P_3S_3) + (P_4S_4) \, , \]

where \( M_{\text{recreated}} \) is the recreated movement, \( P_{\text{reference}} \) is the reference posture, \( P_{1-4} \) are the four eigenpostures and \( S_{1-4} \) are the scores that are associated with the eigenpostures (Figure 8).
Figure 6. Four representative eigenpostures for one subject during the drop jump test.

Figure 7. Four representative scores associated with the drop jump test eigenpostures across time.

Eigenpostureₙ*scoreₙ + reference posture at n gives you the recreated motion at frameₙ.
In order to perform the second principal component analysis, a second matrix was created for each individual movement using each participant’s reference posture, eigenpostures and scores across the columns, where each row described the PCA data for each participant. Therefore, the matrix that was used for the second PCA was \([n \times 794]\), where \(n\) was the number of athletes completing that motion and included in the analysis. In some instances, certain athletes did not perform every task and in some cases marker occlusion and other data collection errors required that some trials be removed. Therefore, each task had a unique number of athletes and therefore matrices' sizes. A second PCA was applied to the principal components and scores. Each participant has an individual score corresponding with each principal component. The scores describe the amount each participant’s whole-body movement deviates from the mean. Due to the size of the dataset and in order to robustly investigate the PCA-driven pattern recognition technique as a proof of principle, a case-study approach was used for the thesis. Four cases were created, with the first

**Figure 8.** A) The original positional data for the drop jump test for one subject. B) The reconstructed motion data for the drop jump test for one subject using the equation: reference position + eigenposture 1*score 1 + eigenposture 2*score 2 + eigenposture 3*score 3 + eigenposture 4*score 4.
two cases geared towards methodological concerns and the last two cases looking at implementation of the PCA-driven pattern recognition technique. Chapters 4-7 will go through the specific methods, results and discussion pertaining to each case.

3.3.2.3 Interpretation

For a traditional PCA, loading vectors can be used to interpret results. However, for the PCA technique used in the current thesis, since the second PCA is being applied on a reference posture, four principal components, and the scores associated with each of the four principal components, interpreting what each PC represents from the loading curve is not intuitive or easily identifiable. Therefore, single component reconstruction (SCR) (Brandon et al., 2013) was used to confirm which aspect of the movement each principal component represents.

For each principal component, a mean movement, a low-scoring movement and a high-scoring movement was recreated. The mean movement calculated by averaging the data across all of the athletes. The 5th percentile movement (low-scoring) was recreated by: 5th Percentile Movement = Mean movement + (PCn * 5th percentile score). And, the 95th percentile movement (high-scoring) was recreated by: 95th Percentile Movement = Mean Movement + (PCn * 95th percentile score). Videos and figures were made with the mean, low, and high-scoring movements overlaid in order to see side by side comparisons. In the videos and figures provided in chapters 4-7, the blue avatar is the motion reconstructed from the mean score. The red avatar represents the motion of an athlete that had a score in the 95th percentile (high-scoring) and the black avatar is the reconstructed motion of an athlete that had a score in the 5th percentile (low-scoring).
Chapter 4

Case 1: Local vs. Global Reference System

4.1 Introduction

The purpose of case 1 is to assess the influence of a global versus local coordinate system on the interpretability of movement patterns characterized using PCA. As noted by Federolf et al. (2014), if an appropriate reference system is not chosen, then the principal components may be harder to analyze and interpret than principal components from a more appropriate reference system. By exploring this effect, we will generate evidence to help determine which reference system is most appropriate for a given situation.

4.2 Case-Specific Methods

The number of participants as well as the average age, height and weight for both the bird-dog right and drop jump tasks can be found in Table 2. Three reference systems were examined, two local (pelvis and right shank) and the global reference system. Visual3D was used to calculate data relative to the centre of mass of the right shank, the centre of mass of the pelvis and the global reference system and then all data were exported to MatLab for further analyses. The pelvis was chosen as it is the segment that is closest to the midpoint of the body. The shank was chosen since it has easily identifiable anatomical bony landmarks, and thus is less likely to have researcher error due to misplacement of markers. Qualitative comparisons were made between the three conditions (global reference system, pelvis reference system, and shank reference system) using visual inspection. In order to look at a task with and without displacement, the bird-dog right (no displacement) and the drop jump (displacement) task were examined. The bird-dog right task refers to the bird-dog task in which the right arm and left leg are extended. Only the first 7 PCs
were examined for this case. The percentage of explained variance for each task and each reference system used can be found in Table 3.

Table 2. The mean and standard deviations of age, height and weight by sport for the bird-dog and T-balance tasks

<table>
<thead>
<tr>
<th>Task</th>
<th>n</th>
<th>Age (yr)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Right</td>
<td>388</td>
<td>20.5 (4.3)</td>
<td>183.9 (21.0)</td>
<td>83.7 (23.4)</td>
</tr>
<tr>
<td>Drop Jump</td>
<td>280</td>
<td>20.5 (4.5)</td>
<td>183.4 (17.0)</td>
<td>85.2 (24.3)</td>
</tr>
</tbody>
</table>

Table 3. The percent of variance explained by each principal component for data relative to the pelvis, shank, and global reference systems for bird-dog right and drop jump tasks. Total is the sum of the first 7 PCs.

<table>
<thead>
<tr>
<th>Task</th>
<th>Ref. Sys.</th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>PC 4</th>
<th>PC 5</th>
<th>PC 6</th>
<th>PC 7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Right</td>
<td>Pelvis</td>
<td>86.71</td>
<td>3.89</td>
<td>1.78</td>
<td>0.96</td>
<td>0.83</td>
<td>0.67</td>
<td>0.54</td>
<td>95.38</td>
</tr>
<tr>
<td></td>
<td>Shank</td>
<td>26.78</td>
<td>17.51</td>
<td>10.36</td>
<td>5.11</td>
<td>4.28</td>
<td>4.01</td>
<td>2.56</td>
<td>70.61</td>
</tr>
<tr>
<td></td>
<td>Global</td>
<td>79.25</td>
<td>4.85</td>
<td>2.92</td>
<td>2.17</td>
<td>1.5</td>
<td>1.11</td>
<td>0.89</td>
<td>92.69</td>
</tr>
<tr>
<td>Drop-Jump</td>
<td>Pelvis</td>
<td>61.31</td>
<td>34.53</td>
<td>0.92</td>
<td>0.83</td>
<td>0.63</td>
<td>0.32</td>
<td>0.27</td>
<td>98.81</td>
</tr>
<tr>
<td></td>
<td>Shank</td>
<td>96.3</td>
<td>1.46</td>
<td>0.56</td>
<td>0.32</td>
<td>0.25</td>
<td>0.15</td>
<td>0.14</td>
<td>99.18</td>
</tr>
<tr>
<td></td>
<td>Global</td>
<td>39.13</td>
<td>32.65</td>
<td>11.88</td>
<td>7.31</td>
<td>1.96</td>
<td>1.23</td>
<td>1.1</td>
<td>95.26</td>
</tr>
</tbody>
</table>

4.3 Results

Manipulating the frame of reference between a global (lab) reference system, the local right shank coordinate system, or a local pelvis coordinate system, affects the interpretation of the principal components.

4.3.1 Bird-Dog Right

Analysis of the bird-dog task allowed exploration into how alternate frames of reference can influence the interpretation of resulting principal components during a whole-body movement task. During the bird-dog right, although the right arm and left leg are moving, the right knee and left hand are firmly planted on the ground throughout the task. When comparing the bird-dog right
task for PC 1 between the global, pelvis, and shank coordinate systems (Videos 1-3; Figure 9-11, respectively), few differences can be seen regarding the movement of the task. From all three videos, PC 1 can be interpreted as the range of motion the elbow and knee move through during the task. As can be seen in the videos and figures (Video 1-3; Figure 9-11), notice that the black avatar (low score) achieves more extension of the arm and leg at the beginning and end of the task and more flexion towards the midline during the middle of the task compared to the red avatar (high score). Therefore, PC 1 was interpreted as the amount of extension and flexion achieved throughout the task. However, with the global coordinate system, the avatars are not all facing the same direction (Video 1; Figure 9). The mean (blue) and the high-scoring (red) avatars are parallel with each other, while the low-scoring (black) is perpendicular to the other two avatars. These results demonstrate that consistent alignment of athletes within the lab space is important when expressing data relative to the global coordinate system. Expressing data relative to a local, stationary coordinate system may overcome limitations due to positional misalignment with respect to the global lab space.

Figure 9. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the bird-dog right movement where data were expressed relative to the global coordinate system. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).
For PC 2, when motions were expressed relative to the global and pelvis coordinate systems, the movements, as seen in the video, were not as intuitive to interpret as the reconstructed motions did not seem to resemble features of the bird-dog movement (Video 4-5; Figure 12-13, respectively). As can be seen in the videos and figures (Video 4-5; Figure 12-13), the avatars start to move the elbow towards the knee, however the movement is minimal and the elbow and knee are not close to touching in the centre. Because there is minimal movement, it is difficult to interpret what the principal component refers to. For the global coordinate system, comparable to PC 1, not all the avatars are facing the same direction, again suggesting that not all athletes performed the task in the same position relative to the global coordinate system. When the coordinate system is referenced around the shank for PC 2, in the starting position, the leg and arm are fully extended, the right elbow and left knee are then brought together at the midline and then are fully extended again. (Video 6; Figure 14). The full range of motion expected to be seen
throughout the task is being exhibited. Therefore, using motion data expressed relative to the right shank coordinate system, PC 2 was interpreted as a relative speed of movement feature.

Figure 12. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the bird-dog right movement where data were expressed relative to the global coordinate system. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 13. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the bird-dog right movement where data were expressed relative to the local coordinate system of the pelvis. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 14. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the bird-dog right movement where data were expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle-left: 25% of movement, middle: 50% of the movement, middle-right: 75% of the movement, right: 100% of movement (end).

4.3.2 Drop Jump

Analysis of the drop jump task allowed exploration into how alternate frames of reference can influence the interpretation of resulting principal components during a whole-body movement task. When motion was expressed relative to the global reference system, data reconstructed using PC 1 (Video 7; Figure 15) was interpreted as vertical motion or jump height. Jump height is an
outcome often only made when data are in reference to the global system. However, when motion was expressed relative to the right shank or pelvis local coordinate systems, PCs become more challenging to interpret. Video 8-9 and Figure 16-17 show the drop jump motion reconstructed from PC 1 considering motion data expressed relative to the pelvis and right shank, respectively. This is likely a result of the underlying motion of the selected reference frames. In this case, the use of local (internal) reference systems challenged the ability to interpret PCs that explained the greatest amount of variability in the data. However, similar to results found with the bird-dog task, when the motion was expressed relative to the global coordinate system, later PCs (Video 10; Figure 18, data reconstructed from PC 7) highlight differences in the athletes’ orientation within the global system during data collection. This can be seen by the horizontal offset of the avatars in the initial pose.

Figure 15. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the drop-jump movement with the data expressed relative to the global coordinate system. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 16. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the drop-jump movement with the data expressed relative to the local coordinate system of the pelvis. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).
The purpose of case 1 was to examine the differences between using a local (pelvis or right shank) versus a global reference system. Changing the reference system from a local to a global coordinate system affected the ability to interpret PCs. In order to get interpretable results, the motion data reconstructed from each PC should be somewhat intuitive to permit interpretation using single component reconstruction. The global reference system is the ideal reference system to use because it provides information regarding how athletes are moving relative to a fixed frame of reference. As can be seen in PC 1 of the drop jump, this is important for tasks where the overarching movement objective is expressed relative to the global coordinate system, such as

4.4 Discussion

Figure 17. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the drop-jump movement with the data expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 18. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 7 for the drop-jump movement with the data expressed relative to the global coordinate system. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).
maximizing the vertical or horizontal distance during jumping. However, when using the global reference system, the analysis is sensitive to how subjects are positioned relative to the origin. This can be seen in PC 1 and 2 of the bird dog and PC 7 of the drop jump, where those PCs likely explain positional differences of the athletes rather than movement variance. Therefore, when expressing motion data relative to a global coordinate system is imperative that participants be oriented consistently relative to the origin of the global space. Although this may be feasible in a laboratory setting, it may become increasingly more difficult when testing subjects in the field or a mobile laboratory. If the same relative position cannot be achieved for each athlete, either a virtual coordinate system can be made using external landmarks (Federolf et al., 2014), such as the box being used for the drop jump, or a stationary local coordinate system can be used, such as the right shank.
Chapter 5
Case 2: Moving vs. Stationary Local Reference System

5.1 Introduction

The purpose of case 2 is to assess the influence of a moving versus a stationary local reference system. As discussed in the previous chapter, there are instances when a global reference system cannot always be used, such as, when participants do not perform the task in the same position relative to the global reference system. Therefore, this case will explore whether a moving or a stationary local reference system is more appropriate for given situations in order to be able to provide evidence-based recommendations for choosing local reference systems.

5.2 Case-Specific Methodology

The number of participants and the mean age, height, and weight for each task can be found in Table 4. For this case study, the right shank was used as the reference system. Visual3D was used to calculate the data relative to the centre of mass of the right shank and then all data were exported to MatLab for further analysis. The bird-dog and T-balance tasks were performed on both the left and the right side. A qualitative comparison was made between the left and right bird-dog trial and a second comparison was made between the left and right T-balance trial in regards to the right shank using visual inspection. During the right bird-dog and right T-balance trials, the right shank is stationary, whereas during the left bird-dog and left T-balance trial, the right shank is moving. Only the first 7 PCs were examined for this case. The percentage of explained variance for each task and each reference system used can be found in Table 5.
Table 4. The mean and standard deviations of age, height and weight by sport for the bird-dog and T-balance tasks

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Age</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Right</td>
<td>388</td>
<td>20.5 (4.3)</td>
<td>183.9 (21.0)</td>
<td>83.7 (23.4)</td>
</tr>
<tr>
<td>Bird-Dog Left</td>
<td>384</td>
<td>20.5 (4.4)</td>
<td>183.8 (21.3)</td>
<td>84.0 (24.0)</td>
</tr>
<tr>
<td>T-Balance Right</td>
<td>395</td>
<td>20.4 (4.3)</td>
<td>183.7 (21.1)</td>
<td>84.1 (24.0)</td>
</tr>
<tr>
<td>T-Balance Left</td>
<td>395</td>
<td>20.4 (4.3)</td>
<td>183.4 (20.3)</td>
<td>84.1 (23.8)</td>
</tr>
</tbody>
</table>

Table 5. The percent of variance explained by each principal component for the bird-dog and T-balance tasks. Total is the sum of the first 7 PCs.

<table>
<thead>
<tr>
<th></th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>PC 4</th>
<th>PC 5</th>
<th>PC 6</th>
<th>PC 7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Right</td>
<td>26.78</td>
<td>17.51</td>
<td>10.36</td>
<td>5.11</td>
<td>4.28</td>
<td>4.01</td>
<td>2.56</td>
<td>70.61</td>
</tr>
<tr>
<td>Bird-Dog Left</td>
<td>81.79</td>
<td>5.51</td>
<td>2.53</td>
<td>2.05</td>
<td>1.32</td>
<td>0.96</td>
<td>0.74</td>
<td>94.9</td>
</tr>
<tr>
<td>T-Balance Right</td>
<td>31.98</td>
<td>20.52</td>
<td>6.88</td>
<td>5.9</td>
<td>5.37</td>
<td>3.25</td>
<td>2.57</td>
<td>76.47</td>
</tr>
<tr>
<td>T-Balance Left</td>
<td>26.07</td>
<td>17.21</td>
<td>10.15</td>
<td>7.2</td>
<td>6.28</td>
<td>4.07</td>
<td>3.22</td>
<td>74.2</td>
</tr>
</tbody>
</table>

5.3 Results

5.3.1 Bird-Dog

As mentioned in Chapter 4, PC 1 for the right-bird dog was interpreted as a range of motion feature pertaining to the left knee and right elbow (Video 3; Figure 11) and PC 2 was interpreted as a relative speed of movement feature (Video 6; Figure 14). The avatar’s movements appear to be reflective of the bird-dog motion profile.

When examining the bird-dog left, PC 1 can be interpreted as a range of motion feature, similarly to PC1 of the bird-dog right (Video 11; Figure 19). Higher scores were observed in those using less range of motion throughout the task. Since the reference system is expressed relative to the right shank, when reconstructed, by default the right shank appears to not move (even though it is moving during the task). Although aspects of the task can be detected in the video, such as the elbow and the knee touching and then extending back outwards again, the avatar does not visually mimic what the athletes looked like during the test, making this PC less intuitive to interpret. For
PC 2, it becomes difficult to interpret what the differences are between the three avatars in terms of the bird-dog movement (Video 12, Figure 20). One can see that the black avatar has the greater vertical displacement compared to the red and blue avatars, however, it is difficult to interpret what that means with respect to their overarching movement performance.

Figure 19. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the bird-dog left movement with the data in reference to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 20. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the bird-dog left movement with the data in reference to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

5.3.2 T-Balance

For the T-balance right, PC 1 was interpreted as a hip forward rotation feature (Video 13; Figure 21). Lower scores performed the motion with greater forward rotation, whereas higher scores performed the motion with less forward rotation. This can be seen as the black (low score)
avatar’s trunk and left leg are more parallel to the ground during the ‘T-position’ compared to the other red (high score) and blue (average score) avatar. PC 2 refers to the amount of flexion and extension of the knee, hip, shoulder, and elbow performed throughout the task (Video 14; Figure 22). The lower the score, the more range of motion through flexion and extension of the knee, hip, shoulder, and elbow occurs. In the beginning frames, the black avatar can be seen to have its thigh segment above the other two avatar’s thigh segments (greater hip flexion) and greater knee flexion. The black avatar’s hands are also closer to the trunk and above the other two avatar’s hands, suggesting greater elbow and shoulder flexion. Later in the movement, during the ‘T-position’, it can be seen that the black avatar’s leg is higher and straighter than the other two avatar’s leg and its arms are more perpendicular to the trunk. This suggests greater extension at the hip, knee, and shoulder joints. Similar to the bird-dog right, the movements performed by the avatar mimics the movement performed by the athletes during the test, making interpretation more intuitive.

For the T-balance left, similar to the T-balance right, PC 1 was interpreted as the amount of forward rotation about the hip (Video 15; Figure 23). In the video, the black avatar can be seen to have its trunk and right leg more parallel to the ground compared to the red and blue avatar. For PC 2, the avatars appear to have similar postures during the starting and ending position and when laid out in the ‘T-position’ (Video 16; Figure 24). However, the black avatar reaches each position first, suggesting that PC 2 refers to the speed of the movement. Comparable to what was seen with the bird-dog left, the T-balance left does not imitate the movement that was performed by the athletes during the test. Although components of the task, such as the starting position, the ‘T-position’, and the final position can be seen in PC 1 and PC 2, the movement is relative to a relative reference system instead of a fixed reference system.
Figure 21. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the T-balance right movement with the data expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 22. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the T-balance right movement with the data expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

Figure 23. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 1 for the T-balance left movement with the data in expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).
5.4 Discussion

The purpose of case 2 was to explore the differences in results between using the local reference system of a stationary versus a moving segment. When the right shank was stationary throughout the task, PCs could be intuitively interpreted for both the bird-dog and the T-balance task. However, similar to case 1, when the reference coordinate system was moving throughout the task, the PCs were less intuitive to interpret. This is due to the right shank being the origin. Since the right shank is stationary during the bird-dog right task, the reconstructed data appear to be that of absolute motion. Whereas, during the bird-dog left task, the shank is moving and therefore, the reconstructed motion appears to be that of relative motion. If using a local coordinate system, a stationary segment with easily identifiable bony landmarks should be used in order to be able to accurately interpret the PCs. If all segments are moving throughout the task, a virtual, local coordinate system can be used. In a study that examined downhill racing skiing technique, a local coordinate system was constructed at the midpoint between the two skis (Federolf et al., 2014). This allowed for the coordinate system to move along with the skier downhill, but also remain relatively stationary in respect to the skier.

Figure 24. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 2 for the T-balance left movement with the data in reference to the local coordinate system of the shank. Left: 0% of movement (start), middle-left: 25% of movement, middle: 50% of the movement, middle-right: 75% of the movement, right: 100% of movement (end).
Chapter 6
Case 3: Differentiating by Skill Level

6.1 Introduction

The purpose of case 3 is to assess whether PCA can detect differences in movement patterns between athletes of varying skill level during non-cyclical, constrained tasks. It was hypothesized, based on previous research, that there would be differences in movement patterns between recreational and elite athletes (Glofcheskie, 2015; Hrysomallis, 2010; Paillard and Noé, 2006).

6.2 Case-Specific Methods

For the purpose of this thesis, elite athletes were defined as professional and university-level athletes and the recreational category was comprised of youth, recreational, and high-school athletes. The number of athletes and mean age, height and weight for each task can be found in Table 6. Application of principal components analysis to motion data allowed for motion patterns to be scored (PC score), permitting statistical comparisons of those patterns between elite and recreational athletes. Since Case 1 and 2 demonstrated that data expressed relative to the right shank were most intuitive to interpret during tasks where the right shank was stationary, this case focused on the bird-dog right and T-balance right tasks. An ANCOVA with height, weight, and sport played was used in SPSS 20 (IBM Corporation, Armonk, NY, USA) to determine significant differences (p < 0.05) in scores between elite and recreational athletes. Statistics were only run on the first 7 PCs. The percentage of explained variance for each PC per task can be found in Table 7. Normal distribution of the data was assumed based on the parametric nature of PCA, where the scores are calculated to be normally distributed about zero.
Table 6. The mean and standard deviations of age, height and weight by sport for the bird-dog right and T-balance right tasks

<table>
<thead>
<tr>
<th></th>
<th>Bird-Dog Right</th>
<th>T-Balance Right</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>Age (yr)</td>
</tr>
<tr>
<td>Recreational</td>
<td>111</td>
<td>16.8 (3.3)</td>
</tr>
<tr>
<td>Elite</td>
<td>238</td>
<td>22.3 (3.3)</td>
</tr>
<tr>
<td>Total</td>
<td>348</td>
<td>20.5 (4.2)</td>
</tr>
</tbody>
</table>

Table 7. The percent of variance explained by each principal component for the bird-dog right and T-balance right tasks. Total is the sum of the first 7 PCs.

<table>
<thead>
<tr>
<th></th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>PC 4</th>
<th>PC 5</th>
<th>PC 6</th>
<th>PC 7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Right</td>
<td>26.78</td>
<td>17.51</td>
<td>10.36</td>
<td>5.11</td>
<td>4.28</td>
<td>4.01</td>
<td>2.56</td>
<td>70.61</td>
</tr>
<tr>
<td>T-Balance Right</td>
<td>31.98</td>
<td>20.52</td>
<td>6.88</td>
<td>5.9</td>
<td>5.37</td>
<td>3.25</td>
<td>2.57</td>
<td>76.47</td>
</tr>
</tbody>
</table>

6.3 Results

6.3.1. Bird-Dog Right

Elite and recreational athletes’ scores for PC 1, the range of motion feature, were significantly different (F(1,343) = 10.294, p = 0.001). The elite athletes had a mean score of -0.322 (0.140), whereas the recreational athletes had a mean score of 0.0643 (0.230). Drawing on cases 1 & 2, PC 1 from the bird-dog (expressed relative to the right shank) was interpreted as a range of motion feature (Video 2; Figure 11). At the beginning and end of the movement, the black avatar (low score representing the elite athletes) has greater extension of the arm and leg compared to the red avatar (high score representing the recreational athletes) and the blue avatar (average score). During the middle of the movement, the black avatar has greater flexion of the knee and elbow towards the midline, allowing the avatar to draw its elbow closer to the its knee compared to the
red and blue avatar. There is an inverse relationship between range of motion and score, the lower the score, the greater the range of motion throughout the task was and the higher the score, the less range of motion was achieved throughout the task.

6.3.2 T-Balance Right

For the T-balance right task, the scores for PC 2 were significantly higher (F(1,348) = 21.717, p < 0.001) for the recreational athletes (1.006 (0.252)) compared to the elite athletes (-0.544 (0.161)). As mentioned in Chapter 5, PC 2 referred to: knee, hip, elbow, and shoulder flexion at the beginning of the movement; knee, hip, elbow and shoulder extension at the middle phase; and, then knee, hip, elbow, and shoulder extension at the end of the movement (Video 14; Figure 22). The professional athletes were able to achieve greater knee, hip, elbow and shoulder flexion at the beginning. As can be seen in the video, the black avatar has its knee, elbow and hands raised higher than the other two avatars. When the avatars are laid out in the ‘T-position’, the black avatar’s leg is straighter and raised higher than the other two avatars, its arms are more perpendicular to the trunk, suggesting greater shoulder extension and the trunk is rotated more anteriorly, making the trunk more parallel to the ground. At the end of the movement, the avatars look similar to the beginning of the movement. Similar to the bird-dog task, there was an inverse relationship between scores. The lower the score, the more range of motion through flexion and extension of the knee, hip, elbow and shoulders was performed and vice versa.

6.4 Discussion

Case 3 examined differences in movement patterns between elite and novice athletes for the bird-dog and the T-balance task. During the bird-dog task, elite athletes demonstrated greater extension of the leg and arm during the beginning and end of the movement and were able to draw
their elbow and knee closer together in the middle of the movement compared to the novice athletes. For the T-balance task, elite athletes were able to have significantly greater flexion of the knee, hip, elbow and shoulder at the beginning and end of the movement and greater extension of the hip, knee, elbow and shoulder and forward rotation of the trunk during the ‘T-position’ phase of the movement. This result might be explained the hypothesis that elite athletes have greater postural control than less proficient athletes, as supported in past research (Glofcheskie, 2015; Paillard et al., 2006; Paillard and Noé, 2006; Sell et al., 2007). It is suggested that the superior postural control of elite athletes is due to repetitive training, influencing improvements in motor responses, the athlete’s ability to attend to proprioceptive and visual cues, neuromuscular coordination, strength, and range of motion (Bressel et al., 2007; Glofcheskie, 2015; Hrysomallis, 2010). Therefore, it is suggested that the elite athletes were able to have greater extension and flexion of the leg and arm during the bird-dog task and greater flexion and extension of the knee, hip, elbow, and shoulder and greater forward trunk rotation during the T-balance task due to greater postural control compared to novice athletes. For both the bird-dog right and the T-balance right task, PCA was able to effectively distinguish differences in movement patterns between elite and recreational athletes.
Chapter 7
Case 4: Differentiating by Sport

7.1 Introduction

The purpose of case 4 was to assess whether PCA could detect differences in movement patterns between athletes competing in different sports during non-cyclical, constrained tasks. It was hypothesized that there would be differences between athletes of different sports. It was hypothesized that golfers would have superior postural control of the trunk during the bird-dog task (Glofcheskie, 2015) and that soccer players would have superior postural control during the T-balance task (Bressel et al., 2007).

7.2 Case-Specific Methods

Since case 1 and 2 demonstrated that data expressed relative to the right shank were most intuitive to interpret during tasks where the right shank was stationary, this case focused on scores from the bird-dog right and T-balance right tasks. In order to ensure statistical power, only sports with greater than 25 athletes were used for the statistical comparisons. Therefore, only athletes that played soccer, football, golf, basketball, and baseball were used for this case study. However, it is important to note that all athletes were used for the second PCA in order to compute the scores. The number of athletes and the mean age, height, and weight broken down by sport can be found in Table 8. An ANCOVA with height, weight, and skill level as covariates was used in SPSS 20 to determine significant differences (p < 0.05) in scores between athletes who played baseball, golf, soccer, football, and basketball. Statistics were only calculated on the first 7 PCs. The percentage of explained variance for each PC per task can be found in Table 7. Normal distribution of the data was assumed based on the parametric nature of PCA. The scores are calculated to be
normally distributed about zero. Post-hoc tests were used to further investigate differences between sports when there was a significant main-effect.

Table 8. The mean and standard deviations of age, height and weight by sport for the bird-dog right and T-balance right tasks

<table>
<thead>
<tr>
<th></th>
<th>Bird-Dog Right</th>
<th></th>
<th>T-Balance Right</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>Age</td>
<td>Height</td>
<td>Weight</td>
</tr>
<tr>
<td><strong>Baseball</strong></td>
<td>74</td>
<td>20.9</td>
<td>184.0</td>
<td>90.0</td>
</tr>
<tr>
<td></td>
<td>(3.7)</td>
<td>(11.5)</td>
<td>(17.5)</td>
<td></td>
</tr>
<tr>
<td><strong>Basketball</strong></td>
<td>119</td>
<td>22.0</td>
<td>196.0</td>
<td>94.8</td>
</tr>
<tr>
<td></td>
<td>(3.8)</td>
<td>(15.7)</td>
<td>(18.3)</td>
<td></td>
</tr>
<tr>
<td><strong>Football</strong></td>
<td>43</td>
<td>20.3</td>
<td>186.2</td>
<td>104.1</td>
</tr>
<tr>
<td></td>
<td>(3.7)</td>
<td>(10.5)</td>
<td>(31.9)</td>
<td></td>
</tr>
<tr>
<td><strong>Soccer</strong></td>
<td>55</td>
<td>20.5</td>
<td>177.9</td>
<td>67.9</td>
</tr>
<tr>
<td></td>
<td>(5.4)</td>
<td>(36.8)</td>
<td>(15.0)</td>
<td></td>
</tr>
<tr>
<td><strong>Golf</strong></td>
<td>57</td>
<td>17.2</td>
<td>171.7</td>
<td>65.5</td>
</tr>
<tr>
<td></td>
<td>(2.0)</td>
<td>(8.6)</td>
<td>(11.9)</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>348</td>
<td><strong>20.5</strong></td>
<td><strong>185.4</strong></td>
<td><strong>85.9</strong></td>
</tr>
<tr>
<td></td>
<td>(4.2)</td>
<td>(20.7)</td>
<td>(23.4)</td>
<td></td>
</tr>
</tbody>
</table>

7. 3 Results

7.3.1 Bird-Dog Right

There was a significant main effect for PC 2 (F(4,340) = 4.068, p = 0.003), PC 3 (F(4,340) =3.636, p=0.006), and PC 5 (F(4,340) = 6.090, p <0.001). As mentioned in Chapter 4, PC 2 was interpreted as a speed of the movement feature, where lower scores represented faster movements and high scores represented slower movement speeds (Video 6; Figure 14). On average, for PC 2, baseball players scored significantly lower than basketball (p=0.023), football (p=0.001), and soccer (p=0.009) players (Figure 25), meaning baseball players performed the task relatively faster than athletes from the other sports. However, there were no significant difference between golf and baseball (p = 0.375), suggesting that the two group of athletes, on average, performed the task at a similar rate. Additionally, golfers had significantly lower scores than football (p = 0.029), but
not significantly lower than basketball ($p = 0.449$) or soccer ($p = 0.139$) (Figure 25). This suggests that golfers moved at a significantly faster rate than football players and may have been moving faster than basketball and soccer players, but not at a high enough rate to be significant.

![Figure 15. PC 2 average scores for the bird-dog right task for baseball, basketball, football, golf and soccer players. Red lines represent significant differences between sports.](image)

PC 3 was interpreted as the amount of axial rotation of the trunk during the movement. (Video 17; Figure 27). As can be seen in Video 17 and Figure 27, the lower the score, the less trunk axial rotation occurs. This can be seen as the right shoulder of the black avatar is below the shoulder of the blue and red avatar at the beginning and end posture of the task, and is above the shoulder of the blue and red avatar while the elbow is being drawn into the knee. Baseball scores on average were significantly lower than basketball ($p = 0.029$), football ($p = 0.005$), and soccer ($p = 0.037$), but there was no significant difference between golf and baseball ($p = 0.844$) (Figure 26). Golf was also significantly lower than football ($p = 0.009$) and soccer ($p = 0.034$), but not significantly lower than basketball ($p = 0.069$) (Figure 26). This suggests that baseball and golf
players use less trunk axial rotation to complete the task compared to basketball, soccer, and football players.

Figure 26. Average scores for PC 3 for the bird-dog task for baseball, basketball, football, golf and soccer. Red lines represent significant differences between sports.

Figure 27. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 3 for the bird-dog right movement with the data in reference to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

PC 5 was interpreted as a spine arch feature. As shown in Video 18 and Figure 29, this PC seemed to explain the amount of back arch when drawing the elbow and knee towards the midline of the body. Lower scores were associated with less back arch. Baseball had significantly
lower scores than basketball (p = 0.002), football (p < 0.001), golf (p < 0.00), and soccer (0.029), meaning they produced less back arch when performing the bird-dog action (Figure 28). Another significant difference was that soccer was significantly lower than golf (0.029) (Figure 28).

Figure 28. Average scores for PC 5 for the bird-dog task for baseball, basketball, football, golf and soccer. Red lines represent significant differences between sports.

Figure 29. Single component reconstruction of the 95th (red), 50th (blue) and 5th (black) percentile score for PC 3 for the bird-dog right movement with the data in expressed relative to the local coordinate system of the shank. Left: 0% of movement (start), middle: 50% of movement, right: 100% of movement (end).

7.3.2 T-Balance Right

There were no significant differences between sports for any of the T-balance right principal components.
7.4 Discussion

This case examined the differences between athletes competing in different sports. For the bird-dog task, baseball players and golfers moved relatively faster and with less axial trunk rotation throughout the task than basketball, football and soccer players. Baseball and soccer players tended to arch their back less during the task. Previous research has found that golfers had greater postural control of the trunk (less axial rotation) when perturbed compared to runners and non-athletes (Glofcheskie, 2015). This is thought to be due to the nature of the golf swing. The golf swing requires the golfer to move through a large range of motion about the transverse plane (Glofcheskie, 2015). In order to change distance, height, and/or velocity of the shot, golfers will change the position of the body about this plane. Therefore, having the ability to detect small changes in trunk position is necessary for a golfer to be successful (Glofcheskie, 2015). Similar to a golf swing, throwing a baseball, requires large amounts of range of motion about the transverse plane, suggesting that baseball players may also have a better ability to detect small changes in trunk position. For the bird-dog right task, by using PCA, movement patterns of athletes competing in different sports were able to be differentiated.

There were no significant differences between sports for the T-balance task. This is contradictory to what previous research has found. Previous research found that soccer players had superior postural control during unipedal and bipedal dynamic balance tasks compared to basketball players (Bressel et al., 2007; Hrysomallis, 2010). A possible explanation for the difference in findings could be due how postural control was calculated. The current study was looking at whole-body movement patterns, while the previous study was examining the distance one could extend the non-weight bearing foot in 8 different directions while standing on one foot.
Although there were no significant differences in athletes between sports, PCA was able to be used to calculate and interpret PCs to represent specific movement patterns for the T-balance task.
Chapter 8
General Discussion and Conclusion

The purposes of the current study were: 1) to address methodological considerations by determining differences in the feasibility of interpreting results when data are referenced to different reference systems when using PCA, and 2) to use what was learned in purpose 1 to assess the application of pattern recognition for differentiating whole-body movement patterns in athletes of different skill level and sport during non-cyclical, constrained movements using PCA.

As can be seen in case study 1 and 2, the ease of interpretability of each principal component changes based on the coordinate system the data are reference to. The ideal coordinate system to reference the data in changes based on the nature of the task. If absolute differences are important, such as jump height in the drop jump task, then the global coordinate system should be used. However, it is necessary to ensure that all participants are performing the task in the same position relative to the origin. If relative differences are important, such as during the bird-dog and t-balance task, then a local reference system can be used. However, it is important that the local reference system is stationary during the task. Previous research has referenced data to both global and local coordinate systems (Federolf et al., 2014; Troje, 2002). The global coordinate system was used in a study looking at movement patterns while walking. The participants walked on a treadmill for the duration of the test (Troje, 2002). Since the participants were limited to staying on the treadmill belt, it was feasible to ensure that all participants were in the same position relative to the origin. However, in a study looking at different skier positions during alpine racing, a local coordinate system was used (Federolf et al., 2014). The researchers were interested in relative differences in skier position rather than absolute differences, such as skier speed. The data were referenced to the local coordinate system of the skis, which had minimal movement throughout...
the task. In future research, we plan on using a body-centered global coordinate system in order to be able to detect both relative and absolute differences in movement patterns.

As can be seen in case study 3 and 4, the PCA-driven movement pattern recognition technique was able to detect significant differences between elite and novice athletes and athletes that compete in different sports. Because the technique was able to distinguish differences between different types of athletes, the PCA-driven pattern recognition technique may be used to help better performance and rehabilitation for athletes. Observational learning is a method of learning through visual demonstration. Researchers have found that observational learning can lead to improvements in form, movement pattern recall, error recognition, timing of movement sequences, and motivation (Hand and Sidaway, 1993; Wesch et al., 2007). Previous research has shown that athletes of all sports and all skill levels use observational learning to better skill level and motivation, however varsity athletes employ observational learning more often than recreational athletes (Wesch et al., 2007). In addition, observational learning increases performance whether the individual is skilled or new to the task (Pollock and Lee, 1992). Coaches and trainers could use observational learning with their athletes by showing the reconstructed movement patterns of their athletes’ compared to that of elite level athletes from their sport. For rehabilitation purposes, the clinicians can show direct comparisons of the patient’s movement patterns pre- and post-injury. The PCA-driven pattern recognition technique can be used as a training tool to better athletes’ movement patterns that capitalizes on observational learning.

In addition to improving performance, the technique could be used to increase adherence to training and rehabilitation programs. Researchers looking at exercise program adherence in middle-aged adults found that those whom partook in an intervention of efficacy-based information had significantly greater frequency and duration of exercise (Mcauly et al., 1994). The
efficacy-based information included tracking and discussing objective progress in bi-weekly meetings and social modeling (Mcauly et al., 1994). The PCA-driven pattern recognition technique could provide a tool for coaches and clinicians to track and detect differences in athlete progress in order to increase adherence to training or rehabilitation programs. In addition, the technique and data base could also provide coaches and clinicians a tool for social modeling. Athletes would be able to compare themselves to athletes within a desired demographic (e.g. age, skill level, height, etc.). Researchers have found that observing individuals like themselves performing exercises increases performance measures and adherence to the exercise program (Mcauly et al., 1994). The scores from the technique could provide an alternative training and rehabilitation tool for coaches, athletes and clinicians.

The ability to study and assess whole-body movement patterns can be beneficial to researchers and clinicians beyond sport biomechanics. The technique can be used in ergonomics to help determine movement patterns that increase the risk of injury in manual material handling workers or jobs that require employees to perform repetitive tasks. Previous researchers have used a form of PCA, uncorrelated multilinear PCA, to examine different whole-body patterns of individuals entering and exiting different models of cars (Masoud et al., 2016). The results from the study can be utilized to benefit the design of car models (Masoud et al., 2016). Studying whole-body movement patterns can help improve performance and injury prevention not only in sports biomechanics but also in other fields such as ergonomics.

A limitation of using the discussed PCA-driven pattern recognition technique is that it is assumed that after applying the first PCA to the data, all PCs represent the same features of motion for all participants. We tried to reduce the likelihood of combining PCs that may not have captured the same features by taking only the first four PCs from the first PCA. The sum of the first four
PCs comprised of over 95% of the movement variance for each participant, allowing us to keep a robust amount of data and decrease the likelihood of taking non-matching PCs. The first PCs explain the variance, which we believe is likely to represent fundamental motor patterns within the movement, whereas the latter PCs might be more likely to represent individual-based nuanced differences in the overarching movement strategy, where the features may not be directly comparable between individuals. The gross motor patterns are more likely to be the same between individuals. Due to the constraints of the movement tasks, the athletes had to achieve certain positions in the beginning, middle and end of the movement, therefore gross motor patterns should be similar between athletes. In future research, we plan on analyzing the data using a stacked PCA (all data in a single PCA) approach, in order to overcome this limitation.

Since the PCA-driven movement pattern recognition technique used in this thesis can detect differences in fundamental movement patterns in select screening activities on the basis of expertise or sport, future research should focus on using machine learning to determine if athletes can be identified based on sport and/or level of play based on the score received. Being able to differentiate athletes would allow for the development of customized training and rehabilitation programs based on the sport and/or level of play of the athlete. In addition, OpenSim and optimal-control models can be used to try and identify movement patterns (using the PC scores) that are optimal based on reduced joint loading and cost-effectiveness. Based on results from the models, individuals’ movement patterns can be identified on a scale that denotes risk of injury. The identification of optimal movements could lead to better training programs to help decrease injury and improve performance.

In conclusion, the PCA-driven pattern recognition technique discussed in this thesis is an effective multivariate statistical technique to study whole-body motion patterns. Important
methodological considerations need to be made when using the technique, especially in terms of reference coordinate system used. Ideally, a global coordinate system can be used, however, if not all subjects are positioned the same relative to the origin, then a local coordinate system should be used. When choosing a local coordinate system, the segment that is chosen should be stationary during the task or a virtual local coordinate system can be made, if all segments are moving. Significant differences were seen between elite and novice athletes as well as, between athletes competing in different sports. Future research should look at using machine learning to try to differentiate athletes based on sport and/or skill level. In addition, OpenSim models should be used to simulate forces acting on the body given a certain score calculated by the discussed PCA-based movement pattern recognition technique to determine movement patterns that are more at risk for injury.
References


Appendix A

Mutual Nondisclosure Agreement

This Nondisclosure Agreement (the "Agreement") is entered into by and between Core Sports Technology Group, LLC (DBA Motus Global) with its principal offices at 5394 Merrick Road, Massapequa, NY 11758, USA ("Disclosing Party") and ______________, located at ______________ ("Receiving Party") for the purpose of preventing the unauthorized disclosure of Confidential Information as defined below.

The parties agree to enter into a confidential relationship with respect to the disclosure of certain proprietary and confidential information ("Confidential Information").

1. Definition of Confidential Information. For purposes of this Agreement, "Confidential Information" shall include all information or material that has or could have commercial value or other utility in the business in which Disclosing Party is engaged. If Confidential Information is in written form, the Disclosing Party shall label or stamp the materials with the word "Confidential" or some similar warning. If Confidential Information is transmitted orally, the Disclosing Party shall promptly provide a writing indicating that such oral communication constituted Confidential Information.

2. Exclusions from Confidential Information. Receiving Party's obligations under this Agreement do not extend to information that is: (a) publicly known at the time of disclosure or subsequently becomes publicly known through no fault of the Receiving Party; (b) discovered or created by the Receiving Party before disclosure by Disclosing Party; (c) learned by the Receiving Party through legitimate means other than from the Disclosing Party or Disclosing Party's representatives; or (d) is disclosed by Receiving Party with Disclosing Party's prior written approval.

3. Obligations of Receiving Party. Receiving Party shall hold and maintain the Confidential Information in strictest confidence for the sole and exclusive benefit of the Disclosing Party. Receiving Party shall carefully restrict access to Confidential Information to employees, contractors, and third parties as is reasonably required and shall require those persons to sign nondisclosure restrictions at least as protective as those in this Agreement. Receiving Party shall not, without prior written approval of Disclosing Party, use for Receiving Party's own benefit, publish, copy, or otherwise disclose to others, or permit the use by others for their benefit or to the detriment of Disclosing Party, any Confidential Information. Receiving Party shall return to Disclosing Party any and all records, notes, and other written, printed, or tangible materials in its possession pertaining to Confidential Information immediately if Disclosing Party requests it in writing.
4. **Time Periods.** The nondisclosure provisions of this Agreement shall survive the termination of this Agreement and Receiving Party's duty to hold Confidential Information in confidence shall remain in effect until the Confidential Information no longer qualifies as a trade secret or until Disclosing Party sends Receiving Party written notice releasing Receiving Party from this Agreement, whichever occurs first.

5. **Relationships.** Nothing contained in this Agreement shall be deemed to constitute either party a partner, joint venturer or employee of the other party for any purpose.

6. **Severability.** If a court finds any provision of this Agreement invalid or unenforceable, the remainder of this Agreement shall be interpreted so as best to effect the intent of the parties.

7. **Integration.** This Agreement expresses the complete understanding of the parties with respect to the subject matter and supersedes all prior proposals, agreements, representations, and understandings. This Agreement may not be amended except in a writing signed by both parties.

8. **Waiver.** The failure to exercise any right provided in this Agreement shall not be a waiver of prior or subsequent rights.

This Agreement and each party's obligations shall be binding on the representatives, assigns, and successors of such party. Each party has signed this Agreement through its authorized representative.

<table>
<thead>
<tr>
<th>Disclosing Party</th>
<th>Receiving Party</th>
</tr>
</thead>
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<tr>
<td>By: ______________</td>
<td>By: ______________</td>
</tr>
<tr>
<td>Printed Name: ______</td>
<td>Printed Name: ______</td>
</tr>
<tr>
<td>Title: ______________</td>
<td>Title: ______________</td>
</tr>
<tr>
<td>Dated: ______________</td>
<td>Dated: ______________</td>
</tr>
</tbody>
</table>
Appendix B

WAIVER OF LIABILITY

In consideration of the opportunity afforded to me to obtain a biomechanical analysis or related services or advice from Motus Global Lab, I, the undersigned, parent, or legal guardian, ______________, hereby affirm that I am at least 18 years old and intending to be legally bound HEREBY AGREE AS FOLLOWS:

1. I knowingly, freely, voluntarily, waive, release, and forever discharge Core Sports Technology Group LLC, DBA – Motus Global, and all of their parent, subsidiary, related, or affiliated companies, and their/its agents, servants, officers, directors, employees, members, shareholders, attorneys, landlords, and property owners, and/or guests and patrons (hereinafter referred to collectively as “Motus”), of and from any and all claims, actions, causes of action, suits, damages, losses, attorneys’ fees, compensation, expenses and claims, whether in law or equity, whether known or unknown, whether foreseen or unforeseen, or whether contingent or not contingent, (hereinafter referred to collectively as the “Claims”), arising out of or in connection with, or as a result of my participation or involvement in any Motus biomechanical analysis service, Motus advice, Motus activities or any other services work or advice provided by Motus at the above-described premises or Motus biomechanical analysis.

2. This agreement does not serve as a release or waiver of any Claims for any injury resulting from the willful, wanton, reckless, or intentional misconduct of Motus, their/its officers, directors, agents, servants, or employees.

3. If any portion or term of this Agreement is held or determined to be void, unenforceable or invalid, then such portion or term shall be severable from the Agreement and it shall remain in full force and effect.

4. I hereby grant Motus the right to use all of the data and subsequent findings from their analyses, present and future, in their biomechanics database research. Furthermore, I grant permission to use all photographs, videos, and computer generated renderings for promotional purposes unless otherwise expressly agreed upon.

5. Motus Global is a separate and independent company from the __________. Therefore, the results of this study will not be shared with the __________ unless you indicate that you wish the results to be shared with your coach, trainers, or other staff at the __________. By indicating below, you may elect to have the results shared with the __________ as you designate.

I elect to have my results shared with the following staff:

Sport Coaching Staff:  Yes □  No □  Athletic & Personal Development Staff:  Yes □  No □
Appendix C

Demographic Information:

- Name: ________________________________
- Date of Birth __________________
- E-mail : ______________________________
- Gender:  Male    Female
- Height (ft):____ (in):_____  Weight (lbs):_____

Athletic Background:

- Level:  Professional    College    High School (9-12)    Middle School (6-8)    Youth

- Primary Sport:  Tennis    Golf    Soccer    Baseball    Basketball    Lacrosse    Football    Other
  ________________

- Position(s): ________________________________

- Age you started playing: ________________

- Current Team/Organization: ________________________________

- Throw:  Right    Left  Kick:  Right    Left  Bat/Swing:  Right    Left

Injury History:

- Currently injured?  Yes    No
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<th>Time Missed</th>
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Motus Marker Set
Fall 2014

Posterior Aspect
### Appendix E

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<th>Defining Segment</th>
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<td>Head</td>
</tr>
<tr>
<td>Back of head</td>
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<td>Head</td>
</tr>
<tr>
<td>Right side of head</td>
<td>Right squamous suture</td>
<td>Head</td>
</tr>
<tr>
<td>Left side of head</td>
<td>Left squamous suture</td>
<td>Head</td>
</tr>
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<td>Thorax</td>
</tr>
<tr>
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<td>Right acromioclavicular joint</td>
<td>Thorax</td>
</tr>
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<td>Sternum</td>
<td>Xyphoid process</td>
<td>Thorax</td>
</tr>
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<td>Thorax</td>
</tr>
<tr>
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<td>Left sternoclavicular joint</td>
<td>Thorax</td>
</tr>
<tr>
<td>Sternum</td>
<td>Sternal notch</td>
<td>Thorax</td>
</tr>
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<td>Left bicep</td>
<td>Left upper arm</td>
</tr>
<tr>
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<td>Right bicep</td>
<td>Right upper arm</td>
</tr>
<tr>
<td>Left medial elbow</td>
<td>Left medial epicondyle of the humerus</td>
<td>Left humerus/forearm</td>
</tr>
<tr>
<td>Left lateral elbow</td>
<td>Left lateral epicondyle of the humerus</td>
<td>Left humerus/forearm</td>
</tr>
<tr>
<td>Right medial elbow</td>
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<td>Right humerus/forearm</td>
</tr>
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<td>Right humerus/forearm</td>
</tr>
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<td>Left forearm</td>
</tr>
<tr>
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<td>Left radial styloid process</td>
<td>Left forearm</td>
</tr>
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<td>Right ulnar styloid process</td>
<td>Right forearm</td>
</tr>
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<td>Left lateral wrist</td>
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<td>Right forearm</td>
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<td>Pelvis</td>
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<td>Right anterior superior iliac spine</td>
<td>Pelvis</td>
</tr>
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<td>Left low back</td>
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<td>Pelvis</td>
</tr>
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</tr>
<tr>
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<td>Left greater trochanter</td>
<td>Left femur</td>
</tr>
<tr>
<td>Right hip</td>
<td>Right greater trochanter</td>
<td>Right femur</td>
</tr>
<tr>
<td>Left medial knee</td>
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<td>Left femur/shank</td>
</tr>
<tr>
<td>Left lateral knee</td>
<td>Left lateral epicondyle of the femur</td>
<td>Left femur/shank</td>
</tr>
<tr>
<td>Right medial knee</td>
<td>Right medial epicondyle of the femur</td>
<td>Right femur/shank</td>
</tr>
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<td>Left medial knee</td>
<td>Right lateral epicondyle of the femur</td>
<td>Right femur/shank</td>
</tr>
<tr>
<td>Left medial ankle</td>
<td>Left medial malleolus</td>
<td>Left shank/foot</td>
</tr>
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<tr>
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<tr>
<td>Right middle toe</td>
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<td>Right foot</td>
</tr>
<tr>
<td>Left heel</td>
<td>Left calcaneus</td>
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</tr>
<tr>
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<td>Right foot</td>
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## Appendix F

<table>
<thead>
<tr>
<th></th>
<th><strong>Start</strong></th>
<th><strong>End</strong></th>
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<tbody>
<tr>
<td><strong>Bird-Dog</strong></td>
<td>The initiation of movement of either the ankle or the wrist</td>
<td>Once the velocity of both the wrist and the ankle reached zero and positional data were close to that of the starting position</td>
</tr>
<tr>
<td><strong>T-Balance</strong></td>
<td>The initiation of movement of either the ankle or the wrist</td>
<td>Once the velocity of both the wrist and the ankle reached zero and positional data were close to that of the starting position</td>
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<tr>
<td><strong>Drop Jump</strong></td>
<td>The initiation of movement of either the ankle or the wrist</td>
<td>Once the athlete reached a velocity of zero and reached peak jump height after the second jump</td>
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</tbody>
</table>
QUEEN'S UNIVERSITY HEALTH SCIENCES & AFFILIATED TEACHING HOSPITALS RESEARCH ETHICS BOARD (HSREB)

HSREB Initial Ethics Clearance

December 10, 2015

Miss Gwyneth Ross
School of Kinesiology and Health Studies
Queen's University

ROMEO/TRAQ: #6017208
Department Code: PHE-157-15
Study Title: Quantifying whole-body movement dynamics using principal component analysis
Co-Investigators: Dr. S. Fischer, Dr. R. Graham
Review Type: Delegated
Date Ethics Clearance Issued: December 10, 2015
Ethics Clearance Expiry Date: December 10, 2016

Dear Miss Ross,

The Queen's University Health Sciences & Affiliated Teaching Hospitals Research Ethics Board (HSREB) has reviewed the application and granted ethics clearance for the documents listed below. Ethics clearance is granted until the expiration date noted above.

- Protocol
- Nondisclosure Agreement
- Consent Waiver Form

Documents Acknowledged:

- CORE Certificate — G. Ross
- CORE Certificate — S. Fischer
- CORE Certificate — R. Graham

Amendments: No deviations from, or changes to the protocol should be initiated without prior written clearance of an appropriate amendment from the HSREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

Renewals: Prior to the expiration of your ethics clearance you will be reminded to submit your renewal report through ROMEO. Any lapses in ethical clearance will be documented on the renewal form.
Completion/Termination: The HSREB must be notified of the completion or termination of this study through the completion of a renewal report in ROMEO.

Reporting of Serious Adverse Events: Any unexpected serious adverse event occurring locally must be reported within 2 working days or earlier if required by the study sponsor. All other serious adverse events must be reported within 15 days after becoming aware of the information.

Reporting of Complaints: Any complaints made by participants or persons acting on behalf of participants must be reported to the Research Ethics Board within 7 days of becoming aware of the complaint. Note: All documents supplied to participants must have the contact information for the Research Ethics Board.

Investigators please note that if your trial is registered by the sponsor, you must take responsibility to ensure that the registration information is accurate and complete.

Yours sincerely,

[Signature]

Chair, Health Sciences Research Ethics Board

The HSREB operates in compliance with, and is constituted in accordance with, the requirements of the TriCouncil Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the International Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Products Regulations; Part 3 of the Medical Devices Regulations; Canadian General Standards Board, and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is qualified through the CTO REB Qualification Program and is registered with the U.S. Department of Health and Human Services (DHHS) Office for Human Research Protection (OHRP). Federalwide Assurance Number: FWA#: 00004184, IRB#: 00001173

HSREB members involved in the research project do not participate in the review, discussion or decision.