Vertical ground reaction force estimation using position data measured from a markerless motion capture system

THESIS

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Abstract

Ground reaction forces (GRFs) are important quantities in biomechanical analyses, as they may be used to diagnose neuromuscular impairments and provide a quantified measure of asymmetries between a patient’s legs. Using force plates, GRFs can be measured accurately, but force plates limit studies to a laboratory setting where subjects may not move as naturally as they would in other settings. Using position data obtained from motion capture systems, GRFs can be calculated without the need for a force plate. With marker-based (MB) motion capture systems, the most widely used motion capture method, studies are still limited to a dedicated laboratory setting. A newer motion capture technique, markerless motion capture (MMC), uses video cameras and does not need a laboratory setting for testing. MMC allows for motion measurements of the entire body without requiring reflective markers on body segments, tracking body segments, or calculating the mass, center of mass, and moments of inertia for each segment. The whole body center of mass position, velocity, and acceleration can be determined without the need for any of these. This thesis is about using MMC to estimate GRFs. In this research, MMC data of nine female subjects performing running and single-leg landing (SLL) movements was recorded. From the center of mass accelerations obtained from this, vertical GRFs were calculated and compared to force plate data to determine the method’s accuracy. Results showed that during running trials,
GRFs were calculated with maximum error of less than 10%, but during SLL trials, errors greater than 50% were observed during impact. Visual hulls in running and SLL trials had additional volume that may have caused errors in center of volume position, which would then result in errors in calculated vertical GRFs. The errors caused by extra volume were analyzed using three different approaches. First, the volume of each subject was calculated using an average density value and compared to the visual hull volume. Second, the volumes of basketball visual hulls were compared to the computed volume for a sphere. Third, the change in volume of a cylinder, used as a model of the human body, caused by an increase in radius and height was calculated. These experiments suggested that visual hulls had greater volume than the calculated value because of additional volume and increased thickness of the outside of the body. Improved results could be obtained with the same method if we have more cameras or cameras with higher resolution. Additionally, accuracy would be improved during studies involving impact if cameras with higher frame rates were used. Given that our method used only the center of volume of the visual hull, there is potential for improving ground reaction force calculations using methods that take advantage of other information in the visual hulls, for instance, by fitting segmental models to the visual hulls.
Dedication

This thesis is dedicated to my family for their support and encouragement throughout my education.
Acknowledgments

I would like to thank both of my advisors, Alison Sheets and Manoj Srinivasan, as well as Ajit Chaudhari, for their help with developing, guiding, revising, and troubleshooting my research project. Additionally, I would like to express my gratitude to the Department of Mechanical and Aerospace Engineering at The Ohio State University for funding me with a Graduate Teaching Associate position during my final year in graduate school. I would also like to thank Evan Kohler and Joe Ewing for their assistance in processing motion capture data and learning the markerless motion capture software. Finally, I would like to thank Laura Housley for her help in modifying and debugging a C program I used extensively in this project.
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Table of Contents

Abstract......................................................................................................................... ii

Dedication ....................................................................................................................... iv

Acknowledgments ........................................................................................................ v

Vita................................................................................................................................. vi

Fields of Study ............................................................................................................. vii

Table of Contents ......................................................................................................... vii

List of Tables ................................................................................................................. x

List of Figures ............................................................................................................... xi

Chapter 1: Introduction ............................................................................................... 1

1.1: Background .......................................................................................................... 1

1.1.1: Ground reaction forces and their applications ............................................. 1

1.1.2: Common techniques for GRF measurement ................................................ 2

1.1.3: Ground reaction force calculation using movement data ............................... 4

1.1.4: Marker-based motion capture ...................................................................... 5

1.1.5: Markerless motion capture ........................................................................... 7
1.1.6: Some prior work on estimating GRFs from position data ............................................. 9

1.2: Scope and significance of this thesis .................................................................................. 11

1.3: Organization of the thesis ................................................................................................. 12

Chapter 2: Testing methods for markerless motion capture study ...................................... 13

Chapter 3: Analysis of markerless motion capture data of human subjects ....................... 19

3.1 Estimating ground reaction forces of human subjects performing running and
single-leg landing trials using data collected with a markerless motion capture system
.................................................................................................................................................... 19

3.1.1 Markerless data processing and visual hull creation for human subjects .......... 19

3.1.2 Visual hull center of volume calculation ........................................................................ 22

3.1.3: Differentiating the position data ................................................................................... 22

3.1.4: Comparison of estimated vertical GRFs to force plate data ...................................... 26

3.1.5: Understanding the errors in the estimated vertical GRFs ......................................... 30

Chapter 4: Estimating ground reaction forces of a basketball bouncing using a marker-
based motion capture system ................................................................................................. 42

Chapter 5: Areas for Improvement and Future Work .......................................................... 47

Chapter 6: Summary and Conclusion ....................................................................................... 51

viii
Appendix A: Medial-lateral and anterior-posterior GRFs calculated from MMC data ... 55
List of Tables

Table 1: Test subject information .................................................................................. 14
Table 2: Average speed of each subject during running trials obtained by differentiating
MMC center of volume position data .................................................................................. 18
Table 3: Bounding box coordinates .................................................................................. 20
Table 4: Effect of phantom volume on center of mass height ........................................ 39
List of Figures

Figure 1: Simplified model of human body showing vertical ground reaction forces ....... 4

Figure 2: Example visual hull of a subject running ......................................................... 8

Figure 3: MMC camera orientation. Solid blue dots indicate cameras. The top image shows a vertical view of the setup, and the bottom image shows a view looking opposite the direction the subjects moved during running trials ............................................. 14

Figure 4: Internal calibration grid for the MMC system .................................................. 15

Figure 5: External calibration object for the MMC system .............................................. 16

Figure 6: Visual hulls of subject S01 during running trial R1. Frontal views are shown in the top, and side views of the same visual hulls are shown on the bottom. Phantom volumes are seen between the subject’s legs when close together ......................... 21

Figure 7: Raw and smoothed center of mass position data of Subject S01 in running trial R1 ........................................................................................................................................... 25

Figure 8: Center of mass velocity of Subject S01 in running trial R1 calculated with smoothing splines and finite differences ................................................................. 25

Figure 9: Center of mass acceleration of Subject S01 in running trial R1 calculated with smoothing splines and finite differences ........................................................................... 26
Figure 10: Vertical GRFs estimated from MMC position data were within 10% of the force plate data for Subjects S01 (top), S02 (center), and S03 (bottom) during running trials.

Figure 11: Vertical GRFs estimated from MMC position data were unable to match force plate data during impact for Subjects S01 (top), S02 (center), and S03 (bottom) during single-leg land trials.

Figure 12: Visual hull volume fluctuation over time for Subject S01 during running trial R1 (left) and SLL Trial SLL1 (right).

Figure 13: Subject volumes obtained from mass and average density were always smaller than the visual hull volumes.

Figure 14: Cylinder dimensions used to investigate the effect of additional thickness on total volume.

Figure 15: Basketball volume obtained from MMC visual hull data is largest when the ball is in contact with the ground (center of mass height also obtained from MMC data).

Figure 16: Basketball visual hulls had extra volume added at times when the ball was in contact with the ground.

Figure 17: Model of human body showing additional mass caused by phantom volume concentrated near, roughly, the foot, thigh, chest, and head.
Figure 18: Vertical center of mass position during force plate contact for Subject S03 during running trial R1................................................................. 41

Figure 19: Marker-based and markerless vertical position of basketball centroid as a function of time. Impact occurs when centroid height reaches a minimum. .......................... 44

Figure 20: Vertical velocity of basketball centroid, obtained by differentiating marker-based data, as a function of time. Ball flight is indicated by the slanted line segments, and ball contact occurs at the bottom-right of these segments and during the points in which velocity suddenly increases................................................................. 45

Figure 21: Vertical acceleration of basketball centroid, obtained by differentiating marker-based data, as a function of time. Ball contact occurs where the vertical peaks are seen. ................................................................................................................................................. 45

Figure 22: Comparison of estimated basketball vertical GRFs and force plate data. The vertical GRFs at all five impact peaks match the force plate data with errors of less than 15%. ................................................................................................................................................. 46

Figure 23: Calculated medial-lateral and anterior-posterior GRFs for running trials (Subject S03 shown here) did not match force plate data when the same smoothing parameter used for the vertical GRFs was applied. ................................................................. 55

Figure 24: Calculated medial lateral and anterior-posterior GRFs for running trials (Subject S03 shown here) matched force plate data more closely when different
smoothing parameters were applied for each component, but large errors were still observed.
Chapter 1: Introduction

1.1: Background

1.1.1: Ground reaction forces and their applications

In biomechanics, the forces between the human body and the ground are called “ground reaction forces” (GRFs). This thesis is about estimating vertical GRFs from human movement data. GRFs are important quantities that have many uses in areas such as biomechanical analyses of injury risk and musculoskeletal impairments. GRF patterns during walking have been used as a descriptive criterion of human walking and running gait for decades (Chao 1983; Munro 1987). It has been shown that GRFs during activities such as distance running can be as high as 2.5–3 times larger than body weight, and repeated impacts may increase the chances of injury while performing strenuous activities (Cavanagh 1980). GRFs are used in inverse dynamics analyses to calculate net joint torques (i.e., ankle, knee, and hip torques) and net intersegmental forces, which are also commonly reported quantities in biomechanical analyses.

Vertical GRF magnitudes and profiles are also criteria that are used to quantify the level of locomotor function in patients with neuromuscular impairments such as stroke, Parkinson’s disease, muscular dystrophy, and Down syndrome (Kim 2003; Winiarski 2009). In healthy individuals, GRF profiles are almost completely symmetrical (i.e. GRF magnitudes are the same for both legs), but in stroke patients, a significantly smaller force is applied to the paretic limb (Kim 2003). The significant correlation between GRF symmetry and gait speed in stroke patients provides support for
programs that aim to increase weight-bearing capacity in the paretic limb (Kim 2003), and if a method to accurately determine GRFs without the use of a force plate existed, more programs like these could be developed.

Another application of GRFs is in the analysis of patients who have undergone procedures like total hip arthroplasties (THAs) and total knee arthroplasties (TKAs). GRFs can be used to evaluate the effectiveness of interventions such as these surgeries. As seen in stroke patients, there are asymmetries in weight-bearing in patients who have undergone THAs. The magnitudes of first and second peak vertical GRFs are both smaller in the affected limb than in the unaffected limb, and time to the first peak vertical GRF occurs significantly later in the affected limb (McCrory 2001). Favoring one leg in this way results in increased loading in the unaffected leg and could eventually lead to osteoarthritis (OA) in that leg (McCrory 2001). For OA patients who underwent TKAs, vertical GRFs were found to be lower pre-operatively than post-operatively and when compared to a control group (Solak 2005). GRF measurements allow gait asymmetries such as these to be analyzed quantitatively and could be used to develop training programs to help patients avoid complications such as arthritis.

1.1.2: Common techniques for GRF measurement

The most common way that GRFs are measured is by using a force platform that records the 3D forces, center of pressure (or point of force application), and moment about the vertical axis while a subject is in contact with the plate. For best accuracy, these platforms must be rigidly mounted in the ground and isolated from surrounding
vibrations, which limits studies to a dedicated laboratory space or expensive specialized clinical settings instead of more natural environments like conventional clinical settings or a track or playing field when athletes are studied. If GRFs could be known without the use of a force plate, biomechanics research would be much more versatile, and previously impossible experiments could be performed.

Another method that could be used to derive GRFs is through the use of pressure insoles, which record the pressure in the vertical direction underneath the sole of the foot, Pressure insoles are advantageous compared to force plate because subjects do not have to alter their foot placement during walking or running (Forner 2004). Vertical GRFs could be obtained by integrating the measured pressures; however, there may be accuracy limitations due to measurement sensitivity to foot positioning and repeatability.

Pressure mats are another technology that can be used to measure vertical GRFs. These are advantageous because they are much lighter and do not require a solid surface for subjects to stand on. Pressure mats such as the GAITRite (CIR Systems, Inc) can be used to record information regarding spatiotemporal aspects of gait, commonly in situations in which gait asymmetries are expected. In one study, the GAITRite systems was shown to more finely discriminate alterations in gait than an established clinical assessment scale did (Shore et al., 2005). Pressure mats can also be used to directly measure vertical GRFs.
1.1.3: Ground reaction force calculation using movement data

As an alternative to direct measurement of GRFs using force sensors between the feet and the ground, we can aim to estimate GRFs using observations of body movement, using Newton's 2nd Law, which related forces and acceleration. To accurately estimate GRFs, however, the mass properties of the subject and the exact 3-D position would need to be known. For a one-segment inanimate object (Equation 1), mass and acceleration are relatively easy to determine, but for a multi-segment model like the human body (Figure 1), it is more complicated to accurately know both the mass of each segment and the position of each center of mass (Equation 2).

![Diagram](image)

Figure 1: Simplified model of human body showing vertical ground reaction forces

\[ m \times a = \sum F_{\text{external}} = GRF - m \times g \]  \hspace{1cm} (1)

where

\( m = \text{total mass} \)

\( \sum F_{\text{external}} = \text{sum of the external forces on the body} \)
GRF = ground reaction force on the body

a = acceleration of the center of mass

g = gravitational constant

For an object consisting of many rigid segments,

\[ m * a = \sum m_i * a_i \]  \hspace{1cm} (2)

where

\( m_i = \) mass of the \( i^{th} \) segment

\( a_i = \) acceleration of the \( i^{th} \) segment

Body segment parameters such as mass, moment of inertia, and centroid position can be estimated using regression equations from the literature that incorporate subject height and weight (Clauser 1969; Zatsiorsky 1983; Dempster 1967), or they can be adjusted to more closely match the dimensions of particular subjects by taking factors like sex, obesity, and age into account (Hatze 1980; Hatze 2005). Acceleration can be calculated using motion capture systems that acquire position data or measured directly using accelerometers. Error is present in both body segment parameters and segmental motion data, and it is important to minimize these errors so that force estimates are as accurate as possible (Riemer & Hsiao-Wecksler 2009).

1.1.4: Marker-based motion capture

Motion capture is one way to acquire position data that can be used to calculate GRFs without the use of a force plate. Position data can be differentiated to obtain
acceleration data, and if a subject’s mass properties are known, GRFs can be estimated. Marker-based (MB) motion capture systems track active or passive markers that are fixed to the person or object of interest. Active markers light up and can be tracked by cameras that sense the change in light intensity, whereas passive markers are highly reflective and appear brighter than their surroundings. Both active and passive markers need to be the brightest objects in the capture volume in order to be detected and tracked consistently.

In MB motion capture, six to 24 cameras are typically used so that there are multiple cameras that can see the same markers.

MB motion capture is the most frequently used motion capture method in biomechanical and clinical studies, but it has several shortcomings that limit the method’s effectiveness. Marker occlusion and soft-tissue movement are two issues that result in inaccuracies with marker-based motion capture. Marker occlusion occurs when a marker is unable to be seen by at least two cameras and requires estimation of the hidden marker’s position, which likely contains error. Soft-tissue movement is caused primarily by movement of skin, muscle, and fat. This movement causes inaccuracies because the motion of soft tissue is different than the movement of bones, which are the structures of interest in biomechanical studies. Furthermore, the need for a dedicated laboratory environment and large numbers of reflective markers fixed to each subject can result in experimental errors caused by subjects altering their movements (Mundermann 2006).
1.1.5: Markerless motion capture

Markerless motion capture (MMC) is a newer method of measuring position data that is an alternative to MB methods. Although they are still used far less frequently than MB motion capture, MMC systems have become more popular in recent years because of their versatility and potential uses in biomechanics, analysis of sports injuries, and the entertainment industry (Sheets 2011; Corazza 2010; Laurentini 1994). There are several advantages and disadvantages to MMC systems when compared to traditional MB methods. First, MMC systems typically only require (usually multiple) off-the-shelf video cameras and do not require extensive marker systems to be applied to the body (80 or more markers are used in some marker sets such as the point cluster set) (Andriacchi 1998). The elimination of the marker-placing step shortens the time required to collect data.

Validating MMC systems to prove that they can produce results that are as accurate as MB systems has been a continued effort in the last decade. A validated MMC system would be preferable in biomechanical studies because it would eliminate the need for markers and errors caused by marker occlusion, reduce error due to soft tissue movement, and allow measurements to be made outside of a laboratory environment. MMC systems typically need at least eight cameras to provide comparable accuracy of MB methods (Andriacchi 2010), and using more cameras generally produces more accurate position and volume results (Corazza 2006; Mundermann 2006). Many MMC methods create 3-D models called visual hulls (Figure 2), which are defined as “a locally convex representation of the volume of an object or body obtained through volume
intersection techniques generally called shape-from-silhouette” for each frame that the video cameras are recording the subject (Laurentini 1994; Corazza 2006). The visual hulls that these methods create rely on the ability to automatically differentiate the subject from the background, and many approaches use differences in color (Andriacchi 2010). Therefore, results can be greatly affected if the subject matches the background. The portion of the subject’s body that is similar in color to the background may be subtracted along with the background, which removes this volume from the reconstructed visual hulls and increases error.

![Example visual hull of a subject running](image)

**Figure 2: Example visual hull of a subject running**

The visual hulls do not directly give us position and orientation of the individual body segments. Instead, MMC systems may obtain those kinematics by fitting the known size and shape of the person's various body segments to the visual hulls (Corazza 2010). Subject-specific shape models of a person's body can be obtained using two
different methods: (1) using laser scanners or (2) using visual hulls from the MMC systems themselves (Corazza 2010). Laser scanners are an active method because they use reflected light, whereas one method of creating visual hulls involves using a passive method, which relies only on image capture (Mundermann 2006). Laser scanners produce more accurate results (Cyberware scanner has 1mm error, and 4mm resolution), but a laser scan takes up to 30 seconds to be completed, making these scans only useful for static poses. Visual hulls can be created during walking, running, or other activities involving movement (Laurentini 1994). The body models obtained using either a laser scan or a visual hull consist of thousands of points that are connected by a triangular mesh that forms a representation of the surface of the subject’s body. Because visual hulls and laser scans are constructed from thousands of points and triangles, errors due to localized regions of soft-tissue movement can potentially be reduced (Andriacchi 2010). The error is averaged over hundreds of points per segment instead of relying on a few markers like MB methods do (Corazza 2006), which illustrates another advantage of MMC.

This thesis will be an exploration of using MMC systems to estimate GRFs. Further advantages and disadvantages of MMC systems will be discussed later in the context of their application to estimating GRFs.

1.1.6: Some prior work on estimating GRFs from position data

Several past studies have demonstrated the possibility of calculating GRFs from kinematic data. One such study used a MMC system to acquire motion data during
single-leg hopping (Sheets 2008). Peak vertical GRFs were calculated using the acceleration of the whole body center of mass and had error of less than 1% for the one subject who was analyzed. This method demonstrated that MMC could be used to accurately predict vertical GRFs, but the work in this thesis will attempt to expand a method like this to other types of movement.

An existing method for estimating vertical GRFs using marker-based positional data was able to reduce errors at the impact force peak to less than 10% (Bobbert 1991). In this method, position data was obtained from markers that were fixed to wooden links designed to reduce error caused by soft tissue movement that happens when markers are placed directly on skin. Vertical coordinates of marker positions were then filtered and differentiated twice to obtain acceleration data for each body segment. Acceleration values were then multiplied by the segmental masses to get GRFs. Estimated GRFs were then compared to force plate measurements. Although this study produced more accurate estimations of GRFs than past studies, it focused only on impact during running and was thus limited since it did not other types of motions like landing.

In another study, GRFs during walking were determined from position data obtained using passive reflective markers tracked by two digital video cameras (Winiarski 2009). A set of 18 markers placed on subjects’ main upper and lower body parts, as defined by the Clauser model (Clauser 1969), was used. Vertical GRFs were calculated based on the center of gravity for the entire body, so the issue of force-sharing between feet was not addressed. Results showed that GRFs calculated from kinematic data were generally over-estimated but were suitable to be used in clinical settings in
which force platforms were not available because the error between estimated vertical GRFs and force plate data was less than 10% (Winiarski 2009). This method was limited, however, because it only used 18 markers and two video cameras to obtain kinematic data. Only having two views of the markers likely introduced error in the position data.

1.2: Scope and significance of this thesis

The need for a force plate restricts the types of studies that can be performed. The goal of this research is to develop a method for calculating vertical GRFs during walking, running, and landing using position data from a markerless motion capture system. Calculations will be compared to force plate data to determine the accuracy of the method. The primary aim is for this new method to be at least as accurate as any of the existing methods, which means that peak vertical GRFs must be estimated with less than 10% error when compared to force plate data. Marker-based motion capture systems are used much more frequently than MMC systems in biomechanics studies, so this research also has the possibility of further validating or demonstrating a novel use for MMC.

If vertical GRFs could be estimated accurately enough without the use of a force plate, biomechanical analyses of patients with neuromuscular impairments and of athletes performing sport-specific tasks such as running, jumping, and cutting could be conducted in settings that are more natural for the subjects performing them. For athletes, data could also be collected in a gymnasium or on a playing field. Testing in non-laboratory environments would likely yield better results because subjects would move more
similarly to how they do in practices or games. For patients with musculoskeletal or neuromuscular conditions, testing could be done in clinical settings, which would allow it to be used for a much greater number of patients since it would not have to be done in a laboratory.

1.3: Organization of the thesis

This thesis is organized in the following way. In Chapter 2, the testing methods used in the motion capture study conducted in this research are described. Chapter 3 contains the analysis of MMC data of human subjects performing running and landing movements, including comparison of calculated vertical GRFs to force plate data. Chapter 4 evaluates the accuracy of the vertical GRF estimation method. In Chapter 5, MB motion capture data of a basketball bouncing is analyzed in order to further study some of the errors seen in the MMC data. Chapter 6 contains areas for improvement and suggestions for future work. Finally, Chapter 7 summarizes the thesis and presents the conclusions that can be drawn from it.
Chapter 2: Testing methods for markerless motion capture study

In this chapter, we describe an experimental study we performed involving motion capture of various human movements, the data from which we use to develop and test methods for estimating vertical GRFs from markerless motion capture data.

The kinematics of nine female subjects between the ages of 21 and 33 were measured using a nine-camera MMC system. The MMC system used Allied Vision Technologies Prosilica GX1050C cameras (1024 x 1024 pixels, 100 frames per second). All trials were recorded using the same camera configuration throughout testing (Figure 3). Two Bertec force plates (900 Hz) were connected to the system.

The mean height, age, and mass of the subjects were $24.33 \pm 4.56$ years, $1.67 \pm 0.064$ m, and $62.1 \pm 5.6$ kilograms, respectively (Table 1).
Figure 3: MMC camera orientation. Solid blue dots indicate cameras. The top image shows a vertical view of the setup, and the bottom image shows a view looking opposite the direction the subjects moved during running trials.

Table 1: Test subject information

<table>
<thead>
<tr>
<th>Subject #</th>
<th>Age</th>
<th>Height (m)</th>
<th>Mass (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S01</td>
<td>21</td>
<td>1.63</td>
<td>56.7</td>
</tr>
<tr>
<td>S02</td>
<td>21</td>
<td>1.78</td>
<td>63.9</td>
</tr>
<tr>
<td>S03</td>
<td>21</td>
<td>1.65</td>
<td>57.7</td>
</tr>
<tr>
<td>S04</td>
<td>21</td>
<td>1.70</td>
<td>68.9</td>
</tr>
<tr>
<td>S05</td>
<td>26</td>
<td>1.57</td>
<td>68.8</td>
</tr>
<tr>
<td>S06</td>
<td>25</td>
<td>1.68</td>
<td>55.7</td>
</tr>
<tr>
<td>S07</td>
<td>21</td>
<td>1.73</td>
<td>67.5</td>
</tr>
<tr>
<td>S08</td>
<td>33</td>
<td>1.60</td>
<td>56.0</td>
</tr>
<tr>
<td>S09</td>
<td>30</td>
<td>1.68</td>
<td>63.2</td>
</tr>
</tbody>
</table>
Before we conducted any tests with subjects present, we performed internal and external calibrations the MMC system, as described below, to compute camera parameters and relative and absolute camera locations (Bouguet 2010). On the first and last day of testing, we completed an internal calibration for the MMC system. The procedure for the MMC internal calibration was to translate and rotate a board with a black and white grid (Figure 3) around each MMC camera’s field of view for about 15 seconds so that intrinsic camera parameters such as focal length, principal point, skew, lens distortion, and pixel error, could be determined. We then placed an object (Figure 4) with known marker positions (measured using a Vicon marker-based motion capture system) in the capture volume to perform an external calibration for the MMC system. The external calibration provided information about where the MMC cameras were in relation to each other and where they were positioned in the room.

Figure 4: Internal calibration grid for the MMC system
After we gave subjects a brief overview of the study and obtained their informed consent to participate, as approved by the Ohio State University Internal Review Board, we asked them to change into red spandex shirts and compression shorts. There were two reasons for having subjects wear brightly colored, tight clothing. The first was to ensure that subjects would stand out against the white background, as previous testing had yielded poor results if subjects wore clothing that matched the background. The second reason was to prevent loose-fitting clothing from adding volume to visual hulls that would be reconstructed using the markerless motion capture software. Subjects were also asked to be barefoot during testing because previous experiments had shown that shoes reduced the quality of visual hulls. Shadows and the blending of subjects’ shoes with the floor or force plates could add additional material to visual hulls, which would cause error in center of mass position.
The first trials that we recorded were of the subjects standing in reference poses for the MMC system. For the MMC reference pose, subjects stood with their ankles, knees, and hips aligned vertically and their upper arms extended with bent elbows. Finally, with the subject outside of the view of all of the MMC cameras, we recorded a video of the background for each camera, because background subtraction is a necessary step in creating visual hulls. An additional background video was recorded with the box in the capture volume since it was not there for the running trials.

Subjects performed four repetitions of running and single-leg landing (SLL) tasks, as well as three other dynamic movements that were a part of a broader study and were not considered within the scope of this thesis. These tests were chosen because they involved one leg in contact with the ground, so no assumptions about force sharing between feet needed to be made. Running is a commonly investigated movement in biomechanics, and both movements may be of interest to the athletic and biomechanics community. Also, SLLs simulate motions during sports that have been shown to have high rates of ACL injury, such as volleyball and basketball. For example, SLLs replicate off-balance landings in sports like basketball or volleyball that involve jumping from a non-stationary position. Similar tests have been conducted in other ACL injury studies done previously (Hewett 2006).

In the running tasks, subjects started two to three meters away from a force plate and then moved toward the force plate at a self-selected pace. The average running speed of all of the subjects was $2.87 \pm 0.36$ meters per second (Table 2). Care was taken to ensure that the one of the subject’s feet landed entirely within the boundaries of the force
plate each time. An additional trial was recorded if the subject missed the force plate or if her entire foot did not make contact with the force plate. For the SLL trials, subjects began by standing on a 12-inch tall box. SLLs were accomplished by balancing on one leg on the 12-inch box, jumping off the box, landing on one leg, and holding the landing position for approximately two seconds.

Table 2: Average speed of each subject during running trials obtained by differentiating MMC center of volume position data

<table>
<thead>
<tr>
<th>Subject #</th>
<th>Average Running Speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S01</td>
<td>2.68</td>
</tr>
<tr>
<td>S02</td>
<td>3.35</td>
</tr>
<tr>
<td>S03</td>
<td>3.06</td>
</tr>
<tr>
<td>S04</td>
<td>2.77</td>
</tr>
<tr>
<td>S05</td>
<td>2.31</td>
</tr>
<tr>
<td>S06</td>
<td>2.97</td>
</tr>
<tr>
<td>S07</td>
<td>2.73</td>
</tr>
<tr>
<td>S08</td>
<td>3.40</td>
</tr>
<tr>
<td>S09</td>
<td>2.52</td>
</tr>
</tbody>
</table>
Chapter 3: Analysis of markerless motion capture data of human subjects

3.1 Estimating ground reaction forces of human subjects performing running and single-leg landing trials using data collected with a markerless motion capture system

3.1.1 Markerless data processing and visual hull creation for human subjects

The first data we processed was markerless data from human running and SLL trials. A program (Mundermann 2005) developed for this purpose was used to create visual hulls for a given subject. The main steps in processing the MMC data were internal calibration, external calibration, and visual hull creation.

Once the internal and external calibrations described in section 2.1 were completed (Bouguet 2010), a visual hull was created for every frame by subtracting a static background image from each video frame in the trial. We used nine cameras to create visual hulls of the subjects’ bodies. Finally, settings for voxel size (0.006 m) and boundaries of the capture volume (Table 3) were specified.

The coordinate system for the laboratory and bounding box was defined in the following way. The origin was set as the corner of one of the force plates. The x-direction was roughly parallel to the subject’s frontal plane, the y-direction was roughly parallel to the subject’s sagittal plane, and the z-direction was vertical. Trial videos and background videos from each of the cameras were selected, and then the visual hulls were created by combining the two-dimensional silhouettes from each camera view.
Table 3: Bounding box coordinates

<table>
<thead>
<tr>
<th>Coordinate</th>
<th>Minimum (m)</th>
<th>Maximum (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>-1</td>
<td>3</td>
</tr>
<tr>
<td>y</td>
<td>-1</td>
<td>2</td>
</tr>
<tr>
<td>z</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

A visual hull was created for every frame that the subject was in contact with the force plate (e.g. Figure 5). It should be noted that the computed visual hull is not a perfect representation of the person’s body. One problem that can affect visual hull quality is additional volume (phantom volume) from shadows and the floor that is added to a subject’s feet. The issues caused by shadows were resolved by deleting any computed volume beneath the floor level. Volume beneath floor level was removed by making the minimum height of the bounding box, which was the rectangular prism that contained the volume of interest that subjects passed through, equal to zero meters. It can also be seen in examples of visual hulls for a running trial (Figure 5) that extra volume is added during periods in which the subject’s legs or arms are close to the rest of the body, which occur periodically during running.

The tracking step during which the position of individual limbs was determined from the visual hull was not performed. Instead, we made the assumption that the subject’s body had a constant density, and thus center of mass position could be approximated as center of volume position of the visual hulls.
Figure 6: Visual hulls of subject S01 during running trial R1. Frontal views are shown in the top, and side views of the same visual hulls are shown on the bottom. Phantom volumes are seen between the subject’s legs when close together.
3.1.2 Visual hull center of volume calculation

As noted in Chapter 1, we can compute the vertical GRFs either using accelerations of all body segments (Equation 2), or by simply using the acceleration of the body's center of mass (Equation 1). In this thesis, we use the center of volume of the whole body to approximate the center of mass. We assume that all parts of the body have the same density, so that the center of mass is estimated as the center of volume of the computed visual hulls. In order to calculate center of mass position and volume for every visual hull, we used a program created by Brian Mirtich that was designed to calculate the volume integrals necessary to solve for mass properties such as center of mass and moment of inertia for polyhedrons (Mirtich 1996). This program could also compute other quantities requiring volume integrals, such as total volume and various moments of inertia.

We modified the program to write the three coordinates of the center of mass position and the volume of each visual hull to a text file for later analysis.

3.1.3: Differentiating the position data

From the center of mass position data, we calculated vertical GRFs and compared them to force plate data. Recalling Equation 1, in order to compute the acceleration of a body’s center of mass, we need to twice differentiate the position of the center of mass. Differentiating a noisy signal can result in large errors in the computed derivatives. Therefore, because of noise due to errors in the center of mass position data caused by camera inaccuracies (e.g. poor focusing and resolution errors) and phantom volume
present in visual hulls, it was necessary to fit a smooth function through the data to make it possible to calculate vertical GRFs accurately. To accomplish this, smoothing splines were applied to the center of mass position data using MATLAB’s “spaps” function. The smoothing splines fit a function with less noise than the experimental data within an arbitrary tolerance. A smoothing parameter with a tolerance of 0.5 centimeters was selected based on the estimated error in the center of mass position (1 centimeter) and then adjusted slightly to fit the force plate data more closely. This parameter was kept the same when analyzing data from other subjects performing a running trial. Errors for all subjects were approximately the same, so using a different parameter for each subject was deemed unnecessary. Consistency was a main objective for this method, so using the same parameter was desirable.

Figure 6 shows the smoothing spline (with the smoothing parameter of 0.5 cm) passing through the sequence of center of mass positions. It can be seen that the smoothing splines do not reach the peaks of the raw center of volume position data. The maxima and minima may have been affected by phantom volume, however, because they correspond to portions of the gait cycle in which the subjects’ arms were close to their bodies or their legs were close together. Because of this, the splines may provide a better approximation of the true center of mass by reducing the variation in the raw data.

Because a spline is essentially a piecewise cubic function, it has exactly computable derivatives, here computed using MATLAB’s “fnder” function. Figure 7 shows the smooth first derivative of the vertical position, obtained by differentiating the
smoothing spline. Figure 8 shows the smooth second derivative of the vertical position, obtained by differentiating the smoothing spline.

It should be noted that Figure 8 also shows a sequence of noisy accelerations. These accelerations were calculated using a simple finite difference of the original raw positions. To differentiate noisy signals such as the position data using finite differences, one has to use appropriately large step sizes. Before the smoothing splines were applied, every three points in the center of mass data, rather than every point, were differentiated as a first attempt to limit the effect of the noise, which is why the number of acceleration values in Figure 8 (its sampling rate) is less than the number of position values in Figure 6. Notice that these finite difference based derivative estimates fluctuate much more wildly and are not reflective of the actual total accelerations.

The accelerations were calculated for both the running and the single leg land trials using the splines method, as described above. The only difference was that the smoothing parameter for single leg lands was 0.003, as using the same parameter as for the running trials gave much less accurate results. Forces at impact were significantly underestimated using the running parameter, so it needed to be adjusted. Larger accelerations associated with the sudden impact at landing can explain why a smaller tolerance was needed for the smoothing function.

After the splines were differentiated, GRFs in the z-direction (Figures 9) were calculated as before. Subjects’ masses were measured from force plate data recorded when the subjects were standing stationary on the force platform.
Figure 7: Raw and smoothed center of mass position data of Subject S01 in running trial R1

Figure 8: Center of mass velocity of Subject S01 in running trial R1 calculated with smoothing splines and finite differences
3.1.4: Comparison of estimated vertical GRFs to force plate data

Once acceleration of the center of mass was obtained, vertical GRFs were calculated using Newton’s second law (Equation 1). For this calculation, the subject's total mass was computed using the ground reaction force on the force plate when standing still.

Estimated vertical GRFs compare favorably with force plate data for the running trials (representative plots shown in Figure 9), as the largest error between estimated and measured peak GRFs is less than 10% for all nine subjects. Errors did not appear to be affected by the subject’s running speed (Table 3).

Vertical GRF estimates for SLL trials (Figure 10) have much more error than the running trials. It can be seen that the force at initial impact cannot be reconstructed.
because it occurs too quickly (approximately 0.07 seconds or seven video frames, which does not provide enough data to capture the acceleration at initial impact). After that impact, the GRF estimates match the force plate data more closely, but even during this after-impact period, errors greater than 20% are seen at some points in time. Estimated GRFs were larger than the force plate data at some times after impact but smaller than force plate data at others, so there were no consistent trends in the errors. Large errors like this suggest that a faster frame rate should be used for motions that involve impacts like landings if the maximum impact force is an important quantity.

Medial-lateral and anterior-posterior GRFs were also calculated during running trials. When the same smoothing parameter that was used in the vertical GRF calculations was applied to this data, however, resulting GRF calculations were very inaccurate (Figure 23, Appendix A). The GRF calculations in these directions were zero or very close to zero throughout force plate contact. When a smaller smoothing parameter was used, results matched force plate data more closely than previously, but there were still large errors (Figure 24, Appendix A). A different parameter was needed for the medial-lateral and anterior-posterior directions to fit the force plate data as closely as possible, but the medial-lateral GRFs still had errors greater than 200%. Because we appear to need different smoothing parameters for different directions, we do not consider this method sufficiently general at this point. It would be better to derive the smoothing parameter directly from the center of volume data or the visual hull data, if possible, rather than having to choose it from fits to ground reaction force data.
Figure 10: Vertical GRFs estimated from MMC position data were within 10% of the force plate data for Subjects S01 (top), S02 (center), and S03 (bottom) during running trials.
Figure 11: Vertical GRFs estimated from MMC position data were unable to match force plate data during impact for Subjects S01 (top), S02 (center), and S03 (bottom) during single-leg land trials.
From these results, it is clear that the data collection setup was able to estimate vertical GRF during running trials more accurately than during SLL trials and was unable to estimate GRF during impact. One potential application for this method is in biomechanical analyses of people recovering from injury. As long as the patient is able to run, vertical GRFs could be calculated during running for landings on each leg, and differences in the force on the injured leg and the non-injured leg could be compared. Because errors of less than 10% (and typically less than 5%) were seen in the results, relatively small differences in the force on each leg could be discriminated.

In stroke patients, average GRF asymmetries during walking of 12.8% have been reported (Kim 2003). In patients who underwent total hip arthroplasties, the magnitudes of peak GRFs were smaller and time at which the first peak GRF occurred 13.3% later in the affected limb than in the other limb (McCrorry 2001). Thus, if this method could be generalized to walking while maintaining about 5% error seen in our GRF estimation, it can potentially be used in such cases such as these when GRFs that need to be discriminated differ by much larger than 5%.

3.1.5: Understanding the errors in the estimated vertical GRFs

In this section, we discuss possible sources of errors in obtaining vertical GRFs from the visual hulls. The main source of error is due to the reconstruction of the visual hull itself. One source of error with the visual hulls was that extra volume (phantom volume) was added when a subject’s arms were close to her body or when her legs were close together. The phantom volume was observed during poses like these because there
were times in which subjects’ legs were too close together for any camera view to
distinguish the small amount of space between the subject’s legs during this portion of
the running cycle (e.g. the right visual hull in Figure 5). As a result, the volume of each
subject’s visual hulls was not constant during any of the trials.

The total volume of the visual hulls typically fluctuated by approximately six
liters (0.006 m$^3$) for all subjects throughout the course of a running or SLL trial, as shown
in Figure 11. The maxima in the left plot of Figure 11 correspond to portions of the
running cycle in which the subject’s legs are close together during midstance, and the
minima in this plot correspond to times when the subject’s legs were farther apart during
heel contact and toe-off. The maximum in the right plot occurred shortly after the subject
jumped off the box, when her body was in a crouched position.

Figure 12: Visual hull volume fluctuation over time for Subject S01 during running trial
R1 (left) and SLL Trial SLL1 (right)

Given the visual hull volume fluctuations in Figure 11, what can we say about the
actual total volume of the person? Two methods for computing the total volume more
accurately than the visual hull are to: (1) use a laser scanner and (2) find the volume of
water displaced by the person when fully submerged. We did not use either, although there was one exception, which will be discussed later. Instead, we estimated the volume of each subject from their total mass and by assuming an average density of the human body to be 1010 kg/m$^3$ (Ozen 2007). This estimated volume was then compared to the volume of each subject’s reference pose visual hull. We used the reference pose visual hull for comparison because the subject’s arms and legs were away from her body, thus reducing the impact of the phantom volume. In other trials, phantom volume was observed when a subject’s arms were close to her body or when her legs were together. Results showed that the reference pose visual hulls had 35% more volume than the calculated value, and running visual hulls had 41% more volume than the calculated value (Figure 12). This finding leads to the conclusion that during this experiment, visual hulls always had greater thickness or extra material (e.g. concavities, self-intersections, and extra volume resulting from subjects wearing reflective markers) that could not be removed by the volume intersection method. Because of these factors, visual hull volume was always greater than the true volume of a subject’s body.
Subject volumes obtained from mass and average density were always smaller than the visual hull volumes.

In order to further explore the reasons for the volume fluctuation in the visual hulls, several other analyses were performed. First, a laser scan of one subject, which had been obtained during previous testing at another site, was observed to see how its volume compared to visual hulls reconstructed from this testing. The subject’s volume was calculated using her mass and the average density value (1010 kg/m$^3$) and then compared to the laser scan volume. The laser scanner had a surface reconstruction accuracy of 1 mm for static poses, which was more accurate than any of the visual hulls created in this study. The calculated volume from the subject’s mass was 0.055 m$^3$, and the laser scan volume was 0.060 m$^3$, resulting in an 8.21% difference. The laser scan volume was still greater than the calculated value, but the difference was much smaller.
than when the subject’s visual hulls were compared to the calculated value (39.2% for running visual hulls). One possible reason for the greater volume in the laser scan was residual air in the subject’s lungs after the subject exhaled. Other possibilities for the volume difference include inability to separate body segments (e.g. the subject’s arms from the torso) and an assumed body density that was too large. The subject could have moved as well, but the scan did not look blurry, making this unlikely.

As a final way to understand the volume discrepancy, the volumes of two objects with simpler geometries than the human body were analyzed: a cylinder and a sphere. The cylinder was studied using a modeling approach, and the sphere was analyzed with both an experimental and modeling approach. The advantages of studying these shapes were that their volumes can be known exactly, unlike a complicated shape like the human body, the volume measurements of which contain errors and assumptions. The hope was that the findings of these simple analyses could elucidate the reasons for the visual hull volume increase.

First, a cylinder was used as a rough model of the human body limbs, and the effect of slightly increasing its thickness on its volume was determined (Figure 13). Increasing the diameter and height of the cylinder by 1 centimeter resulted in a volume increase of 22%. This is smaller than differences between the theoretically calculated and measured visual hull volume of 35.4% and 41.6% (Figure 12), but it illustrates that a small increase in thickness of a simple object can cause a significant increase in volume. Applied to a more complex shape like a human body and combined with the effect of
phantom volume, an increase in thickness on the order of 1 cm can explain the larger visual hull volumes that were consistently seen in this experiment.

![Diagram of cylinder dimensions](image)

Figure 14: Cylinder dimensions used to investigate the effect of additional thickness on total volume

Finally, the volume of a sphere was analyzed. MMC data of a basketball falling was recorded, and the volume of the basketball visual hulls was computed and compared to the calculated volume for a sphere. It should be noted that a sphere is a hard shape to reconstruct exactly using visual hulls because an infinite number of triangles and an infinite number of cameras are needed to capture the curvature of a sphere. Regardless, the results of this analysis can still be applied to gain insights into the volume inconsistency seen for each subject. The volume of a standard men’s basketball was calculated to be 0.0071 m$^3$, and the maximum visual hull volume was 0.0086 m$^3$ for a 21% difference, which is again comparable to the human visual hull volume difference. The visual hull volume fluctuated during testing but was always greater than the
calculated value (Figure 14). Maximum volume was observed when the ball was in contact with the floor, which can be explained partially by shadows and deformation of the ball (Figure 15). The volume was consistently greater than the calculated value, however, even when the ball was in flight and well within the boundaries of the capture volume.

Figure 15: Basketball volume obtained from MMC visual hull data is largest when the ball is in contact with the ground (center of mass height also obtained from MMC data)
We have established that there are several possible errors that could result in additional volume in the visual hulls, but which of these errors can explain the observed errors in the calculated vertical GRFs?

If additional volume is added equally over the entire surface of the visual hulls, the measured center of mass may remain aligned with the actual center of mass to a first approximation, and the vertical GRF estimates would not be affected. Thus, a homogenous increase in a visual hull’s thickness would probably not significantly affect the center of mass or vertical GRF estimates.

On the other hand, if most of this extra volume is added to the visual hulls randomly, then the center of mass and resulting vertical GRF calculations will contain errors. Phantom volume was unevenly distributed between the subject’s upper and lower body, and this distribution changed as the subject changed shape. Thus, the error caused by the phantom volume changed from frame to frame. A simple model of a person

Figure 16: Basketball visual hulls had extra volume added at times when the ball was in contact with the ground
(Figure 15) with an additional six kilogram mass added to different portions of the visual hull can be used to explain how phantom volume can affect center of mass. Six kilograms was chosen based on the average amount of volume fluctuation during a running trial. The model’s height of 1.6 meters and center of mass height of 1.0 meter were chosen based on approximate numbers from testing data.

Adding phantom volume to different locations on the visual hull changed the overall center of mass height to varying degrees. The effect of the mass added by the phantom volume on the overall center of mass is given in Equation 3. Results of adding the additional mass to four different spots on the body — the feet, thigh, chest, and head (Figure 16) — show that the phantom volume could result in a change in center of mass height of as much as nine centimeters (Table 4). From inspection of visual hulls, however, it is likely that adding the mass 0.25 m below or 0.3 m above the center of mass best represent where phantom volume was actually added. Those locations are closest to where the arms and upper legs are. In these cases, center of mass height could still be altered by two to three centimeters from the center of mass height of the body without any phantom volume. This center of mass error would result in significant errors in subsequent vertical GRF estimates. Phantom volume rarely appeared to be completely concentrated at a single height, but these calculations show that it can cause inaccuracies in center of mass position.
Figure 17: Model of human body showing additional mass caused by phantom volume concentrated near, roughly, the foot, thigh, chest, and head

\[
COM_{\text{height}} = \sum (\text{percent mass})_i \times COM_{\text{mass}_i}
\] (3)

Table 4: Effect of phantom volume on center of mass height

<table>
<thead>
<tr>
<th>Figure 17 case</th>
<th>Change in Center of Mass Height (m) Caused by Additional Mass</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.091</td>
</tr>
<tr>
<td>b</td>
<td>-0.023</td>
</tr>
<tr>
<td>c</td>
<td>0.027</td>
</tr>
<tr>
<td>d</td>
<td>0.055</td>
</tr>
</tbody>
</table>
3.2: A consistency check between the center of mass and ground reaction forces

In order to evaluate the accuracy of the center of mass estimates and vertical GRF estimates discussed in the previous section, vertical GRF data from the force plate was integrated to determine the theoretical vertical center of mass position. Theoretical vertical center of mass position was calculated (Equation 6) by integrating the equations of motion of the vertical motion of a human body (Equations 4 and 5). Values for the initial velocity $v_0$ and center of mass position $z_0$ were estimated from MMC data.

\begin{align*}
C\ddot{O}M_z &= \frac{F_z}{m} - g \quad (4) \\
C\dot{O}M_z &= \int (\frac{F_z}{m} - g) dt + v_0 \quad (5) \\
COM_z &= \int C\dot{O}M_z dt + COM_{z_0} \quad (6)
\end{align*}

where

$C\ddot{O}M_z = \text{second derivative of vertical center of mass position \( \frac{m}{s^2} \)}$

$C\dot{O}M_z = \text{first derivative of vertical center of mass position \( \frac{m}{s} \)}$

$COM_z = \text{vertical center of mass position (m)}$

$F_z = \text{force plate data in vertical direction (N)}$

$g = \text{gravitational acceleration \( \frac{m}{s^2} \)}$

$v_0 = \text{vertical center of mass velocity at time } t_0 \left( \frac{m}{s^2} \right)$

$COM_{z_0} = \text{vertical center of mass position at time } t_0 \text{ (m)}$
It can be seen that center of mass position results from the smoothed center of mass experimental data matches integrated force plate data very closely for a subject (Figure 17). This finding instills some confidence in the experimental center of mass position measurements and resulting vertical GRF estimates that were calculated from differentiated position data shown previously in section 3.1.4. Furthermore, it justifies the use of smoothed data instead of differentiating the raw center of mass position data.

Figure 18: Vertical center of mass position during force plate contact for Subject S03 during running trial R1
Chapter 4: Estimating ground reaction forces of a basketball bouncing using a marker-based motion capture system

We also collected motion capture data for a basketball falling and landing on a force plate in order to evaluate the proposed method of estimating vertical GRFs. A basketball was chosen because it is an object with a simpler geometry and mass properties that we could model more accurately than a human. From this data, we hoped to learn why some of the errors we saw in the MMC position data were occurring and whether the MB position data was more accurate.

Five reflective markers were placed on the basketball, and the basketball was suspended from the ceiling directly above one of the force plates using fishing line. The MB system used eight Vicon T20 cameras (2 MPix used at 300 frames per second, capable of up to 500 frames per second). We made sure that we were not blocking any of the MB or MMC cameras by running fishing line along the ceiling and across the laboratory. We simultaneously collected data with the MB and MMC systems for the basketball in free fall and for several impacts when it hit the force plate. The MMC data was used in the analysis in section 3.1.5. Whenever the MMC system recorded a frame, it sent a five-volt square wave to the MB system so that data from the two systems could later be synced, as the MB system began recording data before the MMC system.

The centroid of the basketball was determined at every point in time using the following procedure. First, the midpoint between all 10 possible combinations of marker pairs (e.g. marker 1 and marker 2, marker 1 and marker 3, etc.) was calculated. A plane
perpendicular to this midpoint and also passing through the centroid was then determined for each combination by setting the dot product in Equation 7 equal to zero, and the intersection of these 10 planes was solved for using MATLAB’s linear least squares optimization built into the “\” operator.

\[
(r_c - m_{ij}) \cdot (r_j - r_i) = 0
\]  

(7)

where

\[
r_c = (x_c, y_c, z_c) = \text{centroid position (m)}
\]

\[
m_{ij} = (x_{mij}, y_{mij}, z_{mij}) = \text{midpoint between markers i and j (m)}
\]

\[
r_i = (x_i, y_i, z_i) = \text{position of marker i (m)}
\]

\[
r_j = (x_j, y_j, z_j) = \text{position of marker j (m)}
\]

Once the position of the centroid was known (Figure 18), the vertical component was numerically differentiated using the forward-difference formula (Equation 8) to calculate the centroid velocity and acceleration (Figures 19 and 20, respectively).

\[
f'(i) = \frac{f(i+1)-f(i)}{\Delta t}
\]

(8)

where

\[
f'(i) = \text{value of derivative of } f \text{ at point } i
\]

\[
f(i) = \text{value of function } f \text{ at point } i
\]

\[
\Delta t = \text{time between points } i \text{ and } i + 1
\]

After calculating the centroid’s vertical acceleration as a function of time, vertical GRF could be calculated (Equation 9) and compared with the force plate data (Figure 21).

\[
GRF_z = m_{basketball} \times (a_{basketball} + g)
\]

(9)
where

\[ GRF_z = \text{vertical component of GRF (N)} \]

\[ m_{\text{basketball}} = \text{basketball mass (kg)} \]

\[ a_{\text{basketball}} = \text{basketball acceleration } \left( \frac{m}{s^2} \right) \]

\[ g = \text{gravitational acceleration } \left( \frac{m}{s^2} \right) \]

Figure 19: Marker-based and markerless vertical position of basketball centroid as a function of time. Impact occurs when centroid height reaches a minimum.
Figure 20: Vertical velocity of basketball centroid, obtained by differentiating marker-based data, as a function of time. Ball flight is indicated by the slanted line segments, and ball contact occurs at the bottom-right of these segments and during the points in which velocity suddenly increases.

Figure 21: Vertical acceleration of basketball centroid, obtained by differentiating marker-based data, as a function of time. Ball contact occurs where the vertical peaks are seen.
The estimated vertical GRFs align with the force plate data well temporally, but the magnitude of the estimated GRFs is only within 10% for the second, fourth, and fifth impacts (Figure 21). Because the impact time was so short (approximately 0.025 seconds or only seven to eight MB position data points), there were not enough data points to accurately match the force plate data. The MMC data for the basketball was not analyzed because the MMC cameras captured even fewer position data points during impact (two to three) than the MB cameras, and so the calculated vertical impact forces would be even less accurate.
Chapter 5: Areas for Improvement and Future Work

Our results here regarding the estimation of the ground reaction forces using markerless motion capture should be interpreted with caution. Phantom volume and the apparent increased thickness of visual hulls compared to subjects’ actual bodies were a major source of error when using the volumetric approach of the MMC method. Only two motions were analyzed (running and single-leg landing), and the 100 Hz frame rate was only appropriate for calculating vertical GRFs with errors of less than 10% for the running trials. Not enough data was collected during the 0.07 second initial impact of the SLL trials to accurately calculate these vertical GRFs.

Superficially, one can infer that the extra volume in visual hulls did not cause excessive error in the calculated vertical center of volume position because the estimated vertical GRFs matched the force plate data with less than 10% error. However, note that we did have to use a smoothing parameter for spline-smoothing the center of mass motion. This spline smoothing parameter was derived by fitting the estimated GRFs to the actual GRFs. While the same value of the smoothing parameter worked well for all the vertical GRFs for running, different smoothing parameters were required for different tasks and different (medial-lateral and fore-aft) directions. Even with an appropriately chosen smoothing parameter, the estimated GRFs for non-vertical and non-running trials had larger errors.

It is clear that visual hulls greatly over-estimate the volume of each subject. It would be advantageous to develop a way to correct the extra volume while reconstructing
the visual hulls so that they would more closely match the subject’s body. Having laser scans or a more accurate value of subjects’ volumes to compare visual hulls to would be useful.

For all vertical GRF estimates, center of mass was estimated as center of volume, so a constant density assumption for the human body was made. If the error between center of mass position and center of volume is consistent, this error would be small. A method that utilizes subject-specific body segment parameters or average values for each segment’s density could yield more accurate results because it would account for factors like body fat percentage and muscle mass that would cause some subjects’ densities to deviate more from the average value.

During running trials, vertical GRFs were calculated with peak error of less than 10%, but given the small sample size and the fact that subjects were running barefoot in a small laboratory setting, it is uncertain whether these results would extend to other settings. Subjects probably ran more softly than they would if they wore shoes, and they may have altered their running style (e.g. running toe-heel instead of heel-toe). It is possible that subjects would run faster with shoes on, which could result in larger impact forces and shorter contact time with the force plate. Either of these factors could result in less accurate vertical GRF calculations because of limitations with the cameras used in this data collection setup. Further testing with a larger, more varied sample of subjects should be done to validate the results of this work.

One major limitation of this work was that the only trials analyzed were ones in which subjects landed on a single leg. Many movements including walking, landing, and
cutting require both legs to be in contact with the ground, so it is important to develop a method that can study such motions. During double-support or landing, a way of determining load sharing between the subject’s legs, such as an optimization technique (Koopman 1995), would need to be further developed so that it can be seen if one leg is dominant in the movement. If a method for estimating vertical GRFs were going to be used in a clinical setting for patients recovering from stroke or other neuromuscular impairments, patients would likely not be able to run or jump and land on a single leg. Walking trials and two-legged landings should be analyzed to determine if this method can be used successfully in these situations.

If this experiment were going to be repeated, several changes in the experimental setup could be made to improve the accuracy of the results. First, cameras with faster frame rates could be used, and the orientation of the cameras could be adjusted. Faster frame rates would allow for vertical GRFs at impacts (e.g. during SLLs or for the basketball impact experiment) to be estimated more accurately. It was beneficial to have cameras at different heights in this experiment, but the setup could still be improved. For instance, having a camera higher up directly in front of the subject during running trials could provide a view that would reduce phantom volume between the arms and the body. Based on the center of mass results from integrating force plate data, it was clear that center of mass position was more accurate for the smoothed data than for the position calculated directly from the visual hulls. Reducing phantom volume by adding cameras, using cameras with higher frames rates and resolution, or changing the camera setup
could improve the accuracy of the visual hull position data. Another possibility would be to filter or smooth the position data differently.

Finally, note that in our estimation of the ground reaction forces, we only used the center of volume information from the visual hulls. However, the data from the markerless system has much more information — in particular, information about the position and orientation of the human limbs. By taking advantage of this extra information, either by explicitly fitting a model of a person into the visual hull or other model-based smoothing, we may be able to reduce the errors in the center of mass position estimates and eventually the ground reaction forces. Thus, because we have not used all the information available to us, the performance of the simple methods used in this thesis should not be taken as a true limit on how well the GRFs can be estimated from even the collected data. We may well be able to obtain better estimated with more sophisticated techniques.
Chapter 6: Summary and Conclusion

A method for calculating vertical GRFs using position data obtained using a markerless motion capture system was introduced. Using a nine-camera setup, visual hulls were reconstructed during running and SLL trials. Center of mass position was approximated as center of volume by using a constant density assumption, and vertical GRFs were calculated using differentiated center of volume position data. Results showed that the method can estimate vertical GRFs during running with maximum error of less than 10%. The main expected source of error in the GRF estimates is phantom volume in visual hulls that caused inaccuracies in center of volume position data and the force estimates calculated from this data. During SLL trials, however, error was much greater because the cameras used in this setup did not have a high enough frame rate to reconstruct the large forces at impact. This method could be used in applications in which load-bearing capacity in each leg is compared, such as for an athlete recovering from an ACL tear or other lower-limb injury, but it is limited to motions in which only one leg is in contact with the ground. More work needs to be done to improve this method’s performance and expand its uses to different movements, but this method shows promise for increasing the versatility of biomechanical studies.
References


motion capture system for biomechanical analysis [5665-37]. Proceedings- SPIE The International Society for Optical Engineering 5665, 278-287.


Appendix A: Medial-lateral and anterior-posterior GRFs calculated from MMC data

Figure 23: Calculated medial-lateral and anterior-posterior GRFs for running trials (Subject S03 shown here) did not match force plate data when the same smoothing parameter used for the vertical GRFs was applied.

Figure 24: Calculated medial-lateral and anterior-posterior GRFs for running trials (Subject S03 shown here) matched force plate data more closely when different smoothing parameters were applied for each component, but large errors were still observed.