-- Independent Work Report, Fall 2015 --

Single Camera Stride Analysis on a Lower Body Positive Pressure Treadmill: Is there a difference in stride at different body weight percentages?

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Abstract

Lower Body Positive Pressure Treadmills are a cutting edge training and rehabilitation tool for distance runners. In this paper, we present a minimally invasive stride capturing system designed to work on a Lower Body Positive Pressure Treadmill. We believe this capturing system might allow researchers to better understand the effect of unweighting on running stride, which in turn might help us understand how to best incorporate the devices into athletic rehabilitation and training. As a proof of concept, we use our system to examine how stride changes at different body weight percentages (100% and 80%) over three different speeds (easy, medium and hard). We find that right knee angles change significantly from 100% body weight to 80% body weight when participants ran at medium and hard paces. However no statistically significant change was observed during easy running.

1. Introduction

Overuse injuries -- especially bone stress injuries (BSI) -- are all too common in novice and elite distance runners. The vertical force experienced while running at an average pace is approximately 2.5 times body weight [1]. Beneath this large mechanical load, a runner's bones are strained, deform and accumulate small amounts of micro-damage [8, 12]. Under normal conditions this damage remodels at approximately the rate with which it occurs, resulting in zero net effect [8, 12]. However, if the load is too great or easy time between runs insufficient, the

micro-damaged from running will accumulate and can lead to BSI such as stress reactions, stress fractures and fractures [8, 12].

Overuse injures are incredibly disruptive to distance runners and their competitive training cycle. Running is thought to be the cause of approximately 72% of stress fractures seen in athletes [10]. These injuries force an immediate break from training and can keep an athlete sidelined for several weeks to several months [12]. Such breaks in training significantly undermine a runner's ability to train and compete at a high level. Therefore, improving prevention and treatment of BSIs would greatly benefit the athletic health and performance of runners.

Over the last decade, Lower Body Positive Pressure Treadmills (LBPPTs) have become a cutting-edge tool for bone injury rehabilitation. LBPPTs simulate reduced gravity, thereby decreasing the load on an athlete during a treadmill run [1, 2, 10, 11]. This reduced load decreases the strain on a runner's bones, which has significant implication for bone stress injury rehabilitation and treatment. The injury prone runner may integrate LBPPT running into his or her normal training cycle to decrease the chances of developing a BSI. The injured runner may use the LBPPT as a rehabilitation tool to control the load imposed on a healing BSI [10]. Since AlterG Inc.'s launch of their commercially available Anti-Gravity Treadmill in 2005 (Figure 1), LBPPTs have become widely used in collegiate and professional athletic training facilities and physical therapy centers [10]. However the effect of reduced body weight on running stride and mechanics is not fully understood.

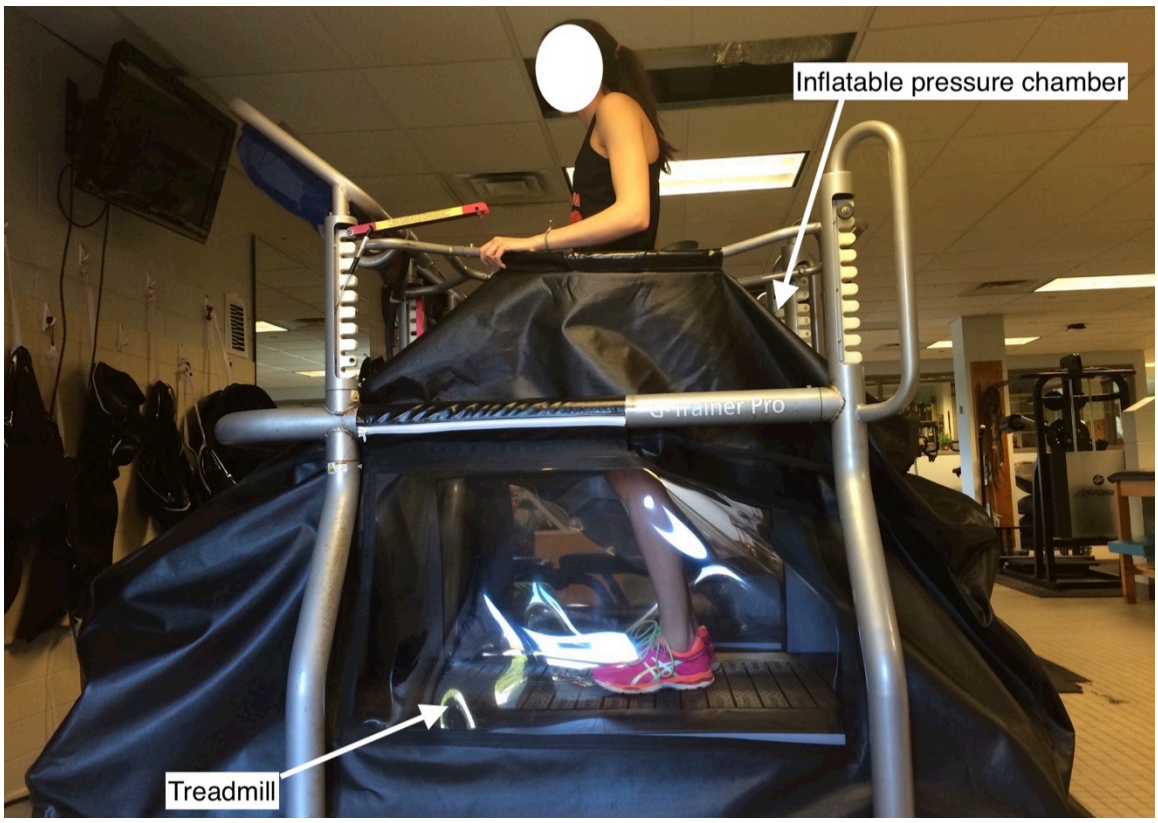


Figure 1: AlterG Inc.'s Anti Gravity Treadmill Pro 200

Most of the previous work examining gait at reduced body weight has focused on ground reaction forces (GRF) over different body weight (BW) percentages [5, 6, 11]. While these studies have revealed that reduced body weight effects stride in a complex manner, looking at GRF alone does not provide a full picture of a runner's stride or how it may change at different body weight percentages. More specifically, these studies do not capture hip, knee and ankle joint angles, which are critical measurements in evaluating stride [3].

In this paper, we propose a new stride analysis system which captures hip and knee angles on AlterG Inc.'s Anti-Gravity Treadmill (AGT). This system has the potential to enable any number of gait analysis studies on the AGT and, as a proof of concept, we used our system to analyze how a person's stride changes at three different speeds (easy, medium and hard) over two different body weight percentages (100% and 80%).

Our main objective and challenge was to create a minimally invasive and affordable system that captures a full view of an athlete's stride despite AGT's view obstructive pressure chamber. Our key idea in achieving this was to place a single, fixed RGB/Depth camera inside the AGT pressure chamber itself. This camera positioning allowed us to capture both knee and hip joints, which, as far as we know, is not possible using other stride analysis systems on the AGT. We achieve our full stride analysis system in three parts: (1) capture RGB and depth data using a single, fixed camera inside the AGT pressure chamber; (2) identify 2D joint coordinates by detecting colored joint markers in the RGB image; and (3) calculate 3D joint coordinates and joint angles using the depth image.

In summary, the main contribution of this paper are: (1) We propose a minimally invasive stride analysis system which captures an athlete's 3D hip and knee angles while running (or walking) on an AGT. (2) We gather data using our system to analyze how an athlete's stride changes at three different speeds (easy, medium and fast) over two different body weight percentages (100% and 80%). (3) We use study data to evaluate the stride analysis system and discuss future improvements.

2. Background and Related Work

In this section, we give a brief history and description of AlterG Inc.'s Anti-Gravity Treadmill. We then review a few key studies that examine the effect of reduced body weight on stride, particularly focusing on the systems they used to capture stride and the results of their studies. Finally, we will give a brief review of stride analysis methods with commentary on why we could or could not use the system to gather joint angle data on the AGT.

2.1 AlterG Inc.'s Anti-Gravity Treadmill

Conceptually, a treadmill system that simulates reduced gravity must exert upward force on a user so that he or she experiences a net force similar to what might be experienced when running on a different planet [1]. Initial attempts at implementing such a treadmill used overhead springs and rock-climbing-like hip belts to provide an upward force on participants (Figure 2). However, these systems were cumbersome, difficult to use and designed for lab research as opposed to rehabilitation or performance enhancement. Because of this, LBPPTs were not applicable to the average athlete.

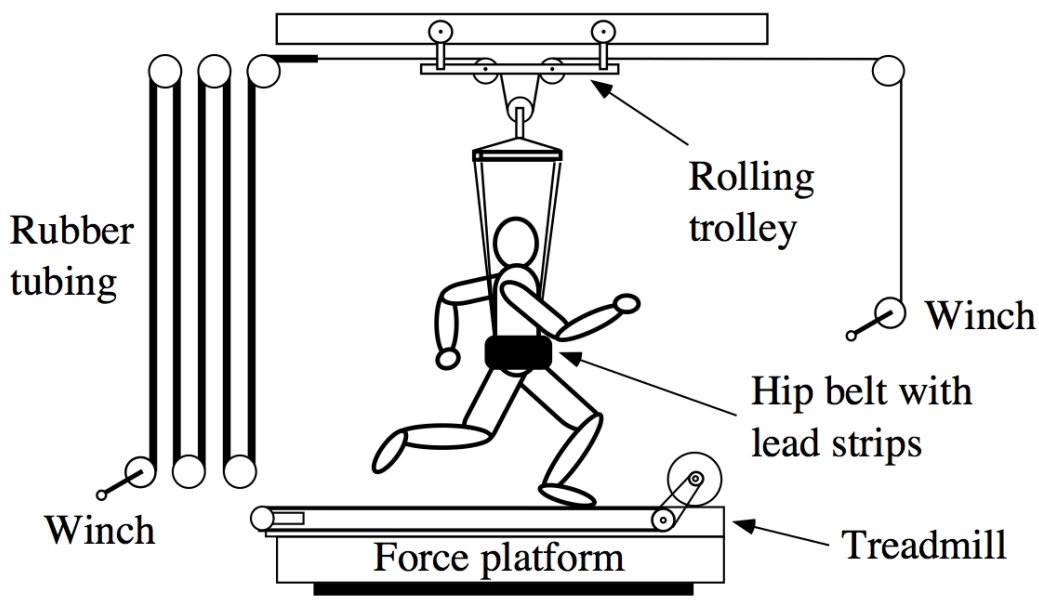


Figure 2: Chang et al.'s implementation of a LBPPT using a modified rock climbing harness and pulley system to simulate reduced gravity [1].

That all changed when NASA researcher, Robert Whalen, designed a chamber-based LBPPT, which eventually became AlterG, Inc.'s Anti-Gravity [7]. Whalen's design allowed users to wear neoprene shorts to zip into an airtight pressure chamber which enclosed them from the waist down (Figure 3). If the pressure inside the chamber is defined as P_1 and the pressure outside the chamber is defined as P_2, then the pressure differential across the chamber,

$\Delta P = P_2 - P_1$. $P_2 > P_1$ will create an upward force on the subject (lower body positive pressure), simulating gravity reduction [13]. Whalen also added pressure sensors, a processor and control panel to his design to allow users to easily select their desired percent body weight, ranging from 20% to 100% (Figure 4). Because the neoprene shorts were flexible and minimally invasive and the control panel made the system easy to use, Whalen's LBPPT had applications in athletic rehabilitation and performance. To bring the product to fruition, Whalen's son, Sean Whalen founded Alter-G Inc. in 2005 and brought the Anti-Gravity Treadmill to commercial markets [7]. Since then, AGTs have become an integral part of many bone stress injury rehabilitation programs and performance athletic training regimens.

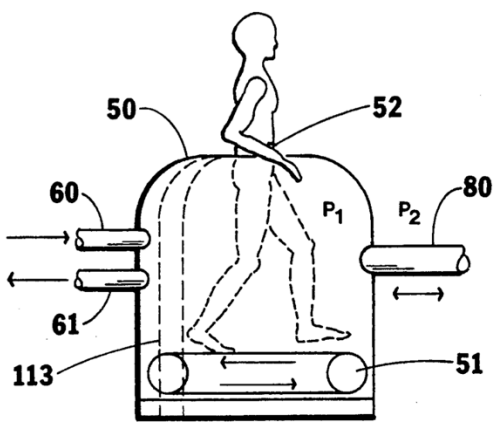


Figure 3: Whalen's pressure chamber design [13]

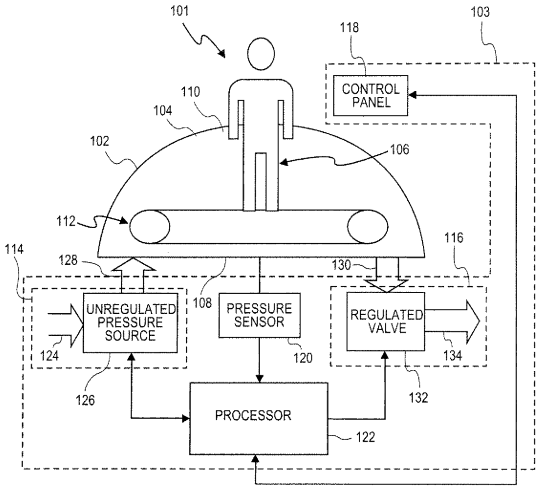


Figure 4: Whalen's initial AGT design [13]

2.2 Stride Analysis on the Anti-Gravity Treadmill and Similar LBPPTs

Due to it's wide use in rehabilitation and training, there has been much interest in studying how reducing gravity on the Anti-Gravity Treadmill affects a runner's stride. Such studies are pertinent to our paper because they explain how other researchers have captured stride on the AGT and discuss results which are relevant to our study examining how an athlete's stride changes at three different speeds (easy, medium and hard) over two different body weight percentages (100% and 80%).

In 2005, Cutuk et al. studied gait analysis with simulated fractional gravity using LBPPTs. They used force-sensitive insoles to capture GRF and reflective markers and video cameras placed outside the LBPPT chamber to get knee and ankle joint angles [2]. They were unable to gather hip-angle data because the LBPPT chamber obstructed their view of the hips [2]. Culuk et al. found that GRF decreased with decreasing BW and that stride length increased with decreasing BW. However they observed no change in knee or ankle joint angles over different body weights when participants walked at 3.0mph nor when they ran at 6.0mph [2]. While these results provided ample evidence that walking and running on LBPPTs was safe, the 6.0 mph "running" speed is far below the pace a competitive runner would go on the AGT. Therefore, these findings are not indicative of how a competitive runner's stride is affected at reduced body weight.

To test the effect of reduced gravity on stride in more elite runners, Smoliga et al. (2015) used in-shoe regional loading sensors to understand how different body weight percentages affected collegiate and former-collegiate runners. Like Culuk et al., Smoliga et al. found that GRF decreased with decreasing BW; however, they noticed that GRF did not decreased evenly across the entire foot. Instead GRF decreased more in the heel of the shoe than in the toe, suggesting that the treadmill changed the biomechanics of a persons stride [11]. While the running speeds of Smoliga et al.'s test are on par with the speed at which competitive runner might rehab or train, in-shoe pressure sensors do not provide a full stride profile, so it is difficult to determine how stride has changed.

In summary, Culuk et al. used a system that captured joint angles of the knee and ankle thus providing a holistic stride profile; however they conducted trials at speed inapplicable for competitive runners and were unable to capture hip joint angles. On the other hand Smoliga et al.

tested speeds applicable for competitive runners yet only captured foot loading data, which does not provide a comprehensive stride profile. In light of this, our goal is to create a complete system that can capture hip and knee angles and run a trial studying the effect of reduced body weight on an AGT at speeds applicable for competitive runners.

2.3 Review of Stride Analysis Systems

Gait analysis system can be classified as (1) image processing systems (2) floor sensors and (3) wearable sensors [9]. Image processing systems typically use cameras and markers to gather gait information and can detect joint angles. Floor sensors gather foot strike information to track gait but cannot detect joint angles. Wearable sensors are attached to users in order to gather data on their movement; certain sensors can detect joint angles while others cannot [9]. Since we wanted to track joint angles with our system we will focus our background discussion on wearable sensors and image processing systems.

Wearable sensors such as inertial sensors and goniometers can track joint angles over time. However inertial sensor are very expensive (around $135.27 per sensor) and require complex algorithms to capture joint angles [9]. Goniometer's are relatively inexpensive and easy to use, however they often require being connected to an external device which could not be placed inside the AGT pressure chamber. Furthermore, we felt that wearable systems in general were fairly intrusive and may alter the running stride of users.

Given this, we turned to image processing systems. Most image processing gait analysis systems are incredibly expensive (costing as much as $200,000) and require multiple camera angles [9]. Systems of this sort could not be used to capture stride on the AGT since the pressure chamber would block most if not all of the camera views. However, depth sensor cameras are becoming more and more affordable, and are a promising new way of tracking gait and joint

angles. Most notably, Gabel et al. (2012) used Xbox's Kinect to gather a full body gait analysis including joint angles and found this single, fixed camera system to be sufficiently accurate.

3. Implementation

The key idea behind our stride analysis system is to capture data from inside the AGT pressure chamber. Of the previous work which tracked joint angles on the AGT there is a common problem. The pressure chamber obstructs the view of the hips making it impossible to capture hip joint data. Instead of fighting to gather images from outside the AGT, we decided to capture data from within. We achieved this by placing a single, fixed RGB/Depth camera inside the AGT pressure chamber itself.

We can divide our implementation into two parts: (1) we implemented stride analysis system which captures hip and knee angles on AlterG Inc.'s Anti-Gravity Treadmill and (2) we used our system to analyze the effect of body weight percentage (100% and 80%) on a person's stride at three different speeds (easy, medium and hard). In this section, we will first discuss the implementation of our stride analysis system. Then we will discuss the methods we used to implement our trial.

3.1 Setting up a stride analysis system on AGT

We implemented our stride analysis system in three phases: (1) capture stride on the AGT by gathering RGB and depth data using a single, fixed camera inside the pressure chamber; (2) identify 2D joint coordinates by detecting colored joint markers in the RGB image; (3) calculate 3D joint coordinates and joint angles using the depth image. We will discuss each of these individually.

3.1.1 Capturing stride on the AGT

The key idea of our stride analysis system is to capture data from inside the AGT pressure chamber using a single, fixed Depth/RGB camera. Although a major inspiration for our system, the Kinect itself does not work for our purposes since it must be connected to a computer or Xbox which cannot fit inside the AGT's pressure chamber. Instead we turned to Occipital's Structure Sensor. Like the Kinect, the Structure Sensor gathers RGB and depth data; however instead of requiring connection to a large device like a computer or TV, the Structure Sensor connects and streams data directly to an iPhone or iPad. Since the former is small enough to fit inside the AGT pressure chamber, we decided that we could capture data from inside the AGT pressure chamber using an iPhone and Structure Sensor (Figure 5).

Figure 5: The Structure Sensor attached to an iPhone

To do this, we built an iOS app called StrideRight, which saves the color and depth images returned by the Structure Sensor. Upon opening the app, you are prompted to enter a user name (Figure 6) and then you are taken to the recording screen (Figure 7). When you toggle the record button, the app begins to the save depth and color PNG files returned by the Structure Sensor. These images are aligned as closely as possible using the Structure Sensor's calibrator. The files are saved in a subfolder describing the data and time the recording started, which is in a user subfolder inside the app's documents folder. After a recording is complete, you can download all files via iTunes's file sharing tab (Figure 7).

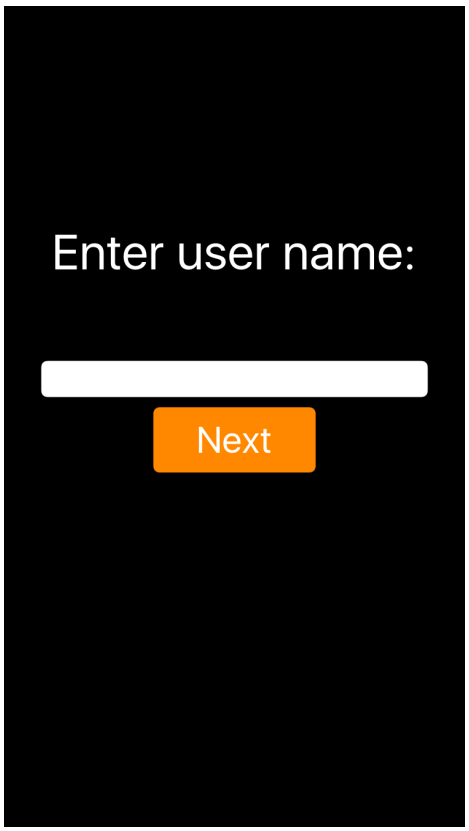


Figure 5: StrideRight's startup screen

Figure 6: StrideRight's recording screen

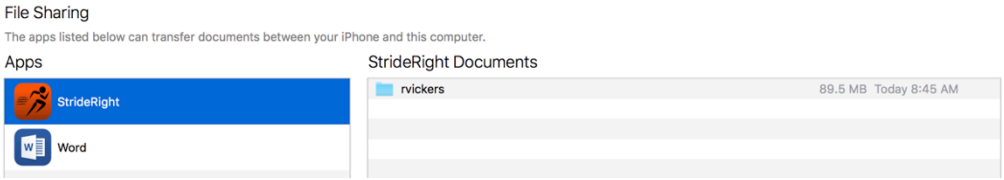
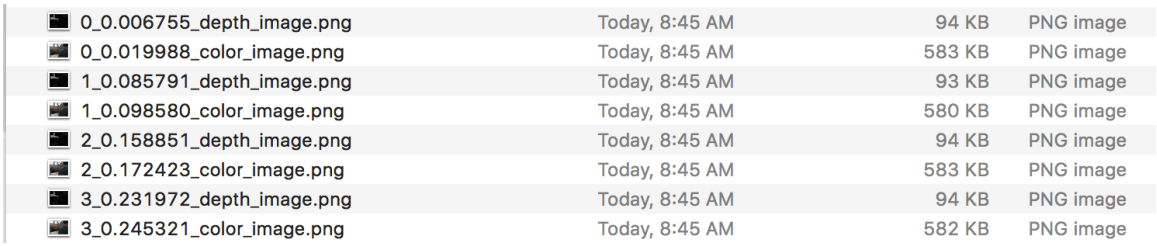


Figure 7: Accessing StrideRight's app data.

StrideRight names each image with an index number, time stamp and whether it is a depth or color image (Figure 8). Because the app records depth and color images separately, the index number for corresponding depth and color images are the same while the time stamps are slightly different.



0_0.006755_depth_image.png	Today, 8:45 AM	94 KB	PNG image
0_0.019988_color_image.png	Today, 8:45 AM	583 KB	PNG image
1_0.085791_depth_image.png	Today, 8:45 AM	93 KB	PNG image
1_0.098580_color_image.png	Today, 8:45 AM	580 KB	PNG image
2_0.158851_depth_image.png	Today, 8:45 AM	94 KB	PNG image
2_0.172423_color_image.png	Today, 8:45 AM	583 KB	PNG image
3_0.231972_depth_image.png	Today, 8:45 AM	94 KB	PNG image
3_0.245321_color_image.png	Today, 8:45 AM	582 KB	PNG image

Figure 8: An example of files saved by StrideRight

This brings us to our main challenge in implementing the app: we must save corresponding depth and color images as close together as possible. Initially, we wrote images to the apps document folder as we received them. However, in this implementation, the depth and color images were saved approximately 0.03 seconds apart. With this time difference, a runner was often in a different position in corresponding depth and color images. To remedy this problem, we implemented a sampling recording system in which we first saves images to an array for 10 seconds and then writes a group of images to the app's document folder. While the writing process causes a delay in recording, it allows for acceptable depth and color image timestamps and increases our recording frame rate. Furthermore, 10 second samples are sufficient to gather the data we need.

With a working app, our final step in capturing stride on the AGT was to place the recording system in the AGT. We use an iPhone car holder and a custom mold to mount the iPhone and Structure sensor to a processor inside the AGT pressure chamber (Figure 9). This mounting method gives us a full view of each participant's legs including their hips (Figure 10), which is the goal of our AGT stride capturing system.

Figure 9: iPhone and Structure Sensor mounted inside the pressure chamber

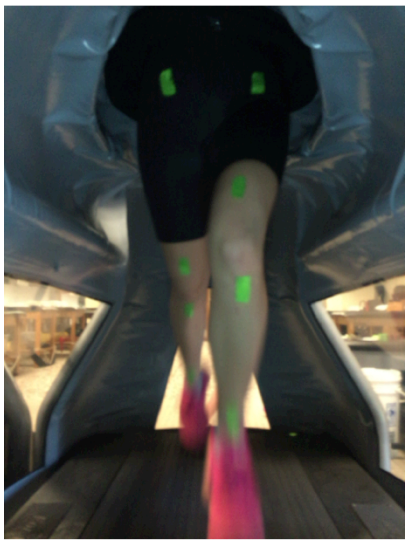


Figure 10: A color image captured by the AGT stride capturing system

3.1.2 Identifying 2D joint coordinates

This portion of the project was implemented by co-investigator Nicole Marvin and her paper discusses this in great depth. This section gives a brief overview of Nicole's 2D joint location finder, JointFinder.

To detect joints, we placed green colored markers on our participants and used a modified version of BlobFinder (Nicole Marvin, COS 126) to create JointFinder.java which takes a color image and threshold number and detects the green markers in the picture. We then used the tree-like structure of the human body to label each marker with the appropriate name: left hip, right hip, left knee, right knee, left shin, right shin, left ankle or right ankle. If we define the coordinate plane as seen in Figure 11, JointFinder detects the (x, z) coordinates of each joint.

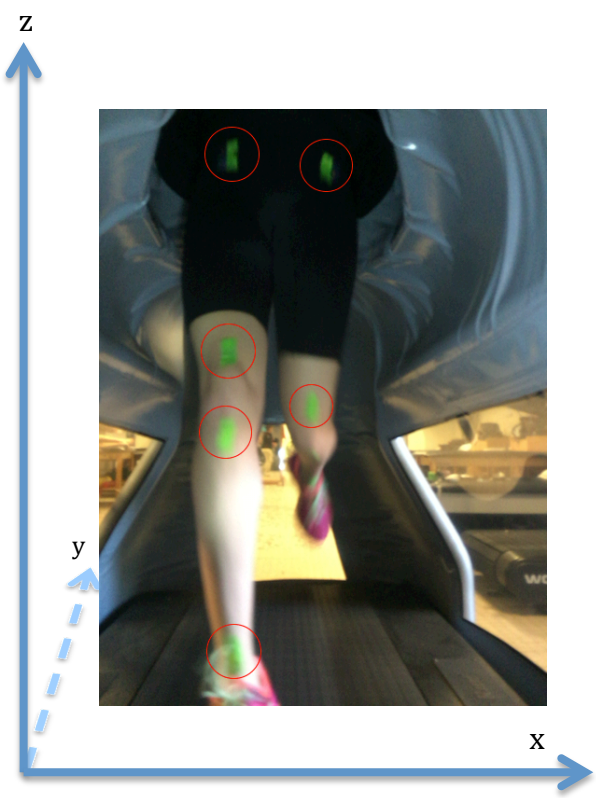


Figure 11: JointFinder's identification of the *(x, z)* coordinates of each joint in the image

3.1.3 Identifying 3D joint coordinates and joint angles

To identify 3D joint coordinates, I first find the 2D joints coordinates for a given color image and then query the corresponding depth image to find the joint depth (y coordinate) at each joint point. StrideRight saves depth images in the conventional 16-bit greyscale image format where each pixel represents the depth in millimeter of that pixel from our AGT capturing system. When querying pixel values in color images, we

used Picture.java (Princeton Computer Science). However, since Picture.java strictly handles RGB pictures, we cannot use it to find the 16-bit greyscale values in our depth images. Instead we modified Picture.java to create DepthPicture.java, which takes in a 16-bit greyscale picture and can return the value at each pixel. In this way, we were able to query our depth images to find 3D joint coordinates.

Finally, we used the angular structure of the human body to compute 3D joint angles. A joint is a location where two bones meet. Therefore, the joint angle is simply the angle between the main bones that make up that angle. For example, the knee joint angle is the angle between the femur and the tibia. Similarly, the hip joint angle is the angle between the pelvis and the femur. Therefore, if we describe each bone (i.e. the tibia, femur and pelvis) as a vector, we can calculate joint angles via the angle between the vectors which describe the joint-defining bones (Figure 12).

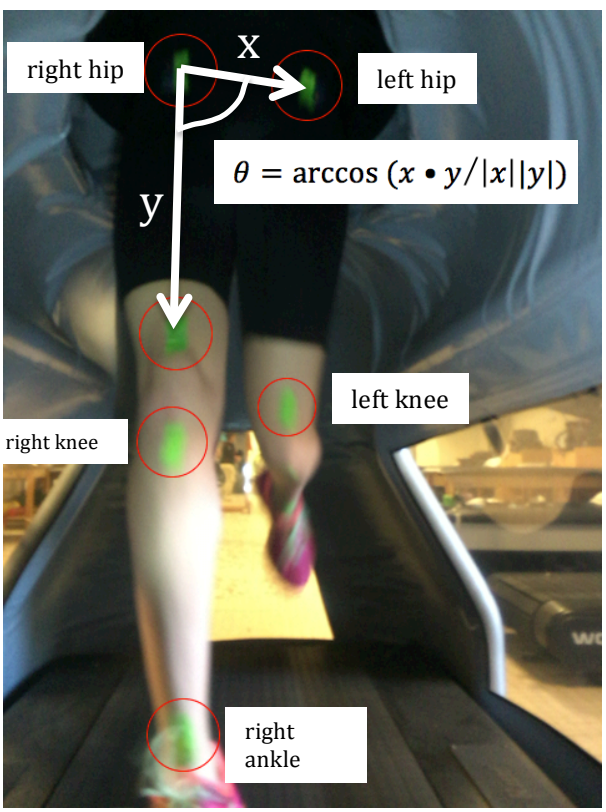


Figure 12: Calculating the angle between a 3D vector which describes the pelvis and a 3D vector which describes the femur yield the hip joint angle.

To give a concrete example, let's say you are trying to calculate the right knee joint angle. The right knee joint angle is the angle between the right shin and the right femur. If know the 3D coordinates of the right ankle and shin are (x_1, y_1, z_1) and (x_2, y_2, z_2) respectively, we can calculate the right shin vector as follows.

$$\overrightarrow{right\ shin} = \begin{bmatrix} x_1 - x_2 \\ y_1 - y_2 \\ z_1 - z_2 \end{bmatrix}$$

Using the same algebra, we can calculate the right femur vector via the right knee and right hip markers. Finally we can calculate the right knee angle using the following formula:

$$right\ knee\ angle = \frac{\overrightarrow{right\ shin} \bullet \overrightarrow{right\ hip}}{|\overrightarrow{right\ shin}||\overrightarrow{right\ hip}|}$$

Given that the knee and ankle joints together define the shin vector, the knee and hip joints together define the femur vector and the two hip joints define the pelvis vector, we were able to calculate hip and knee joints using this process.

In summary, we used JointFinder to calculate 2D joint coordinates. We used DepthPicture to find 3D joint coordinates. We then used vector algebra to find the 3D joint angles. In a given image, if the three points defining a given joint angle were not all present, we calculated no angle for that joint. In this way, we found 3D joint angles for the hips and knees of participants as they ran on the AGT.

3.2 Methods for testing the effect of body weight on stride

We used our system to analyze the effect of body weight percentage (100% and 80%) on a person's stride at three different speeds (easy, medium and hard). This section will detail the methods used to conduct this trial.

3.2.1 Subjects and Procedure

Fourteen women on the Varsity Princeton Cross Country Team participated in this study (age 20 ± 1.1, height $65'' \pm 2.43$, weight $122.85lbs \pm 13.48$). However, we were unable to collect data from 5 of these participants because we used a different colored marker, which JointFinder could not be modified to detect. Therefore we analyzed data from nine participants in our study. We received IRB approval to conduct trials on human subjects and we obtained informed written consent from each participant in accordance with IRB protocol (Appendix A).

Each participant put on a pair of neoprene AGT shorts and was marked with 8 pieces of green tape (Kinesio-Tape, KT Tape Inc.) on their right and left femoral head, distal end of the femur, tibial tuberosity, and talocrural joint (Figure 10). They were given a description of the workout they would run and a tutorial on the AGT (71% of participants had run on the AGT prior to the trial).

Participants ran on the AGT (Anti-Gravity Treadmill Pro200, AlterG Inc.) at three different paces (easy medium and hard) at two body weight percentages (100% and 80%). Participants first pressed "record" on StrideRight. They then zipped into the AGT and allowed the machine to calibrate. They ran at each interval (i.e. easy pace, 100% BW) for 1 minute. They then received 30 seconds of rest and had 10 to 20 seconds to acclimate to the next interval. (For a full description of the workout, see Appendix B) The running paces were entirely self-selected but each pace represents a specific type of training session that these athletes would typically run. "Easy" running is relaxed almost to the point of non-exertion. "Medium" running is a pace you could hold for an hour or two. "Fast" running is around 6k race pace. The Princeton Cross Country Team's week-to-week training incorporates each of these types of runs so each participant has a very good idea of what speed "easy," "medium" and "hard" means for them.

3.2.2 Data Collection and Analysis

We collected video data using our AGT stride capturing system. Since we were not able to start and stop the video feed between intervals of the workout, we collected timestamps at the start and end of each interval and used this information to identify the corresponding color and depth images. We then found joint angles over time for each interval using the joint-angle gathering system detailed in sections 3.1.2 and 3.1.3.

As we will discuss in the Results section, our AGT stride capturing system was only able to capture knee angles when a participant was in the "foot strike" phase of their stride. Therefore, we decided to compare the average knee and hip angles during foot strike. Since each foot strike is theoretically the same throughout a run, we felt this measurement was a good description of a participant's stride during each interval.

We gathered foot strike data using the following assumptions. We assumed that our system was only able to gather knee data when a participant was in the process of a foot strike. Therefore, any image that contained a right knee angle was considered a right foot strike image. Any image that contained a left knee angle was considered a left foot strike image. While this "foot strike" measurement is far more rudimentary than the foot strike data gathered using in shoe pressure sensors or force plates, a visual inspection of many images revealed that it does, in fact, capture a participant in a very similar stride phase. We therefore found these assumptions reasonable.

3.2.3 Statistical Analysis

The goal of our study is to determine whether or not stride changes from 100% BW to 80% BW at medium, easy and hard paces. Therefore, we conduced paired t-tests between 100% BW and 80% BW for a given pace. We computed t-tests in python using SciPy's statistics module. We used the ttest_rel function to calculate a paired t-test between two groups and set significance values at $\alpha = 0.05$. To visualize these results, we graphed each t-test using SciPy's matplotlib library.

4. Results

In this section, we will consider the results of both our AGT stride capturing system and our trial. We will begin with an evaluation of our stride capturing system and then move on to the results of our trial.

4.1 Evaluation of the stride analysis system on LBPPT

As noted earlier, we implemented our stride capturing system in three phases. (1) capture stride on the AGT with StrideRight; (2) identify 2D joint coordinates with JointFinder; (3) calculate 3D joint coordinates and joint angles using the depth image. We will evaluate each of these pieces individually.

4.1.1 Evaluating StrideRight

The purpose of StrideRight is to capture RGB / depth images over time. In order for this system to be successful, we must gather accurate depth images, be able to couple corresponding depth and color images and have a sufficient frame rate to capture many frames per stride. Therefore, to evaluate this system we will examine three properties: (1) the accuracy of the Structure Sensor, (2) the average timestamp difference between corresponding depth and color images and (3) the average frame rate per second.

To test the accuracy of the depth images returned by the Structure Sensor we examined three metrics: If we point the Structure Sensor at a flat wall from a known distance, (1) what is the average depth of the returned images? (2) what is the standard deviation of pixels in a given image? (3) what is the standard deviation of a given pixel over time? Based on our set up on the Anti-Gravity treadmill, we estimated that a runner is at least 419mm (15 inches) and at most 762mm (30 inches) from the Structure Sensor. Therefore we examined three metrics at three distances: 381mm, 508mm and 762mm.

After conducting trials at the three distances, we found that the Structure Sensor returns accurate and consistent depths. We defined picture depth as the average depth of pixels in a given image. As seen in Figure 13, the average picture depth of a set of images collected at a given depth is almost identical. For example, the average picture depth of the images returned from StrideRight when the device was placed 381mm from a wall was 385mm, a mere 4mm off of the real value. What is more, the average standard deviation of pixels in a given image was relatively small ranging from 5.19 at a true depth of 381mm to 10.96 at a true depth of 762mm. Additionally, we found that the average standard deviation of the depth at a given pixel over time ranges from 0.36 to 0.51. This indicates that the depth value at a given pixel does not change very much over time. All of these metrics suggest that Structure Sensor's depth images are within the tolerances needed for our purposes.

True Depth (mm)	Average Picture Depth (mm)	Distance from True Depth (mm)	Average Standard Deviation of Picture	Average Standard Deviation of Pixel
381	385	4	5.19	0.48
508	510	2	4.82	0.51
762	763	1	10.96	0.36

Figure 13: The test results of the Structure Sensor at three different known depths.

Next we will examine the average timestamp difference between corresponding depth and color images. Initially we wrote the depth and color images to memory as they were returned by the Structure Sensor. With this system we achieved an average timestamp difference of 0.037 seconds. Unfortunately this timestamp difference is long enough to allow significant movement between corresponding depth and color images (Figure 14). Since we use corresponding depth image pixels to find the depth at certain color image pixels, this depth to color picture movement was unacceptable for our application.

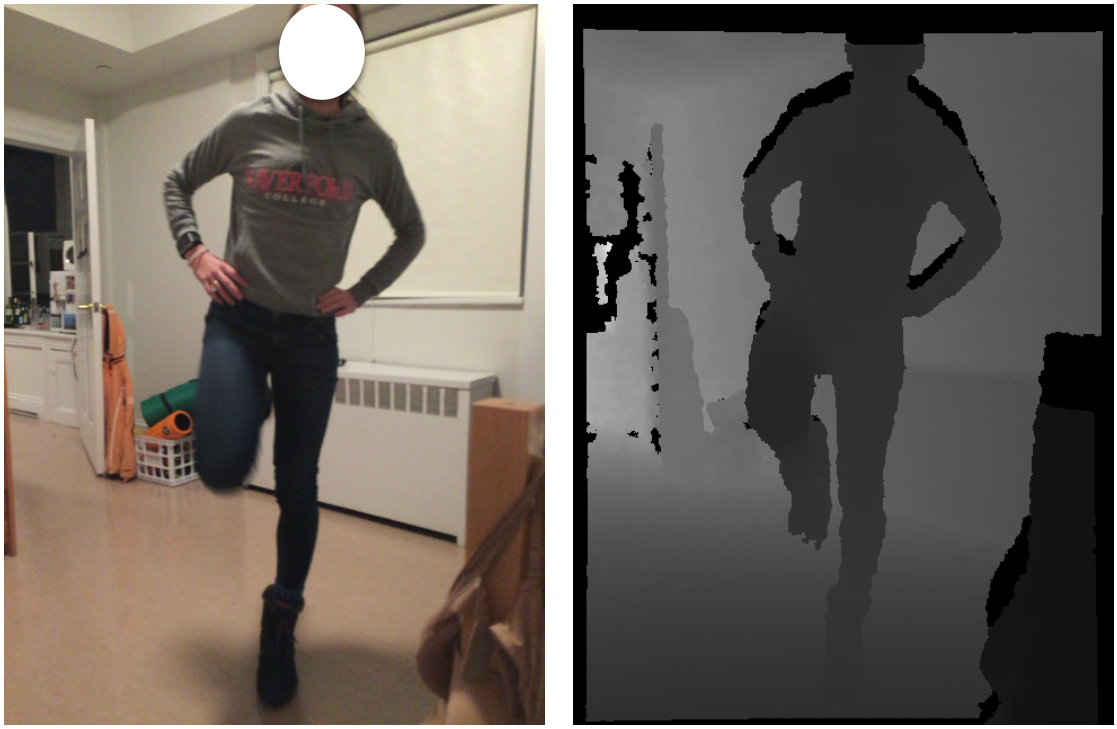


Figure 14: Two corresponding color and depth images captured by the first implementation of StrideRight collected 0.037 seconds apart

To remedy this problem, we decided to implement StrideRight using a sampling system. We save color and depth PNG files to an array for 10 seconds, and then pause the video feed to save the PNG files to memory. With this implementation we achieve an average timestamp difference of 0.019 seconds. From visual inspection, the 0.018 second timestamp improvement is enough to yielded minimal movement between corresponding depth and color images (Figure 15). Because of this, we believe StrideRight is successful in capturing an acceptable timestamp difference between corresponding depth and color images.

Figure 15: Two corresponding color and depth images captured by the second implementation of StrideRight collected 0.017 seconds apart

The final goal of our system is to use the depth / color images to capture a person's stride. In order to do this, we must capture enough frames per second (fps) to yield many pictures of a single stride. Our first implementation yields around 18.4 fps whereas our second implementation yields 21.85 ± 2.77 fps. From visual inspection, it appears that 21.85 ± 2.77fps captures around 9 frames per stride at medium pace (Figure 16). Future releases of StrideRight will achieve higher fps in order to capture more images per stride.

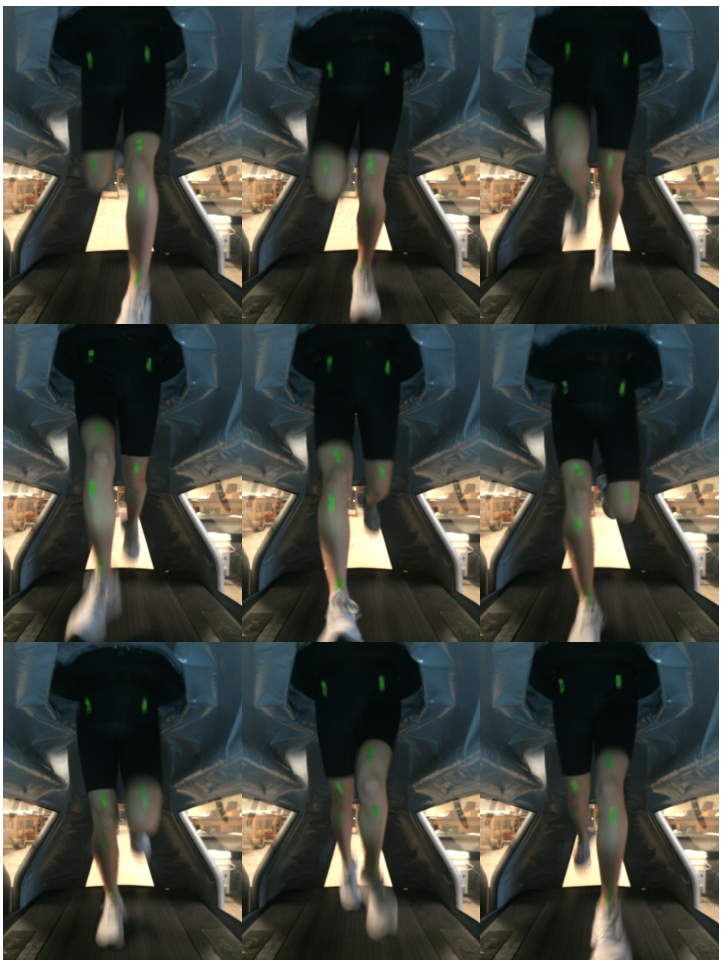


Figure 16: StrideRight captures around 9 frames per stride at medium pace.

In conclusion, the Structure Sensor is accurate within an acceptable margin and StrideRight is able to capture corresponding color and depth images with minimal delay. These two properties suggest that we are able to accurately find the depth of a given pixel in a color image by querying the same pixel in the corresponding depth image. StrideRight's frames per second rate is sufficient to capture 9 frames per stride at an average pace; however, the system would benefit significantly from a greater frames per second capturing rate.

4.1.2 Evaluating JointFinder

Since co-investigator Nicole Marvin implemented JointFinder, she evaluated this section of our setup and talks about it extensively in her paper. I will provide a brief summary of her findings here.

Nicole found that JointFinder is able to successfully and accurately locate green Kinesio-Tape. It almost never falsely marks something as green Kinesio-Tape when it is not. In other words JointFinder finds green Kinesio-Tape with very few false positives. However JointFinder is sometimes unable to mark a piece of green Kinesio-Tape that the human eye might detect. In other words, JointFinder finds green Kinesio-Tape with some false negatives.

In the grand scheme of this project we would much prefer JointFinder to forgo a labeling which is present than label something that is not green Kinesio-Tape. So while JointFinder would ideally have fewer false negatives, we are satisfied that it has very few false positives.

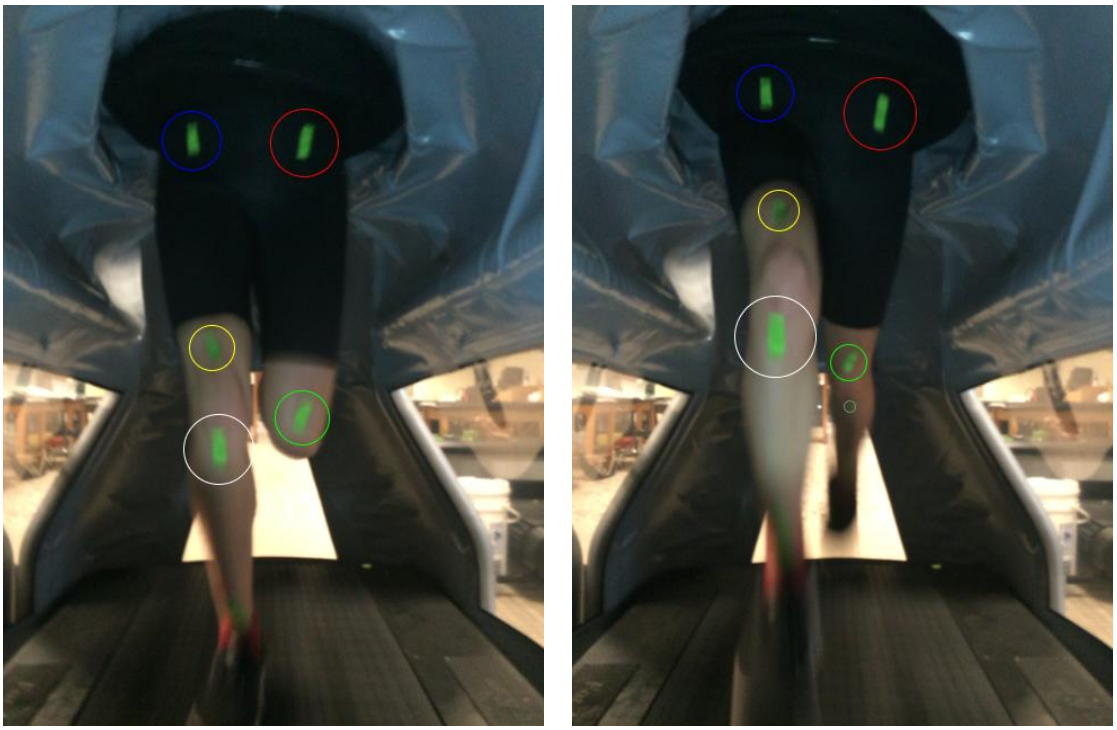
Nicole also found that JointFinder correctly identifies the correct joint (i.e. left hip, right hip etc.). However it mislabels right limbs as left limbs and visa versa when a lower limb crosses the midline between the hips. Because this does not happen very often, Nicole did not correct for this mislabeling.

4.1.3 Evaluating 3D joint angles

There are two questions we would like to address in an evaluation of our ability to calculate 3D joint angles: (1) how often were we able to find the angle of a given joint? (2) do joint angles over time display a cyclical pattern?

Our data suggests that we are able to capture hip joint angles approximately 93.0% of the time while were are only able to capture knee joint angles approximately 24.7% of the time. We

believe that knee joint angles are found so infrequently because the ankles and shins frequently disappear from view (Figure 17a) or are too blurry for JointFinder to detect (Figure 17b).



a) Both the left ankle and left shin are out of view of the camera.

b) The right angle in this image is too blurry for JointFinder to detect.

Figure 17: Participant 4 running the hard pace, 100% BW interval

Our data shows that hip angles display a relatively cyclical pattern, while knee angles do not have enough data points to display any pattern. Figure 18 shows a graph of a test subject's left hip angle over time. It is evident that there is a cyclical pattern occurring; however we do not capture enough data points per stride to get a very clear picture of this cyclical pattern. Most of our test subjects display similar cyclical patterns in their joint-angle over time for right and left hips. These data indicate that we are calculating repeatable hip angle measurements with our AGT stride capturing system. Figure 19 shows a graph of a test subject's left knee angle over time. It is evident that we do not capture enough knee data points to identify a pattern. However, it does appear that the knee data points cluster around several values. For example in Figure 19, there appears to be at one cluster of knee angle data points appear around 170 degrees. Since our

system is only able to capture knee angles at certain stride phases (namely the foot strike phase) these results suggest that our system captures similar values for knee angles at the foot strike. Though not nearly as compelling as our hip data, these data also suggest that we have repeatable knee angle measurements over time.

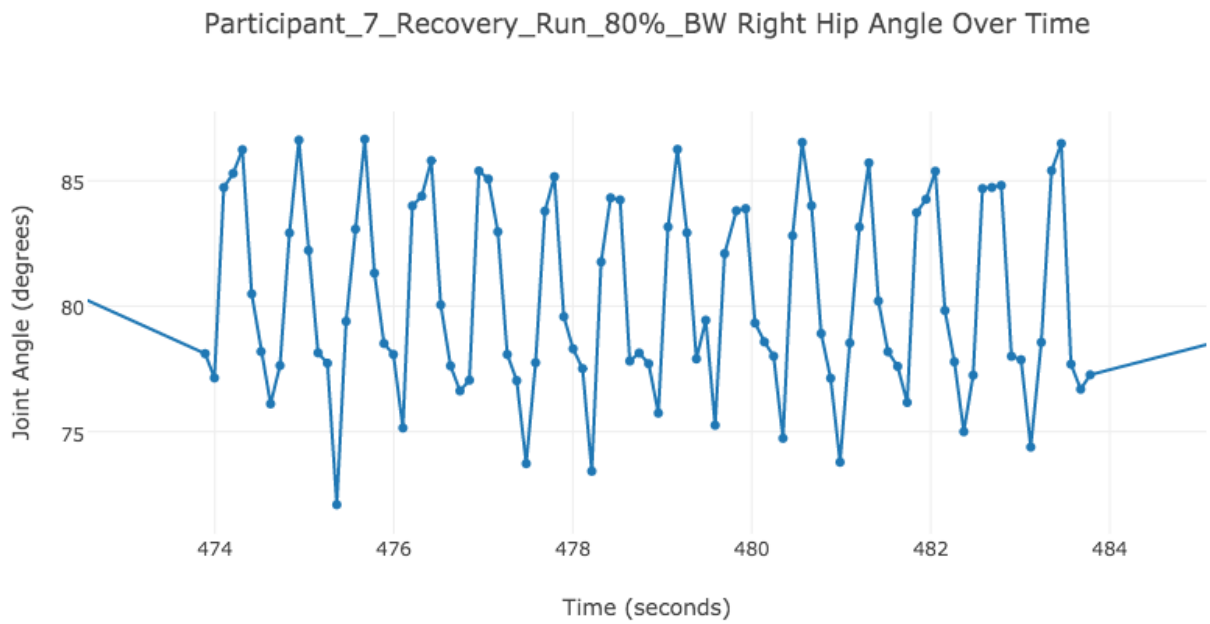


Figure 18: Participant 7's right hip angle over time during the easy run at 80% body weight interval. Connections between points represent angles which were calculated from consecutive images.

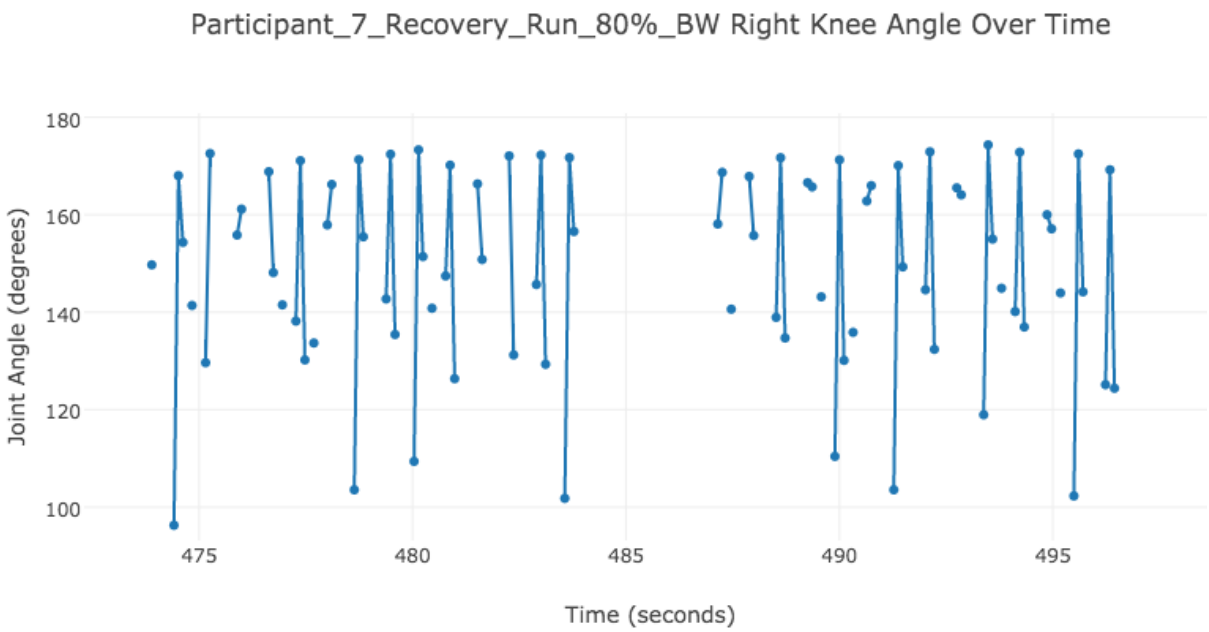


Figure 19: Participant 7's right knee angle over time during the easy run at 80% body weight interval. Connections between points represent angles which were calculated from consecutive images.

4.2 Results from Trial

In order to analyze our data, we first estimated foot strike images from joint angles. We then compared the mean joint angles during different intervals (i.e. left hip angles during medium running at 100% BW and 80% BW). In this section we will first briefly discuss the validity of our foot strike image identification. We then discuss our finding for joint angles at different body weight percentages.

4.2.1 Foot strike image identification

In order to conduct our statistical analysis we wanted a metric to capture participants in a uniform stride phase. In an attempt to achieve this goal, we estimated right and left "foot strike" images defined as images in which the right or left knee angle was defined. Though this seems like a very rudimentary estimate, the images we gathered using this assumption were strikingly similar for a given participant running at a hard pace (Figure 20) and even between participants

running at a hard pace (Figure 21). That being said, our right and left “foot strike” data yielded less accurate results at lower speeds (Figure 22) likely because the AGT stride capturing system was able to detect a wider range of knee positions (Figure 23). While we ultimately decided to use this metric for statistical analysis we would like to acknowledge that it is certainly not the most accurate way of measuring foot strikes and it seems to lose accuracy at slower paces.

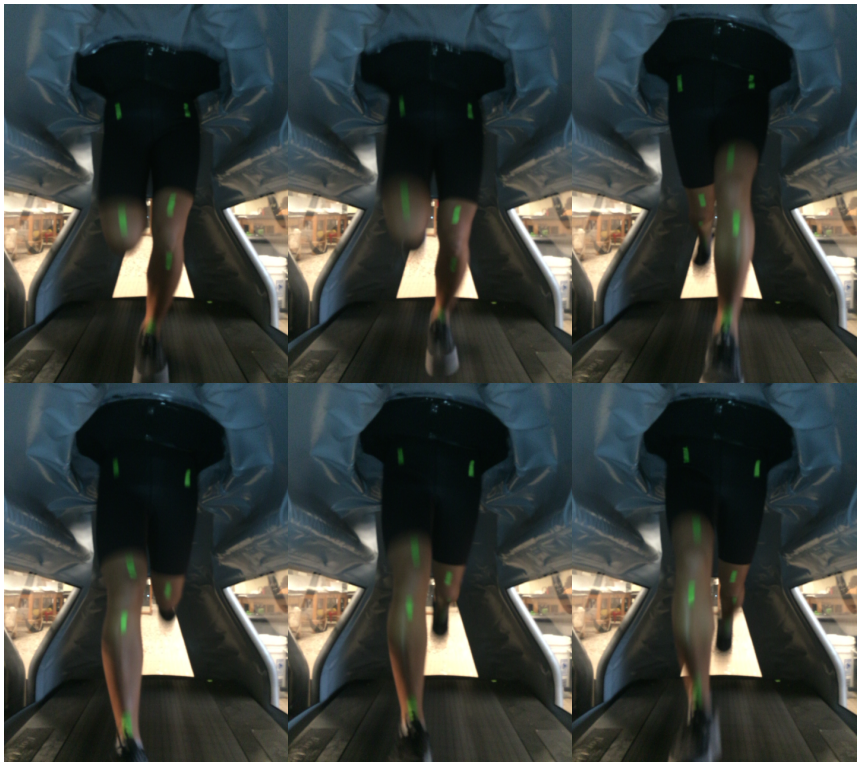


Figure 20: Six of participant 1’s right and left foot strike images during a hard run at 100% BW.

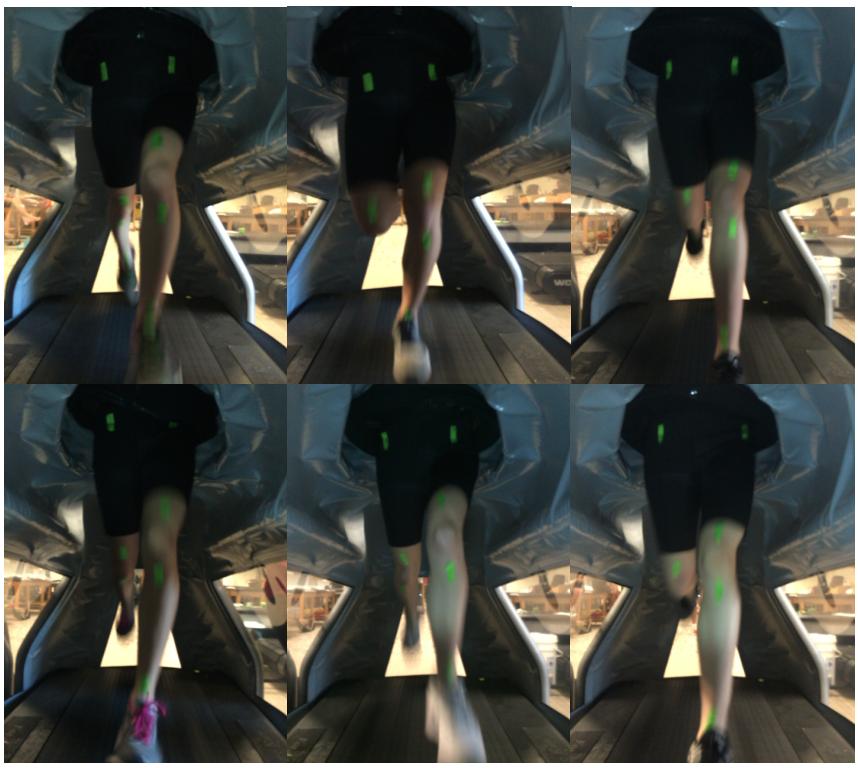


Figure 21: The left foot strikes of 6 different participants during a hard run at 100% BW as defined by our system

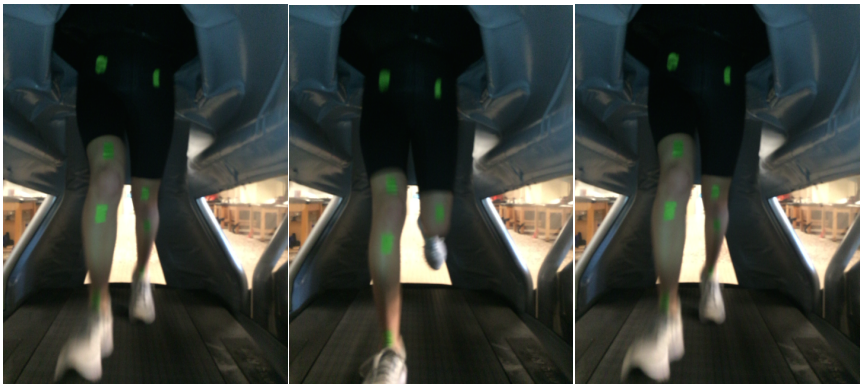


Figure 22: Three right foot strikes of participant 9 during an easy run at 100% BW

4.2.2 Results and Discussion of trial: is there a difference in stride at different body weight percentages?

We found no statistical difference between joint angles during easy running at 100% and 80% BW (Figure 23). However, we did find statistically significant differences between right knee angles from medium paced running at 100% BW compared to medium paced running at

80% BW (Figure 24, $p < 0.05$). Similarly, we found significant differences between right knee angles from hard running at 100% to hard running at 80% BW (Figure 25, $p < 0.05$). These results indicate that decreasing BW alters runners form, particularly at faster speeds.

Looking more closely at Figures 24 and 25, it appears that on average, participants right knee angles increase at 80% BW as opposed to 100% BW. This finding makes sense given the nature of the AGT. When participants are hoisted from 100% BW to 80% BW, the AGT physically lifts them up. In response the participant might have to extend their leg further to make contact with the ground. This finding is also concurrent with the standard AGT practice of increasing incline as you decrease body weight to counteract the over striding that is thought to occur at lower body weights.

Finally, it is interesting and unexpected that specifically the right (and not left) knee angle changes from 80% BW to 100% BW. However, upon further reflection we hypothesize that this leg-specific variation might be explained by right-side dominance. Of our participants, 86% are right-handed. Based on our own personal experience running on the AGT, running at lower body weights does feel very different. It is possible that the dominant leg (in an average participant's case the right leg) compensates more for this different sensation. To test this hypothesis, it might be interesting to conduct a similar study on left-footed individuals to see if this shifts the change from the right to left side.

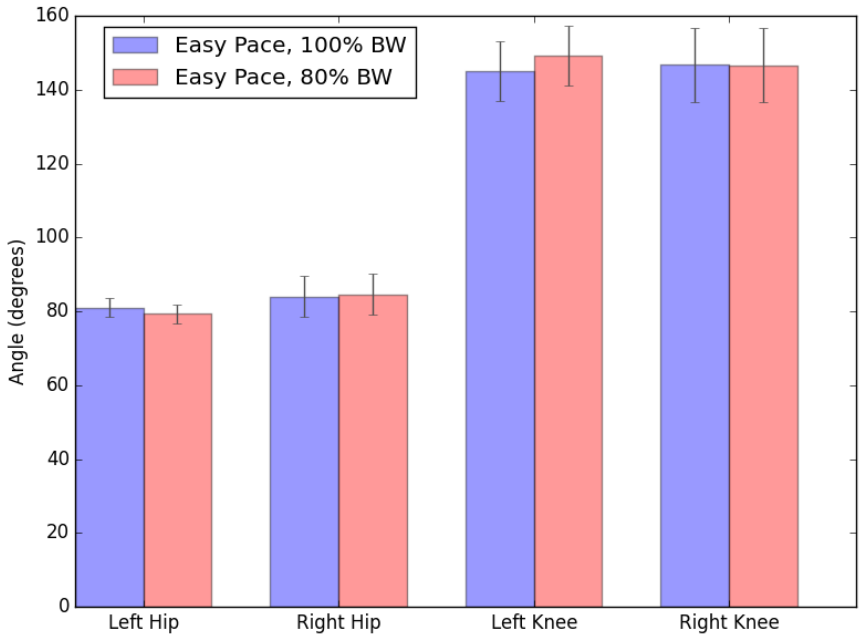


Figure 22: Comparison of mean joint angles during easy running at 100% and 80% body weight (all values are mean ± S.E.). There is no statistically significant difference between any of the joints at 100% and 80% body weights (n = 9).

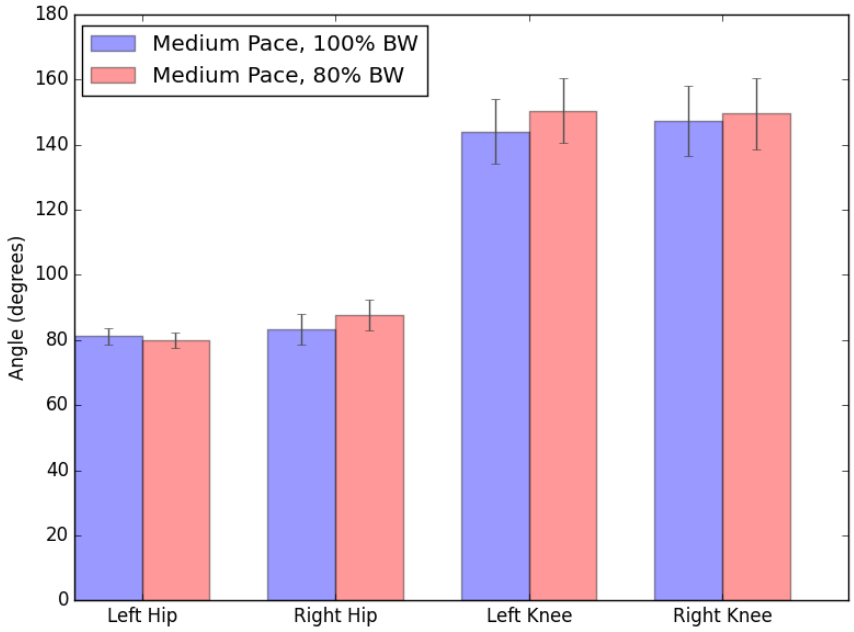


Figure 23: Comparison of mean joint angles during medium running at 100% and 80% body weight (all values are mean ± S.E.). There was a significance difference between average right knee angles at 100% BW and right knee angles at 80% BW ($p < 0.05$, t-test n = 9).

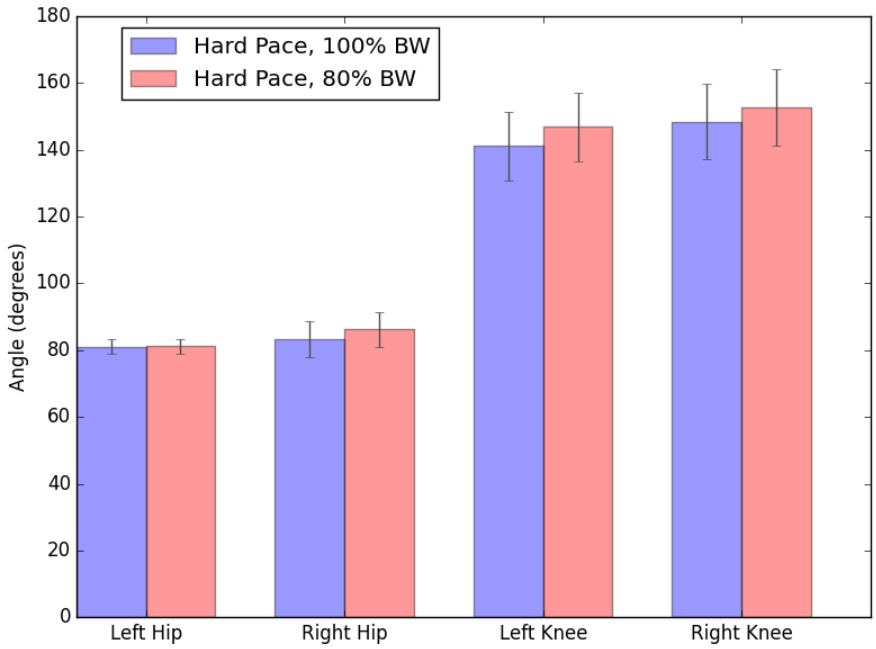


Figure 24: Comparison of mean joint angles during hard running at 100% and 80% body weight (all values are mean ± S.E.). There was a significance difference between average right knee angles at 100% BW and right knee angles at 80% BW ($p < 0.05$, t-test $n = 9$).

5. Conclusion and Future Work

In summary, we have introduced an AGT stride capturing system which calculates knee and hip joint angles over time during a running session. Our system was able to capture hip angles in 93% of images captured. As far as we know, no system has been able to successful capture hip joint angles on the AGT. We attribute our success in this area to our key idea of putting the stride capturing system inside the AGT. It allowed us to gain an unobstructed view of a participant's hip joints during the majority of their run.

That being said, there are a few ways the AGT stride capturing system could be improved. Currently, it does not capture enough frames per second to yield a smooth graph of joint angles over time. The system would benefit significantly from increasing the frame-rate of StrideRight. Additionally, while we were able to capture hip joint angles almost all of the time, we were unable to capture knee angles the majority of the time because the ankle joint was often

out of view of the camera or undetectable. While this ultimately allowed us to detect foot strike images, the system might produce more comprehensive and useful data if it were better at detecting knee joints. However, based on our experiences, we feel that in order to do this, another camera is necessary. From a single, front facing camera, the ankle and tibia markers will inevitably move out of view. A potential next system might use the front-facing camera to capture hip joint and foot strike angles and use an additional camera outside the AGT to gather knee angle data during other portions of the stride.

Using the AGT stride capturing system we found that right knee angles seem to increase significantly from 100% BW to 80% BW at medium and hard paces. These results are concurrent with the popular practice of increasing AGT incline in order to counteract the over striding which might occur due to decreased BW percentages. Additionally the fact that we saw no differences in stride at BW percentages at easy pace suggests that the percent BW might have more of an effect on stride at faster paces. Future studies examining a wider variety of BW percentages at faster speeds might help illuminate these preliminary findings.

6. Acknowledgements

I would like to thank Jodi Schneider and the Princeton Athletic Training Room staff for letting us use the AGT for our trials. I would also like to thank all of my teammates who participated in our study (which was neither a quick nor effortless task). Finally, I would like to thank our advisor, Thomas Funkhouser, for helping us on this project throughout the entire semester.

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Appendix A: Informed Consent Form

ADULT CONSENT FORM
PRINCETON

TITLE OF RESEARCH: Stride Analysis on the Alter-G Lower Body Positive Pressure Treadmill

PRINCIPAL INVESTIGATOR: Kaitlin Hanss

PRINCIPAL INVESTIGATOR'S DEPARTMENT: Computer Science

You are being invited to take part in a research study. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. Please take the time to read the following information carefully. Please ask the researcher if there is anything that is not clear or if you need more information.

Purpose of the research:
This research is investigating how the angles formed by a runner's hip, knee, and ankle joints while running on a lower body positive pressure treadmill (Alter G) at reduced body weight compare to those angles formed while running at full body weight. The research uses a Structure Sensor with an iPhone mounted inside an Alter G to record video footage of Alter G runners and capture depth information on the knee, hip, and ankle joints. Participants must be healthy athletes who compete in track and field at the varsity level and who normally participate in cardiovascular exercise. Participants' knee, hip, and ankle joints will be marked with reflective tape before a workout on the Alter G. Participants will first be recorded for a brief trial period at 0% incline and 100% body weight in order to establish a baseline. Participants will then be free to complete a workout of their own design and adjust speed, incline, and percent body weight settings as desired. Data gathered will be used to perform stride analysis.

Study Procedures:
The study uses non-invasive cameras and non-invasive skin sensors to capture video and depth data while athletes complete a workout that is a normal part of their training routine.

Your total expected time commitment for this study is: one hour

Benefit and Risk:
The risks of participating in this study involve running on the Alter-G treadmill. Exertion on the Alter-G treadmill is similar to that of running on land. If you feel that running on a treadmill or land poses high risk for you, please inform one of the principal investigators, Kaitlin Hanss and Nicole Marvin.

Confidentiality:

All records from this study will be kept confidential. Your responses will be kept private, and we will not include any information that will make it possible to identify you in any report we might publish. Research records will be stored securely in a locked cabinet and/or on password-protected computers. The research team will be the only party that will have access to your data. Video recordings will be erased after the completion of the research papers in January 2016.

Compensation:
Participants will receive no compensation for participation in this study.

Who to contact with questions:

1. PRINCIPAL INVESTIGATOR:
   Kaitlin Hanss
   khanss@princeton.edu
   (646)-660-1544

2. If you have questions regarding your rights as a research subject, or if problems arise which you do not feel you can discuss with the Investigator, please contact the Institutional Review Board at:

   Office of Research Integrity and Assurance
   Human Research Protection Program
   Assistant Director
   Phone: (609) 258-0865
   Email: irb@princeton.edu

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3. I understand the information that was presented and that:

A. My participation is voluntary, and I may withdraw my consent and discontinue participation in the project at any time. My refusal to participate will not result in any penalty.

B. I do not waive any legal rights or release Princeton University, its agents, or you from liability for negligence.

4. I hereby give my consent to be the subject of your research.

_____
Subject's Signature

_____
Date

_____
Person Obtaining Consent's Signature

_____
Date

Audio/Video Recordings:

With your permission, we would like to video-record your workout and download relevant data of speed, incline, percent body weight, and elapsed time from the Alter G. Please sign below if you agree to be videotaped and to have your workout recorded.

I hereby give my consent for audio/video recording:

_____

Appendix B: Full workout description

Duration	Speed	Percent Body Weight
0:30	Walk	100
1:00	Easy	100
0:30	Walk	100
1:00	Medium	100
0:30	Walk	100
1:00	Hard	100
0:30	Walk	80
1:00	Easy	80
0:30	Walk	80
1:00	Medium	80
0:30	Walk	80
1:00	Hard	80