ME-18 Final Project Report

Professor Huang

Instrument/Experiments

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Project Introduction

This experiment will focus around the game of cornhole. The fundamental question that will be answered is, what are the optimal parameters for the perfect cornhole throw? This question spiked interest from us considering that we all enjoy taking part in a good game of cornhole. As we get to know our way around the game of cornhole, we want to investigate what factors make for the optimal bean bag toss. We will be taking into account multiple parameters, including launch velocity of the bean bag, launch angle, and the type of throw used (underhand or overhand).

From the searches that we conducted at the start of our project, there does not seem to be many studies showing the optimal way to throw a bean bag to score consistently in cornhole. However, people who play competitively seem to have come to an agreement that an underhand throw is the most optimal throw to win. This is not backed by any data, besides their own experience. We hope to gather data and either prove them right or find out that they might actually be wrong, and an overhand approach might be better to score consistently.

Methods

Due to the COVID-19 pandemic that occurred at the time of data gathering, we were forced to switch to less traditional data gathering systems than we had previously planned for. We could no longer use equipment found at Tufts University, so we transitioned from using an Arduino set up, so using video processing software. Because we could no longer work together physically, a member of our groups was assigned the task of taking all the videos with his own cornhole setup that he had at home. Those videos were then shared with the other two members of the groups who took over most of the analyzing and gathering of data from the videos.

The videos analyzed showed a person throwing the bean bag. With the camera focused on the arm motion and at the time of release. Each throw was documented and measured to see how far away it was from the intended target. Due to the nature of how sensitive the video processing software we were using was, the videos had to be recorded in front of a darker background in order to have a good color contrast between the bean bag and the background. This helps the videos software follow the bean bag as it moves in the swing. Allowing us to gather more accurate results.

We used Kinovea, a sports video analysis software, to measure the angle of launch and initial velocity of each beanbag. While this software is very useful for finding the angle, we had a hard time getting an accurate launch velocity. As a result, we found that the velocity measured in Kinovea was higher than the actual velocity. When trying to determine the error that is present in our experiment, we investigated the effect that drag would have on a bean bag. The graph below comes from an online calculator, that shows the difference between a throw in a vacuum and a throw with drag. For reference, the mass of the bean bags was about .45 kg. Though the properties of the object thrown are different, they are close enough to demonstrate that objects with a weight greater than or equal to 300 g and the size of the object is slightly different, the trajectory of an object in a vacuum is almost identical to an object with drag.

Results

After recording all of the data points, we used MATLAB to explore the relationships between variables, the performance of the thrower over time, and the velocity discrepancies due to our video analysis software, Kinovea.

When we were analyzing videos in Kinovea, we noticed that the velocities we were recording were higher than they should have been. By plugging in the initial conditions to a trajectory calculator, we found that the recorded initial velocities would give us a distance of over 10 m farther than the actual landing locations. To see why this was happening, we investigated the effect of drag and saw that it would have a negligible effect. We determined that the reference geometry in our video could be incorrect, but after adjusting the reference geometry found the velocity to still be too high. Though we couldn't figure out exactly what caused the error, we were able to demonstrate the effect of velocity on the error and how we would need to scale the projected velocity to match the actual landing position. Hypothetically, if we collected enough data about the scaling, we could use the scaling to correct the projected velocity if we wanted to predict a landing location given initial height, velocity, and angle.

We also explored the discrepancies between the measured distance from each throw and the modeled distance based on the determined throw parameters from Kinovea. A paired two sample t-test at 95% confidence was able to decide that the means were not are not the same (t-stat = -24.068, $p < 1.2698e-21$). Correlation plots were produced for actual vs predicted performance data, as well as plots for performance over time. The plots for x-distance (Fig.4) over time showed a weak linear trend, as well as that of the y-distance (Fig.5) and radial distances (Fig.6) from the target. The plot for predicted range of throw vs actual range (Fig. 7) showed no correlation (R-squared = 0.027). Neither were able to produce useful patterns to the benefit of our original aim, but they all but confirmed the existence of error in our experimental data collection.

Due to unforeseen circumstances, the original scope of the project had to be reimagined and reduced. Motion-capture data from video is a rather novel concept compared to our originally intended method of data collection in sensors (accelerometer, gyroscope, etc.) that would have been used in a controlled environment instead. This would have allowed for an efficient and accurate collection of relevant parameters of projectile motion, with fewer unpredictable errors.

Theoretical errors in our models were explored, namely unaccounted drag forces from the wind. Following research, we concluded that drag forces are not present at the given throw speed, mass, and surface area of the beanbag. The primary instrumental error stemmed from applying incorrect reference geometry in Kinovea outside of the plane of the throw. Even after correction, error was still present, though quantified to a degree (Fig.3)

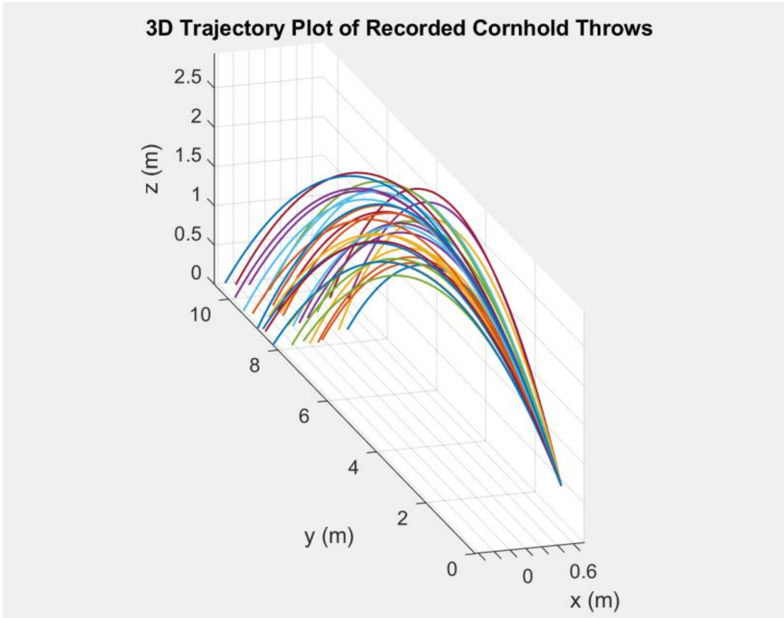

Figure 1: This figure shows the 3D plot of the approximate trajectories of all 32 throws that we recorded. Because the recorded velocities were inaccurate, we found the actual initial velocity by using the landing location and angle to solve for the initial velocity. Once we had the initial velocity, we could plot the trajectories of the bean bags. We only recorded the path of the bean bags in one direction, but we can assume that the top view trajectories are linear given that gravity is not affecting the motion in that plane.

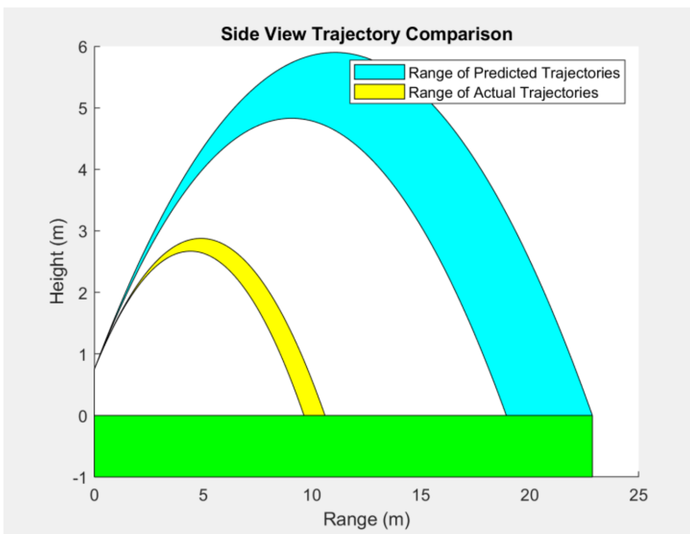

Figure 2: The graph above is a side view of the trajectory above. However, this graph displays the difference between the trajectories we predicted using kinovea and the actual trajectories. Obviously, the prediction is very far from the truth. Because the initial velocity has a squared relationship with the landing position, small errors in the velocities are magnified.

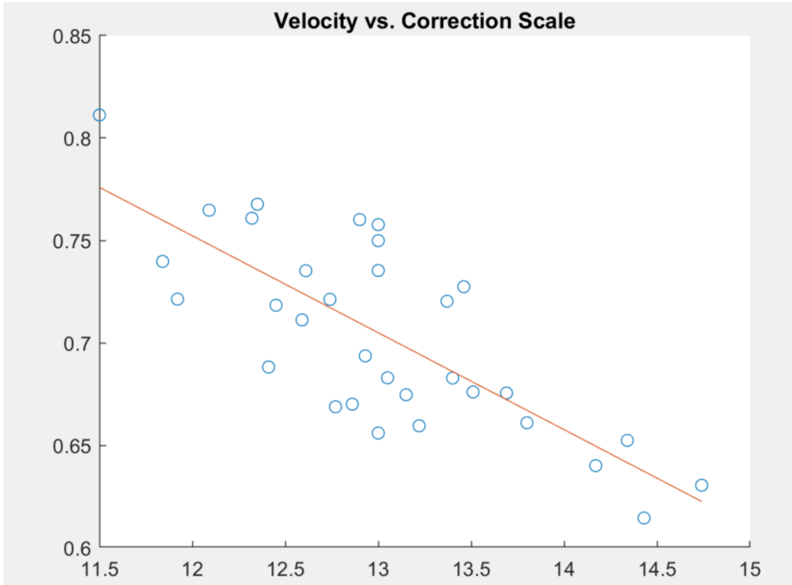

Figure 3: This figure shows the relationship between velocity from kinovea, on the x axis, and the scaling factor needed to correct the initial velocity. As the graph demonstrates, we observed that when the velocity is increased, the proportion between the actual and kinovea velocity becomes smaller. This means that the error increases proportionally to the velocity.

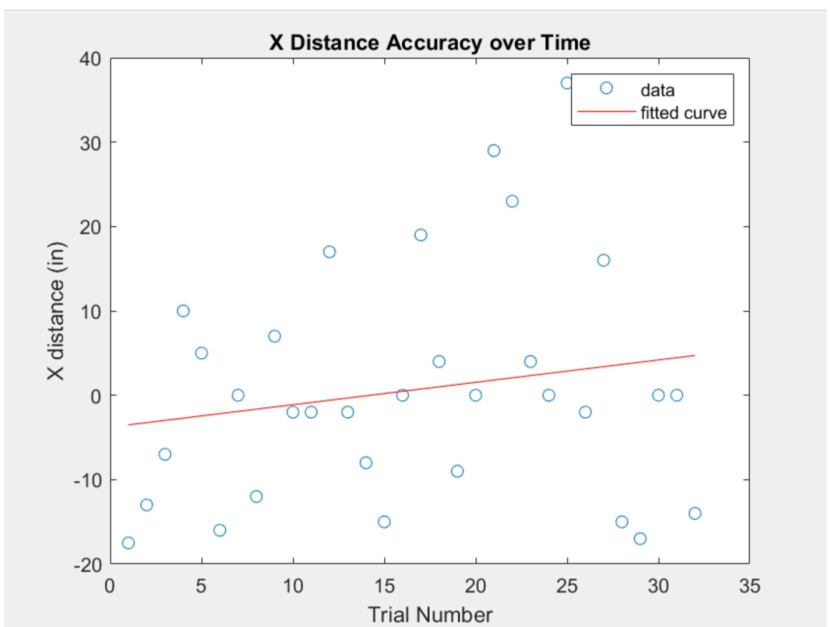

Figure 4: The accuracy in the X direction shows that there was not much improvement in the throws over time. The later trails seem just as inaccurate as the first couple of trials. However, after adding a fitted line, we can see that there might be some actual correlation. The thrower began throwing a little to the left and as time went on they started throwing to the right. With more data points we could potentially see a better trend of improvement.

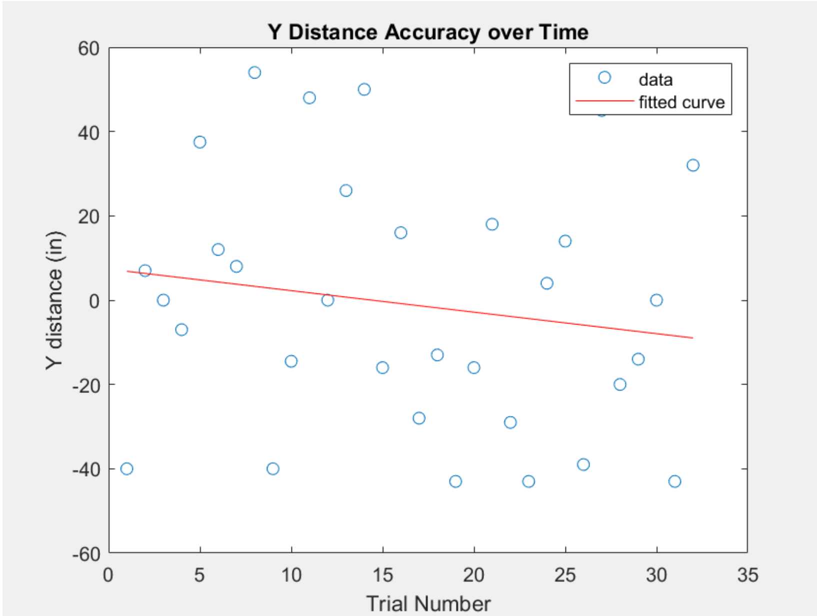

Figure 5: The accuracy in the Y direction shows that there was not much improvement in the throws over time, just like in the X direction. However, with the trend line added, we see that the thrower started by overshooting the target, then adjusted, but began undershooting it. Just as in the X direction, with more data points we might be able to see a better correlation.

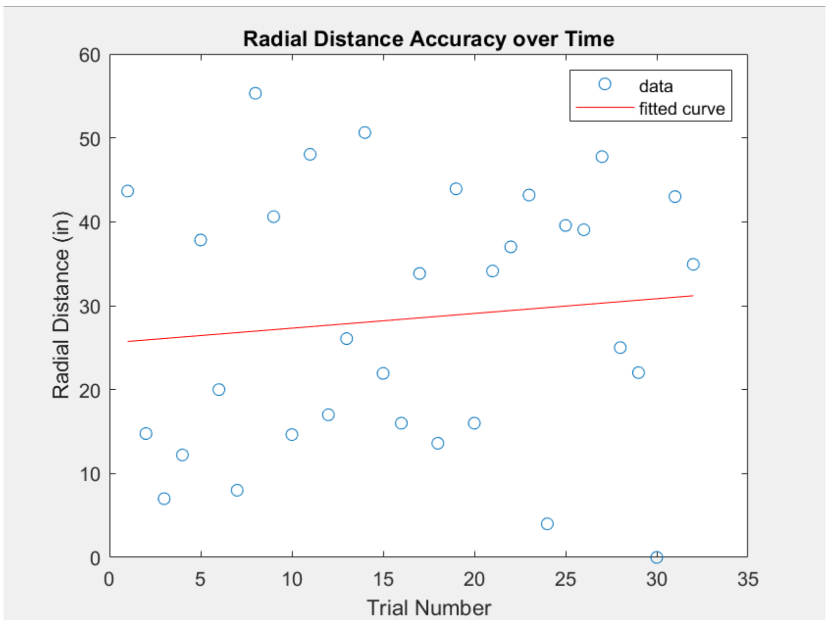

Figure 6: The accuracy in the radial distance as the trials increase shows that there is almost no correlation between the radial distance and the trials. The fitted line is almost horizontal with a small tilt, indicating that from the data points that we gathered, the thrower is actually getting worse with each trial. Due to these points, we can say that there was no improvement over time.

Two Sample Student's T-test for Difference of Means between Modeled Toss vs Measures

Degrees of freedom	p-value	t-statistic	Confidence Interval (95%)
31	1.2698e-21	-24.0683	[-9.1154, -7.6912]

Table 1: The miniscule p-value and large t-statistic indicate a strong rejection of the null hypothesis that there is no difference in the means of the predicted throw distance from kinematics vs actual throw distance. At a 95% confidence interval, the difference of means is described by the confidence interval. We accept the alternate hypothesis that the means are significantly different.

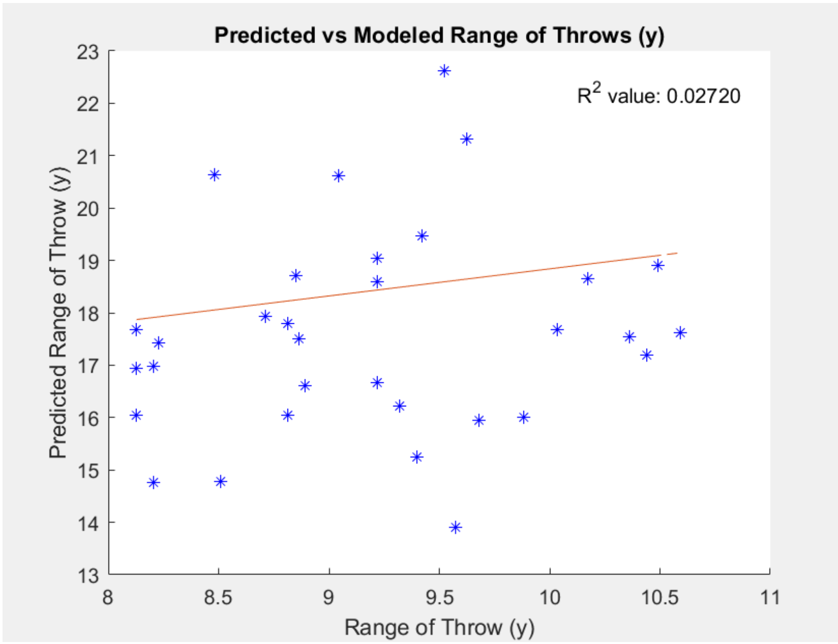

Figure 7: The above scatter plot shows the total distance travelled along the y-axis of the cornhole board for actual trials vs our modeled trials.The R-square value of 0.0272 is exceptionally low and suggests a really weak correlation exists between our model and actual trials. In the y-direction, the cornhole bean bag is subject to several factors which may explain the low correlation value. As a group, we discussed the effects of wind drag, data collection methods, and variability of the thrower as possible sources for this discrepancy.

Impact and Conclusion

Understanding the optimal throw of a corn hole toss could impact the way the game is played up to a professional level. Although in this experiment we were not able to gather the results that we had anticipated, this experiment itself could serve as a way for other competitive sports to be viewed differently. If we could have reduced some of the errors that we encountered, have better equipment, along with having many more points of data, we could have been able to actual data proving that some cornhole throws are better than others. This type of experiment could potentially be applied in other ways as well. For example, this type of experiment could be used in finding what is the better posture for a football to be thrown with better accuracy.

Though I am sure many scientists have analyzed the aerodynamics of balls in sports, people have not really analyzed how to win at cornhole because it is a backyard game and there is no money or fame in cornhole, so there has never been a practical need to use technology to improve the way cornhole is played. However, we think that our project is a fun demonstration of analyzing projectile motion. If our project had been at school, we would have had a more efficient data collection procedure that would allow us to take much more data and identify trends in a large dataset. We could have even used the data collection to give live feedback to throwers about how they could improve their throw.

We found that using video software may not yield the best data for measuring the speed of the throw, but if we had an accurate measurement of velocity for the beanbags, we could use kinematics and predict the landing spot given only the throwing video. It would be a very interesting demonstration of data analysis and video processing if we could write a program to predict the probability of success based on the parameters from the video.

In doing this project, we developed a testing procedure that can be adapted for many other sports   This type of experiment would be able to be used in multiple other sports: baseball, basketball, tennis, etc. Using better equipment and processing programs, sport teams could find what is the optimal swing, toss, throw, and hit for their players. It could revolutionize how well the player scores, and this would in turn potentially affect the earning of many people considering that sports leagues are a multi-million-dollar industry. If this type of analysis were to grow to this bigger scale, the probability that there would be engineering breakthroughs to make these tests more accurate would be high. Taking into consideration that sports teams would want to have an advantage, they would hire the best engineers and scientists to develop new ways to analyze this type of data.

Overall, this project was an exploratory investigation of cornhole, and we could apply the data we collected to find trends, assist cornhole throwers, and maybe even develop a model to use for a cornhole throwing robot. We learned a lot about how easily data can be recorded using only your phone and software. Though we would have liked to have more data to work with, we were still able to conclude that cornhole is a sport with a lot of variability. For people that aren’t professionals, it is very difficult to be consistent in your throwing.