Aerodynamic Characteristics in the Development of a Supervisory Program with Deterministic Algorithms for a Predictive Trajectory Model

Vanessa Ross, Leiana Omine, Brandon Nguyen, Taylor Monroe, Gabriela Lucas

Department of Physics ◆ Edmonds College ◆ WA USA

Abstract

In the United States alone, there are approximately 350,000 people without at least one arm and 50,000 new amputations each year. The presence of 'smart' prosthetics is far behind the advances of other technologies. The simple action of throwing a ball has a multitude of aerodynamic components that need to be considered for a 'smart' prosthetic to successfully throw a ball to a precise target. We developed a predictive trajectory model using analytical predictions based on both theoretical calculations and physical tests. The development of a computational supervisory model with deterministic algorithms aids as a predictive trajectory training program for 'smart' prosthetics. We conducted three different experiments to gather the data needed for our program; ball drop, projectile motion, and wind tunnel. Using the data from these experiments we wrote deterministic algorithms to model the same behavior. We anticipate our software program to predict successful trajectory outcomes by assessing relevant external conditions and adjusting decisions based on the conditions. At this time, our software is not intended to have the actual capability of pairing with any external device. We are only focused on creating the software. However, this software program does have real-world potential that, in future experiments, could be demonstrated with the use of a robotic arm. After that, it is highly possible that our algorithms could be used towards the creation of standard issue 'smart' prosthetics.

Introduction

To produce 'smart' prosthetics one need to produce a training program that teaches the artificial intelligence (AI) technology in the arm correct outcomes. Something as simple as throwing a ball has many factors that need to be considered for an AI arm to throw a ball to a precise target. Through physical tests we gathered data that allowed us to create a computational supervisory model that has the potential to train AI in prosthetics to model the same results. We did three tests; ball drop, wind tunnel, and projectile motion. The data collected in the wind tunnel gave us the drag characteristics of the ball being used. Our ball drop and projectile motion tests provided us with real data to model our software of off. Using our data we compiled a basic computational supervisory model with deterministic algorithms that can aid as a training program for 'smart' prosthetics. By pairing our analysis of real-life test data with a computation model we expect to achieve near perfect simulations.

Methodology

Materials:

- Phantom High-Speed Camera VEO-E 310L
- Phantom Camera Control (PCC) Software
- Physlet Tracker Program Version 5.1.3
- PocketLab Voyager
- Tecquipment AF1300d Subsonic Wind Tunnel 305mm
- Netbeans IDE 8.2

Testing:

To track projectile motion of a ball we used the Phantom High-Speed Camera VEO-E 310L to capture an object's motion. The Physlet Tracker program will calculate the velocity, acceleration, max height, and distance traveled.

In our ball drop experiments we began by measuring the 19.3meter drop from the second floor down to the first floor. We then placed the PocketLab Voyager into a miniature foam basketball and connected it to The Pocket-Lab IOS application. We dropped the ball from the second floor of the building five times. At the end of our experiment we reviewed the data from The PocketLab and extracted the data from between the applicable time stamps.

In our wind tunnel experiment we used a 50 mm diameter sphere with a smooth surface of mass 550g. The software used in conjunction with the wind tunnel, Vdas, reports the measured lift, drag, lift coefficient, drag coefficient, air pressure and more.

We are using the idea of a hypothetical 'smart' prosthetic arm with sensors to act as the source of inputs to the supervisory program. Based on these inputs the program will output the necessary data to ensure the projectile reaches its target. The data from our three tests helped us determine the necessary fields needed in our program and to create model scenarios to test the efficacy our our program. The average speed at which a ball is thrown is 20 m/s. We chose to make velocity a constant value to make the program more accurate. Therefore the only output is the Angle of Attack (AOA) at which the arm needs to throw the ball. For our examples, we had to create a base idea for how the person would be situated or the data would be inaccurate due to many positions a person could be in. We decided to model a person standing upright, with the AOA being measured from the shoulder to the prosthetic arm. We are assuming that the target is larger than the ball being thrown and will have a range of AOA at which would produce an accurate outcome. The range is important because the ball needs to clear any obstructions and yet remain within reach of the target.

Results

Figure 1 : (Left) Our supervisory program's GUI before reading inputs. (Right) Our supervisory program's GUI with inputs displaying the necessary AOA and the outcome in the upper left corner. Image credit : Brogan, Caroline. "Self-Learning Bionic Hand Could Spark 'New Generation' of Prosthetic Limbs." *Tech Xplore - Technology and Engineering News*, Tech Xplore, 3 July 2018, techxplore.com/news/2018-07-self-learning-bionic-prosthetic-limbs.html.

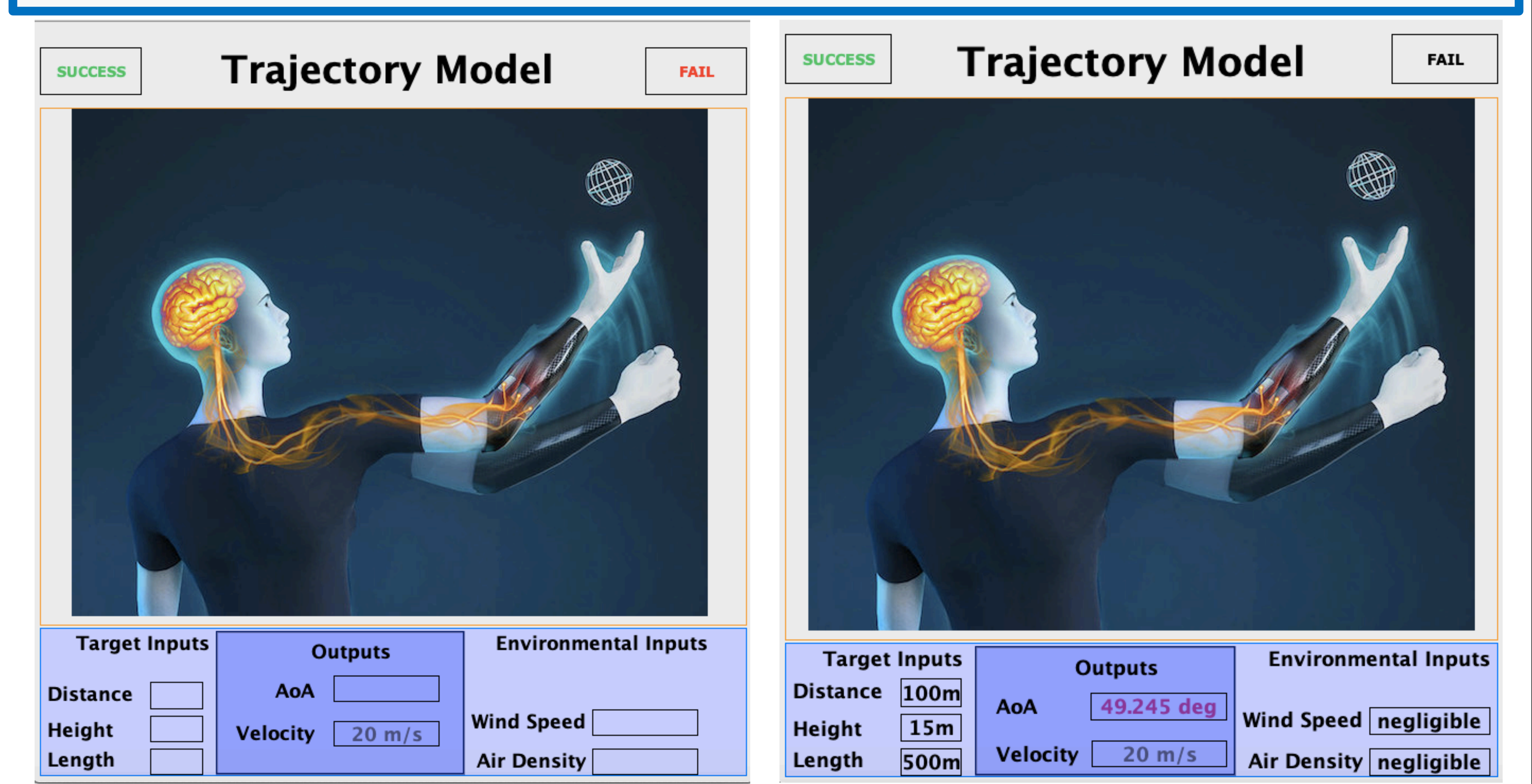

Figure 2 : Shows the relationship between drag and wind speed (m/s) found in our wind tunnel test

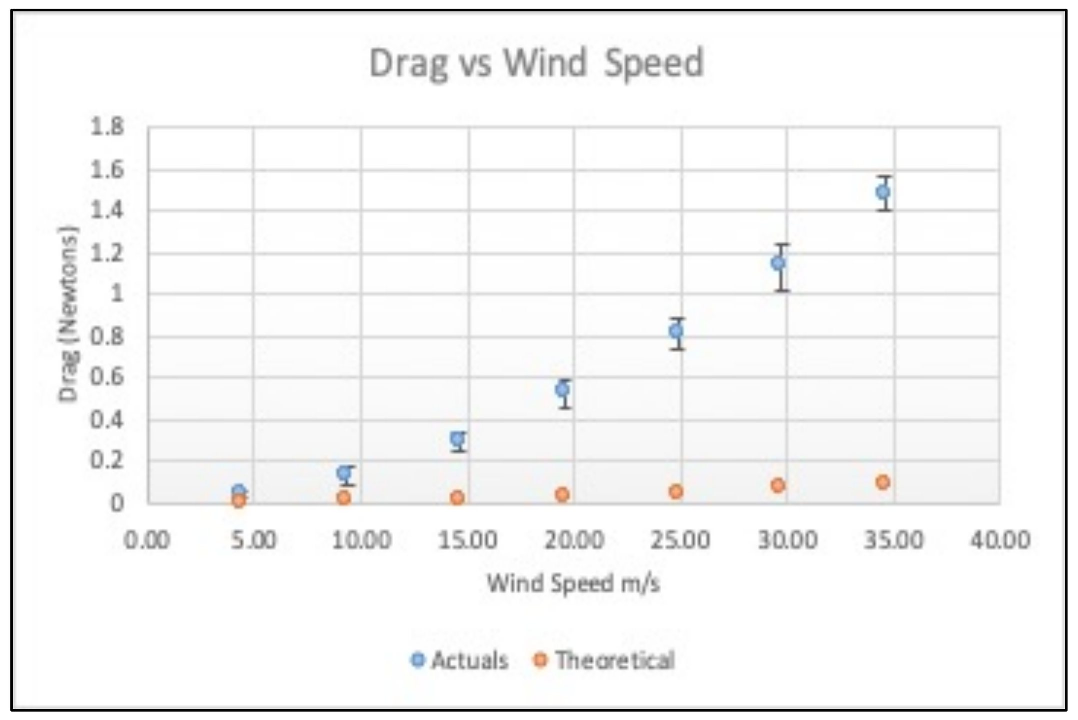

Figure 3 : Flowchart that models the deterministic algorithms decision making process.

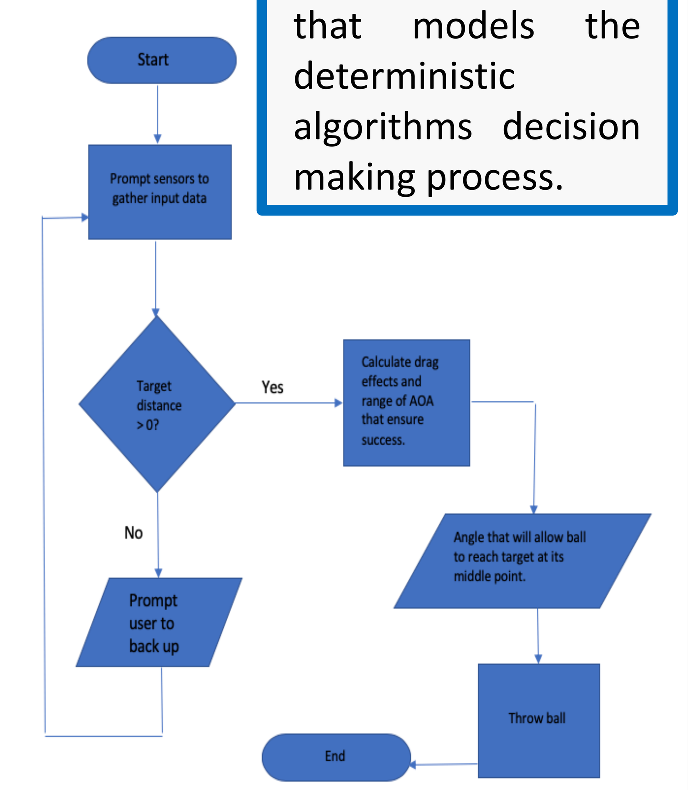

Figure 4 : Data gathered from our projectile motion tests using the Physlet Tracker Program Version 5.1.3

	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9
Total Time for ball to hit ground (s)	0.2830	0.3000	0.3930	0.2740	0.2670	0.2780	0.2830	0.2780	0.2890
Total Horizontal distance traveled (m)	0.6110	0.5580	0.6470	0.6600	0.6300	0.6540	0.6420	0.6400	0.6450
Total Vertical distance traveled (m)	-0.0560	-0.0220	-0.0499	-0.0380	-0.0280	-0.0380	-0.0465	-0.0370	-0.1320
Average Acceleration (m/s^2)	7.4429	5.7612	8.1855	2.7941	-5.5827	2.5857	7.1548	7.9393	2.2311
Average Velocity (m/s)	2.1527	1.8552	1.6428	2.3998	2.3632	2.3517	2.2684	2.3040	2.2284
Average Theoretical Velocity (m/s)	0.772311	0.39	-0.2793896	1.06615912	1.05125056	0.99031799	0.881851237	0.93995827	0.81573391

Analysis

Crucial to our development of the unsupervised learning program was to determine whether wind resistance effects would have any appreciable affect on our scoring algorithms, and hence we conducted wind tunnel tests over typical ball-toss speed domains of 1.00m/s to 35.00ms. Without considering wind effects, typical time-of-flight for a simple ball drop over 19.3m would theoretically be given by

$$t = \sqrt{\frac{2h}{g}} = 1.9s$$

Our wind tunnel tests showed, however, a strong quadratic velocity dependence, $F = kv^2$, which would be modeled by

$$v(t) = \frac{1}{\beta}\tanh(\beta g t)$$

$$x(t) = H - \frac{1}{\beta^2 g}\ln|\cosh(\beta g t)|$$

$$t_o = \sqrt{\frac{m}{kg}}\cosh^{-1}(e^{\frac{k}{m}H}) = 2.1s$$

Conclusion

Our wind tunnel results demonstrated that even over the relatively low velocity domains focused on in the context of unsupervised AI for a ball-toss, that neglecting wind resistance would easily lead to at least an 10% error in unsupervised scoring of time-of-flight decisions and therefore that including wind resistance will be necessary for any kind of realistic unsupervised training algorithms.

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Contact

Vanessa Ross,
V.ROSS9804@edmail.edcc.edu
Leiana Omine,
L.OMINE6769@edmail.edcc.edu
Brandon Nguyen,
B.NGUYEN3132@edmail.edcc.edu
Taylor Monroe
T.MONROE7244@edmail.edcc.edu
Gabriela Lucas
G.LUCAS7989@edmail.edcc.edu