Cost-Effective Baseball Analytical Tool Developed Using Computer Vision and Python

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Abstract

The engineering goal of the project was to develop an affordable baseball analytical tool that can convey statistics on different baseball metrics of a person recorded baseball swing. The goal was to be within 2 percent error of a commercial product called Hittrax measurements. The research targeted towards providing a cheaper resource that produces the same results to help in the development of high school and collegiate athletes. 3 different metrics were tested to compare the created product vs the Hittrax, which include Exit Velocity, Launch Angle, and Projected Distance. The created product measurements were compared to Hittrax measurements, by seeing the percent difference the created product measurements were from the Hittrax. 2 of the 3 metrics met the goal as it was observed that the percentage difference in terms of the means of the data collected was at around 1%. This was verified through a Two One-Sided T Test (TOST), which tests for equivalency. The TOST test showed significance for the Exit Velocity and Launch angle measurements, and Projected Distance was shown as non-significant meaning its percentage error was greater than 2%, accepting the null hypothesis. This is due to lack of accounting for drag and outside factors such as lighting that have a large impact on the computer's ability to track and follow a baseball. Further experimentation includes implementing a live analysis tool, using a Neural Network Approach, and adjusting equations and methods to achieve greater precision in accuracy.

Keywords: Hittrax, TOST, Exit Velocity, Launch Angle, Project Distance, Baseball

Introduction

The game of Baseball has shifted increasingly towards a data driven game. First started with the “Moneyball” era in which the Oakland Athletics used the power of using analytics as a way to assess players accurately to the value (Triady, 2015). Players were assessed on numerous baseball statistics that assess a player’s performance, and skill level. These same metrics which include Exit Velocity, Launch Angle, Bat Speed, are all metrics that are measured to assess a ball player's hitting ability (Kim et al., 2019). For players that are currently in a developmental phase, an age group of high schoolers to college players, these metrics are constant things that are looked at to assess their progress and performance as a player (Cole, n. d). Currently, way players can measure these metrics are through available products sold on the market which include Hittrax, Rapsodo, and Trackman. These tools here are motion-tracking devices that can provide metrics by seeing a person hit a ball and capture the ball's movement. All these products cost upwards to 20,000 dollars which aren’t affordable to the common person and rather targeted to colleges, larger teams, and professional organizations (Suzuki, 2021).

The goal of this engineering project is to design and construct a cost-effective and functional baseball data capture system that incorporates motion capture, computer vision, and live display of results. The goal is to create a system that provides the main functionalities that are present in current products such as Hittrax but provides a much more affordable product so that people of all backgrounds can use it. These main functionalities include the main baseball metrics such as distance hit, exit velocity, etc., as well as providing a similar accuracy to the products on the market with a target range of being within 2 percent of the accuracy of products on the market (Cities, n, d).

The cost-effective baseball data capture system, Hittrax, and a radar gun (Control) each represent the Independent Variable levels. The dependent variables are the variety of metrics that each of these methods produces, as they determine how effective these solutions are. The differences between the metrics for each of the IV levels will be used for comparison. The test will consist of one hundred recorded swings in different fashions for all IV levels. These different fashions include hitting off a tee meaning the ball is in place, a ball being pitched at the user, or a ball coming from a machine. Considering that the Hittrax is a professionally marketed product, the accuracy it has is within the 99 percentiles. A statistical test that will be implemented into this project is a Chi square test, as the expected values are preset values that come from the most accurate measuring system(high-speed camera analysis), compared to the observed which is the data collected from the IV Levels. Using the tests, if the results produced by the cost-effective baseball data capture system are within 2% of what the control and Hittrax produce, the project will be considered successful.

There have been recent developments in video analysis of sports and computer vision techniques that have achieved significant improvements in previous Computer vision technologies in different spirits (Kim, J.-S et al, 2017). Sports video analysis is utilized for various applications of high-level analysis in sports such as detection and classification of players, tracking player or ball in sports and predicting the trajectories of player or ball, and classifying various events in sports (Naik et al., 2022). Naik Banoth and his colleagues are professors in the Department of Electronics and Computer Engineering at the National Institute of Technology, in India, that discusses some of the artificial intelligence applications in sports, graphics based workstations and other embedded systems used in this field of sports. The research also discusses probable challenges, and future trends of visual recognition in sports. The main way that scientists have used computer vision is through highlighting key events in the video it records. From there it sectors these key events into a frame-by-frame analysis that is used for these multiple different purposes in sports (Nalik et al, 2022). It was also found that RNN and Convolutional Neural Networks (CNN), which are two forms of Machine Learning models, are the most efficient types of AI to use for visual analysis. Nalik's research applies to this topic as a form of a CNN will be used to create the AI system that will track the movement of a baseball and provide the metrics to the player. Konig Johansson and his colleagues presented the abilities of the Trackman system and its effects on players through its analysis of 275 semi-pro and professional players. The overall purpose of the experiment was to see if the trackman system can show non-trivial or general patterns in the data to see what differentiates between a skilled and poor golfer. Their data showed that the Trackman was able to accurately predict whether a golfer was considered handicapped versus skilled to an accuracy of 95 percent (Johansson et al., 2015). Trackman has a very similar system to other baseball statistical products like Rapsodo, and Hittrax in that they all use an AI visualization algorithm to track movements of different objects. The same data collected here in the sport of golf is applicable in baseball as Johannson's research shows that the concept that these software's use, are accurate in providing data and metrics to users for development. Some of the ideas used to construct the AI for Trackman can be used to help develop my version of the software but will be adjusted to meet the needs of the goal.

Methodology

The goal of this engineering project is to design a cost-effective and functional baseball data capture system that incorporates motion capture, computer vision (CV), and real-time displayed results. The system is divided into 3 separate parts which include camera position and mounting, capturing of live feed of swings, and applying the live feed to code written to provide the analytics of the swing. First, it had to be decided what metrics were going to be found, which is later narrowed down to Launch Angle, Exit Velocity, and projected distance a ball traveled. These three metrics are chosen, as they are the three most looked at metrics for a hitter as well as keeping simplicity in this project as they are possible to be implemented with the materials accessible. These metrics are going to be compared between the metrics provided by the system and metrics provided by a commercial product like Hittrax.

After narrowing down what was being tested, the mounting positions for the Camera must be decided. In this system a two-camera system is implemented. One placed in which its field of view is directly parallel to where the batter is facing. This position was chosen, as it allows for the greatest range of view of the balls flight path, and certain aspects of the balls flight path can be captured easily from this position to perform frame by frame analysis. Another camera being placed directly behind the batter to find the peak height the ball traveled. The camera that is being used in experimentation will be phone cameras as they are easily accessible for people to use.

After the camera position is decided, the code can start to be constructed. A motion detection algorithm is constructed with 3 separate functions to calculate the 3 different metrics. To calculate Exit velocity, two frames are captured from the balls flight path 1 second apart. These frames are then split into a coordinate grid in which the distances between each square in the grid are on scale with distances in the real world. Then, the computer algorithm will detect the positions of the ball on the grid in each of those frames. This will lead to two separate coordinates, which can then be applied onto the distance formula, to get a measurement of distance traveled which will be measured in feet. It is measured in feet because it would be the most practical considering the distance that is being measured in the brief time frame. Since this is the ball's flight period over one second, the time value can be divided into the distance to get a value in ft/s for the ball's velocity right when it comes off the tee as it was hit. Then the value is converted into miles per hour, as that is the standard measurement used in baseball statistics. To calculate launch angle, the back camera view has the same computer algorithm that figures out the peak distance before the movement of the ball is shifted due to a net or wall. This peak height is then used as a reference point to construct a triangle with the location of the where ball is when on the tee. From there we convert our exit velocity as well as peak height into SI units meaning meters and meters per second and plug these values along with 9.8m/s for gravity into an equation which will result in providing the launch angle of that certain hit. Projected distance is calculated through a series of projectile motion equations whose results are combined to get a final value on distance traveled.

To perform this experimentation, 100 swings will be taken by a person in a batting cage that has access to a Hittrax or similar system. The comparison between the two systems will happen simultaneously along with the control being a radar gun, so that a machine does not need to be built to reproduce the same swing. Each of the phones is connected to a computer that receives the footage and then runs the program on. A person will take a swing off the tee, and then the cameras will capture the ball's movement, send it to the computer, and then the computer performs its algorithm on the video and returns out the metrics for that swing. The values that Hittrax and the radar gun return are also recorded so that comparisons can be made. The radar gun is also being used to measure Exit Velocity speeds manually to the highest of accuracies so that hand calculations can be done to compare it to the results provided by the machines.

The building is considered a success if the accuracy of the metrics provided by the system built is within 2 percent of the metrics returned by Hittrax, as it is a commercially sold product with very high accuracy. 2 percent is chosen because that represents the percent error that the Hittrax systems have, meaning that the system built should produce similar results to Hittrax to be considered a success.

Data and Results

Table 2: *Data Summary*

	Hittrax Velocity	Created Tool Velocity	HIttrax Distance	Created Tool Distance	Hittrax Launch Angle	Created Tool Launch Angle (2)
N	150	150	150	150	150	150
Missing	0	0	0	0	0	0
Mean	65.5	65.5	138	139	11.7	11.8
Median	66.4	65.7	127	128	14.0	13.7
Standard deviation	9.34	9.56	64.6	64.9	6.79	6.80
Minimum	39.6	39.6	22	21.8	-12	−12.0
Maximum	83.1	85.3	268	271	24	24.2

The information in Table 2 summarizes the descriptive statistics for the metrics measured on both the Hittrax and created product. For velocity, distance, and launch angle, the difference between the means is one showing large similarities between both of the testing devices. The Standard deviations are irrelevant to the data as large standard deviation values here represent the wide range of measurements that were being recorded to test the different products. For example, for distance the Standard deviation is at around 64 which means there is very large disparity in the dataset, but really the data represents the large ranges of distances that were measured and tested by both the Hittrax and created product. This is the same pattern represented by the Maximum and Minimum values as it represents the domain of which the values were measured showing a wide range of testing for comparison.

Fig 1: *Hittrax Exit velocity vs Created Tool Exit Velocity*

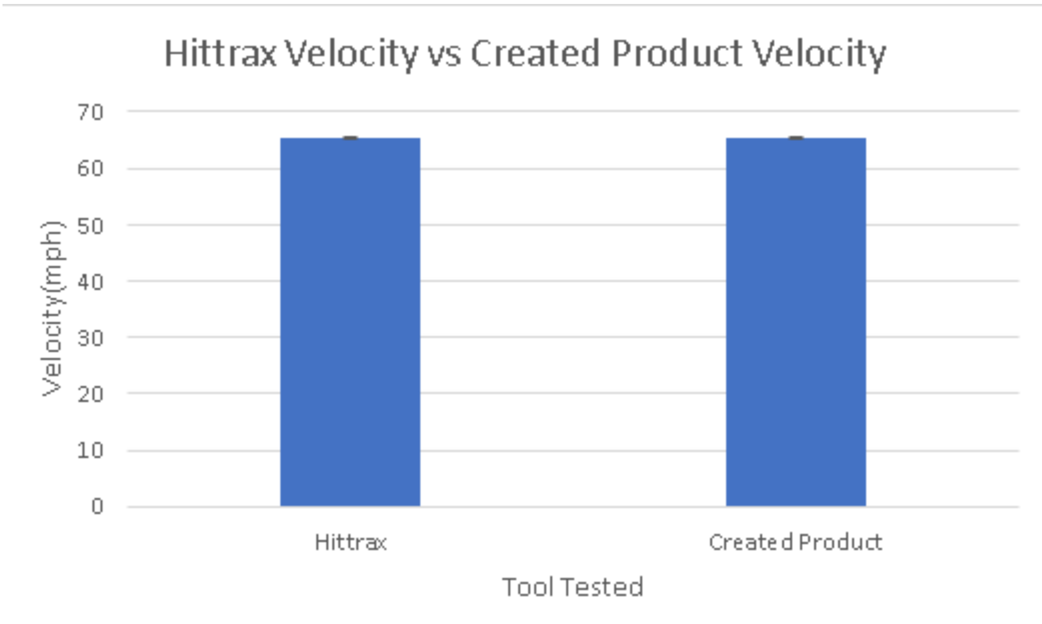

Fig. 1 displays the comparison in means between the measurements of velocity from the Hittrax compared to the measurements in velocity of the created product. The engineering goal was to achieve within 2 percent error of the measurements provided by the Hittrax in the similar situation or circumstance. There is more nuance in determining equivalency, as a t-test can only show significant difference or fail to show significant difference. As such, two different t-tests will need to be conducted. First, to check for equivalency. The graph shows means that look almost identical with only a .1 difference separating the two values. The error bars present are based on the standard deviation of the dataset for the velocity metric.

The null hypothesis is that the percent error of the created product would be anything greater than 2% error in reporting its measurements, where the percent error is a value chosen based on the percent error that the Hittrax produces. This makes the alternative hypothesis become when the percent error is 2% or less in terms of the measurements produced by the created product compared to the Hittrax. A suitable alpha value for this scenario would be 0.05, as neither type 1 nor type 2 error are critically important. As this is a “negativist” null hypothesis, two one-sided t-tests must be performed (TOST/equivalence testing).

Table 3: *TOST Results for Hittrax Exit Velocity vs Created Tool’s Exit velocity*

TOST Results

			t	df	p
Hittrax	Created Tool	t-test	0.193	149	0.847
		TOST Lower	4.547	149	< .001
		TOST Upper	−4.161	149	< .001

As shown in Table 3, a two sample equivalence test (TOST) was conducted to compare the Exit Velocity measurements from the Hittrax compared to the engineered product, to check for equivalency. The TOST test showed significance between the two as both of the p values were less than the alpha value which is set at 0.05, which therefore rejects the null hypothesis.

Fig 2: *Hittrax Launch Angle vs Created Tool Launch Angle*

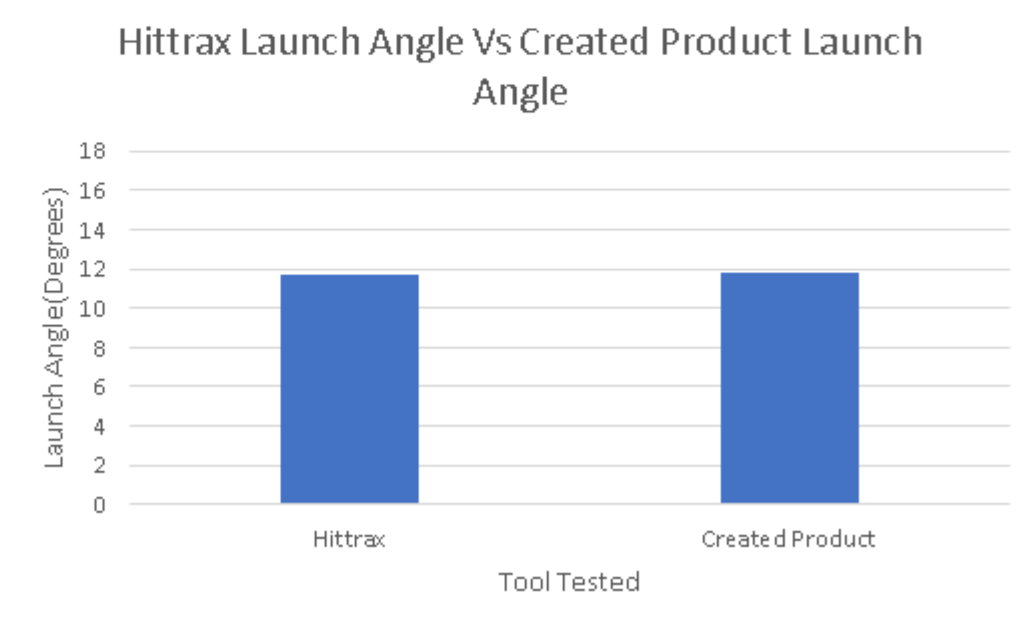

Fig. 2 displays the comparison of means of the Launch Angle values produced by the Hittrax compared to the Launch Angle values produced by the Created Product. The engineering goal was the same here as a 2% error was trying to be achieved for the Launch Angle metric. The means again, appear very identical to each other with error bars that represent the standard deviation of that specific part of the dataset. This hints at some sort of equivalency but can only be proved through a TOST test that conducts equivalence testing.

The null hypothesis is that the percent error would be greater than 5% for the Launch Angle values, and thereby making the alternative hypothesis whenever the percent error is 2% or less for the Launch Angle values. A suitable alpha value for this scenario would be 0.05, as neither type 1 nor type 2 error are critically important. As this is a "negativist" null hypothesis, a TOST test must be performed, to check for equivalency.

Table 4: *TOST Results for Hittrax Launch Angle vs Created Tool's Launch Angle*

TOST Results

			t	df	p
Hittrax Launch Angle	Created Tool Launch Angle (2)	t-test	2.21	149	0.028
		TOST Lower	45.19	149	< .001
		TOST Upper	−40.76	149	< .001

As shown by Table 4, the TOST test was significant, as the p-value for both the TOST Lower and Upper range were less than the alpha value of a = 0.05. The lower was 45.19 and the Upper was -40.76. This means that for Launch Angle, equivalence can be accepted between the two, and the null hypothesis is able to be rejected.

Fig 3: *Hittrax Projected Distance vs Created Tool's Projected Distance*

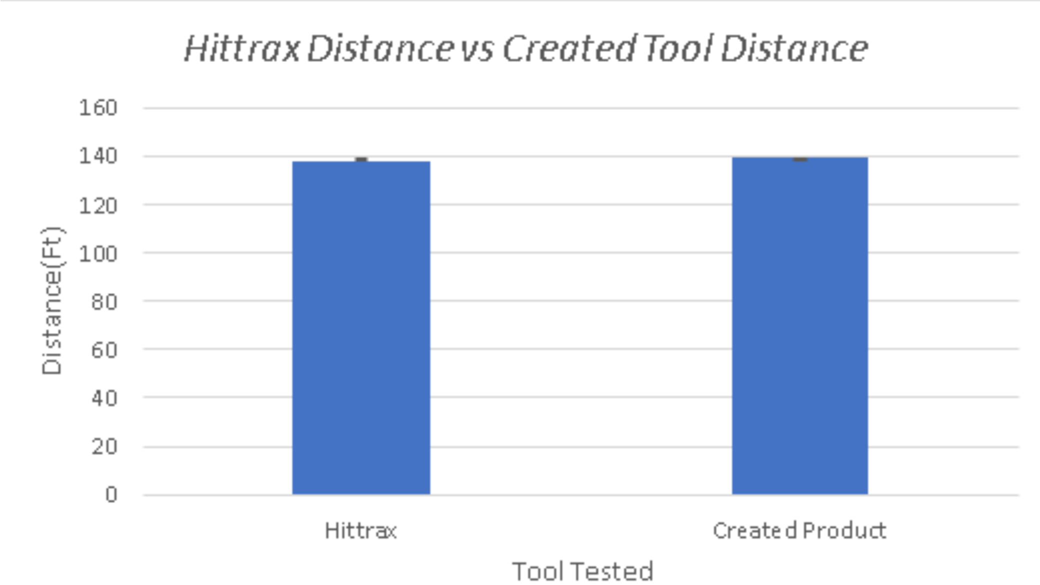

Fig. 3 displays the comparison of means of the Distance values produced by the Hittrax compared to the Launch Angle values produced by the Created Product. The engineering goal was the same here as a 2% error was trying to be achieved for the Distance metric. The mean's again, appear very identical to each other with error bars that represent the standard deviation of that specific part of the dataset. This hints at some sort of equivalency but can only be proved through a TOST test that conducts equivalence testing.

The null hypothesis is that the percent error would be greater than 5% for the Distance values, and thereby making the alternative hypothesis whenever the percent error is 2% or less for the Distance values. A suitable alpha value for this scenario would be 0.05, as neither type 1 nor type 2 error are critically important. As this is a "negativist" null hypothesis, a TOST test must be performed, to check for equivalency.

Table 5: *TOST Results for Hittrax Projected Distance vs Created Tool's Projected Distance*

TOST Results

			t	df	p
HIttrax Distance	Created Tool Distance	t-test	3.29	149	0.001
		TOST Lower	4.73	149	< .001
		TOST Upper	1.86	149	0.967

As shown in Table 7, a TOST test was conducted to compare the Projected Distance measurements from the Hittrax and created product, to check for equivalency. Because the p value of the upper range of the TOST test is greater than the alpha value a=0.05, equivalence can't be accepted, failing to reject the null hypothesis.

Conclusion

The engineering goal of this project is to develop an inexpensive baseball analysis that can achieve an error within 2% of commercialized products in three baseball metrics, Exit Velocity, Projected Distance, and Launch Angle. 2% was chosen as that is the percent error that Hittrax, the commercial product used in experimentation, has for its measurements (*Hittrax)*. For the Launch Angle measurement, the experimental control is a standard handheld radar gun whose means are compared to both the Hittrax and created product. For the other two metrics, the percentage error of the created product was compared to the Hittrax to evaluate its effectiveness as well as t-tests to identify statistical significance.

Shown by the data, the created product was shown to have some level of effectiveness, but not to the level of the commercial product. When the measurements of the means were compared between the Hittrax and created product, the mean exit velocity produced by the created product was 2% less than the mean exit velocity of the Hittrax. This shows that there was a significant percent error produced, meaning that there are outside factors affecting the accuracy of the created product. The distance metric was the only one that reported an insignificance in its statistical test. Because the p value of the upper range of the TOST test is greater than the alpha value a=0.05, equivalence can't be accepted, failing to reject the null hypothesis. This insignificance can lead to the conclusion that there are other factors that can affect the accuracy of the created product, as the null hypothesis can't be rejected meaning that factors of chance must be accounted for (Suzuki et al., 2021).

The engineering goal of having a 2 percent error compared to Hittrax, the commercial product in this project, was partially met. In the 3 metrics measured, only two of the metrics Launch Angle and Exit Velocity was within 2 percent meaning only 66.6% of the metrics satisfied the goal.

The reasoning behind the goal not being made is due to 2 reasons. First, the way the baseball was tracked was very inefficient, resulting in major inaccuracies. Using an RGB filter system to decipher a baseball in a field of multiple objects and different lighting conditions is very ineffective, as a computer can decipher any object as a baseball specific to those RGB ranges. Instead, a pre-trained model would have been a better choice as it would lead to much greater accuracies, since they are pre-trained to distinguish between baseballs and other objects. The 2nd reason is since natural factors such as inconsistent lighting as well as wind cause a lot of variation. With inconsistent lighting, an RGB filtering system nearly becomes ineffective as the reflection of light often results in large white circular blurs that fit within the RGB color ranges. This often causes the computer to focus on these regions when it comes across them in the specific frame it processes (Triady & Utami, 2015). Wind and other natural factors are very difficult to account for since it is difficult to obtain specific measurements of how fast the wind is moving, the direction it comes from and more, to account for these variables that can affect the data and measurements collected, thus resulting in lower and varying accuracies.

For future research involving this project, adjusting the way baseballs are classified, by using a deep learning approach. Currently, baseballs are classified between a lower and higher range of RGB values with the lower being light brown and the higher range being white. This is ineffective as other objects and natural conditions can affect the color grades that the computer can detect causing it to focus on the wrong object(Naik, 2022).Using a pre-trained model or network such as You Only Look Once Version 3(YOLOv3) model, as it is a very compact network that achieves well above average performance for detection (Kim et al., 2015). This would also be beneficial as this architecture is very well known and has many implementations and pre-trained networks available. Another model that could be used would be a Faster Recurring Convolutional Neural Network(F-RCNN), potentially providing better results, as it works better for smaller objects like the size of baseballs (Kim et al., 2017). The downside of this implementation is that it would likely have slower inference time, which is the amount of time it would take for it to process new data and make a prediction (Johansson et al., 2015). Another extension of this project is to improve the velocity and distance formulas so that it accounts for more of Earth's natural factors. Air resistance, drag and gravity are considered, but for air resistance and drag, it is only implemented in the horizontal direction neglecting the vertical force that is acting on the baseball. This is one of the main reasons why there were varying results between the commercial product and the created product(Mizels, 2022). Adjusting the formulas should lead to greater improvement in accuracy along with a greater alignment in the physics occurring in the world (Cole & Kopitzke).

Appendix

Raw Data: https://docs.google.com/spreadsheets/d/1jbcfLw1E0Fk7Ka1Vef-wbKlTDtn_DfAB8ccf_QBiZCg/edit?usp=sharing

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