Golf Ball Dynamic Motion Parameter Estimation based on Ball trajectory video and LSTM

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***Abstract*—Golf ball launch monitor is a system that helps individuals train golf. It provides key parameters such as the trajectory, speed, and spin of the ball. Due to the fast ball speed and the complicated dynamic motion of the golf ball with dimple structure, the highly accurate trajectory prediction system requires expensive motion sensors such as high-speed cameras or high-performance radar sensors, which makes the system expensive and consequently prevents many golf athletes from purchasing it to improve their skill. To solve this problem, this paper proposes a deep neural network-based golf dynamic motion parameter estimation method based on continuous ball images acquired through a commercially available smartphone-level camera. According to the previous study [1], golf ball motion dynamics is governed by a physics equation that is a function of initial differentiate ball speed, spin axis and amount of the spin around the axis. Once those key parameters are identified, golf ball trajectory can be predicted by physics equations with reasonable accuracy. Since the launch monitor is supposed to estimate the ball trajectory as early as possible even before the ball is at its peak height, it is important to estimate the parameters with a minimum number of video frame images. To achieve the goal, we have utilized the custom LSTM model, demonstrating its capacity to yield remarkably precise trajectory estimations even when fed 10 sets of initial coordinates. We achieved an exceptional MSE of 0.04, underscoring the high accuracy of our approach.

Keywords—golf trajectory prediction, golf ball tracking, LSTM model, kinematic variables

I. Introduction

Golf, one of the ball games, is a sport that requires a lot of practice for beginners to play on the field. For this reason, various systems are being released so that beginners can practice enough before going to the field. For example, the launch monitor is a system that uses a high-speed camera mounted on a system to provide users with information that can be used for training such as ball direction, distance, height, and spin amount.

Based on these parameters, the monitor can estimate the trajectory of the ball; however, they have several limitations. First, a high-speed camera is mounted inside the device to capture a ball flying far away. Because of this, the price may be burdensome for beginners to purchase as a hobby. Second, low-cost systems only provide distance and height information calculated by simple equations. This, too, is far from accurate and cannot be called a launch monitor function, as it only provides the trajectory of the ball and no other indicators.

To solve this problem, we want to create a system that predicts the ball's direction, distance, and spin rate by grasping the motion of the ball with a regular camera. In addition, since it is difficult to visually check the point where the ball flew during outdoor practice, the entire trajectory of the ball can be predicted using the coordinates of the ball captured at the moment the ball is hit. The coordinate change of the ball for each frame taken at 0.033 second intervals was analyzed through LSTM, and based on this, the main parameters required to predict the entire trajectory of the ball were predicted.

For chapter II, we are going to talk about some basic dynamics of golf balls which can help you to understand some related forces that make the ball go forward. For chapter III, we provide detailed explanation of the proposed model with its feasibility. In chapter IV, experiment results are discussed and based on them, a concrete conclusion is provided in chapter V.

II. Basic Aerodynamics of golf ball

Before introducing how the system works, we would like to describe the physical equations used to estimate the flying trajectory of a golf ball. Unlike other balls, the golf ball has dimples on its surfaces to distinguish it from the movement of other objects. Then, if the trajectory of the golf ball is predicted by defining the x-axis as the forward direction, the y-axis as the vertical direction, and the z-axis as the curving direction from side to side, the ball's flight and distance can be determined by the force acting on these axes.

$$F_x = mx'' = -R(V_x) + F_M(w, v_y, v_z) \quad \textbf{(1)}$$

$$x'' = -\frac{R(V_x)}{m} + \frac{F_M(w, v_y, v_z)}{m} \quad \textbf{(2)}$$

$$F_y = my'' = -mg - R(V_y) + F_M(w, v_x, v_z) \quad \textbf{(3)}$$

$$y'' = -g - \frac{R(V_y)}{m} + \frac{F_M(w, v_x, v_z)}{m} \quad \textbf{(4)}$$

$$F_z = mz'' = -R(V_z) + F_M(w, v_y, v_z) \quad \textbf{(5)}$$

$$z'' = -\frac{R(V_z)}{m} + \frac{F_M(w, v_y, v_z)}{m} \quad \textbf{(6)}$$

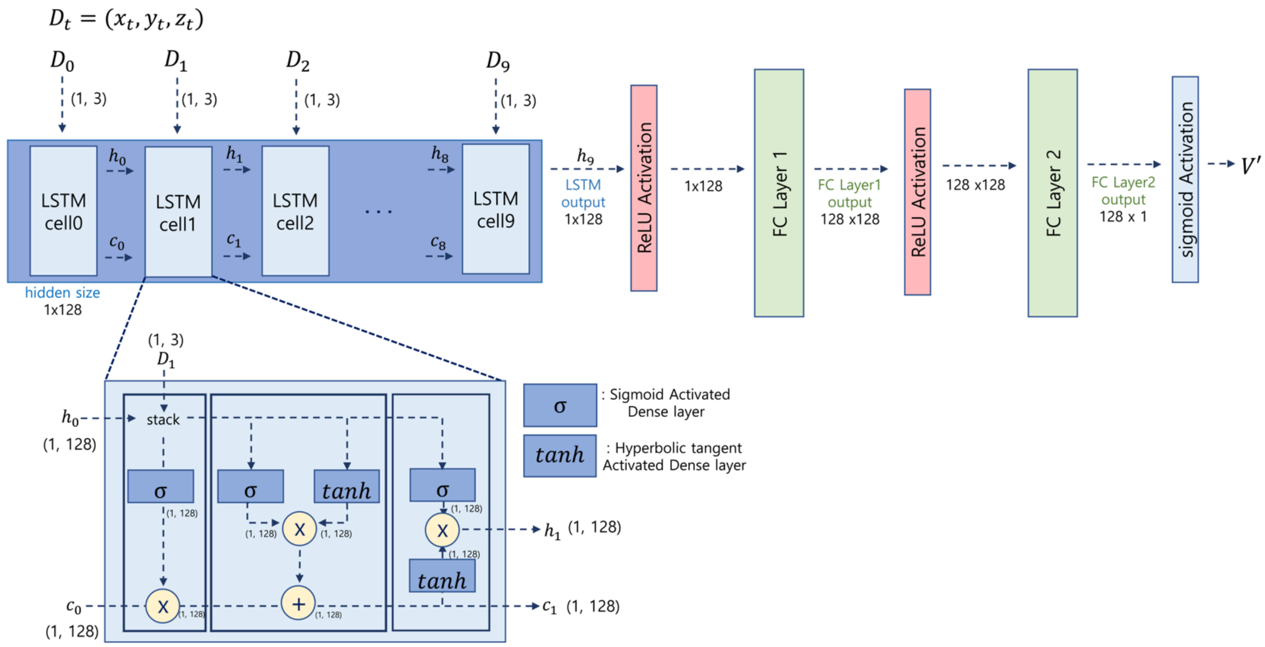


Fig. 1. Model Architecture.

Each force acting on the x, y, z is shown as the **Equation (1), (3)** and **(5)**. In the equation, m is mass and x'', y'', z'' are acceleration which is the result of double differentiation of each displacement. Forces are determined by two elements, $\boldsymbol{R}(\mathbf{V})$, $\mathrm{F_M}$. $\boldsymbol{R}(\mathbf{V})$ is the air resistance which interrupts flight. $\mathrm{F_M}$ is lift force (Magnus Force) which helps the ball stay in the air longer. w means spin rate and V means initial velocity. Air resistance is fixed in constant number, however, as shown in the equation (7), lift force needs to be calculated.

$$F_M = \frac{1}{2} C_L p A v^2 (\vec{w} \times \vec{v}) \qquad \textbf{(7)}$$

In this formula **(7)**, C_L is lift coefficient, p is density of air ($1.23\ \mathrm{kg/m^3}$) and A is the area of the ball ($0.00426\ \mathrm{m^2}$). w (spin-rate) and V (velocity) are required to calculate the lift force. Furthermore, XZ-theta and spin-axis parameters were additionally generated for creating tilted shots such as fade shots and draw shots. XZ-theta is the angle between the x-axis and the z-axis and it determines the ball's curvature. Spin-axis determines the rotation axis. To sum up, including initial velocity and spin rate, we need XZ-theta and spin axis to get the coordinates of golf ball. By predicting those parameters and inserting them into the physical **Equations (2), (4), (6),** we can estimate the entire trajectory.

III. Proposed System

The coordinate information is used to predict the ball's overall trajectory through a high-speed camera mounted on the device. Due to the characteristics of a high-speed camera, many frames are captured per second, which can show better trajectories. However, as mentioned in the introduction, the purpose of this study is to predict parameters for estimating the trajectory of a ball using continuous ball images acquired through smartphone-level camera. For that reason, to predict the next position of the ball, the model needs to read patterns between x, y, z coordinates. The proposed model can be divided into two parts. One is the LSTM for reading the coordinates sequentially, and based on it, the other part, Regression model estimate the next position of the ball.

As shown in **Fig. 1**, the coordinates of the ball are values that change over time, so an LSTM model suitable for time series data is used, and each parameter is predicted by attaching a linear layer to the regression model at the end of the model. These coordinates are sequentially input into the LSTM model, and the model predicts each parameter through a linear layer by analyzing the pattern of these coordinates. The model is trained by comparing these predicted parameters to actual parameters. After training the model, each predicted parameter is put into a physical Equation (2), (4), (6), representing the entire trajectory of the ball and will compare it to the actual trajectory calculated by the actual parameters.

IV. Experiments and Results

A. *Feasibility Study Based on Machine Learning*

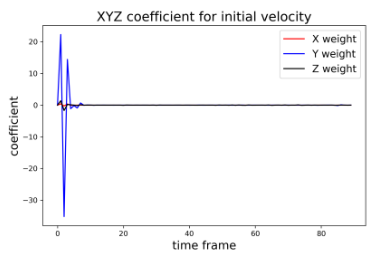
Before training the Deep Neural Network (DNN) model with the coordinates, we first tried to use the Machine Learning (ML) model to check whether each parameter could be predicted only with the coordinates of the ball. Therefore, we used the Linear Regression model among several ML models to figure out the relations between the parameters and coordinates. We selected this model to see the correlation between the X value (independent variable) and the Y value (dependent variable). In addition, since the coefficient of X can numerically determine how much a specific X has affected on Y prediction, it was selected to determine whether the coordinates of the initial few frames are valid for actual parameter prediction.

$$Y = W_0 X_0 + W_1 X_1 + \cdots + W_n X_{tn} = W_t X_t \qquad \textbf{(8)}$$

For the experiment, the entire coordinate of the ball was used as the input of the model, and the actual parameter was used for comparing the predicted value. MAE was used as a metric for comparing results. As you can see in the ***TABLE. 1***., the MAE of each parameter was 0.0026 for $initial\ velocity$, 0.127 for $spin\ rate$, 0.0704 for $xz\ theta$, and 0.117 for $spin\ axis$, confirming that the parameter was predictable through the overall coordinates of the ball. In addition, to see how much the coordinates in each frame affect the parameters, ***Fig. 2.*** shows that only the initial frames of coordinates to their coefficient value were high, which means when we try to predict each parameter, only the first few second frames affect the prediction.

TABLE. 1. MAE for number of frames

Number of frames	**Parameters**			
	Initial velocity	Spin Rate	XZ theta	Spin Axis
90	0.0026	0.127	0.0704	0.117
60	0.00267	0.118	0.0688	0.113
30	0.0027	0.114	0.0736	0.1072
10	**0.0028**	**0.112**	**0.0777**	**0.1056**
9	0.0028	0.112	0.0778	0.1056



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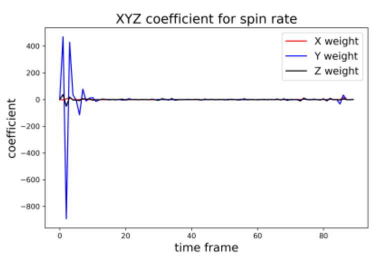

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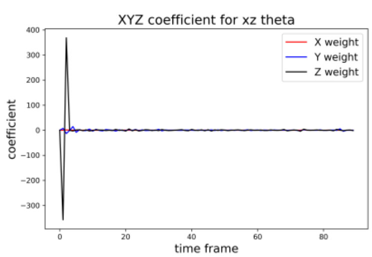

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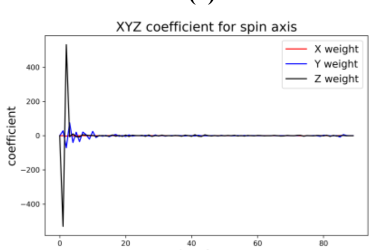


(d)

Fig. 2. Weight of each coordinate on each parameter prediction

Based on this, we reduced the number of frames gradually, and found out the appropriate number of frames to predict each parameter. As a result, only 10 frames of coordinates could be used to predict the parameters accurately, as shown in ***TABLE. 1.***

B. Dataset

The dataset contains 5,000 records and each representing the initial movement of golf ball and its determined values that first shot was made. The attributes of this data are x, y, z coordinates for the first 10 frames, initial velocity, spin rate, XZ theta and spin axis. The coordinates are the input of the model and the other parameters are used to compare the result of the model prediction.

To get the initial 10 frames coordinates, the parameters (initial velocity, spin rate, XZ theta, spin axis) needed to be put into the formula **(2), (4), (6)** which can estimate each coordinate of the ball. We generated random values for parameters within reasonable range from Trackman data. The range of each parameter determined based on the data shown in ***TABLE. 2***.

TABLE. 2. Parameter range setting

Value Range	**Parameters**			
	Initial Velocity (m/s)	*Spin Rate* (rpm)	*XZ theta* (°)	*Spin Axis* (°)
	14~89	2650~6000	-5~5	-7~7

C. Experimental Setup

The total size of the data is [5000, 10, 3], and the batch size is 256. Furthermore, the MAE loss function was used as a metric to evaluate the performance of the model, and the epoch was set to 5000 and the learning rate to 1e-3.

D. Result

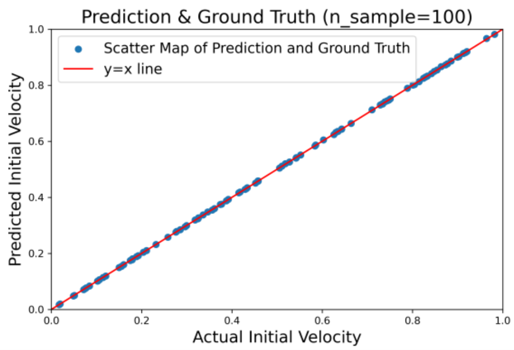
TABLE. 3. is the result of how much is difference between the model's predicted parameters and the actual parameters. We test it for the test set using the MAE metric. In the table, we can see that the model predictions are made about 0.05 higher than ML results in predicting spin rate and XZ theta. We can understand the results more intuitively through ***Fig. 3.*** The predicted and actual values of the model are scattered on each of the x and y axes and the red line is the y=x function to see if the parameters are following the line. As the graph shows, each prediction and actual value correspond to each other and form a linear relationship. Through this, we can figure out that the model predicts the actual situation roughly with low error.

Fig. 4. shows the whole trajectory by directly inserting the predicted parameters into the formula. The coordinates of each x, y, and z used to draw the entire trajectory of the ball. In fact, each x, y, z coordinates are predicted with a very small difference of 0.015, 0.02, and 0.19 respectively compared to the actual coordinates. Thus, through this, we can know that it is possible to estimate the ball trajectory as early as possible even before the ball is at its peak height with predicted parameters, by training our own custom model.

TABLE. 3. MAE for each parameter prediction

MAE	**Parameters**			
	Initial velocity	*Spin Rate*	*XZ theta*	*Spin Axis*
	0.0005	**0.034**	**0.029**	**0.079**

Fig. 3. Weight of each coordinate on each parameter prediction



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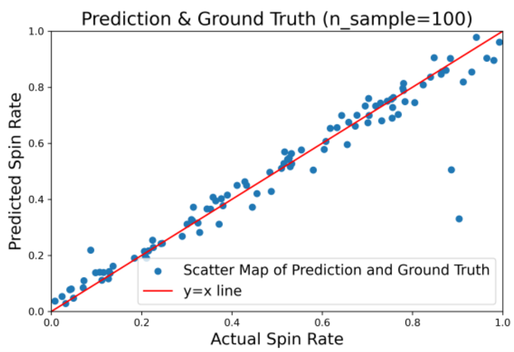

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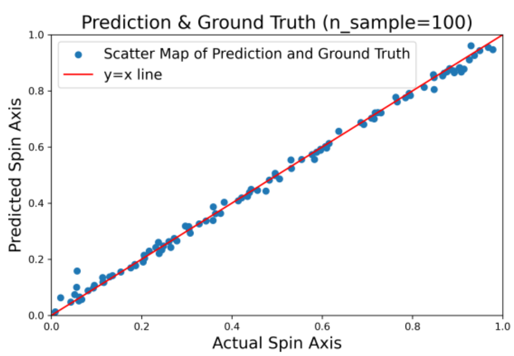

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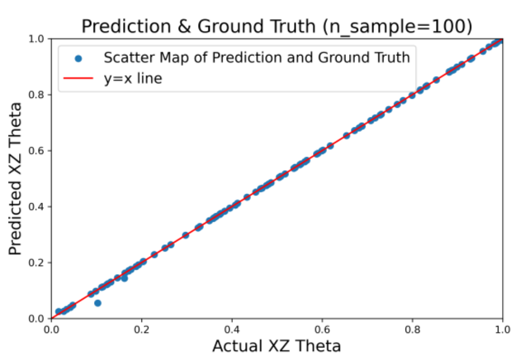

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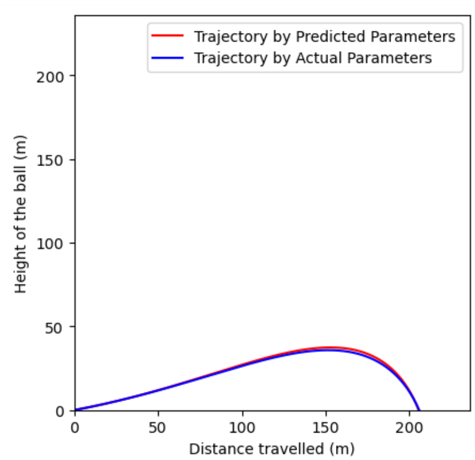
Fig. 4. Comparison of Predicted and Actual Trajectory



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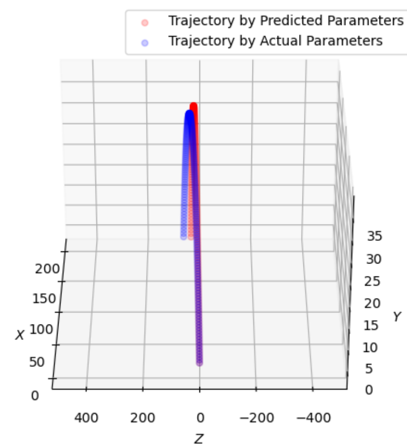

(b)

Fig. 4. Relation between Predicted and Actual parameters

V. CONCLUSION

As the results, the trajectory of the ball can be predicted even if the ball isn't at peak height. We can see that the golf ball position on the x, y, and z in 3 dimensions required to draw the entire trajectory is predicted with high accuracy. Figuring out if the predicted parameters can draw the trajectory well, the plotted result is similar to the actual trajectory of the ball. Furthermore, for the high accuracy, we add 2 parameters (spin axis, xz theta), because with that several shots such as fade shots and draw shot were reproduced for higher reproduction rate and accurate trajectory prediction.

Through this result, we can recognize that the deep learning model can substitute the old prediction technique, using a motion dynamic. With this model, even if you only know the position of the ball in the initial few images, you can draw the entire trajectory accurately. It means that the entire trajectory of the ball can be estimated with a small number of frames, and the model can replace a high-speed camera that shoots multiple frames within the same time. This will allow beginners to train using a smartphone-level camera comparable to expensive equipment with high-speed cameras or high-performance radar sensors which previously had a cost problem for trainees.

To make the Experiment results better, we plan to improve the results through several hyperparameter optimization processes such as increasing the layer of the model. Moreover, we are trying to add the golf ball detection model on our model so that the model can get the initial ball coordinates immediately. This will help people to get the trajectory and other information right after their shooting.

References

[1] Burglund, B., & Street, R. (2011, May 13). Golf Ball Flight Dynamics2. https://www.math.union.edu/~wangj/courses/previous/math238w13/Golf%20Ball%20Flight%20Dynamics2.pdf

[2] Hochreiter, S., & Schmidhuber, J. (1997, November 1). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

[3] Arun K. Kuchibhotla, Lawrence D. Brown, Andreas Buja, & Junhui Cai. (2019). All of Linear Regression.

[4] *Physics*. (n.d.). https://www.golf-simulators.com/physics.htm

[5] Nair, V., & Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)* (pp. 807-814).

[6] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

[7] Leach, R. J., Forrester, S. E., Mears, A. C., & Roberts, J. R. (2017). How valid and accurate are measurements of golf impact parameters obtained using commercially available radar and stereoscopic optical launch monitors?. *Measurement*, *112*, 125-136.

[8] Baek, S., & Kim, M. (2013). Flight trajectory of a golf ball for a realistic game. *International Journal of Innovation, Management and Technology*, *4*(3), 346.

[9] Naik, B. T., Hashmi, M. F., & Bokde, N. D. (2022). A comprehensive review of computer vision in sports: Open issues, future trends, and research directions. *Applied Sciences*, *12*(9), 4429.

[10] Nwankpa, C., Ijomah, W., Gachagan, A., & Marshall, S. (2018). Activation functions: Comparison of trends in practice and research for deep learning. *arXiv preprint arXiv:1811.03378*.