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Using Artificial Intelligence to Provide Visual Feedback for Golf Swing Training

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Abstract

Golf players spend hours perfecting their swing. It takes much practice and dedicated effort to train their body to make an effective swing. In order to train the body in such a way, golf players must be extremely mindful about the placement and motion of key body parts, such as wrists, elbows, shoulders, and torso. With correct placement and motion of key body parts, golf players can achieve great accuracy and consistency in their swings. In this research, we build on our previous work in evaluating the quality of a golf swing. Using a deep neural network, we are able to analyze a golf swing video, determine if it was an effective or ineffective swing, and provide feedback about the specific body parts that need improvement. This feedback can be used to improve player performance. Using this system consistently, a golf player can train their muscles and swinging technique.

Keywords: golf swing, artificial intelligence, deep learning, sports analysis, body motion analysis.

Introduction

Golf is an extremely popular sport, and with the great number of people who play golf or who want to learn to play golf, there comes a need to assist golf players of all skill levels. Golf can be difficult to perfect because it requires much practice to achieve proficiency. It requires physical exertion and coordination of muscle use. [2] shows that a golf swing uses at least 17 muscle groups in the coordinated movement of the hands, wrists, arms, abdomen, and legs. In golf, as in other sports, there is a correlation between physical training and improved performance [3]. Golfers who focus on balance, flexibility, posture, and core stability have better results.

The skills involved in golfing include gripping technique, stance or posture, and swing. It also includes having an effective strategy. Both novice and professional golf players look for ways to improve their performance. There are numerous products on the market that have been developed to improve many aspects of a golfer's technique, including grip, tempo, timing, balance, flexibility, body rotation, and range of motion using a belt, elastic band, weight, etc. Most of these products aim to eliminate bad habits, increase swing accuracy and consistency, and increase the speed of the struck ball and the distance the ball travels. There are also high-end golf simulators equipped with cameras and various types of electronic sensors to estimate swing speed and ball speed, direction, and distance. These systems, however, are designed more for simulation of golfing indoors without providing specific feedback to improve performance.

This work aims to develop an algorithm that uses artificial intelligence to provide the golfer with real-time feedback similar to that given by a professional golf instructor. Our previous success in using a deep-learning network to evaluate a golf swing and provide feedback on how far it is from a good swing with 87.65% accuracy demonstrated that such a system is feasible [4]. This upgraded version of our previous work is designed to provide more detailed feedback about the quality of a swing. With the assistance of a professional golf instructor, we created a system that learns the ideal body motion and coordination of different parts of a golf swing. This allows our program to identify the specific body parts that need improvement.

Motivation

Using deep neural networks, the detection of key body, hand, and foot points on 2D images has improved significantly in the last few years [5] [6]. We attempt to build on this work and apply it to analyzing golf players. Quantifying the difference between data produced by an experienced golf player and an inexperienced golf player can assist a golfer in improving his or her swing. Useful golf swing analysis programs do exist, though they require special equipment and are time-consuming to set up. It can be impractical for many amateur golfers to obtain this special equipment and specialized programs.

The feedback that golf instructors give to golf players is valuable. While viewing a slow-motion video, golf instructors can analyze the key points of the body while performing a swing, then give advice on how the player can improve. According to [16], there are six phases of a golf swing: Set-up, Backswing, Transition, Downswing, Impact, and Follow-Through. Each of these phases is important in correctly striking the golf ball. In this research, we focus on the Downswing, Impact, and Follow-Through phases. While executing these different phases, it is important that golf players have correct body placement and coordination. The feedback they receive from instructors helps them become aware of and improve the placement of key body parts. To help automate this process of analysis and feedback, we introduce an automatic body motion analysis method, which will assist in improving the golf player's technique by highlighting the key body parts that need improvement.

Challenges

One of the challenges of such a method is to ensure the system provides consistent and accurate feedback. The error can be minimized by using a reasonable architecture, which could reduce inference time and maintain the accuracy of each motion. Another challenge is data collection and labeling. Because of the uniqueness of this application, no suitable data-sets are currently available for training and testing. A data-set on golf swings was generated specifically for this work.

Related Work

In recent years, golf swing analysis has been done using sensors [5] [6], multiple cameras [8], and depth cameras [7]. The majority of products that analyze golf swings and body motion use 3D information gathered from multiple cameras or other sensors. Instead of using a 3D field of data obtained from multiple cameras, we use only 2D data extrapolated from a single camera to analyze a golfer's swing, which reduces computational needs. Deep learning techniques are used to determine the quality of a swing. This approach is unique because it attempts to mimic how most professional instructors provide their feedback.

Pose Estimation

Recently, deep learning has become an effective technique to be used in human pose estimation. Traditional computer vision techniques that use images from consecutive frames to trace an object path are becoming obsolete. There are several works that use deep learning to obtain human pose data, such as AlphaPose [9], OpenPose [10], DeepPose [11], and various DNN and CNN based models [12, 13, 14, 15]. However, human pose estimation remains a challenging task. There continue to be errors in localization, though state-of-the-art human body estimators have shown great performance.

Golf Swing Analysis

Previous research done in analyzing the swings of golf players has focused on identifying the individual phases of a golf swing. [17] focuses on sequencing the individual events of a golf swing by detecting key events. [18] identifies the key events in a golf swing as well, and analyzes the movement of the body. While [18] has created a database for analyzing golf swings, we use a custom data set with a higher frame rate and better resolution.

Golf Swing Evaluation

Video Collection

A professional golf instructor recorded the golf swing videos for our research. They include 216 positive (good swing) samples and 122 negatives (bad swing) samples. The data-set provides a total of 216 positive samples and 112 negative samples at 60 fps, with a total of 11614 frames.

Annotation

With a frame rate of 60 fps, the precise moment when the club contacts the ball was rarely captured. Therefore, we chose the frame that is the closest to when contact occurred. A professional golf instructor performed the swings and labeled each one as a good swing or a bad swing.

Key Points Detection

Using AlphaPose, we obtain the key body points for each frame in every 41 frame video clip. Figure 1 shows 16 sample frames of a swing and their key body points. There are 17 key points of interest in each frame, with the default key-point order as follows: Nose, Left Eye, Right Eye, Left Ear, Right Ear, Left Shoulder, Right Shoulder, Left Elbow, Right Elbow, Left Wrist, Right Wrist, Left Hip, Right Hip, Left Knee, Right Knee, Left Ankle, and Right Ankle. Each key point is represented by an x, y coordinate.

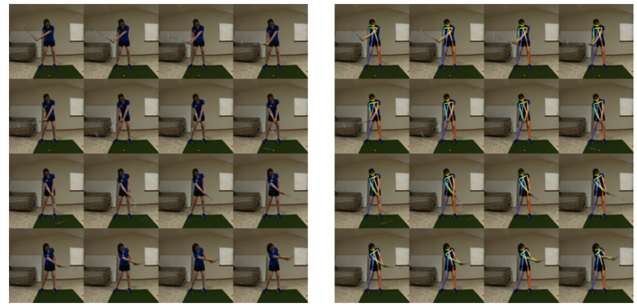

Figure 1. *Key points from pose estimator*

This produces a 41 x 17 x 2 matrix for a single video of 41 frames, 17 key body points per frame, and the x and y coordinates.

Architecture

Our proposed architecture builds off our previous work [4], which consists of six sections: 1) Obtaining the key body points from the pose estimator, 2) putting the left and right wrist key points through a correction filter, 3) normalizing the data, 4) sequencing the key points of the golf swing into a 3 channel array, 5) inputting the 3 channel array into a ResNet for training, and 6) making a prediction on the quality of the swing.

After normalizing the data, we sequence the key points of the golf swing into a Pearson standard correlation coefficient heat map array. This shows that the program is able to detect the specific body parts that need improvement.

Results

We show that our program is able to differentiate between a positive (good) swing and a negative (bad) swing. We compare the results of our model with the ground truth data using a Pearson's correlation coefficient heat map. This is a widely used method to measure the linear relationship between two normally distributed variables. Figure 2 shows the positive sample's correlation between different features for a single video. Figure 3 shows the negative sample's correlation between different features, also using a single video.

$$\rho = \frac{cov(X,Y)}{\sigma_x \sigma_y} \tag{1}$$

The approximation of Equation 1 is shown in Equation 2.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \tag{2}$$

To show our results over the entire positive sample data, we use a heat map of the standard deviation of correlation, shown in Figure 4 Using Equation 2, which is an approximation of Equation 1, we plot a mean of correlation heat map over all of the positive samples, shown in Figure 5. The standard deviation with the mean becomes the anchor correlation.

While some correlation data points in the Mean of Correlation heat map (Figure 5) are greater than two standard deviations 2σ from the mean account, the program is still able to detect both correct and incorrect golf swings, as shown in Figure 6 and Figure 7. Figure 6 shows two negative sample comparison results

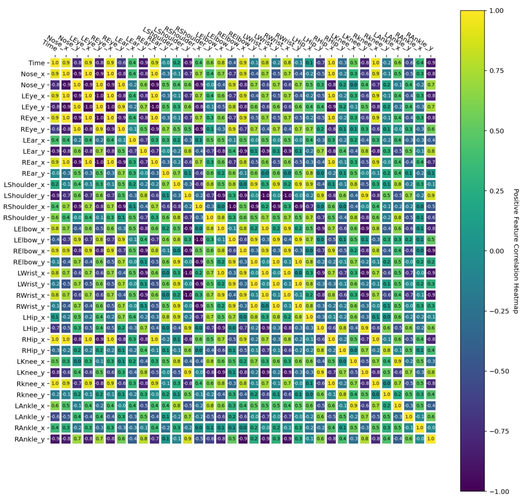

Figure 2. *A Positive Sample's Heat Map*

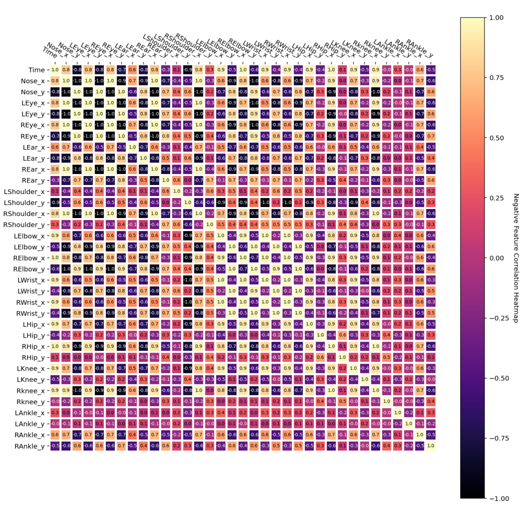

Figure 3. *A Negative Sample's Heat Map*

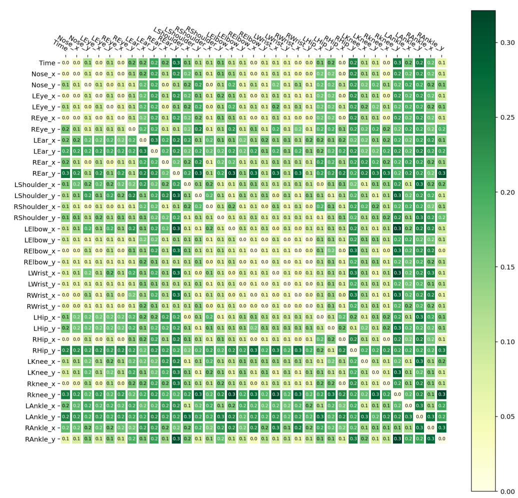

Figure 4. *The Positive Sample Standard Deviation of Correlation*

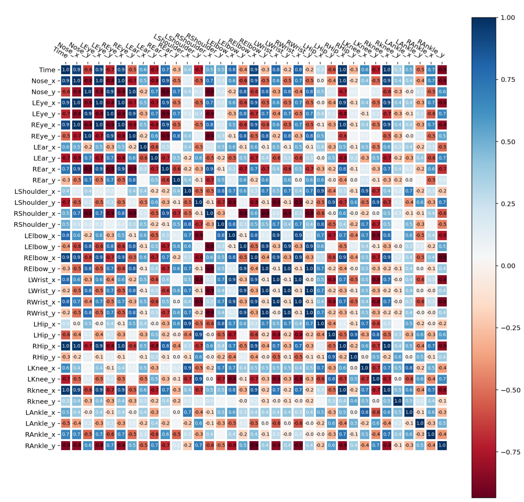

Figure 5. *The Positive Sample Mean of Correlation*

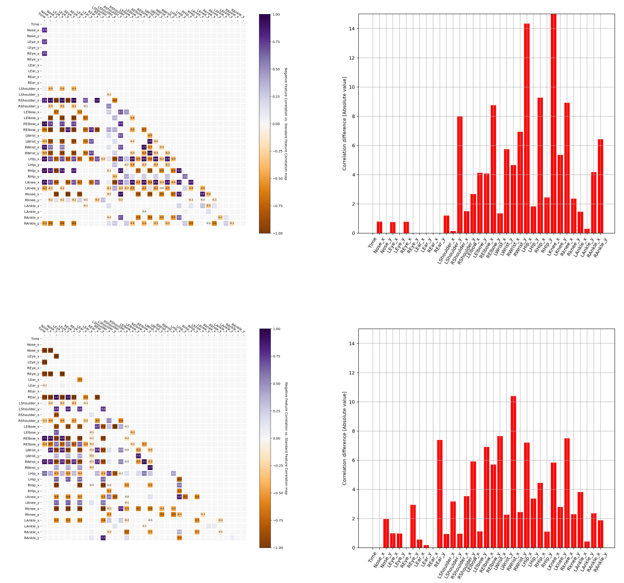

Figure 6. Negative Samples Comparison Result and Correlation Difference Histogram

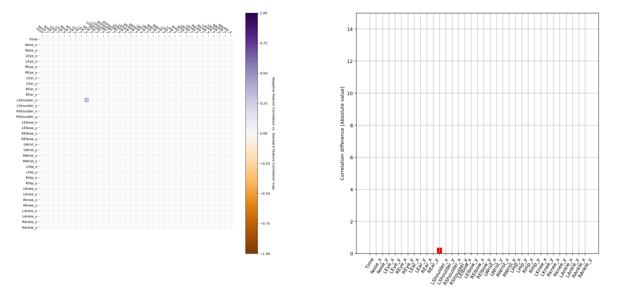

Figure 7. A Positive Sample Comparison Result and Correlation Difference Histogram

and correlation difference histogram. Figure 7 shows a positive samples comparison result and correlation difference histogram.

Our model is able to successfully indicate which body parts are positioned incorrectly in 119 out of 122 videos. Figure 8 shows an example of the feedback given on a poor golf swing. Note that the highlighted areas (the right elbow, the left shoulder, the wrist, and the hip) are the specific areas the program detected were less than ideal.

Conclusion

Artificial intelligence has become a preferred solution for many applications, and is one main focus of enhancing competitiveness for many sports. Both golf instructors and motion analysis programs are very important for athletes. However, not everyone has access to a professional instructor due to both the high cost and limited availability. This work attempts to provide a solution.

In this research, we developed a method to automatically evaluate swing quality, which can help improve a golfer's performance and swing consistency. We will continue to collect video clips to increase the size of our data-set for experiments. Our future work includes bypassing key-point detection and using the video input directly for evaluation, analyzing the impact of frame timing variations, reporting more detailed feedback for improvement, and integrating our algorithm with other motion sensors.

Figure 8. A result of a bad golf swing

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