AI Golf: Golf Swing Analysis Tool for Self-Training

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Abstract - *In the field of the acquisition of sports skills, Imitating the movements of professional athletes is a typical strategy in the field of sports skill development to enhance sports skills, such as golf strokes. Due to various irregular timing and inadequate skills, beginners find it challenging to determine the keyframes on which they should concentrate and the part of the body they should correct. In this study, a neural network-based tool for golf swing analysis is provided to fill this gap. The proposed approach compares two motion sequences and identifies keyframes where substantial variations between the two motions may be seen.*

Additionally, by using comprehensible indicators, the system aids users in easily comprehending how they vary from expert players. This study's key obstacle is identifying the subtle variations between users and professionals that can be used for selftraining. Furthermore, the suggested strategy is significant since it uses an unsupervised learning method without prior knowledge and labelled data, which will assist future applications and research in various sports and skill methodologies.

***Key Words*:** **Unsupervised Learning, comprehensible indicators, Neural network, Key frames, Golf stroke**

1. INTRODUCTION

Many systems have been developed to detect various objects, make predictions for decisions, or even forecast the future thanks to substantial advancements in machine learning technology. The [6] athlete's movement style or motion and the object they are swinging have a significant impact on their ability to succeed in sports. For instance, in golf, the action of the golf club is the primary determinant of the ball's launch parameters, which in turn influence the trajectory and end location of the ball. In [10] this study, we suggest a golf swing analysis tool that uses deep neural networks to assist the user in differentiating between their swing and the swing of an expert. We [2] plan to develop a technology that will serve as a golf practice assistant with the help of accurate detection of essential golf swing characteristics. This tool would speed up user feedback in a low-cost, user-friendly hardware device. Any golfer might use this strategy by bringing a tiny piece of equipment to the driving range to get fast feedback.

1.1 MOTIVATION

The majority of adult populations in most nations participate in the precision sport of golf, which calls for strong physical fitness. The swing is the most crucial element to success in golf. Amateur golfers devote a lot of time and energy to honing their stroke mechanics. The environment, physical ability, and financial issues all have an impact on how well a player can play golf, thus it is important to keep track of all these variables and develop tools for improved golf swing analysis.

1.2 OBJECTIVES

The swing is the most integral part for golf performance. A good way to tell if someone is performing a motion correctly is to compare their motion to others whose motion is recognized as accurate. The suggested technique can be applied to self-training systems that compare 3D human poses at the detected frames and detect discrepant motion frames by measuring the distance between golf strokes in latent space. We create a single graphical user interface for the motion synchronizer, motion discrepancy detector, and motion manipulator as a prototype application.

1.3 PROBLEM STATEMENT

The goal of a golf swing analysis is to pinpoint any defects or shortcomings in a player's swing and offer recommendations for development. An analysis of a golfer's swing may include a problem statement that identifies particular areas that require work, such as the takeaway, backswing, or downswing, and offers specific suggestions for how the golfer may enhance their swing to boost power and accuracy. Examining the golfer's alignment, grip, posture, and other elements that may have an impact on the swing's quality may be necessary. A golfer's overall performance and pleasure of the sport are the ultimate goals of a swing analysis.

1.4 MACHINE LEARNING USING PYTHON

Python is a sophisticated, widely used programming language. In 1991, "GUIDO VAN ROSSUM" invented it. Numerous libraries, including pandas, numpy, SciPy, matplotlib, etc., are supported by Python. It supports Xlsx, Writer, and X1Rd, among other packages. Complex science is performed extremely effectively using it. There are numerous functional Python frameworks. Machine learning is a branch of artificial intelligence that allows computer frameworks to pick up new skills and enhance their performance with the help of data. It is employed to research the development of computer-based algorithms for making predictions about data. Providing data is the first step in the machine learning process, after which the computers are trained by using a variety of algorithms to create machine learning models. Software engineering's branch of machine learning has significantly altered how people analyze data.

2. RELATED WORK

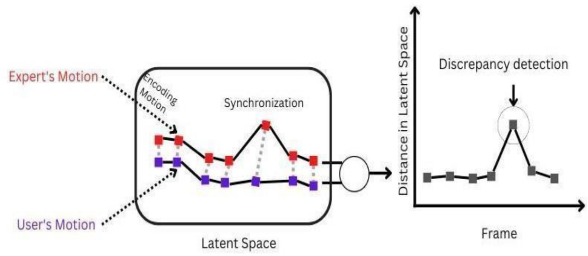
A lot of research has gone into creating artificial intelligence (AI) and machine learning (ML) systems that can evaluate golf swings and give users feedback so they may improve. These systems typically extract elements from the golf swing using video or other sensor data, and then utilise a variety of algorithms, including pattern recognition, classification, and regression to identify important swing components and give the player feedback. The "Smart Coach" system created by researchers at the University of Maryland is one example of an AI-based golf swing analysis tool [3]. In order to evaluate video data of a golfer's swing and provide feedback on many parts of the swing, such as clubhead speed, angle of attack, and clubface alignment, this system combines machine learning and computer vision techniques [6]. Another illustration is the "GolfSense" system, which collects data on different components of the swing, like clubhead speed and tempo, using a small sensor connected to the golfer's glove and then delivers feedback via a mobile app. Additionally, there are a variety of commercial tools available on the market that analyze golf swings and offer feedback for self-training. In these items, features from the swing are often extracted using sensors and/or video data, and feedback is given via a mobile device. The "Zepp" and "Arccos Caddie" systems are a couple of examples. Overall, artificial intelligence (AI) and machine learning (ML) can be effective tools for analyzing golf swings and providing feedback for selftraining, but it is crucial to remember that these systems are only as good as the data they are trained on and the algorithms they utilize. It is always a good idea to speak with a skilled golf coach or instructor who can assist you in comprehending and interpreting the feedback offered by these systems so you can use it to better your game.

3. IMPLEMENTATION

The purpose of this project is to create a system that captures user motions and provides accurate feedback to users in order to help them improve their forms by comparing their motions to those of experts. The method suggested in this study is to achieve the goal of creating such an application by first training a neural network with motion data from experts. After network training, the system compresses network-based user motions into a latent space, where it contrasts them with expert motions. The procedure of the technique consists of motion synchronization, motion discrepancy detection, and motion manipulation. It has been demonstrated in AI Golf: Golf Swing Analysis Tool for SelfTraining that cycleconsistency approaches may be used to match video inputs with various phasing and timing characteristics. The temporal cycle consistency (TCC) learning approach serves as the model for our approach. The TCC network is built to enable the network to learn both the similarity of motion and the overall motion's temporal sequence. The base networks employ the video TCC (V-TCC), skeleton TCC (STCC), and skeleton-attention TCC network types (SA-TCC). A network that accepts video as input is called V-TCC.

We obtained golf swing data online and assembled a fictitious database of raw video data, video without a backdrop, and 3D posture data in order to assess the precision and efficacy of the three modules mentioned in the previous section (Figure 4). Then, using TCC loss and three network models (V-TCC, S-TCC, and SA-TCC), we implemented the models and performed statistical analysis under the following four scenarios:

- V-TCC utilizing background-video inputs Important phase.
- V-TCC utilizing background-free video inputs.
- S-TCC leveraging inputs from 3D human poses.
- Using 3D human posture inputs for SA-TCC.



3.1 VIDEO DATASET

The video footage of golf swings recorded from various perspectives would likely make up a video dataset for golf swing analysis. Then, using this video, a machine learning model may be trained to recognize and evaluate several elements of the golf swing, such as the posture, grip, and club movement. Such a technology would be designed to provide golfers specific feedback on their technique, enabling them to self-train and enhance their swing. A neural network would need to be trained on a sizable collection of labelled video data in order to be used in a deep learning method for golf swing analysis. GolfDB [11], a video dataset collection for all golf iron swing and driver swing types, was utilized as the training dataset. It contains 1400 high-quality golf swing footage of male and female professional players. We produced a second video dataset without any background information in addition to clean videos. This was done because, according to our theory, background information, like the shadow of a person, might affect how the network is aligned.

3.2 3D POSE DATASET

We developed a new pseudo dataset with 3D point data of human body positions in order to do a more accurate analysis of just human poses. Video of golf swings recorded by numerous cameras to give a 3D picture of the action would make up a 3D posture dataset for golf swing analysis[14]. The essential postures and motions of the golfer during the swing, such as the grip, movement of the club, and posture, would then be noted on this video. In order to recover the time series of 2D human postures from golf swing videos for this dataset, we initially employed HRNet. While 2D poses might roughly reflect human motion in time series, due to camera positions, 2D poses could vary greatly, making it challenging to solve the normalization problem in 2D space. The straightforward linear network structure suggested in was therefore used to create human 3D postures. To recover the 3D human poses, a linear network received the estimated 2D poses from the HRNet .

3.3 EVALUATION METRICS

We trained the network until the TCC loss converged since we utilized a self-supervised learning technique. By using an accurate metric that measures the accuracy of the alignment using the two label types important events and phases, we were able to assess how effectively the network had been trained. Frame shows a specific instant, and the phase is a time series between two significant occurrences.

4. RESULTS

This presents the results of an early qualitative investigation investigating the capability of the proposed technique to detect discrepant motion differences, followed by further indepth findings comparing several modules. The intermediate human postures on the motion manipulator are finally visualized for qualitative study. In our study, we performed a qualitative analysis by probing the latent space to determine whether the network could recognize minute differences. First, we used the V-TCC to synchronize the swing movements of professionals and beginners.

Following the calculation of the latent space separations between the aligned motions, the 3D human locations with their overlays were shown for qualitative comparison. We estimated Pearson's correlation coefficient using the four models. The Pearson's correlation coefficient for background-free video was 0.72, while the correlation value for regular video inputs for inputs was 0.69. For the qualitative outcomes, we calculated and displayed the middle human pose between two human postures while taking into account the following three conditions:

- Only one individual took the two poses. The two positions were at various stages.
- The two postures were taken by separate people. The phases of the two stances were the same.
- The two postures were taken by separate people. The two positions were at various stages.

5. FUTURE SCOPE

Golf swing analysis and self-training systems driven by AI have a bright future. These tools are probably going to get better and more accurate at helping golfers develop their swing as AI technology develops. Future advancements in this field may involve the following: Improved body position and movement identification, enabling the instrument to offer more thorough and individualized feedback. Integration of additional technologies to deliver even more in-depth and immersive teaching and analysis experiences, such as wearable sensors and virtual reality. the capacity to provide more thorough and precise coaching by learning from a wider range of data, such as historical records of effective golf swings and the on-course performance of professional players. The instrument may now deliver more precise and useful feedback thanks to the development of new algorithms and approaches to better comprehend and evaluate the intricate mechanics of the golf swing.

Overall, the future of artificial intelligence (AI)-powered golf swing analysis and self-training tools appears promising, and these tools are going to become a more and more important resource for golfers trying to raise their game.

6. CONCLUSION

We present a golf swing analysis tool that makes use of neural networks to assist users in intuitively understanding how they vary from professional players. Discrepancy detection, manipulation, and synchronization are the three categories into which we split our job. The motion synchronizer first lines up movements with various timings and phases. Second, utilizing the suggested networks, we employ a motion discrepancy detector to locate tiny or big variations between golf swings in the latent space.

Third, based on the synchronization and discrepancy detection results, we introduce a motion manipulator decoder structure to recover motion from the latent space. In addition, the motion manipulator can give beginners an intermediate pose that is more appropriate for them to begin with. With the mentioned three main contributions of this work, we develop an application for analyzing and visualizing the discrepancy between two input golf swing motions. Users who engage in self-training can rapidly understand the differences between their swings and those of various specialists. Users of the suggested system can select an ideal shape to emulate and learn to play sports on their own during self-training. The suggested prototype application will be improved, and user testing will be done to assess its efficacy.

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