HIT THE BALL - BUT HIT IT RIGHT: DETECTING THE GOLFBALL- CLUBFACE IMPACT LOCATION USING IMU DATA

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The aim of this proof of concept study was to identify the possibility of estimating the golf ball impact location on the golf club face via IMU data using a machine learning algorithm. The IMU data of 494 golf swings performed by one golf professional using a 7 iron were collected and merged with the impact location detected via a dual-laser technology (TrackMan). After a pre-processing the raw data with normalization and data augmentation stages a neural network, based on convolutional and dense layer, was created. The network was trained on the given data and its performance analysed. As a result, the network was able to predict the horizontal offset to the ideal impact location for 92% of all swings within ±5 mm. Hence a proof of concept could be found.

KEYWORDS: golf, IMU data, machine learning, wearable sensors.

INTRODUCTION: In golf, the precise point of contact between the clubhead and the ball holds significant importance in dictating the subsequent movement of the ball. Each golf club possess an optimal point of contact, which usually is situated in close proximity to the center of the club's striking area. Hitting the ball in areas that are either too close or too far away from this sweet spot may result in less efficient ball trajectories. Consequently, obtaining feedback regarding the exact location of the clubface-ball interaction is imperative for enhancing the ability to strike the ball effectively. In a recent study, we proved that is the estimation of the general area (inside, central, outside) of the clubface-ball impact using shaft-acceleration data and a machine learning approach is possible with an accuracy of 93% (Hollaus, Heyer, Steiner, Strutzenberger, 2023). To provide more detailed feedback to the athlete the absolute distance to the impact sweet spot would be beneficial. Currently, this information can be measured by employing techniques such as stationary dual laser technology, slow-motion high-speed cameras, and rudimentary methods like the use of chalk spray (TrackMan). All of these techniques are either stationary in nature or can only be utilized on a singular occasion. Consequently, they restrict an athlete's freedom to acquire feedback at any given time and place. Simultaneously, athletes are required to alter their training routines in order to incorporate these systems into their regular golf practice.

Since the rise of artificial intelligence over the last decade, classification in sport is ubiquitous (Cust, Sweeting, Ball, Robertson, 2019). Many scientists focused on the recognition of specific movements in various sports or the segmentation of a specific movement (Kim, Park, 2020). In contrast Hollaus et al, who also used a classification algorithm, a regression approach may be possible to have more detailed feedback on the performance in golf. According to Van Eetvelde, Mendonca, Ley, Seil and Tischer in 2021 regression works well to predict the injuries of athletes. Also, in betting and performance prediction regression models, which are based on machine learning, are quite common nowadays. Transferring the given methods to the performance prediction in golf may be possible with the given data set recorded by Hollaus et al in 2023.

Therefore, the aim of this study was to identify in a proof of concept study the possibility to not only detect the impact area but also the absolute distance to the sweet spot using one IMU sensor on the golf shaft. This would set the frame for the development of a potential mobile application that can be attached to the golf club and used during a regular golf-routine without the limitations associated with the aforementioned systems.

METHODS: A golf professional (male, 184 cm, 79 kg) performed 494 golf swings at an indoor golf laboratory. The golf club was equipped with an IMU sensor (Ultium motion, Noraxon, USA) placed on the shaft 8 cm below the grip (Figure 1) collecting at 400 Hz. Simultaneously, for each golf swing the absolute distance between the sweet spot and the impact location was recorded using a dual laser technology (TrackMan 4. Vedbæk, Denmark) and a DV-Camera (Miqus, Qualisys, Gothenburg, Sweden) for documentation (Figure 2).

Figure 1: IMU Sensor placement

Figure 2: Laboratory set-up

Eleven sessions were used for the data gathering, with 20 to 30 samples taken in each session. The IMU data was thus collected into eleven .csv files, each of which had values for acceleration and magnetic flux densities in three axes that were each expanded with three corresponding angular velocities. As a consequence, each of the eleven.csv files had a total of nine recorded signals. The measurement ranges for acceleration were ±200 g, for angular velocity ±7000 °/s and for magnetic flux density ±16 Gauss. The TrackMan data was exported into a separate .csv file. The captured data needed to be further processed in order to create an algorithm the can connect the nine signals with the horizontal hit location.

Initially, cuts were taken from each IMU data session using a one-second time window, leading to 400 samples of each signal. With the peakfinder function from the Python library scypi the time steps of the impacts in each IMU data session have been identified. With the information on the time steps, cuts of the data have been made. Each cut includes the impact value itself and runs from 200 values before the initial impact to 200 values after. Subsequently, the nine signals were normalized using the range values mentioned above. This led to 9 × 400 values (acceleration, angular velocity, and magnetic flux density) for each cut ranging from 0 to 1. After the normalization the data has been merged with the corresponding horizontal offset of the TrackMan data. As the TrackMan delivers the horizontal offset in millimeter, it had to be normalized as well to range from 0 to 1. Therefore, a normalization value of 50 mm was chosen (Hollaus et al., 2023).

The pre-processed data was augmented to have more samples to train on. On the given 494 cuts, data augmentation was performed by means of adding noise and time warping leading to augmented 988 cuts and 1482 cuts in total. The augmentation methods were carried out using the Python library tsaug (Analytics 2024).

The architecture, which was based on a convolutional layer for feature detection with several dense layers, was trained quickly thanks to the use of a Nvidia T4 Cloud GPU (NVIDIA, Santa Clara, CA, USA) in the Google Colaboratory environment. In figure 3 the architecture can be seen. With a shuffle split a training (90%) and validation (10%) fold was created. Figure 4 illustrates the loss of the training and validation procedure, which took 260 epochs until the early stopping callback forbids the model from becoming overfit. The network contained 210,753 trainable parameters in total. Adam was employed as the optimizer with mean squared error as loss function and a learning rate of 0.0003.

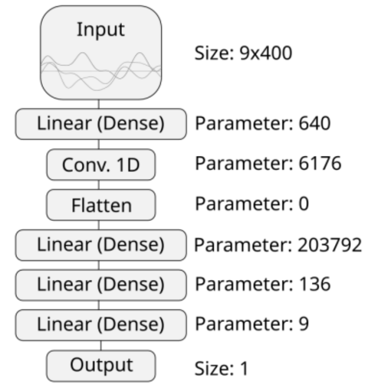

Figure 3: Network Architecture

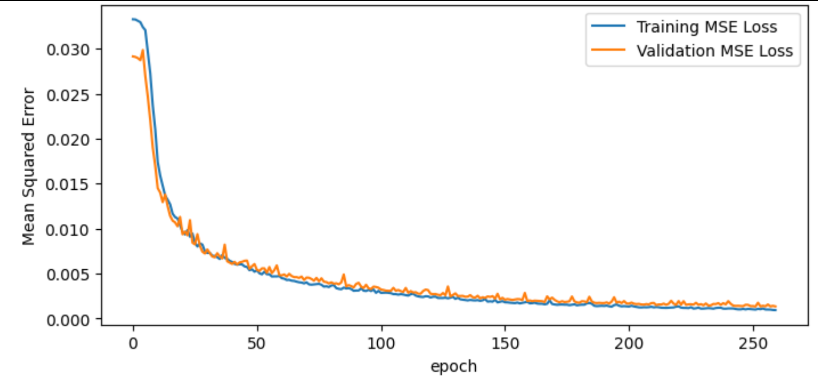

Figure 4: Training and Validation Loss (Mean Squared Error) over all 260 epochs

RESULTS: The estimation of the regression network is shown in figure 4. Based on the strong accordance of the true and estimated horizontal offset it can be said, that the proof of concept has been delivered in this study. Figure 5 shows the Bland-Altman plot for the comparison of the two measurement methods. The error between the TrackMan method and the IMU based estimation is less than 5 mm for more than 92% of all swings.

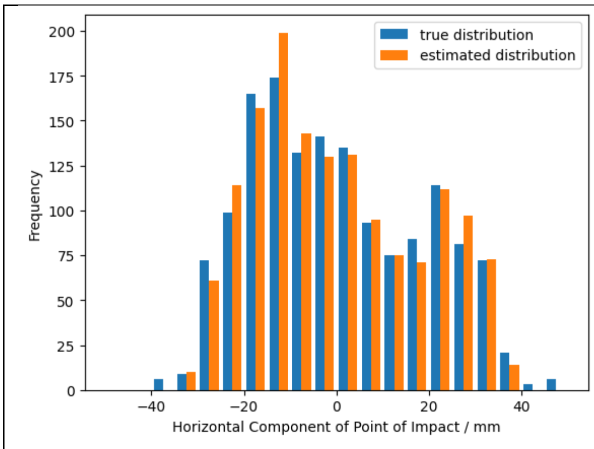

Figure 4: The horizontal offset distribution. In blue the true distribution, in orange the estimated distribution is shown

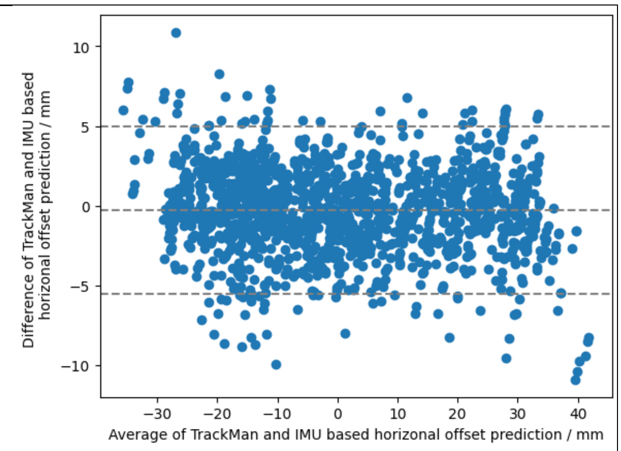

Figure 5: Bland Altman Plot for the true (TrackMan) and predicted (IMU based) horizontal offset

DISCUSSION: The initial goal was to carry out a feasibility study in order to produce a proof-of-concept. The major finding is a novel method for predicting the horizontal offset to the ideal impact location between a golf club and ball based on a mobile solution, that does not interfere with mobility of the athlete and daily training routines. The method in this study creates a high degree of agreement with the measured gold standard Trackman 4 data.

Nevertheless, there are many limitations to the finding. E.g. the study was conducted with only one participant, one golf club, one ball type in one location. Especially by extending the number of participants the variety in swing motion would drastically change (Lai et al. 2011). These circumstances have to be considered when this method is used. The prediction error would most likely increase if one of the mentioned boundary conditions would change. At the same time, it has to be said, that the goal was a feasibility study and a proof of concept, Therefore, it is not necessary to have variations in all these circumstances. For a better robustness of the algorithm against changes in the boundary conditions, it would be necessary to get much more data. Implementing a study, with many athletes, gold clubs, balls, etc. has to be the next step to find a more robust algorithm. Based on the given results, the outcome of that study could be the frame for the development of a potential mobile application.

CONCLUSION:

Overall we conclude, that based on the collected pilot data it is generally possible to determine within one participant and one golf club the impact location with respect to the sweet spot in absolute distance with an accuracy of 5 mm in 92% of the swings using one IMU sensor at the shaft of the golfclub. This implicates that the acceleration characteristics of the impact vary depending on the impact location. In a further step data of different participants and golf clubs needs to be collected to identify the feasiblitly of this approach in a more general context.

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