Development of Pattern Recognition Methods for Golf Swing Motion Analysis

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Abstract. The golf swing is one of the most complex movement sequences in any sports. Even human experts can be overwhelmed by the amount of details that have to be taken into account for its analysis. We present a novel pattern recognition approach that can help in this analysis by automatically and robustly evaluating even tiny swing differences.

Our approach is based on the accurate 3D spatiotemporal information about the posture of the golfer and the position of the club that the TaylorMade MAT-T™ motion-capture based swing measurement system provides. Golf club fitting experts have been using these systems throughout the last decade and have captured more than 500 000 swings worldwide. Based on the positional data contained in this unique database, we developed a feature description of the golf swing with the goal of classifying even small differences between groups of players. In this manuscript, we show the results of the application of several classifiers to two selected problems of group classification.

The presented system can be used for example to distinguish expert from novice players. The information that is calculated by our software tool can substantially support the process of golf club fitting and furthermore assist coaches and golfers to improve performance.

Keywords: TaylorMade MAT-T™, golf swing analysis, biomechanical data classification, feature extraction, pattern recognition

1. Introduction

The golf swing is one of the most complex movement sequences in any sports. Muscle groups of the whole body are involved to provide the biomechanical prerequisites to transfer the swing energy efficiently and accurately to the golf ball [1]. In this process, a large number of kinematic variables are involved that affect the shot outcome and that can possibly be optimized in order to increase performance. It is therefore a challenge for players and coaches alike to select the correct optimization in order to improve the swing effectively. An extensive review paper of golf swing analysis came to the same conclusion and stated that research should target predictors of golf swing technique to improve golf performance [2].

Several previous studies have targeted golf motion analysis. A subset of them investigated specific sensor data that does not measure the swing movement directly, for example the weight shift during the swing [3, 4] or the electromyographic signal changes of various muscle groups [5-7]. An obvious basis for the analysis of the swing movement itself are 2D video images, which have been used in several studies [8, 9]. Other studies have also investigated golf swings based on full kinematic movement data captured with 3D motion analysis systems [10, 11].

While these previous studies have contributed important new knowledge, several aspects that are important to swing analysis and therefore to giving direct feedback to golfers were not addressed. In order to identify those predictors of golf swing technique that can be used to improve performance, indirect measurements such as weight shift [3, 4] or electromyography [5-7] are of limited value. Rather than these measurements, 3D motion capturing can be used to provide the basis for swing analysis. 3D video analysis has already been shown to be an effective way to increase performance in golf [12]. However, from the video analysis alone no conclusion can be drawn which variable is the one that is most performance relevant.

Such a method that is based on 3D kinematic data and objectively analyses the features of a golf swing with respect to their importance for performance has previously not been shown in the literature. The purpose of this paper is therefore to present our first steps in the development of an objective, data driven pattern recognition approach that is capable of identifying those predictors of golf swing technique that are most relevant to performance improvement.

2. Methods

2.1. Data Collection

3D kinematic data of the golfers' posture and the position of the club during the swing was collected by TaylorMade™ (TaylorMade-adidas Golf Company, Inc., Carlsbad, CA, USA) using the Motion Analysis Technology by TaylorMade™ (MAT-T™) motion-capture system. A total of 34 markers were tracked by this system. 28 markers were attached to the player in a way that the player was not disturbed when performing the swing (Fig. 1a & 1b). The remaining six markers were attached to the golf club, three at the club head (Fig. 1c) and three at the grip.

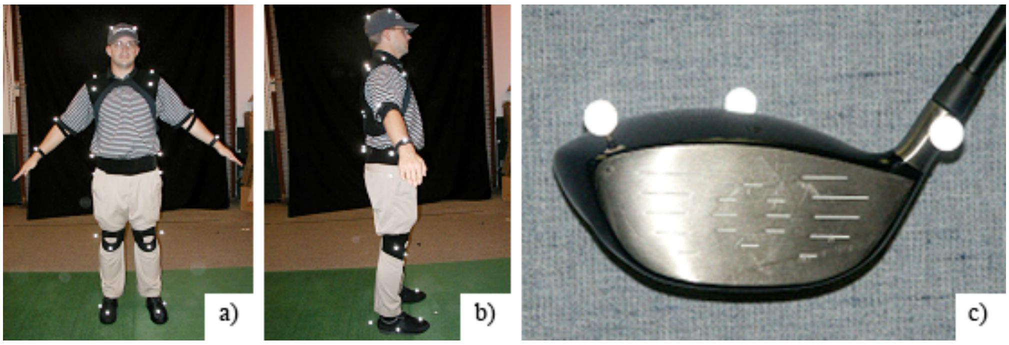

Fig. 1: Overview of the marker placement.

Using this system, TaylorMade has collected more than 500 000 swings in the last decade worldwide. For each swing, the positional data of each marker was collected. In order to be able to compare the data, each swing was segmented into its three basic phases: backswing, downswing and follow-through. Each phase was normalized to have 100 samples, resulting in 300 samples for each individual swing.

For feature development and initial classification experiments, two subsets of the originally collected swings were drawn using specific boundary conditions. *Subset one* consisted of 400 swings of 197 right-handed players. 195 players contributed one swing with a driver and one swing with a 6-iron to the data set, one player contributed two swings and one player contributed three swings using each club type. *Subset two* consisted of 1000 driver swings of 199 right-handed players. 198 players contributed five swings with the driver, one player contributed ten swings with the driver to the dataset. For every player, the individual handicap (0-30) at the time of data collection was available as meta information.

2.2. Features

We developed two sets of features. The first set could be used for the classification of *individual swing aspects* and the second set could be used for the classification of *individual player aspects*.

The set of features for the classification of individual swings can be further subdivided into features that are *specific to the club movement* (175 features, Tab. 1) and to features that are *specific to the human movement* (452 features, Tab. 2). A detailed description of these features is beyond the scope of this paper, a thorough discussion of all features can be found in [13].

The set of features for the classification of individual player aspects directly used the individual swing feature set and computed statistical features across all swings of one player. Specifically, we calculated the mean, variance, range, median, maximum and minimum value for all swings of one player. This feature set comprised of 1065 features specific to club movement and 2727 features specific to human movement.

In order to avoid problems during classification that were due to different ranges of the computed features [14], each individual feature was normalized to be in the range of [0, 1].

2.3. Classification

We conducted two classification experiments. The first classification experiment used the data from subset one and the feature set for the classification of individual swings. This experiment tested the ability of the employed classifiers to correctly distinguish between individual swings made with the two different club types (driver and 6-iron) that were present in the dataset.

Table 1: Overview of the club movement specific features.

Feature	Description
1-3	Timing [s]: takeaway, transition, impact, finish
4-9	Timing relations [1/1]: derived from features 1-3
10-14	Speeds [km/h]: impact, swing phases
15-18	Speed relations [1/1]: derived from features 10-14
19-24	Distances [m]: club butt at takeaway, transition, impact and finish
25-39	Distance relations [1/1]: derived from features 19-24
40-81	Distances [m]: maximum and minimum of the swing parts and relative positions
82-83	Distance relations [1/1]: derived from features 40-81
84-104	Distances [m]: sample pairs of the swing parts and relative positions
105-109	Distance relations [1/1]: derived from features 80-41 and 84-104
110-113	Angles [deg.]: different lines and planes defined by swing
114-117	Distances [m]: maximum of swing points to the planes defined by swing and relative positions
118-129	Tilts [deg.]: between different swing part planes and coordinate planes
130-147	Tilt relations [1/1]: derived from features 118-129
148-168	Shaft parameters [1/1]: derived from club droop, twist, kick and orientation
169-171	Sampling rates [1/s]: backswing, downswing and follow-through
172-175	Transition point [a.u.]: specific descriptors for duration, covered distance and velocities

Table 2: Overview of the human movement specific features.

Feature	Description
1-7	Distances [m]: hip positions at the swing events takeaway, transition, impact and follow through
8-28	Angles [deg.]: hip orientation at the swing events
29-142	Angle relations [1/1]: hip orientation at the swing events
143-158	Angles [deg.]: spine twist, forward bend, lateral bend and stretch at the swing events
159-202	Angle relations [1/1]: spine twist, forward bend, lateral bend and stretch at the swing events
203-216	Angles [deg.]: left and right knee flexion at the swing events
217-232	Angle relations [1/1]: left and right knee flexion values at the swing events
233-274	Angles [deg.]: left and right wrist radio/ulnar deviation, rotation and flexion at the swing events
275-322	Angle relations [1/1]: left and right wrist radio/ulnar deviation, rotation and flexion values at the swing events
323-364	Angles [deg.]: left and right shoulder transverse, sagittal and frontal rotation at the swing events
365-412	Angle relations [1/1]: left and right shoulder transverse, sagittal and frontal rotation values at the swing events
413-452	Angle relations [1/1]: hip, knee and shoulder angle relations at the swing events

The second classification experiment used the data from subset two and the feature set for the classification of individual player aspects. This experiment tested the ability of the employed classifiers to correctly distinguish between low handicap players (handicap $\leq$ 10, 107 players) and high handicap players (handicap > 10, 92 players).

We compared two classifiers in our experiments, a soft margin ($C = 1$) Support Vector Machine (SVM) with linear kernel [15] and a nearest neighbour (NN) classifier [14] with variable number of neighbours k. For the purpose of testing the results for generalizability we performed leave-one-player-out cross-validation.

3. Results

The results for the first experiment (club type) are listed in Table 3. The SVM performed always better than the k-NN classifier. The best result was obtained using only the club specific feature set and the SVM.

The results for the second experiment (handicap level) are listed in Table 4. The k-NN classifier only outperformed the SVM when using the club specific feature set. However, the best classification result was obtained when using only the human specific feature set and the SVM.

Table 3: Results for the first classification experiment. Reported are the mean classification rates.

Classifier	Club specific feature set	Human specific feature set	Combined feature set
SVM	**0.980**	0.923	0.958
k-NN	0.883	0.833	0.873

Table 4: Results for the second classification experiment. Reported are the mean classification rates.

Classifier	Club specific feature set	Human specific feature set	Combined feature set
SVM	0.704	**0.824**	0.799
k-NN	0.759	0.719	0.739

4. Discussion

This manuscript presents our first results in the development of a data driven pattern recognition approach that is capable of identifying those predictors of golf swing technique that are most relevant to performance improvement. The initial step in this process was to come up with a set of features that describe the kinematics of a golf swing in a way that differences in swing execution can be robustly classified.

We have developed such a feature set based on the worldwide unique golf swing database that TaylorMade has collected throughout the last decade. Using these features, we successfully conducted two classification experiments. The nature of the first experiment was rather academic, however our ability to distinguish club types with high accuracy showed the applicability of our feature sets to the differentiation of swing execution. When applying the player specific feature set derived from the swing specific feature set, we also showed our capability to differentiate low and high handicap players with good accuracy.

In both experiments, the SVM demonstrated its capability of obtaining good results when applied to kinematic data and mostly outperformed the *k*-NN classifier. This had been shown previously in other studies [16, 17]. A more surprising finding was that the club or human specific feature sets alone resulted in better classification rates than the combined feature set. This revealed that there existed a subspace of the combined feature space that is capable of discriminating groups even more accurately. We will use this result in the future and investigate by objective feature reduction techniques which combination of features leads to the best classification results. This will also be an important step for our intended goal of revealing which golf swing features are most performance relevant.

For this purpose, we will conduct classification experiments that use a higher number of datasets. While the TaylorMade database contains more than 500 000 swings, we have restricted ourselves to a subset of these swings in order to test efficiently so far. Since all results are cross-validated, we are confident that these result will generalize well [14] to data that were not included in our experiments. However, in order to come up with robust recommendations for golf club fitting and effective coaching advice for players, we will extend our experiment to more data. We are quite certain that the results of these experiments will lead to a better understanding of the performance relevant predictors of golf swing execution.

5. References

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