Sensor-based Instant Golf Putt Feedback

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Abstract. This paper presents a golf putt feedback system based on sensor data collected at the putter head. The system comprises of out-of-the-box body area network components that are lightweight, mobile and inexpensive. More specifically, we employ a SHIMMER™ sensor node with an inbuilt three-axis gyroscope and accelerometer for measurement and an Android™ smartphone for data analysis and presentation.
We collected data from five expert and six completely inexperienced subjects in order to facilitate the development of our algorithms. In a first step, we used a matched filter algorithm that enabled us to segment the unrestricted putting data into actual golf putts and other movements like training swings. In a second step, we analyzed the stroke phases in more depth in order to distinguish expert from inexperienced players. This was facilitated by extracting predefined movement parameters as a basis for explicit putt feedback.
Finally, we transferred the algorithms that were developed during an offline data analysis to an Android™ implementation. It is capable of detecting putts and displaying instant feedback to guide players to a better putt execution. Therefore, the system can be used as an innovative personal putting coach for real-world use.

Keywords: sensor data analysis, golf putt, coaching, SHIMMER™ sensor platform, Android™ app

1. Introduction

Putting is a crucial part of the golf game. It can be defined as the final approach played on low cut grass ("the green") to hole the ball in a rolling matter [1]. Statistics reveal that up to 40% of all golf strokes during tournament are putts [2]. Precise putt execution is therefore obligatory for good performance. In preparation of a successful putt, the golfer has to estimate the correct speed and direction given the green conditions. Subsequently, the golfer attempts to hit the ball with the planned speed and putter head orientation to ensure optimal impulse transfer. In this process, instant objective feedback about the putt execution could help coaches and players to improve performance.

Although being such a crucial part of the game, golf putting has not received as much research attention as golf swings. While kinematic and biomechanical aspects of the putting movement are well studied [3,4], efficient direct feedback applications are still not much addressed in the literature. Different authors investigated putting kinetics and kinematics using camera-based body and golf club tracking and pressure mat data [3,5]. However, such systems are stationary and therefore not ideally suited to give instant feedback. Fortunately, the proceeding miniaturization of MEMS sensors and the increasing computational power of embedded microcontrollers opened up new possibilities for mobile motion analysis. Several groups [1,6] are currently working on a golf-training device with low-cost sensors integrated in the club shaft and have already shown the applicability of these devices.

In contrast to these studies, our research focused on the analysis of the putter head kinematics by using an external sensor that could, in principle, be fixed to any putter. This data recording system is highly mobile, easy to use and independent of the type of putter the golfer uses. By wirelessly transmitting the collected data to a smartphone and running our analysis algorithms on it, we were capable of realizing a mobile coaching system based on the collected sensor data. The system gives instant feedback to the golfer on the basis of every single putt execution. The purpose of this paper is to report the status of our current development and to give an outlook of our intended future directions.

2. Methods

2.1. Swing model

We used the swing model, swing part nomenclature and axis definition as illustrated in Fig. 1. The main movement axes were the gyroscope y-axis and the accelerometer x-axis. The optimal impact position was the following. The putter head face had to be perpendicular to the floor plane (zero loft angle), the putt direction matched the planned playing direction (zero face angle) and the head plane was parallel to the floor plane (zero lie angle). Beside these impact parameters, we used additional kinematic features described in the literature [1,3,7] to assess the quality of the putting movement from various distances.

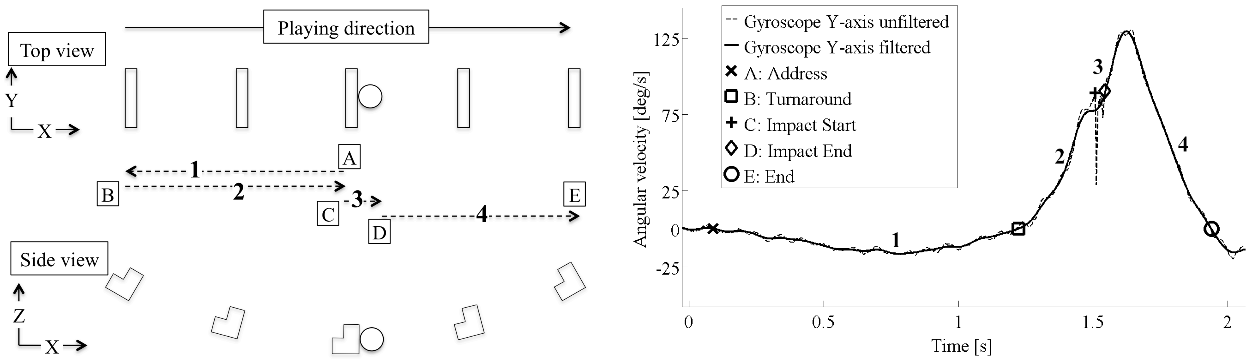

Fig. 1: Left: schematic view of a golf putt. Adapted from [1]. Right: gyroscope Y-axis data view. Swing phases: 1: backswing, 2: forward swing, 3: impact and 4: follow-through.

2.2. Mobile research platform

Our putt coaching system built up on a research platform that we are using for mobile body area network applications. It consisted of SHIMMER™ sensor nodes [8] and an Android™-based HTC Legend smartphone (HTC Corporation, Taoyuan, Taiwan).

We used the gyroscope sensor module and the on-board accelerometer of the SHIMMER™ nodes in our study. Three-axis gyroscope data with a range of ±500 deg/s and three-axis accelerometer data with a range of ±1.5 g from a single sensor node mounted on top the golf club head was recorded with a frequency of 250 Hz and transmitted via Bluetooth radio.

We implemented our coaching software engine on a HTC Legend smartphone that ran Android™ Version 2.1 on a MSM7227 microprocessor (600 MHz) with 512 MB main memory. The resulting app was based on a communication software that was developed within our research group [9].

2.3. Data collection

We collected data from eleven subjects (1 female, 10 male) that were either experienced golfers (n=5) or completely unexperienced (n=6). One participant was a professional golfer. After individually warming up, each subject performed five consecutive putts from three different distances labelled as short (1m), mid (3m) and long (5m) on an even training green at the Golf Club Herzogenaurach, Germany. The subjects were not restricted to any behaviour or technique. We recorded the whole sequence of putts including training swings without hitting the ball and arbitrary movements. Each subject started the experiment with the shortest distance and finished with the longest. The experiment was then repeated with a variation in either the golf club or the ball.

We used two mallet type putters, the TaylorMade™ (TaylorMade Inc. Carlsbad, USA) Spider and the Pro Ace™ (Pro Ace Ltd., London, UK) 20704. As golf balls, the TaylorMade™ Noodle Longest and Burner LDP were used. The variation was arbitrarily chosen and delivered two data sets of 15 putts for each subject. Three blocks of five putts were missing due to sensor malfunction so that we recorded 315 putts overall. Each actual putt was marked in the data set by an external manual trigger for segmentation validation.

2.4. Preprocessing and initial segmentation

The aim of this step was to extract stroke candidates and determine two major swing phases as defined in our swing model. As a preprocessing step, we applied a low-pass Butterworth filter of order 3 with a cut-off frequency of 8 Hz. The following two-step algorithm is based on the filtered data.

First, we implemented a matched filter algorithm to roughly segment the signal in stroke candidates and other signals. In this approach, a template is correlated with a given signal to check for the presence of this template. Equation 1 shows the computation of the correlation value C for an M-dimensional signal $\boldsymbol{x}$ and the M-dimensional template $\boldsymbol{b}$ of length N. The factors α_k scale each dimension for their contribution to the correlation value. The main movement axes of a golf putt contributed to the correlation in our algorithm. We calculated a template out of the ten short distance strokes of the professional golfer and reversed the resulting template to align the signals for the above-mentioned computation. The scaling factors were used to adjust the different value ranges of the axes. The resulting C value was used together with an empirical threshold that was set by observation to identify a set of stroke candidates.

$$C = \sum_{k=1}^{M} \alpha_k \sum_{i=1}^{N} \boldsymbol{x}(t-i) \cdot \boldsymbol{b}(i) \tag{1}$$

Second, we determined the major swing phases in these candidates. They were the backswing (BS) phase on the one hand and the combined forward swing (FS), impact (IP) and follow-through (FT) phase on the other hand. The instants of time that border these two phases were zero-crossings in the gyroscope y-axis data (Fig. 1, right).

2.5. False stroke elimination and stroke segmentation

We eliminated false stroke detections based on the stroke candidates and their corresponding stroke phases from the previous step. We used a two-stage approach including a plausibility analysis of timing and rotation speed and an impact check.

In a first step, the plausibility analysis regarded the temporal ratio of BS to FS/IP/FT and the ratio of minimal backward to maximal forward rotation speed. The temporal ratio was based on typical putt timing from [1] while the rotation speed ratio was chosen to eliminate pendulum movements that violate our swing model. Strokes that did not fit in the predefined bounds were excluded from further analysis.

In a second step, candidate strokes without a distinct high-frequency signal characterizing an impact event were excluded. In contrast to the previous segmentation stages, the unfiltered data was used. We created a characteristic pattern by analyzing the impact of all labelled FS/IP/FT phases. Our algorithm then searched the candidate stroke swing phases for this pattern. On absence of the pattern, the stroke was rejected from further analysis. Otherwise, the stroke was further segmented in forward swing, impact and follow-through. The impact duration was set to a constant value using typical stroke timing [1].

Table 1: Overview of features computed for each golf putt

Number	Description	Number	Description
1	Duration of BS	17	BS rotation angle
2	Duration of FS	18	FS rotation angle
3	Duration of BS and FS	19	FT rotation angle
4	Duration of FT	20	Ratio of FS rotation angle to FT rotation angle
5	Temporal ratio of FS to FT	21	Acceleration change in pre impact phase of accelerometer x-axis
6	Temporal ratio of BS to FS	22	Acceleration change in post impact phase of accelerometer x-axis
7	Duration of stroke	23	Rotation velocity of gyro y-axis at impact
8-10	Summed rotation in BS and FS phase of gyro x-, y- and z-axis	24	Horizontal velocity of accelerometer x-axis at impact
11-13	Summed rotation in pre impact phase of gyro x-, y- and z-axis	25-26	Acceleration maximum (x-axis) in FS (position, value)
14-16	Summed rotation in post impact phase of gyro x-, y- and z-axis	27-28	Velocity maximum (x-axis) in FS (position, value)

2.6. Feature extraction

The coaching feedback we provided is based on putt parameters. Our literature research revealed various parameters that characterize correct putts and also describe kinematic findings that distinguish expert from novice players. We built a set of 28 features (Tab. 1) that were computed for each putt. We defined the pre- and post-impact phases as ¼ of the forward swing and the follow-through, respectively.

2.7. Coaching advices and putt score

We gathered a set of eight coaching advices as putt feedback. Therefore, we analyzed the distribution of different parameter values and combined these findings with expert knowledge and our stroke model assumptions. See Tab. 2 for an overview.

Beside the textual feedback, we introduced an overall putt score based on the coaching advice computation. Perfect fulfilment of an aspect results in two points and partial completion in one point. 16 points could be reached for a stroke in total.

2.8. Implementation

The presented algorithms were implemented in a Matlab™ (The Mathwork Inc., Natick, USA) prototype. They served as the basis for porting the algorithms to Java software running on the device described above.

3. Results

The developed segmentation algorithm reached a false detection rate of 1%. The misdetections appeared in the shortest distance experiment parts. These patterns were manually excluded from further analysis. All stroke phases were recognized correctly according to our stroke model.

We analyzed the mean score for the two population groups for all distances. The mean score was 13.4 (± 2.4) for the experienced golfers and 11.4 (± 2.4) for the unexperienced subjects. The professional golfer reached the full score for every putt performed.

The Android™ app proved to run on the target device. The device displayed the coaching advices, the score, the backswing rotation angle and the horizontal impact speed of a detected putt.

Table 2: List of possible single-stroke coaching advices and related features

Advice	Features	Advice	Features
Stroke with a larger follow-through!	20	Face plane not perpendicular to the ground!	9
At impact: slide the putter head and stir more vertical!	27	Strike the ball with putter head plane parallel to the ground!	8
Do not decelerate in the forward swing!	23	Do not twist the club just before impact!	11,13
Face plane not perpendicular to stroke path!	10	Do not twist the club just after impact!	14,16

4. Discussion

The matched filter approach proved to be appropriate for detecting strokes. The fact that a single template was sufficient for detecting strokes from various distances resulted in a moderate computational complexity suitable for a mobile device with limited computational power. Visual inspection revealed that the three misdetections were random movements generating a putt like pattern and only appeared in low-distance putts. Hence, the algorithm might be capable of handling putts from higher distances without or with only minor changes.

Inertial sensors can determine relative position data at rest based on the earth's gravity field. A proper golf putt address includes a resting position with zero lie, loft and face angle. However, the study participants were absolutely free in their accomplishment and did not start in the assumed address position. The relative impact angles were therefore determined indirectly due to the motion nature in both address and impact.

The feedback in textual form delivered specific advices for golf putt improvement. This coaching regarded the putt execution and was independent from stroke distance. The provided score was an easy tool to estimate the quality of the putt and proved to distinguish unexperienced from experienced subjects. The golfer is also able to train repeatability with the displayed backswing angle and impact velocity output.

The system we developed is based on lightweight, inexpensive and commercially available hardware components. The sensor node can easily be mounted on different kinds of putters and the smartphone fits in a pocket or golf bag. Therefore, our training system is usable for multi-player and outdoor use, can be mounted on different putters and easily be controlled with a touch screen.

5. Outlook

So far, the differences of experienced and completely unexperienced golfers were investigated. A stroke model and the knowledge of experts guided this process. The authors are planning a data-driven evaluation of differences in putt execution between experiences and unexperienced players. Therefore, we will use pattern recognition methods based on the presented features. Together with a feature reduction approach, this could deliver a data view on the main differences in stroke execution.

We also collected data about the final position of the golf ball after stroke execution during the experiments. Correlating stroke execution parameters and stroke result will also be highly interesting.

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7. References

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