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An IMU-based Mobile System for Golf Putt Analysis

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Abstract A mobile system for real-time golf putt analysis and augmented feedback is of high interest for technique training and research. Recently, instrumented golf clubs comprising inertial measurement units (IMU) were introduced as a suitable modality for mobile putt analysis. The high level of sensor integration and its mobile nature enable the unobtrusive and mobile collection of a high amount of data. We developed such a mobile analysis system with feedback capabilities using off-the-shelf components with a removable sensor. The main features are an automatic putt detection with machine learning methods and the real-time parameter calculation in the club coordinate system.

In a validation study, the system detected more than 83% of the putts for 8 out of 11 subjects while maintaining a false positive rate of 2.4%. Thus, it is a suitable tool to analyze putting strokes in real-time and enables feedback intervention applications. As an application example for research, the collected kinematic data of eight players (1946 putts) were used to analyze training progress. Compared to the common analysis of expert and novice differences, the presented results provide a first insight in the motor learning path of inexperienced golfers.

In principle, the presented system can be used to realize mobile data analysis systems for various sports disciplines beyond golf putting. It furthermore provides an innovative tool to analyze motor learning processes in more detail.

Keywords inertial measurement unit · wearable computing · golf putting · motor learning

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1 Introduction

Inertial sensor technology is a promising modality for mobile and ubiquitous computing in sports [1]. Inertial measurement units (IMU) are small, non-stationary and wireless so that they facilitate fully integrated or wearable systems. Due to their mobile nature (e.g. form factor, long runtime), IMUs are capable of addressing the undersampling problem [2]. In medicine, this problem describes the fact that the a doctor's visit can only provide a snapshot of the disease progress. Likewise in sports, a limited number of trials might not represent the true athletic or biomechanical performance. Wearable inertial systems enable data collection in the field and facilitate real-time performance measurement.

Putting is a major part of the golf game and accounts for about 40% of strokes [3]. Putts are performed as the final stroke on the green and require a precise and controlled movement execution. Different aspects like green reading, putter geometry and movement execution determine putt distance and direction accuracy and therefore the outcome of the putt [4]. Coaches especially struggle to completely assess the movement solely by visual inspection due to the precise nature of the putting movement, individual technique variations [5] and the high number of parameters that determine the success of the putt [6]. Biomechanical analysis is needed to understand the key aspects of putting and meaningful quantitative measures are needed for efficient coaching and training.

Multiple studies have investigated the differences between novices and experts in putting and therefore tried to elicit its key aspects [7,8]. Special emphasis has been put on the organization of motor learning. Thereby, the question of how movement variability changes with practice and how novices progress with training was raised [8]. Beside the outcome of a learning process, researchers are also interested in the learning path. However, as video processing is labour intensive, the analysis of large datasets representing the training progress is a challenging task.

For some research questions, environments were restricted to control the influencing factors (e. g. [7,9,10]). However, as sports are not performed in a lab, a mobile analysis setup is needed to assess putting technique in the field and therefore during training routine. Furthermore, real-time analysis is required if augmented feedback should be provided within the training routine. Thereby, the immediate availability of the analysis is a crucial aspect for augmented feedback systems.

Such functionalities are offered by various commercial systems like SAM PuttLab^{TM} (Science&Motion, Rüsselsheim, Germany) [6]. Drawbacks are the sensitivity to loud noise and wind, and limited mobility, as the system comprises sender, receiver and laptop. Alternatively, the TOMI^{TM} system (Pure Motion Inc., Southlake, USA) based on infrared light has been proposed [11]. It also consists of sender, receiver and laptop for analysis.

The design of a fully integrated measurement system in the club shaft and the corresponding data analysis were presented [12]. Alternatively, Burchfield et al. developed a removable sensor system with more advanced club tracking using a Kalman Filter [13]. Both sensor systems included wireless transmission capabilities but processed data offline so that the feedback loop was not closed. A coaching application to optimize putt tempo based on gyroscope data analysis was developed [14]. Augmented feedback was given with a PC interface and therefore restricted coaching to the lab environment.

The purpose of this article is to introduce an alternative approach for a pervasive real-time golf putt data analysis system. One applications for such a system is feedback training in the field. The presented system provided automatic real-time analysis up to putt parameter level. This is an important building block that augmented real-time feedback applications can be based on. Our system collected a large amount of data with low effort and therefore facilitated training progress analysis. We present such an analysis for the purpose of motor learning research. Thereby, the kinematic progress of subjects in a repetitive training intervention was analyzed.

2 Methods

The methods section comprises four parts. First, system hardware is presented. Second, we introduce the data processing pipeline that consists of data calibration and transformation, putt detection and kinematic parameter extraction. Third, data collection is described. Fourth, we describe how putt detection and training progress were evaluated.

2.1 System Hardware

The presented mobile golf putt system consists of an IMU for data collection and wireless transmission as well as a mobile Android^{TM} device (Google Inc., Mountain View, USA) for data analysis and user feedback (Fig. 1).

2.1.1 Inertial Measurement Unit

We used Shimmer^{TM} 2R sensor nodes (Shimmer, Dublin, Ireland) [15] for data collection. They were equipped with the BTStream firmware (Version 1.2) that was provided by the manufacturer. One single sensor was mounted on the club head to collect 3-D accelerometer (range: $\pm$ 1.5 g) and 3-D gyroscope (range: $\pm$ 500 °/s) data. The sensor sampled data at 256 Hz and transmitted data wirelessly via Bluetooth to facilitate a real-time motion tracking. The club-mounted sensor had a form factor of 53 mm $\times$ 32 mm $\times$ 25 mm (height $\times$ width $\times$ depth) and a mass of 22 g including disclosure. The runtime was several hours when fully charged.

2.1.2 Analysis and Feedback Device

An Asus Nexus 7C (Asus Inc., Taipeh, Taiwan) was used as a mobile analysis and feedback device. We developed a custom application that received 6-D motion data from the sensor node and was capable of processing them in real-time. The application was based on the Shimmer Android Driver Library (Version 1.3) provided by the sensor manufacturer and can in general run on every Android^{TM} device.

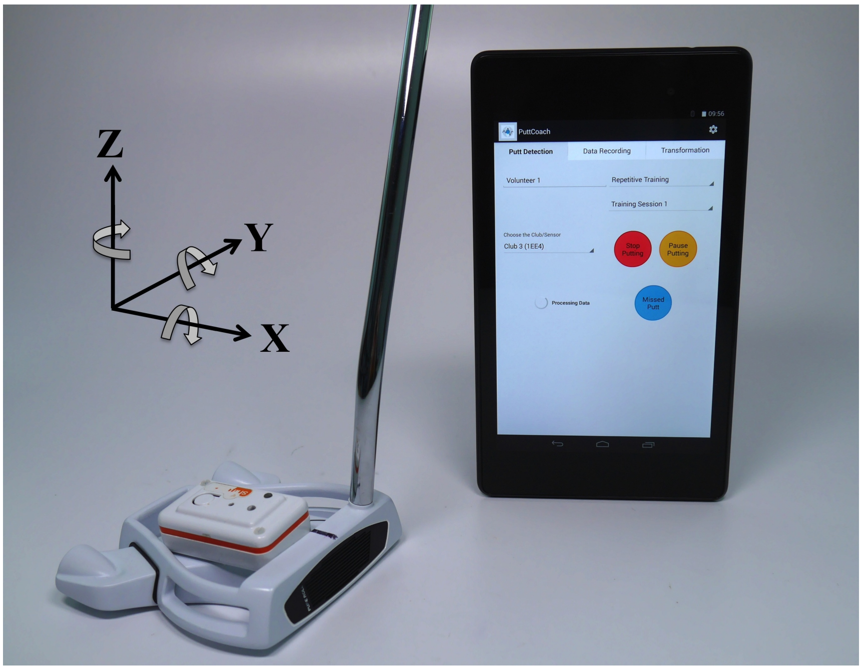

Fig. 1 The mobile golf putt analysis system comprising a club head mounted Shimmer™ IMU and an Android™ tablet for data analysis. The club coordinate system (accelerometer) and the turning axes (gyroscope) are shown.

2.2 Data Processing Pipeline

The data processing pipeline comprised four steps.

1. Sensor data calibration and transformation
2. Putt detection
3. Putt parameters extraction
4. Data logging

2.2.1 Sensor Data Calibration and Transformation

The sensor calibration parameters were determined with the 9DOF Calibration Software (Version 2.3) provided by the manufacturer. This tool implements the calibration procedure as described by Ferraris et al. [16]. The parameters were stored on the sensor node and used to convert raw analog digital converter (ADC) values to acceleration (m/s^2) and angular velocity (°/s) values within the analysis application.

IMU data were transformed to the club head coordinate system for further processing [17]. We used the Direction Cosine Matrix (DCM) $\mathbf{T}_{\mathrm{DCM}}$ to transform a vector $\mathbf{v}_{\mathrm{IMU}}$ to $\mathbf{v}_{\mathrm{CLUB}}$ as

$$\mathbf{v}_{\mathrm{CLUB}} = \mathbf{T}_{\mathrm{DCM}} \cdot \mathbf{v}_{\mathrm{IMU}} \tag{1}$$

Thereby, $\mathbf{v}_{\mathrm{IMU}}$ denoted the raw sensor recording and $\mathbf{v}_{\mathrm{CLUB}}$ the same recording transformed to the club head coordinate system. The transformation matrix $\mathbf{T}_{\mathrm{DCM}}$ was computed with

$$\mathbf{T}_{\mathrm{DCM}} = \begin{pmatrix} \mathbf{x}_{\mathrm{IMU}} \cdot \mathbf{x}_{\mathrm{DEF}} & \mathbf{y}_{\mathrm{IMU}} \cdot \mathbf{x}_{\mathrm{DEF}} & \mathbf{z}_{\mathrm{IMU}} \cdot \mathbf{x}_{\mathrm{DEF}} \\ \mathbf{x}_{\mathrm{IMU}} \cdot \mathbf{y}_{\mathrm{DEF}} & \mathbf{y}_{\mathrm{IMU}} \cdot \mathbf{y}_{\mathrm{DEF}} & \mathbf{z}_{\mathrm{IMU}} \cdot \mathbf{y}_{\mathrm{DEF}} \\ \mathbf{x}_{\mathrm{IMU}} \cdot \mathbf{z}_{\mathrm{DEF}} & \mathbf{y}_{\mathrm{IMU}} \cdot \mathbf{z}_{\mathrm{DEF}} & \mathbf{z}_{\mathrm{IMU}} \cdot \mathbf{z}_{\mathrm{DEF}} \end{pmatrix} \tag{2}$$

It was computed from the sensor coordinate system with base vectors $\mathbf{x}_{\mathrm{IMU}}$, $\mathbf{y}_{\mathrm{IMU}}$, $\mathbf{z}_{\mathrm{IMU}}$ and an arbitrarily defined club coordinate system with base vectors $\mathbf{x}_{\mathrm{DEF}}$, $\mathbf{y}_{\mathrm{DEF}}$, $\mathbf{z}_{\mathrm{DEF}}$. We defined the club head coordinate system as follows. The x-axis was pointing in playing direction, the y-axis was pointing to the player and the z-axis was pointing vertically upwards (Fig. 1). The sensor coordinate system had to be determined in relation to the club coordinate system. It depended on the sensor mounting and was determined by the measurements $\mathbf{z}_{\mathrm{REC}}$ and $\mathbf{x}_{\mathrm{REC}}$. Therefore, a watermark was leveled on top of the club ($\mathbf{z}_{\mathrm{REC}}$) and on the club face ($\mathbf{x}_{\mathrm{REC}}$) as reference to the club coordinate system. The 3-D recording of $\mathbf{z}_{\mathrm{REC}}$ was directly used as base vector $\mathbf{z}_{\mathrm{IMU}}$:

$$\mathbf{z}_{\mathrm{IMU}} = \mathbf{z}_{\mathrm{REC}} \tag{3}$$

As the club top and face were not necessarily perpendicular, the base vector $\mathbf{y}_{\mathrm{IMU}}$ was defined as

$$\mathbf{y}_{\mathrm{IMU}} = \mathbf{z}_{\mathrm{REC}} \times \mathbf{x}_{\mathrm{REC}} \tag{4}$$

Thereby, the cross of the two 3-D recordings $\mathbf{z}_{\mathrm{REC}}$ and $\mathbf{x}_{\mathrm{REC}}$ was used. The remaining axis $\mathbf{x}_{\mathrm{IMU}}$ was computed

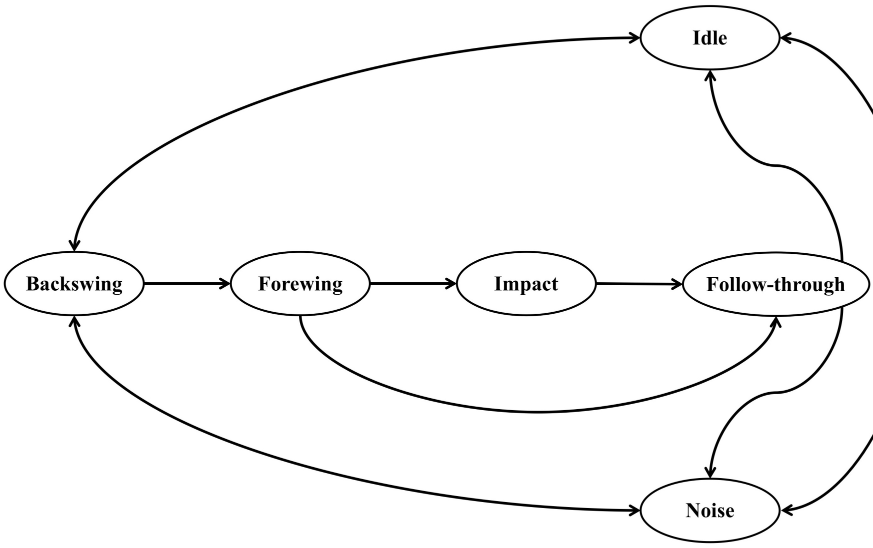

Fig. 2 Simplified Hidden Markov Model for putt detection. States are illustrated as circles and state transitions as arrows. Transitions to the same state (present in every state) are omitted for better readability. The sequence models training swings as well as actual putts with the state transition from foreswing to follow-through.

as cross product of the previously defined sensor coordinate base vectors using

$$\mathbf{x}_{\mathrm{IMU}} = \mathbf{y}_{\mathrm{IMU}} \times \mathbf{z}_{\mathrm{IMU}} \tag{5}$$

Due to the transformation to the club head coordinate system, the sensor can be arbitrarily mounted (e.g. according to the club geometry) to determine the transformation matrix $\mathbf{T}_{\mathrm{DCM}}$. The described procedure has to be repeated if the position changes (e.g. charging, playing without sensor) and was therefore integrated in the analysis application.

2.2.2 Putt Detection

The putt detection consisted of two steps. First, a Hidden Markov Model (HMM) was used to detect putt candidates. Second, an AdaBoost (AB) classifier analyzed putt candidates in more detail for final event detection.

Putt Candidate Detection. HMMs are a common supervised learning technique to analyze sequential data [18,19]. They were mainly applied in speech processing applications [18] and can also be used for the analysis of kinematic data, see for example [20]. We used HMMs to model the phase sequence of a golf putt, detect putt candidates and extract their phase lengths for actual putt classification.

Our model comprised the four putt phases backswing (BS), foreswing (also: forward swing, downswing) (FS), impact (IM) and follow-through (FT). Additionally, we modeled arbitrary movements of the club head with a idle and noise phase (Fig. 2). This supported the analysis in detecting putts without being triggered by the user.

The HMM sequence comprised a state transition from FS to FT as well as a transition from FS to IM. Thus, actual putts containing an impact and training swings (no impact) were modeled. Idle and noise states could be reached from BS or FT to restrict the model for improved detection performance.

Data in training and evaluation phase were processed in a sliding window approach. We set the window size to 500 samples (1.95 s) with 50% overlap to fit a complete putt in one window [13]. The model was trained on labeled training data with the Baum-Welch-Algorithm [18]. We followed existing models for the putt phases labeling (BS, FS, IM and FT) [13,14]. If the main rotational axis (gyroscope y-axis) was below a threshold of 10 °/s, the remaining data were labeled as idle. Above the threshold, data were labeled as noise. All phases were modeled as multivariate Gaussian distributions. The evaluation was performed with the Viterbi-Algorithm [18]. Each sequence that comprised an IM phase was considered as putt candidate. If the impact event was at the border of the window, we repositioned the window accordingly and reran the state sequence determination. Finally, we computed the duration of the putt phases (BS, FS, IM, FT) and the overall putt length for final event detection.

Putt Candidate Classification. A putt candidate found with the HMM was either an actual putt or a misdetected putt. These misdetections were e.g. training swings with a misdetected impact but also ar-

Table 1 Overview of the complete putt parameter set P1 - P31 with axes used and parameter interpretation. Accelerometer axes are abbreviated with A-X, A-Y and A-Z and gyroscope axis with G-X, G-Y, G-Z. Swing phases are abbreviated with BS (backswing), FS (foreswing), IM (impact) and FT (follow-through).

Number	Axes	Description	Unit
P1	G-Y	Duration of putt	s
P2-P5	G-Y	Duration of BS, FS, IM and FT	s
P6	G-Y	Duration of swing (BS + FS)	s
P7	G-Y	Ratio of BS duration to FS duration	AU
P8	G-Y	Ratio of FS duration to FT duration	AU
P9-P10	A-X, A-Y, A-Z	Lie and loft angle at impact, average of 5 samples (~78 ms) before impact	°
P11-P13	G-X, G-Y, G-Z	Summed angle of BS and FS, computed for each axis separately	°
P14-P16	G-X, G-Y, G-Z	Summed angle of phase before IM, phase length of 20 samples (~78 ms)	°
P17-P19	G-X, G-Y, G-Z	Summed angle of phase after IM, phase length of 20 samples (~78 ms)	°
P20-P22	G-Y	BS, FS and FT angle	°
P23	G-Y	Ratio of FS angle to FT angle	AU
P24	A-X	Linear velocity at impact	m/s
P25	G-Y	Angular velocity at impact	°/s
P26	A-X	Summed acceleration of phase before IM, phase length of 20 samples (~78 ms)	m/s^2
P27	A-X	Summed acceleration of phase after IM, phase length of 20 samples (~78 ms)	m/s^2
P28	A-X	Maximum acceleration value in FS	m/s^2
P29	A-X	Maximum acceleration position in FS	% of FS
P30	A-X	Maximum velocity value in FS	m/s
P31	A-X	Maximum velocity position in FS	% of FS

bitrary movements. We used a classification algorithm to exclude these misdetections from further processing.

A classifier, often a mathematical function, is able to identify the category (or class) of a given instance (or pattern) based on a trained model. In the specific case of putt candidate classification, the classifier distinguished between two categories:

1. PUTT: actual putt
2. OTHER: no putt

The classified instances were HMM putt candidates represented with five dimensions (or features). These dimensions were the putt phase lengths of BS, FS, IM, FT and the complete putt in number of samples as returned from the HMM analysis.

Our analysis used a nonlinear AdaBoost classifier. AdaBoost combines a set of weak classifiers to an overall strong decision function [21]. The classifier was trained using the implementation of the Weka software with decision stumps as weak classifier [22]. Other classifiers like artificial neural networks and support vector machines were also tested and reached comparable or lower results.

2.2.3 Putt Parameter Extraction

Detected putts that were confirmed by classification were further processed. We segmented the movement into putt phases, filtered the data and extracted kinematic parameters. The determination of the lie and loft angle is explained in more detail.

Putt Phase Determination and Filtering. The putt phase determination was initialized at the impact phase determined by the HMM analysis. The remaining HMM phase information was discarded as it was found to be error prone. Instead, we used a putt model based on zero crossings of the main rotational axis (gyroscope y-axis) [13, 14]. Additionally, we segmented the impact phase with a threshold approach. Therefore, we computed the squared differences of two subsequent values of the gyroscope y-axis. The minimum of these values in the model creation data was used as threshold and all values above the threshold were assigned to impact phase in detection mode. For further processing, data were filtered with a moving average filter (order 5) to remove high-frequency noise in the kinematic data.

Parameter Extraction. We selected 31 kinematic parameters that can be extracted from the 6-D IMU data (Tab. 1) and were previously described [7, 8, 10, 12, 13]. The selection criterion was that parameters could be implemented with the use of 6-D club head motion data in at most one integration step. Integration of IMU data is affected by drift and error accumulates in repeated integration. Due to this fact, we extracted angles and linear velocities (single integration) and omitted linear displacements (double integration). Error is expected to be low due to short integration times as putts are typically shorter than 2 s [13]. The parameters were categorized in:

1. Phase length and ratios of phase lengths (P1 - P8)
2. Angles and ratios of angles (P9 - P23)
3. Velocity (angular and linear) at impact (P24 - P25)

4. Summed acceleration around impact (P26 - P27)
5. Velocity and acceleration profile in FS (P28 - P31)

For some parameters, an optimal value was described (e.g. P7 [14]). The optimal value for other parameters was defined qualitatively (e.g. P26 [13]). The literature also revealed parameters that reflect the skill level without describing a specific optimal value (e.g. P1 [8]). Further, optimal values for putts from a specific distance (4 m) were deduced from a group of professional players (e.g. P2 [6]). These examples underline that the optimal value for most of the parameters cannot be explicitly and universally defined. Furthermore, optimal values may differ for different techniques and individuals.

Lie and loft angle computation. The lie and the loft angle could not be determined with gyroscope integration and will therefore be described in more detail. These angles described the club orientation at ball impact. We defined a negative lie angle as a rotation in direction of the gyroscope x-axis (arrow direction, Fig. 1). A negative loft angle was defined as a rotation in direction of the gyroscope y-axis (arrow direction, Fig. 1). As the club coordinate system was created according to a zero lie and loft angle orientation of the club head, we used the base vectors and the planes that they define to define lie and loft angle. Thereby, we neglected the movement acceleration before impact by normalizing the measurements to 1 g. The angles were computed as projections in the y-z plane (lie angle) and x-z plane (loft angle). Noise artifacts were reduced with averaging five angle values (~19.5 ms) before impact.

Data logging. The application provided two modes, data collection and data processing. The data collection mode logged 6-D raw data to a file. The processing mode ran the complete processing pipeline as described and saved the extracted parameters to a file. File names were encoded with meta data like the subject ID and the training session number that were input prior to starting the data collection (Fig. 1). Both modes required to run the transformation functionality before collecting data (see sec. 2.2.1).

2.3 Data Collection

We conducted two research studies. Study one collected data for algorithm development and model creation; study two was used to evaluate the putt detection performance on a different population than study one. Further, it was used to assess training progress that represents a learning path. The data collection was approved by the university ethics committee that gave written consent under reference 106_13B.

Table 2 Overview of the data collection protocol in the TRAINING study. All putts were performed from a distance of 3 m to the hole. Transfer tests were performed on a different surface. Collected data were abbreviated with kinematic (KIN), hit count (HC) and distance (DIST).

Week	Name	# Putts	Collected data
1	Pre Test	10	KIN, HC, DIST
2	Training 1	36	KIN
2	Training 2	36	KIN
3	Training 3	36	KIN
3	Training 4	36	KIN
4	Training 5	36	KIN
4	Training 6	36	KIN
5	Training 7	36	KIN
5	Training 8	36	KIN
6	Post Test	10	KIN, HC, DIST
6	Transfer Test 1	10	KIN, HC, DIST
7	Retention Test 1	10	KIN, HC, DIST
7	Transfer Test 2	10	KIN, HC, DIST
9	Retention Test 2	10	KIN, HC, DIST
9	Transfer Test 3	10	KIN, HC, DIST

2.3.1 Model Creation Study (MODEL)

This study contained 15 subjects that were completely inexperienced golfers. The study used the data collection mode of the mobile application. The protocol comprised three putts from three different distances (1.5 m, 3 m, 5 m) with two different putters. The clubs were a TaylorMade™ Manta (TaylorMade Inc., Carlsbad, USA) and a Pro Ace™ 20704 (Pro Ace Ltd., London, UK). Subjects received a basic introduction to the putting movement (grip positioning, putt phases, pendulum movement) but no coaching. Data were collected on an artificial putting green and subjects performed one training swing before each putt. Overall, 272 putts and the same amount of training swings were collected. The collected data were used to train the model for putt detection (HMM) and putt candidate classification (AdaBoost) as well as the threshold for detecting the impact phase.

2.3.2 Evaluation and Training Study (TRAINING)

The system was used to assess putt detection performance and the effects of motor learning in repetitive learning. The study used the data processing mode of the mobile application. Therefore, 11 subjects that were completely inexperienced golfers were recruited to perform putts on an artificial putting green. Their training comprised repetitive putting from the same distance without further coaching.

The putt length was 3 m and a TaylorMade™ Ghost Spider (TaylorMade Inc., Carlsbad, USA) was used. The protocol consisted of pre test, training sessions, post test, retention tests and transfer tests (Tab. 2). The pre and post test assessed the performance right before and after training intervention. The training sessions comprised repetitive training twice a week from the same distance. The transfer tests were performed after training intervention on a different surface to assess transfer capabilities. Retention tests were conducted after training intervention to test persistence of motor learning. Subjects were free to perform training swings prior to the putt and received a short introduction before pre test but no additional coaching afterwards.

For each detected putt, the automatically computed kinematic parameters were logged. If a putt was not detected, the study advisor logged a corresponding entry. Undetected putts were not repeated. The advisor also had the possibility to log misdetected putts. This was done each time the system displayed a detection although the subject did not perform a putt. In addition to the kinematic parameters, the ratio of putts holed (hit count) and the distance from the hole were collected in each test session (not used here) and subjects were videotaped. Data collection comprised 358 putts for each subject. Subject 5 missed training session 8 due to illness. Thus, 3902 putts were performed throughout the TRAINING study.

2.4 Evaluation

We evaluated the system regarding putt detection and analyzed the training progress during repetitive training. Results were drawn from the TRAINING dataset.

2.4.1 Putt Detection

The putt detection was evaluated with the detection rate and false positive rate. The detection rate was calculated as

$$\mathrm{DR} = \frac{N_d}{N_p} \tag{6}$$

Thereby, N_d denotes the number of detected putts and N_p the number of performed putts. An overall detection rate as well as the individual rate for each subject was calculated.

The false positive rate reflects the performance regarding misdetections and was calculated as

$$\mathrm{FPR} = \frac{N_m}{N_m + N_p} \tag{7}$$

Thereby, N_m denotes the number of misdetected putts and N_p the number of performed putts.

2.4.2 Training Progress in Motor Learning

We analyzed the eight training sessions to provide an insight in the training progress of novices. We were interested in

1. The change of putting performance
2. Kinematic parameters representing training progress
3. The change of these parameters during training

The putting performance was measured with the hit count as

$$\mathrm{HC} = \frac{N_h}{N_p} \tag{8}$$

Thereby, N_h denotes the number of holed putts and N_p the number of performed putts. Data from all subjects was combined. The hit count was computed in the pre test and in the post test.

The intervention in the TRAINING study was repetitive training without specific coaching or feedback. The target for the subjects was to improve their hit count. In terms of knowledge of results, the subjects were able to see whether they holed the putt or not. Our analysis intended to reveal the presence and the type of the kinematic parameter change with repetitive training. Thus, we were primarily not interested in the actual parameter values but their progression over time. The training progress was not influenced by a coach and not evaluated for success. The presented analysis therefore observed the training progress instead of evaluating it. We chose a data driven evaluation to describe the change of kinematic parameters and therefore the training progress. This means that we selected and analyzed the change of the parameters without taking expected or predefined training outcome regarding kinematic changes into account.

The training progress was analyzed with data from training 1 to training 8. Pre, post, retention and transfer tests were intentionally excluded from the training progress analysis to ensure that the same amount of data was available for each analysis instance.

The first step in the progress analysis was to determine the relevant kinematic parameters that change with training. From a machine learning perspective, the identification of relevant parameters is a feature selection task. We used the information gain measure to identify parameters that are most relevant for discriminating the training weeks [22]. The information gain is based on the information-theoretical concept of entropy [23]. Parameters with high information gain contain more information for assigning putts to a training week than those with low information gain [23]. Therefore, these parameters are well suited to discriminate training weeks and subsequently reflect the strongest change during training. To restrict the progress analysis to the most relevant parameters, we used the highest ranked 25% of parameters for further analysis. Thus, seven individual parameters were analyzed.

In the second step, we analyzed the change of the parameters selected in step one. Therefore, data were labeled with the sequential training week number it was collected in (1 to 8) and the median was computed. We used the median instead of the mean as this measure is more robust regarding outliers. We intentionally used the complete data of all subjects to identify the inter-individual progress. The Spearman correlation coefficient of each variable was computed to quantify training progress.

3 Results

3.1 Putt Detection

The system detected 2660 out of 3902 putts from the TRAINING study data resulting in an overall detection rate of 68.2%.

The detection rate varied throughout subjects, ranging from 98.9% to 3.1% (Tab. 3). Examining each subject separately, we observed that our system was either satisfactorily detecting putts (8 subjects, detection rate > 83%) or rarely detecting putts (3 subjects, detection rate < 16%).

In total, we observed that in 97 cases during the TRAINING study, a random movement or training swing was detected as putt. In effect, we obtained a false positive rate of 2.4%.

3.2 Training Progress in Motor Learning

The hit count increased from 10.0% before training intervention (pre test) to 39.1% after intervention (post test).

Table 3 Results of the putt detection for each subject of the TRAINING study.

Subject	Detection rate [%]
S1	83.0
S2	88.8
S3	96.7
S4	91.9
S5	84.5
S6	95.8
S7	98.9
S8	15.4
S9	3.1
S10	5.6
S11	88.0

Table 4 Result of the training progress analysis. Parameters were ranked using the information gain criterion. Parameter change is reflected in the Spearman correlation coefficient relating training week and parameter progression.

Rank	Parameter	Information Gain	Correlation Coefficient
1	P5	0.107	0.98
2	P12	0.059	0.88
3	P22	0.054	0.95
4	P29	0.053	0.88
5	P1	0.051	0.90
6	P30	0.044	-0.91
7	P24	0.042	-0.91

The analysis was conducted with data from the eight subjects (TRAINING) that achieved a detection rate of more than 83.0%. The three remaining subjects were excluded due to the limited amount of data (Tab. 3). Overall, 1946 correctly detected putts were used for the analysis.

Seven parameter were selected according to their information gain (Tab. 4). Five of them showed a high positive correlation with the training progress (P1, P5, P12, P22, P29). Two parameters showed a high negative correlation with advancing training (P24, P30). Exemplarily, plots of the parameters P5 (Fig. 3), P22 (Fig. 4) and P24 (Fig. 5) are presented and confirm the correlation tendency. Furthermore, visual inspection revealed training weeks where a general trend is discontinued. These were e.g. training week 7 (P5, P22) and week 6 (P24).

4 Discussion

4.1 Putt Detection

The overall result of the putt detection was 68.2%. However, a more detailed analysis revealed detection rates of over 83% for eight out of eleven subjects. We analyzed the captured video recordings of the three subjects where putt detection failed. Their putts had a limited backswing and overall short movement amplitude. Obviously, the technique variation that caused misdetections was not represented in the MODEL dataset and therefore not detected in the TRAINING study. One explanation might be that subjects in the MODEL dataset received basic pendulum technique instruction. In contrast, the subjects in the TRAINING dataset received only a short task description to omit the influence on the motor learning process. The finding showed that our system detected putts of TRAINING subjects with high probability if the movement followed a pendulum movement that is generally accepted to be most

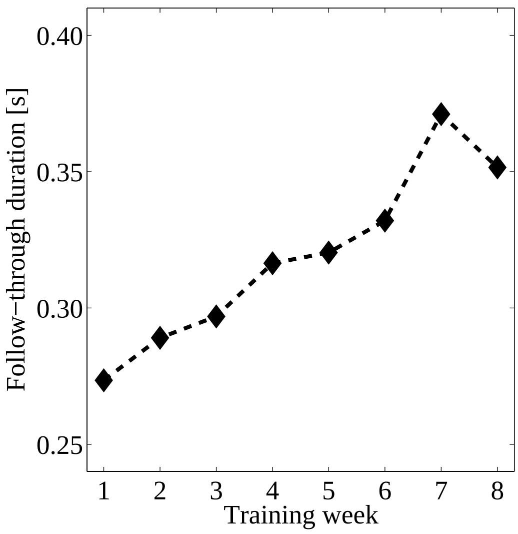

Fig. 3 Median values of follow-through duration (P5, y-axes) for each training week (1 to 8, x-axes).

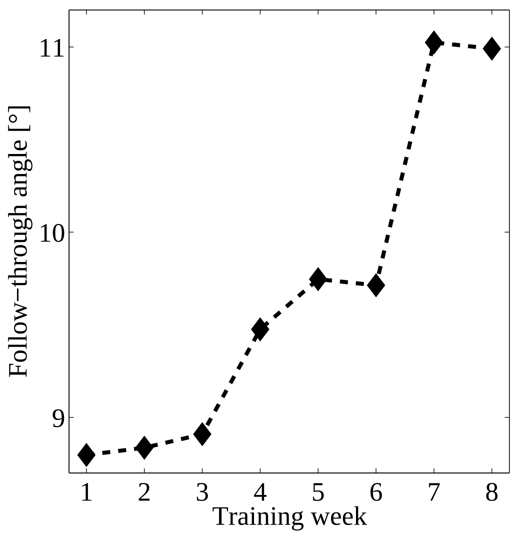

Fig. 4 Median values of follow-through angle (P22, y-axes) for each training week (1 to 8, x-axes).

effective in putting [7]. Despite the fact that it would be possible to improve the putt detection by incorporating the technique of minimum backswing into HMM training, we did not investigate this as we aim at establishing a system for training of effective putting execution based on the pendulum technique.

The low false positive rate of 2.4% showed that random movements and training swings were well distinguished from actual putts. The subjects were free to perform training swings prior to the putt, which is a common procedure in putting.

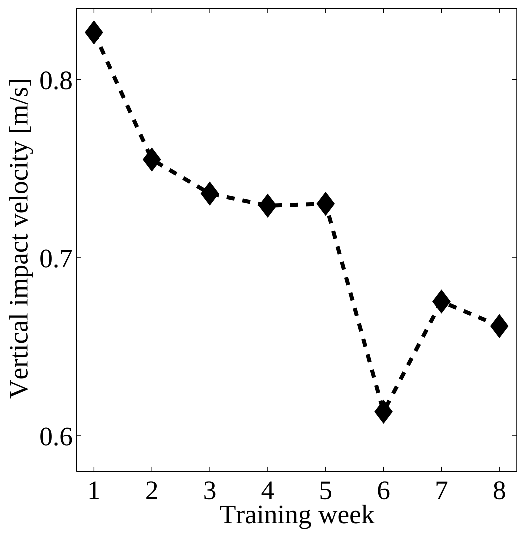

Fig. 5 Median values of vertical impact velocity (P24, y-axes) for each training week (1 to 8, x-axes).

The results of putt detection and false positive rate cannot be compared with literature. Detection algorithms were either not described [6], not existing due to manual labeling [8,12] or not mentioned and evaluated [14].

The results of putt detection rate and false positive rate showed that the presented system is able to automatically detect putts with high probability without a trigger from the user. The system can furthermore differentiate between actual putts and training putts. The real-time computing capabilities and visual display pave the way for augmented feedback applications.

4.2 Training Progress in Motor Learning

The hit count as a measure of putting performance increased considerably with the training intervention. Thus, the subjects were able to hole more putts with repetitive training. The subjects received no coaching instruction regarding movement execution. Thus, they and were free in developing a more successful putting technique. The mobile golf putt analysis system observed this training progress and the following results illustrate the underlying kinematic changes that lead to increased putting performance.

The parameter ranking revealed parameters that are most relevant for distinguishing training weeks. This assumption was supported by the high correlation of parameter progress and advancing training. The results of the data driven analysis will now be qualitatively discussed. We restricted our analysis to these relevant parameters and analyzed the resulting trends in more detail. The discussion of the numerical parameter values and their optimality is beyond the scope of this article.

The list of relevant training progress parameters contained two duration parameters (P1, P5). These were the putt duration and the FT duration which were positively correlated with training progress. Thus, subjects tend to putt slower with repetitive training and we speculate that subjects performed a more controlled movement as a result from learning. Our findings can be contrasted to the results for expert novice differences regarding timing [8]. The authors reported that experts spend considerably more time in FT. In agreement, our training progress analysis revealed an increasing FT duration (P5) with training progress.

The increased duration of the FT was accompanied with an increase in the FT angle (P22) with training progress. Our findings can be contrasted to the results for expert novice differences that revealed a higher downswing amplitude [7]. The authors state that expert players are able to better accompany the putt once the ball was hit. In agreement, our training progress analysis confirm this finding with an increasing FT angle (P22) with training progress.

Our training progress analysis revealed decreasing linear velocity on impact (P24), increasing relative loft angle between aim and impact (P12) and a changing velocity and acceleration profile (P29, P30). Previous results also confirm these findings when being contrasted to novices and experts [7,8].

In contrast to the group differences recorded at a single time instance (e.g. [8]), our analysis revealed trends during training intervention and can therefore not be compared directly. Training progress analysis described a learning path (progress of novices with training) in contrast to the outcome of a learning progress (novices vs. experts). During this learning path phases of discontinued progress could be found for several parameters (e.g. P5, P22, P24). These tendencies should be investigated in further research, as they indicate that movement variability is an important factor in analyzing human movements and sport skill learning [24,25].

4.3 General Discussion

The driving force for these applications is the unobtrusive, mobile and automatic character of the proposed system that offers advantages for athletes (feedback training) and researchers (high number of trials). Athletes, not distracted from recording equipment or markers, can train in their usual training environment and results are available in real-time. Thus, the presented system covers most requirements for measuring and information systems to support sport performance [26,27]. Additionally, researchers have the possibility to collect a higher amount of data as analysis workload is lower compared to traditional video analysis. This facilitates long-term analysis and results can be based on a large amount of data compared to existing literature [7,8].

The attached IMU is expected to have a minor influence on the swing behavior of the club due to its low mass. However, this effect has not been investigated. A further integration of the sensor unit and, therefore, a more suitable weight distribution is needed for more advanced analysis.

A drawback of the presented system is the missing parameter validation. However, the underlying segmentation model is an established approach to define putt phases and the extraction of many parameters is straightforward [14]. Furthermore, the training progress results are meant to underline the advantages of a mobile automated system for motor learning research. For more detailed biomechanical and motor learning analysis, the influence of sensor drift, sensor noise and model inaccuracy needs to be investigated. Techniques to improve accuracy of the tracking like Kalman Filtering were proposed [13] and we are planning to integrate them in a future version of the system.

5 Summary

This article introduced a mobile kinematic golf putt analysis system using IMU data from a sensor mounted on the club-head. Our research contributions are a pervasive analysis system, a method for automatic putt detection and processing and a training progress analysis describing a learning path. The system facilitates training in the field with augmented feedback capabilities and a modality for progress analysis based on large datasets. Our results showed that putts are automatically detected with high probability if a basic swing model is followed. The training progress analysis revealed learning progress and instants in learning where progress changes. The system and methodology might be useful in other sports disciplines or progress data analysis questions.

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