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A sensor-aided self coaching model for uncocking improvement in golf swing

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Abstract This paper describes an autonomous kinematic analysis platform for wrist angle measurement that is capable of evaluating a user's uncocking motion in his or her golf swing and providing instructional multimodal feedback to improve his or her skills. This uncocking motion, which is a characteristic movement of the wrist during the golf swing, is an important factor in achieving accurate ball hitting and long driving distances, but is difficult to measure. In order to efficiently compute the wrist angle for uncocking evaluation, we present a sensor-based intelligent Inertial Measurement Unit (IMU) agent that collects three-dimensional orientation data during the golf swing from two IMU sensors placed on the forearm and on the golf club. It accurately analyzes changes in wrist angle to detect uncocking throughout the sequence of golf swing motions. In this paper, we first introduce the design considerations based on the concept of the uncocking motion and explain the system architecture with the sensors used for quantitative measurement and qualitative feedback generation. Then, we illustrate the detailed algorithms for wrist angle computation, golf swing motion segmentation based on key pose detection, and uncocking evaluation. A multimodal feedback-based user interface for our system is also presented. Experimental results show that the proposed system has the ability to accurately calculate the wrist angle in real time and also that it can be applied to a practical self-coaching system to improve the uncocking motion.

Keyword Golf coaching · Sensor system · IMU · Uncocking

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1 Introduction

Golf is an increasingly popular sport that is played by over 60 million people around the world [29], and the demand for related commercial industries, including clothing, broadcasting, golf equipment, computer games, and so on, is also increasing. Despite the growth in the golf market and its environment, amateurs still find improving their golf skills to be a challenge. Generally, amateur golfers revise their swing through verbal and gestural feedback from professional golfers, but such instruction is expensive. A more accessible method is for golfers to spend a great deal of time improving their swing mechanisms on their own. However, utilizing only repetitive golf swing practice, golfers find it difficult to identify and modify faults in their golf swings because a successful golf swing is accomplished through the correct combination of several related and simultaneous movements of body parts, such as the proper weight shift and changes in wrist angle. To overcome these difficulties and satisfy golfers who want more objective and scientific feedback to improve their skills more easily, golf swing analysis systems have become increasingly attractive.

With the rapid development of the electronics research field in recent years, scientific researchers have attempted to solve golf swing analysis problems via computational approaches using the available sensors [26, 28]. Such systems obtain data related to the movements of body parts by using contact or noncontact sensors, analyzing the data, and reporting the information to users. However, such information is limited to the analytic results of golf swing inputs. Even though such systems provide a quantitative measurement of the swing, most are unable to define the relationship between the measurements and the user's skill with respect to the golf swing. Moreover, some systems are not easily accessible or well-suited to amateur golfers, because they are expensive and require user expertise. Furthermore, some systems require users to attach a great many sensors to their bodies or wear special clothing.

In this paper, among the many golf swing mechanisms, we focus on wrist angle analysis, given that wrist angle plays an important role in increasing club-head velocity, which is closely related to the distance and accuracy of the golf swing. There are two representative motions regarding wrist angle change in golf swing: cocking and uncocking. Cocking, that is, to bend the wrist backwards, occurs naturally from the waist up during the backswing (Fig. 1(b)). The cocking of the wrist is a preliminary action intended to add force to the impact. Uncocking, that is, to straighten the wrist, occurs before the club strikes the ball (Fig. 1(e)). This cocking and uncocking of the wrists during the golf swing make the golfer's arm and club simulate the whiplash action of the high-speed tip segment of a whip. When the wrists are cocked and uncocked, they act as an additional axis around which the club can rotate. The velocity developed from the swing and length of the golfer's arm is multiplied along the length of the club shaft. Without the cocking and un-cocking actions, the arms and clubs move as a fixed unit. Particularly, a golfer can generate additional power to hit the ball with the optimal velocity of the club head by using an ideal uncocking motion, that is, to release the cocked wrist just before the impact.

In order to compute and analyze the wrist angle changes, we utilize Inertial Measurement Unit (IMU) sensors. The IMU sensor we used is an electronics package that provides three axes of rotation measurement from the inertial data, as well as a micro-processing unit for data collection and processing and a wireless link to transmit the data to an external computer. The resulting rotation data is converted into the three-dimensional rotation matrix, of which the column vectors represent the coordinates of the principal axes of the IMU body frame relative to the global frame defined by gravity and the geomagnetic North Pole. Since a golf swing is performed with fast and continuous movements of the body parts and the golf club, a high sampling rate of the IMU sensor is necessary for accurate wrist angle analysis.

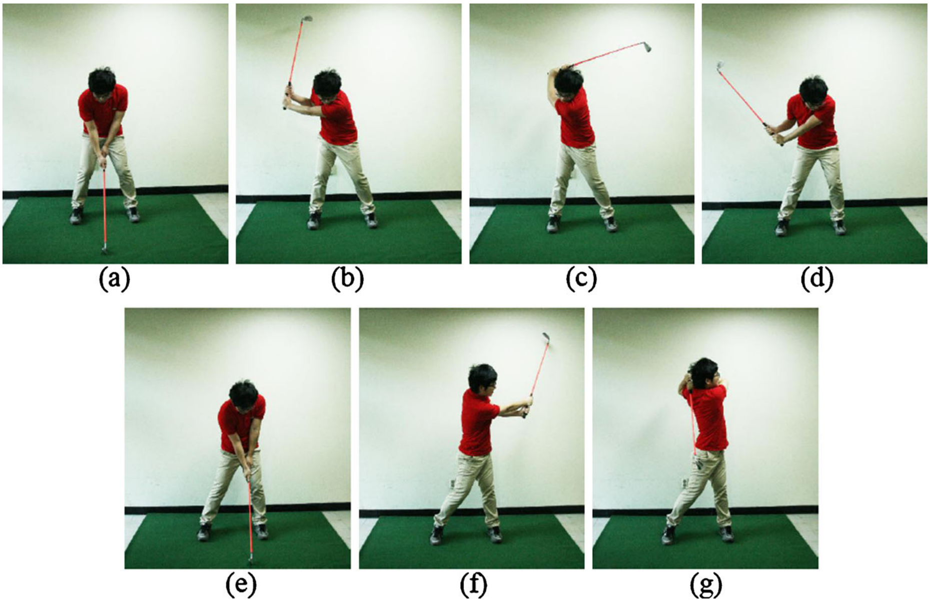


Fig. 1 Golf swing sequence with a seven iron: **a** address, **b** backswing, **c** top of the swing, **d** downswing, **e** impact, **f** follow-through, **g** finish

To meet this requirement, the IMU sensor used transmits the resulting rotation matrix with sampling rate of 100 Hz. Therefore, by using only two IMU sensors attached to the forearm and the golf club, our system can compute the wrist angle and analyze the changes in it in real time.

The proposed system is able to numerically evaluate the effectiveness of wrist uncocking. The evaluation requires the segmentation of the golf swing motion by defining the key poses comprising the golf swing. Thus, details are provided below concerning how to segment the swing motion with the key poses and quantitatively evaluate the uncocking motion. The system gives verbal and graphical feedback to help users identify and revise faults according to the evaluation results. Herein, we will not investigate deeply detailed content or feedback effectiveness. Various evaluation methods related to wrist angle changes in any sport may be applied to the system. Thus, the proposed system can not only be used to improve the golf swing but also to improve players' skills in other activities, such as baseball or hockey, in which wrist movement plays an important role.

The main contributions of this work are:

- A new methodology for wrist angle measurement: The proposed system, which automatically analyzes wrist angle changes during the golf swing, utilizes only two IMU sensors attached to the forearm and the golf club. In contrast to other existing systems that use a separately designed device or club, which restricts or reforms the movement of the user, this system can measure the golfer's wrist angle efficiently in real time by using the IMU sensors that provide three-dimensional orientation (rotation) data.
- An automatic uncocking motion evaluation: In order to define the relationship between the quantitative measurement of wrist angle changes and the user's skill, the system evaluates the uncocking motion. The evaluation unit segments the input golf swing motion by recognizing the key pose moments in the dataset that is sequentially collected from the IMU sensors during the golf swing and generates an uncocking evaluation value based on the difference

between the key pose moments and the user's uncocking moment. In contrast to other existing systems that provide mainly quantitative measurements of the golf swing, our system qualitatively interprets the information on the uncocking moment of the user's golf swing in order to help the user easily understand how he or she can improve the golf swing.

- A multimodal feedback: The proposed system generates and provides graded feedback and a score to improve a user's uncocking motion. The feedback comment and score, which are provided graphically and verbally to the user, are generated according to the uncocking evaluation variable based on the information collected from a golf swing specialist group and stored in the system. Also, 2D and 3D video for the viewpoint-independent display of the user's golf swing is also provided. Through these various kinds of feedbacks, the system helps the user to recognize the faults in his or her golf swing and describes how he or she can improve their skills with respect to the uncocking motion.

The remainder of this paper is organized as follows. Section 2 examines the related literature and the background of our system. In Section 3, we examine the concept of wrist uncocking and discuss developmental considerations for uncocking motion evaluation. Section 4 introduces the IMU sensor used and the system installation. In Section 5, we explain the algorithms implemented in our system, In Section 6, the graphical and verbal user interface is described. Section 7 summarizes the experimental results of our system, and Section 8 offers conclusions and suggestions for future study.

2 Related literature

Moving beyond traditional methods of sports form correction, scientific researchers have recently tried to quantify and analyze the kinematical movements of human body parts by using numerical data [11]. In this paper, we focus on the method used to measure, analyze, and evaluate the golf swing efficiently and to generate feedback for the improvement of the uncocking motion. Existing golf swing analysis methods can be categorized into the contact and noncontact types, depending upon the sensing device used [28].

The noncontact method typically employs a single image or sequential images captured by a visual sensor in order to recognize human body motions. Such methods have been widely assayed due to the advantage that users can perform naturally without having sensors attached to their bodies [2]. However, most existing visually-based motion tracking systems are susceptible to spatial variations in the human body, such as rotation or translation, because of the camera's limited field of view. To alleviate these problems, many researchers have recently attempted to recognize human motion in three-dimensional space from a sequence of monocular images, multiple viewpoints [5, 23, 26, 27], or a depth camera [24]. Even though these systems show good performance for entertainment purposes, they remain unsuited to the precise analysis of human action, particularly because a golf swing consists of complicated mechanisms, such as the fixation of the line of vision, center of gravity, and swing trajectory. Thus, more accurate analysis is required. However, most of noncontact sensor-based approaches cannot guarantee a very high accuracy, due to the nature of the visual sensor. One of the tricky problems to handle is the partial or total occlusion of the human body in the input golf swing image. For example, in Fig. 1(c), a visual sensor-based system cannot detect the hand position exactly, because the golfer's hands are partially hidden by the head. Even though most human body part tracking systems estimate the approximate position of the occluded parts stochastically or statistically in order to solve this problem, the results are prone to error and often not reliable.

In contrast to the noncontact method, the contact method relies on devices that are connected to the human body, such as force plates, accelerometers, gyro sensors, makers in optical motion capture, and Inertial Measurement Units (IMUs). The force plate allows tracking force distribution ratios from heel to toe and the measurement of the location of the center of pressure in order to analyze weight shift [1, 22]. Accelerometers have been used to measure the acceleration of the arms or the club head [16, 17]. However, force plate-based systems are not suitable for the analysis of the uncocking motion in the golf swing, because the sensor used does not provide any information about its own orientation, which is required in order to compute the wrist angle. In the case of accelerometers, they can be used for rotation measurement, along with the use of a potentiometer. However, the use of accelerometers and potentiometers requires a solution for the inverse problem, for which a set of nonlinear equations must be solved. Watanabe and Hokari [28] presented a measurement method and system for sports form that uses three-dimensional gyro sensors, which allow the calculation of the orientation and rotation with respect to the initially chosen coordinate system. They measured rotational motion and estimated translation in the link model of the golf swing. However, to accurately measure the position and rotation of each body part, the length of each body part and the initial angle of each joint in the artificial link model must be manually defined by users and by using an additional sensor, such as an inclinometer. In addition, an estimate of the rotation using only gyro sensors might be not reliable, because small bias errors will quickly result in drift errors in the estimation [10]. Many researchers [8, 12, 18] have studied the kinematic analysis of the golf swing by using optical motion capture, which is one of the systems most often used to detect fast-moving human body parts. They analyzed the fundamental geometric and kinematic characteristics of the hip and trunk movements in the golf swing based on the measurement of the trajectories of target points (markers) attached to the human body by using multiple preinstalled cameras. These systems provide high accuracy, complete freedom of movement, and the possibility of interactions among various actors with a higher computational cost. To exploit this system for human body part tracking, however, the resources necessary to acquire the multi-view image data are a capture room, a body suit, and camera equipment. The capture room must be large enough to allow recording from a large number of viewpoints at a sufficient distance. The moving person should wear a special body suit with markers on certain body parts. Also, multiple cameras should be installed in the capture room, with scrupulous attention to ensuring synchronization, a high frame rate, and a suitable resolution. Therefore, expertise is necessarily required due to such issues, so it is difficult to use the optical motion capture for commercial and practical purposes regarding golf swing analysis, especially for amateur golfers who want to utilize this system personally. Particularly, the above techniques do not provide detailed feedback to help novices improve their swing skills; they focus on the quantitative analyses and measurement methodologies of the given golf swing.

In this paper, we present an IMU sensor-based autonomous kinematic analysis platform for wrist angle measurement that enables the evaluation of a user's uncocking motion in his or her golf swing. As mentioned above, an IMU sensor provides accurate orientation or rotation information so that it can be used for motion capture technology [13]. Because an IMU sensor can sense and transmit the orientation data with a high sampling rate, it is well-suited to the analysis of continuously and unobtrusively fast-moving human motions, especially to sports technologies for technique training [25]. In [6, 7], Ghasemzadeh et al. presented a golf swing training system that incorporates five custom-designed IMUs to obtain information on wrist rotation in relation to the direction of the club face and provide feedback on the quality of movements. To evaluate wrist rotation, they built a quantitative model by using PCA and LDA techniques for dimension reduction and the linear projection of data from sensors. However, the initial parameters for PCA and LDA, such as the number of principal components, must be defined carefully. If not, the evaluation method may be not reliable. Also, their system provides only numerical feedback. Compared to this system, the method proposed in this paper focuses on the wrist uncocking motion, which is to release the bended wrist at impact moment to generate additional power. This system can analyze and evaluate the uncocking motion automatically, without any initial parameters. Moreover, instructional and more specific feedback for the improvement of the user's golf skill is provided. Table 1 shows the various kinds of representative techniques for motion analysis, as well as their limitations.

Our system uses only two IMU sensors to measure the wrist angle quantitatively and has the ability to segment the inputted golf swing motions by recognizing the key poses and to detect the uncocking moment in the sequential swing motions. In order to help the user improve his or her skill, the system provides detailed verbal and graphical feedback based on the measurement result of the uncocking motion. Therefore, our system can be applied to a diagnostic system for swing correction by using multimodal feedback.

3 Wrist uncocking reviewed

In order to discern the important considerations in system development, the concepts of wrist cocking and uncocking in the golf swing must be examined. In this section, we briefly describe the considerations of our system with respect to the changes in wrist angle during the golf swing.

Table 1 Existing techniques for motion analysis, categorized by the sensor type used, and their limitations

Sensor type	Sensor used/data	Author(s)	Purpose	Limitations
Noncontact	Single camera/ Single image	Barrón C and Kakadiaris IA [2]	Pose estimation from a single image	-Lack of precision -No feedback
	Single camera/ Image sequence	Urtasun R et al. [26]	Pose estimation from sequential images	-Lack of precision -No feedback
	Depth camera/ Depth image	Shotton J et al. [24]	Real-time human body parts tracking from a depth image	-Lack of precision -No feedback
Contact	Force plate/Ground reaction force	Richards J et al. [22]	Analysis of weight transfer during the golf swing	-Difficulty with wrist angle computation -No feedback
	Gyro sensor/ Angular velocity	Watanabe K and Hokari M [28]	Golf-swing form measurement based on kinematical model	-Drift error of sensor used -Initial parameter dependency -No feedback
	Optical motion capture/3D positions of markers	Gulgin H et al. [8]	Pelvis rotation analysis using optical motion capture	-Difficulties with practical use -No feedback
	IMU/Inertial data	Ghasemzadeh H et al. [6, 7]	Wrist rotation measurement and evaluation from inertial data	-Initial parameter dependency -No instructional feedback

Before beginning a detailed discussion of wrist cocking and uncocking, it is necessary to describe the golf swing. A full swing consists of a series of key poses: address, backswing, top of the swing, downswing, impact, follow-through, and finish, as shown in Fig. 1. In the process of these sequential motions, many factors, such as upper body twisting, wrist angle changes, weight shift, and so on, affect performance in terms of club speed and acceleration. Among these, the wrist angle, the relative angle between the forearm and golf club, is one of the most important factors in achieving accurate impact and distance.

There are two representative motions in golf swing wrist angle, cocking and uncocking, as illustrated in Fig. 2. Cocking occurs naturally from the waist up during the backswing. At the top of the swing, cocking occurs in the direction of the thumb. If cocking occurs not toward the thumb, but toward the back or palm of the hand, the clubface will be misaligned, making it difficult to hit the ball straight. The golfer can generate additional power at the moment of impact and cause the follow-through to follow the ball by keeping the wrist cocked during the downswing until just before impact and then uncocking. Doing so will also make it easier to hit the ball straight. Thus, cocking and uncocking add power to the swing.

Our system focuses on wrist uncocking in a full swing. In order to implement the detection of the uncocking moment and an evaluation algorithm, we must consider two technical problems: how to recognize key poses and how to quantitatively apply the aforementioned theory to uncocking detection. In the former case, we utilize the three-dimensional rotation of an IMU sensor attached to a golf club. For the latter, our system detects and evaluates the uncocking motion based on previous studies, which have defined the role of biomechanics in maximizing the distance and accuracy of golf shots through qualitative and quantitative evidence [9]. According to such research, a golfer can maximize the distance of his or her drives by uncocking the wrist when the left arm is about 30° below the horizontal on the downswing. Based on this research, the system can detect and evaluate key poses and uncocking by using three-dimensional IMU sensor data. The next section describes the proposed system in detail.

4 Sensor system

4.1 IMU sensor

Prior to explaining algorithmic development, we must introduce the Inertial Measurement Unit (IMU) sensor. It outputs a rotation matrix of its current body frame with respect to a global reference frame. Our IMU sensor consists of a tri-axial accelerometer (LIS3LV02DQ), a gyro (L3G4200D), and a magnetometer (HMC5883L). The angular velocity vector from the gyro

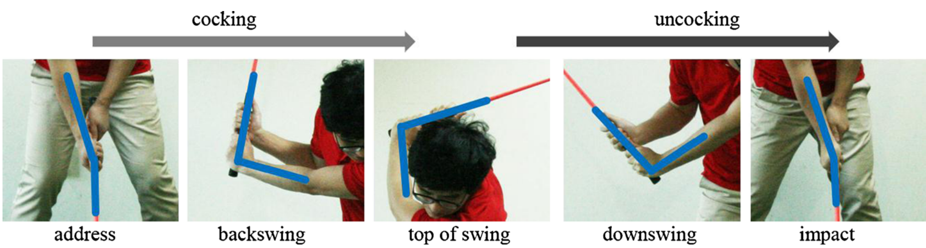


Fig. 2 Cocking and uncocking motions; blue lines indicate the vectors of the left forearm and club

sensor is integrated in order to predict the rotation matrix of the IMU body frame relative to the global reference frame. The gravity and geomagnetic field vectors from the accelerometer and magnetometer are used to adjust the predicted rotation matrix based on the gyro sensor. Figure 3 shows the IMU sensor used in our system.

4.2 System installation

The proposed system can compute the wrist angle in any pose. The system uses two IMU sensors attached to the forearm and the golf club, as well as a server as a processing unit. Additionally, the Microsoft Kinect [15], which is one of the most popular RGB-D cameras and has the capability to capture color images and depth data simultaneously, is installed in front of the golfer in order to generate the graphical feedback. A monitor and a speaker are also installed as output units for multimodal feedback. The system setup is illustrated in Fig. 4.

The IMU sensors can send data in matrix form concerning the three-dimensional rotation of the forearm and golf club to a server via Bluetooth. Any personal computer or laptop can be used as the server. Using the data obtained from the IMU sensors, the system outputs the real-time wrist angle and also stores the raw data of the IMU sensors and the computed wrist angle during the user's swing. After the swing, the system analyzes the uncocking motion based on the stored IMU sensor data, and generates evaluation results and feedback comments. These outputs can be routed into other analysis systems. The algorithms used are explained in detail in the next section (Section 5).

Additionally, the installed Kinect acts as the recorder in order to capture the user's golf swing. It sends the color and depth data streams to the server, and the server stores the data until the end of the swing. After the swing, the system generates 2D video and 3D video that contain the golf motion from the beginning of the swing to the end of the swing and displays them with the feedback comment and score through the output units. This graphical and verbal user interface for multimodal feedback is explained in Section 6.

5 Algorithms

The autonomous wrist angle analysis model of our IMU sensor-based system, which detects the uncocking moment and provides feedback that is beneficial in correcting the uncocking motion, consists of five modules, as shown in Fig. 5. The first module supports rotation data reception from the two IMU sensors using Bluetooth and transfers the data to the next module. This first module is described in the first subsection. In the wrist angle computation

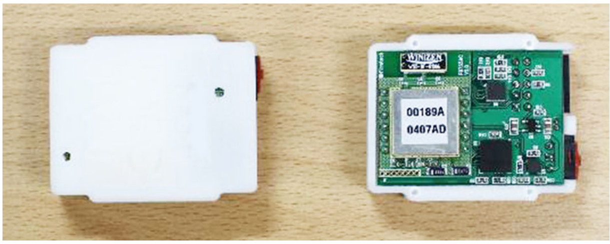


Fig. 3 IMU sensor used in our system; width: 36.9, length: 45.7, height: 15.6 (mm)

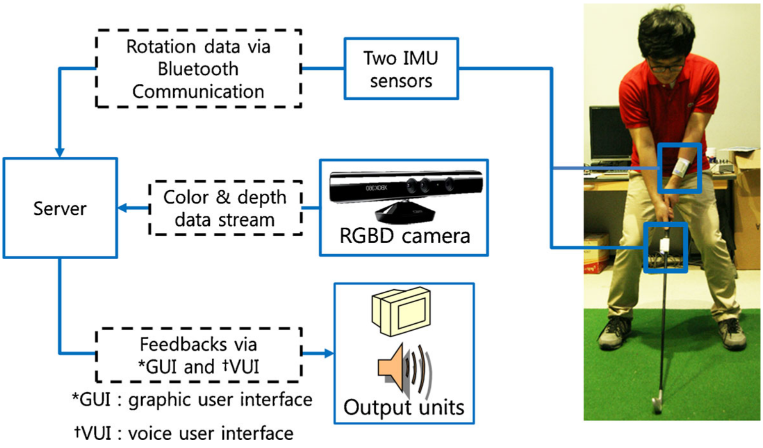


Fig. 4 System installation

module, the system measures and stores the wrist angle by using currently obtained IMU data. The user can see the current wrist angle in real time through this module. After the user's swing, the motion segmentation module detects the four poses of the swing using a sequentially stored dataset. The defined key poses play a significant role in the evaluation of the uncocking motion in the next step. The uncocking evaluation module recognizes and scores the user's uncocking motion, enabling our system to serve as an autonomous intelligent agent designed to improve the user's golf swing. In the last subsection, we briefly provide examples of typical feedback comments and scores.

5.1 Sensing module

In the sensing module, our system receives two streams of raw data from the two IMU sensors. The output of the IMU sensor is a rotation matrix, $R_{imu}(t) \in \mathbb{R}^{3\times3}$, which describes the orientation of the IMU sensor at time t, defined by the relative orientation between a coordinate frame attached to the IMU sensor and a uniquely fixed global coordinate frame. Let $\{A\}$ be the global frame, $\{B\}$ be the body frame of IMU sensor, and $x(t)$, $y(t)$, and $z(t) \in \mathbb{R}^3$ be the

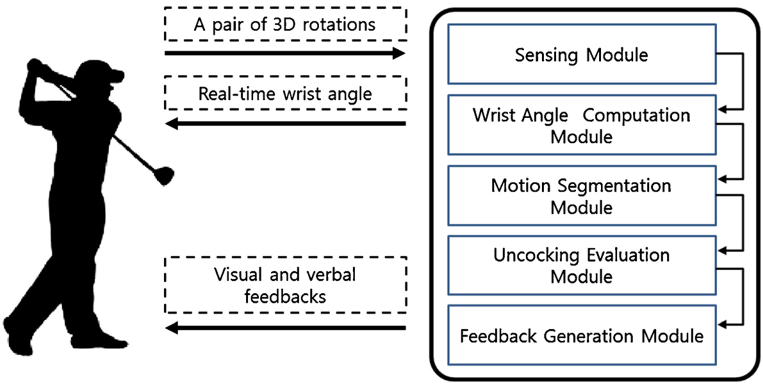


Fig. 5 Software structure of the wrist analysis model

coordinates of the principal axes of $\{B\}$ relative to $\{A\}$. The rotation matrix $R_{imu}(t)$, the output of the IMU sensor, is defined as

$$R_{imu}(t) = \begin{bmatrix} | & | & | \\ x(t) & y(t) & z(t) \\ | & | & | \end{bmatrix} = \left\{ R \in \mathbb{R}^{3\times3} | RR^T = I, \det R = 1 \right\}. \quad (1)$$

Each column vector of $R_{imu}(t)$ is called the x, y, and z vector of the IMU sensor, and they are orthogonal to one another. Figure 6(a) shows the output of the IMU sensor.

In the proposed system, each x vector of the IMU sensor is aligned along the direction of the forearm and the golf club, as shown in Fig. 6(b). Thus, we can derive the included angle between the forearm and the golf club by using the x vectors of the two IMU sensors.

5.2 Wrist angle computation module

As mentioned before, the wrist angle can be defined as the included angle between the forearm and the golf club. Therefore, to measure the wrist angle, we must consider the relationship between two IMU sensors on the forearm and the golf club simultaneously. In the wrist angle computation module, the system calculates the wrist angle in real time by using the pair of rotation matrices obtained from the sensing module.

Let $R_{arm}(t)$ and $R_{club}(t)$ be the rotation matrices from the two IMU sensors on the forearm and the golf club at time t. One method of describing the relationship of $R_{club}(t)$ relative to $R_{arm}(t)$ is to use *ZYX Euler angles* as follows: First, rotate $R_{club}(t)$ about the $z(t)$ of $R_{club}(t)$ by an angle of α. Then, rotate about the new $y(t)$ of $R_{club}(t)$ by an angle of β, and then rotate about the new $z(t)$ of $R_{club}(t)$ by an angle γ. This yields a new rotation matrix, $R\times(\alpha,\ \beta,\ \gamma) \in \mathbb{R}^{3\times3}$, and the triplet of angles (α, β, γ) are called the *ZYX Euler angles.* The rotation matrix $R(\alpha, \beta, \gamma)$ is given as

$$R(\alpha,\ \beta,\ \gamma) = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \\ = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix}. \quad (2)$$

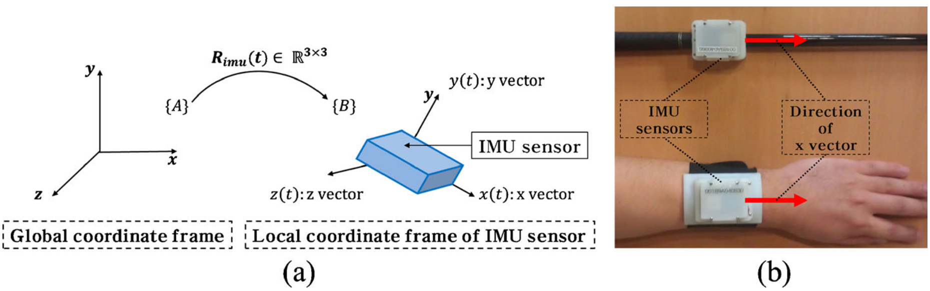


Fig. 6 The output of the IMU sensor (**a**) and its attachment to the forearm and the golf club (**b**), the 3D rotation of the local coordinate system with respect to the global coordinate system. The x vectors, as the first column vectors of the rotation matrices, are aligned along the direction of the forearm and the golf club

Given $R(\alpha, \beta, \gamma)$, then the *ZYX Euler angles* are defined as follows.

$$\begin{aligned}\alpha &= \mathrm{atan2}(\mathrm{r}_{21},\ \mathrm{r}_{11})\\ \beta &= \mathrm{atan2}\left(-\mathrm{r}_{31},\ \sqrt{\mathrm{r}_{11}^2+\mathrm{r}_{21}^2}\right)\\ \gamma &= \mathrm{atan2}(\mathrm{r}_{32},\ \mathrm{r}_{33})\end{aligned} \tag{3}$$

In the system, the two rotation matrices, $R_{arm}(t)$ and $R_{club}(t)$, are given, and $R(\alpha, \beta, \gamma)$ is defined from two matrices as

$$R(\alpha,\ \beta,\ \gamma) = R_{club}(t)R_{arm}(t)^{-1} \tag{4}$$

Thus, the *ZYX Euler angles,* which represent the relationship of $R_{club}(t)$ and $R_{arm}(t)$, can be calculated from (2) and (3).

However, this *ZYX Euler angles*-based method has the singularity problem. This means that in some cases, there exist infinitely many choices of α, β, and γ for the given $R(\alpha, \beta, \gamma)$. It has been proven mathematically that there exists no single parameterization of the rotation that is free from singularity. Therefore, instead of the *ZYX Euler angles*-based method, the proposed system calculates the wrist angle by using only two x vectors of $R_{arm}(t)$ and $R_{club}(t)$, which are aligned along the direction of the forearm and golf club. Figure 7 illustrates the wrist angle computation.

Let $x_{arm}(t)$ and $x_{club}(t)$ be the x vectors of $R_{arm}(t)$ and $R_{club}(t)$ at time t, respectively. We can calculate the wrist angle $\theta(t)$ as

$$\theta(t) = \mathrm{acos}(\mathrm{x}_{\mathrm{arm}}(\mathrm{t})\cdot \mathrm{x}_{\mathrm{club}}(\mathrm{t})), 0 \le \theta(\mathrm{t}) \le \pi. \tag{5}$$

The system outputs the wrist angle and stores not only the wrist angle but also the synchronized set of x vectors from the forearm and the golf club. Data are collected sequentially and stored into memory as an array data type until the end of the user's swing, at which point they are used to analyze the uncocking motion.

5.3 Motion segmentation module

A full swing consists of a series of key poses: address, backswing, top of the swing, downswing, impact, follow-through, and finish, as shown in Fig. 1. Among the successive swing procedures, the uncocking motion occurs in the downswing — the interval from the top of the swing to the impact. Therefore, the motion segmentation used to detect the downswing phase in the input golf swing is required prior to the uncocking motion analysis. In the motion segmentation module, the system recognizes three key pose moments in order to segment the sequential IMU sensor data of the golf swing stored in the dataset and then detects the ideal uncocking moment in the downswing phase. The three key poses are the

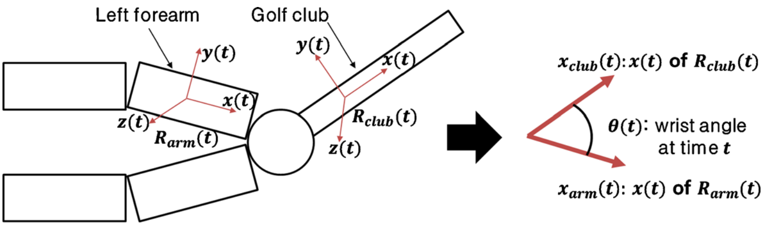


Fig. 7 Wrist angle computation from the two rotation matrices of the IMU sensors on the left forearm and the golf club

beginning of the takeaway (the first movement after the address position), the top of the swing, and the impact. The ideal uncocking moment is defined as the moment at which the left arm is about 30° below the horizontal in the downswing, which is defined as the interval from the top of the swing to the impact.

To detect the key poses and segment the input golf motion, we suppose that the user's initial pose is the address, and set the x vector of the rotation matrix from the IMU sensor on the forearm at the address as an initial vector. Then, the system sequentially compares the x vector of the forearm in the array-type dataset with the initial vector in order to find four key events (beginning of the takeaway, top of the swing, impact, and ideal uncocking moment) and to segment the swing motion (backswing and downswing) based on the following procedures in Table 2.

The system firstly sequentially calculates the included angles between the initial vector (the x vector of the rotation matrix from the IMU sensor on the forearm at the address) and every stored x vector of the forearm. The included angle can be computed from the inner product of the two vectors, as described in Eq. (5). The system removes noise from a series of included angles by using a 1D Gaussian smoothing filter. Then, it detects the beginning of the takeaway based on the above procedures. The 1D Gaussian smoothing filter for the discrete sequential data is derived via the following formula:

$$\widehat{In}(i) = \alpha_{nor} \sum_{j=i-l}^{i+l} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(i-j)^2}{2\sigma^2}} In(i), \tag{6}$$

where σ and l are the standard deviation and the half length of the Gaussian distribution, respectively. α_{nor} stands for the normalization of the Gaussian distribution because the summation of the Gaussian distribution is not 1 when the Gaussian distribution is used for the discrete data.

The system computes the first derivative of the smoothed data to find a local maximum and a local minimum using the central difference method. The central difference method for the first derivative is defined as follows:

$$\widehat{In}'(i) = \frac{-\widehat{In}(i+2) + 8\widehat{In}(i+1) - 8\widehat{In}(i-1) + \widehat{In}(i-2)}{12h}, \tag{7}$$

where h is the interval defined by $h = \widehat{In}(i) - \widehat{In}(i-1)$ for equidistant sample points. In our system, h is 1.

From the first derivative, the first two zero-crossing points after the beginning of the takeaway are defined as the local maximum and the local minimum of the smoothed data. Then, to avoid a loss of information caused by smoothing, the system searches the local maximum and the local minimum of the raw data near the local maximum and the local minimum of the smoothed data and defines the retrieved values as the top of the swing and impact.

After the recognition of the three key poses, the system segments the golf motion from the beginning of the take away to impact into two intervals, the backswing and the downswing. The backswing is defined as the interval between the beginning of the take away (t_b) and the top of the swing (t_t), and the downswing is defined as the interval between the top of the swing (t_t) and the impact (t_i). During the downswing phase, the system detects the ideal uncocking moment based on the above procedures.

Table 2 Procedures of motion segmentation module

Input data: x vectors of the forearm stored in the array-type dataset
Output data: indices of four key events
Variables
- i, j: index of the x vector of the forearm stored in the array-type dataset
- l: the total number of x vectors of the forearm stored in the array-type dataset
- $x_{arm}(i)$: i-th x vector of the forearm stored in the array-type dataset
- x_{init}: initial vector
- $In(i)$: included angle between $x_{arm}(i)$ and x_{init}
- $\widehat{In}(i)$: smoothed included angle between $x_{arm}(i)$ and x_{init}
- $\widehat{In}'(i)$: first derivative of $\widehat{In}(i)$
- t_b, t_t, t_i, t_{id} : indices of the beginning of the takeaway, top of the swing, impact, and ideal uncocking

Procedures

1. Included angle computation
for all $x_{arm}(i)$,
compute the included angle $In(i)$.
2. Smoothing
for all $In(i)$,
compute the smoothed included angle $\widehat{In}(i)$ using a Gaussian smoothing filter.
3. Differentiation of the smoothed included angle
for all $\widehat{In}(i)$,
compute $\widehat{In}'(i)$, the first derivative of the smoothed included angle $\widehat{In}(i)$, using the central difference method.
4. Beginning of takeaway detection
from $i=1$ to l,
find the first $\widehat{In}(i)$ that is more than a threshold (e.g., 5°) and assign i to t_b.
5. Top of swing detection
from $i=t_b$ to l,
find the first local maximum $\widehat{In}(i)$ of which $\widehat{In}'(i)$ is a zero-crossing point,
find the local maximum $In(j)$ near i, and then assign j to t_t.
6. Impact detection
from $i=t_t$ to l,
find the first local minimum $\widehat{In}(i)$ of which $\widehat{In}'(i)$ is a zero-crossing point,
find the local minimum $In(j)$ near i, and then assign j to t_i.
7. Swing motion segmentation
backswing: interval from the beginning of the takeaway (t_b) to the top of the swing (t_t)
downswing: interval from the top of the swing (t_t) to the impact (t_i)
8. Ideal uncocking detection
from $i=t_t$ to t_i,
find the $\widehat{In}(i)$ that is less than 60° in the downswing and assign i to t_{id}.

Figure 8 shows the example result of the motion segmentation module. In Fig. 8, the lower part represents the change of the included angle between the initial vector and the x vector of the forearm ($In(i)$, blue graph), the smoothed data ($\widehat{In}(i)$, red graph), and the first derivative ($\widehat{In}'(i)$, green graph) according to the index of the data stored. As mentioned above, the system finds the beginning of the takeaway (t_b) and detects the top of the swing

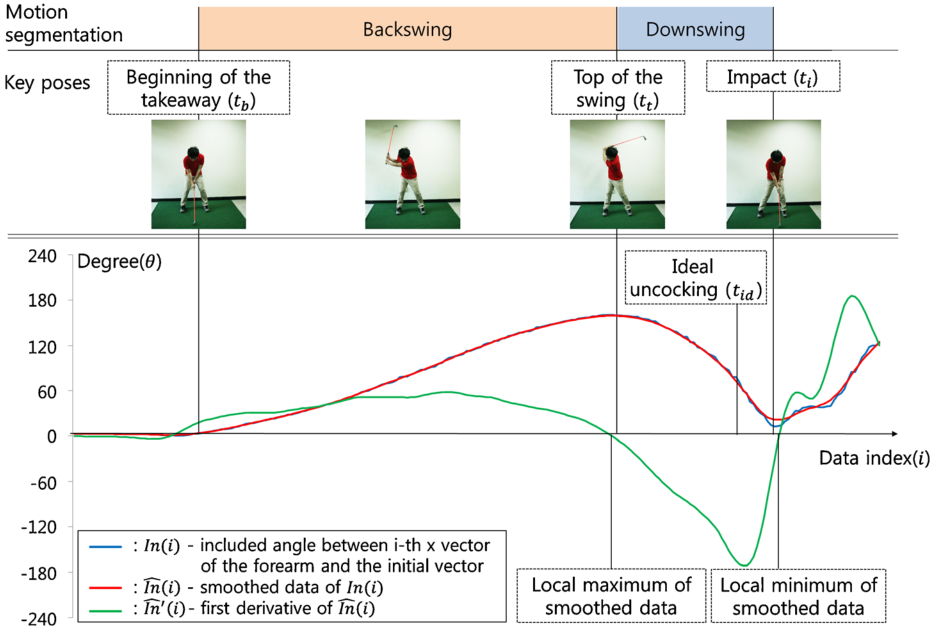


Fig. 8 Example result of the motion segmentation module. The system defines three key poses along the sequential included angles between the x vector and the initial vector of the forearm using smoothing and locally salient point detection, segments the golf motion into backswing and downswing, and then defines the ideal uncocking moment in the downswing

(t_t) and the impact (t_i) based on the local maximum and local minimum of the included angles. From the three key poses, the backswing and downswing can be segmented, and finally, the ideal uncocking moment (t_{id}) is defined in the downswing phase.

5.4 Uncocking evaluation module

As we mentioned above, a golfer can generate additional power at the moment of impact and cause the follow-through to follow the ball by keeping his or her wrist cocked during the downswing until just before impact and then uncocking. This means that it is important to release the cocked wrist at the right time in order to hit the ball further and straighter. Therefore, in the uncocking evaluation module, our system measures how close the user's uncocking moment in the downswing is to the ideal uncocking moment defined in the previous module.

The uncocking evaluation module first runs an uncocking moment detection algorithm that determines the moment of minimal wrist angle in the downswing interval. This work is performed via procedures similar to those used to detect the top of the swing and the impact in the previous module: (1) smoothing the wrist angle data, (2) calculating the first derivative of the smoothed data, (3) detecting the local minimum of the smoothed data, and (4) defining the local minimum of the original wrist angle data near the local minimum of the smooth data as the uncocking moment. The detailed procedures are described in Table 3.

After detecting the uncocking moment, the system calculates the uncocking evaluation score using the temporal distance between the uncocking moment and the ideal uncocking

Table 3 Uncocking moment detection

Input data: sequential wrist angles stored in the array-type dataset
Output data: index of the user's uncocking moment
Variables
- i, j: index of sequential wrist angles stored in the array-type dataset
- l: total number of sequential wrist angles stored in the array-type dataset
- $w(i)$: i-th wrist angle data stored in the array-type dataset
- $\widehat{w}(i)$: i-th smoothed wrist angle data
- $\widehat{w}'(i)$: first derivative of $\widehat{w}(i)$
- t_b, t_t, t_i, t_u : indices of the beginning of the takeaway, top of the swing, impact, and uncocking moment
Procedures
1. Smoothing
for all $w(i)$,
compute the smoothed wrist angle $\widehat{w}(i)$ by using a Gaussian smoothing filter.
2. Differentiation of the smoothed wrist angle
from i=t_b to t_i,
compute $\widehat{w}'(i)$, the first derivative of the smoothed wrist angle $\widehat{w}(i)$, by using the central difference method.
3. Uncocking moment detection
from i=t_t to t_i,
find the first local minimum, $\widehat{w}(i)$, of which $\widehat{w}'(i)$ is a zero-crossing point,
find the local minimum $w(j)$ near i, and then assign j to t_u.

moment in the downswing phase. Let t_u, t_{id}, t_t, and t_i be the indices of the uncocking moment, the ideal uncocking moment, the top of the swing moment, and the impact moment. Then, the evaluation score $S(t_u, t_{id}, t_t, t_i)$ is given by the following formulas:

$$S(t_u,\ t_{id}, t_t,\ t_i) = \begin{cases} (1.0 - m_{eu})\frac{t_u - t_t}{t_{id} - t_t} + m_{eu}, & if \quad t_u < t_{id} \\ (1.0 - m_{lu})\frac{t_i - t_u}{t_i - t_{id}} + m_{lu}, & else \end{cases}, \tag{8}$$

where m_{eu} and m_{lu} are the minimum scores for the early and the late uncocking, respectively.

The above formulas are performed differently when wrist cocking is released before or after the ideal uncocking moment; we define the former as an early uncocking and the latter as a late uncocking. We also assume that late uncocking is better than early uncocking based on the aforementioned interpretation of optimal uncocking: the wrist should remain cocked until just before the impact. Thus, the system assigns a higher minimum score to late uncocking than to early uncocking: m_{eu}=0.4 and m_{lu}=0.8.

An example result from the uncocking evaluation module is depicted in Fig. 9. In Fig. 9, the left part of the figure represents the changes in the wrist angle ($w(i)$, blue graph) that are computed and stored in the wrist angle computation module, the smoothed data ($\widehat{w}(i)$, red graph), and the first derivative ($\widehat{w}'(i)$, green graph) according to the index of the data stored. As mentioned above, the system first generates the smoothed data ($\widehat{w}(i)$) to remove the noise in the sequential wrist angle data ($w(i)$) by using a Gaussian smoothing filter (described in Eq. (6)) and then computes the first derivative of the smoothed data ($\widehat{w}'(i)$). The system detects the uncocking moment (t_u) near the local minimum of the smoothed data between the top of the swing and the impact. Finally, the system calculates the uncocking evaluation score based on the four parameters (indices of the top of the swing, impact, ideal uncocking, and uncocking), as described in the table in the right lower part of Fig. 9.

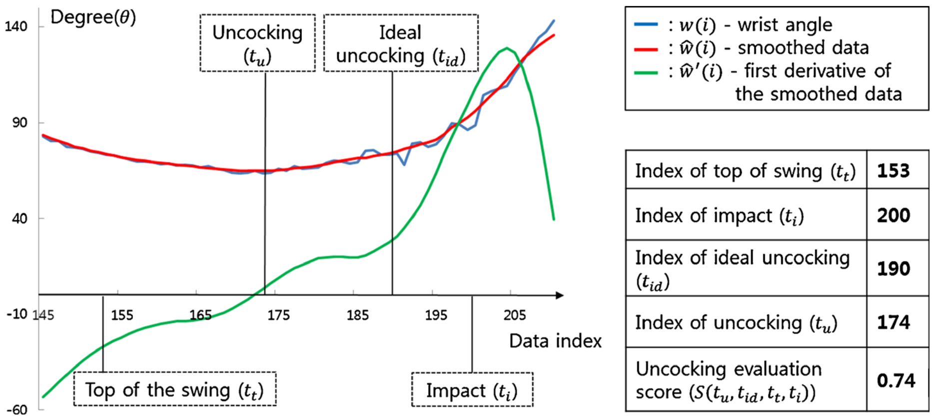


Fig. 9 example result of the uncocking evaluation module. The system evaluates and scores the uncocking motion in the downswing phase based on the indices of the top of the swing, the impact, the ideal uncocking, and the user's uncocking

5.5 Feedback generation module

In the feedback generation module, the system generates feedback based on the uncocking evaluation results. The feedback comments and scores provided graphically and verbally to the user are generated according to the uncocking evaluation variable, which is based on the information collected from a golf swing specialist group and stored in the system. Through this feedback, the system helps the users recognize the faults in their golf swings and announces how they can improve their skills with respect to the uncocking motion. Some examples of such feedback comments and scores are shown in Table 4.

6 User interface for multimodal feedback

In this section, we explain the user interface of our system for providing multimodal feedback to the user. The purpose of the feedback in the proposed system is to help the user recognize his or her faults and improve his or her skills related to the uncocking motion. Even though there are lots of systems for golf swing analysis, they give only quantitative analysis results, such as the maximum degree of rotation of the body joints or the driving distance. Particularly, these kinds of numerical feedback must be interpreted so as to be easy to understand for the golf amateurs. To overcome these limitations, this system automatically

Table 4 Example of uncocking motion feedback

Uncocking type	Score	Comment
Late uncocking	0.95~1.0	Your uncocking is perfect. Good job.
	0.8~0.95	Late uncocking. Please release your wrist more quickly
Early uncocking	0.95~1.0	Your uncocking is perfect. Good job.
	0.8~0.95	Your uncocking is a bit fast. Try to keep your wrist cocked a little longer.
	0.6~0.8	Your uncocking is fast. Try to keep your wrist cocked until just before impact.
	0.4~0.6	Your uncocking is too fast. Try to release your wrist later in your swing.

generates and provides five types of intuitive and instructional feedback: 1) verbal and 2) textual instructions for improving the user's uncocking motion based on the feedback comments and scores defined in feedback generation module, 3) wrist angle sequence visualization using a graph, and 4) 2D video and 5) 3D video based on the color and depth data streams captured during the golf swing by the Kinect installed in front of the user.

Figure 10 shows the user interface, along with the five types of feedback generated by the proposed system. The first verbal instruction based on the feedback comments and scores is provided through a speaker, and the other four feedbacks are displayed in the main window of our system through a monitor. The main window is divided into four sections, as seen in Fig. 10. The sections display the 2D and 3D videos, wrist angle graph, and textual instruction based on the feedback comments and scores.

The verbal and textual instructions are generated based on the feedback comments and scores defined in the feedback generation module. For the verbal instructions, we recorded six audio files containing narrations for each feedback comment in Table 4. After the swing, the system plays the audio file related with the uncocking evaluation results, and also outputs the feedback comments and scores as textual instructions on the right lower part of the main window. To record and play the audio file, the system utilizes the FMOD library [4], which is a programming toolkit for the creation and playback of interactive audio.

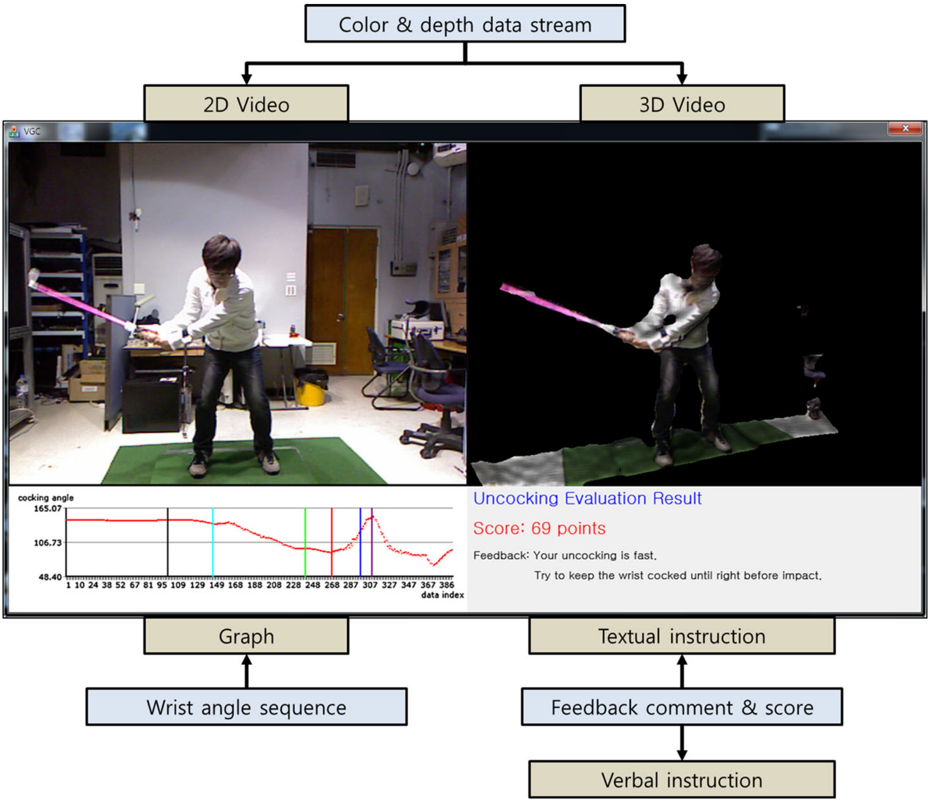


Fig. 10 User interface of our system, including five types of feedbacks: verbal and textual instructions, a wrist angle graph, and 2D and 3D videos

The graph, shown in the left lower part of the main window, visually represents the sequential wrist angle stored during the user's golf swing. As explained before, the system computes and sequentially stores the wrist angles during the golf swing. After the swing, the system plots them in order to help the user visually check how the wrist angle changed as the swing progressed. Additionally, in the graph, the key pose moments are also marked with the vertical lines of different colors so that the user can easily recognize when the uncocking is happened or how far the uncocking is from the ideal uncocking. Figure 11 shows an example of a wrist angle graph.

The proposed system also offers interactive 2D and 3D video-based feedback. To generate the 2D and 3D videos, the Kinect [15], which is one of the most popular RGB-D cameras and has the capability to capture color images and depth data simultaneously, is utilized. Through the Kinect, which is installed in front of the user, the system stores the color and depth data streams during the golf swing. After the golf swing, the system generates the 2D and 3D videos. The 2D video-based feedback, shown in the left higher part of the main window, shows the color video repeatedly displaying the user's golf swing. As with normal video players, the user can play the video backward and forward using the keyboard.

In the case of the 3D video-based feedback, the system generates consecutive 3D models of the user's golf swing from all the pairs of color and depth data streams by using the existing view synthesis method [20]. For each pair of color and depth data, the system first constructs the 3D model from depth data and then refines the model by applying the hole-filling and noise removal techniques to the 3D points on the model. Finally, through projecting the color data onto the refined model, the system renders the resulting scene. In order to produce the final 3D video, these processes are repeated for every pair of color and depth data captured by the Kinect during the user's golf swing.

Figure 12 illustrates an example of the 3D video generated. In contrast to the commonly used 2D video-based feedback, which has limitations in terms of visualizing the human body's motions due to viewpoint dependency, the system offers dynamic and interactive scenes with a wide range of views (58°×45°) field of view), as shown in Fig. 12. Therefore, the user can check his or her swing form by changing the viewpoint. Additionally, although we use a single Kinect, the system may be able to generate more a realistic 3D scene by using more the Kinects to capture the entire human body.

7 Experiments

In this section, we discuss the experimental results of the proposed system, which enables accurate wrist angle detection, uncocking motion analysis using two IMU sensors, and multimodal feedback generation for uncocking improvement. To verify our system, three

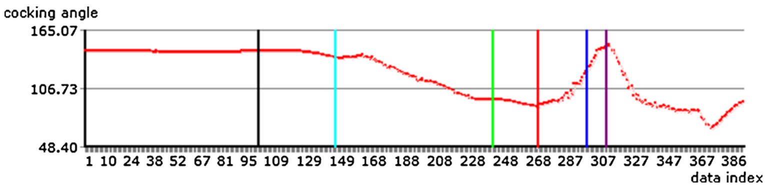


Fig. 11 Example of the graph representing the wrist angle sequence. The *vertical lines* indicate the key poses of the inputted golf swing (from left, beginning of the takeaway (*black*), middle of the backswing (*sky-blue*), top of the swing (*green*), uncocking (*red*), ideal uncocking (*blue*), impact (*purple*))

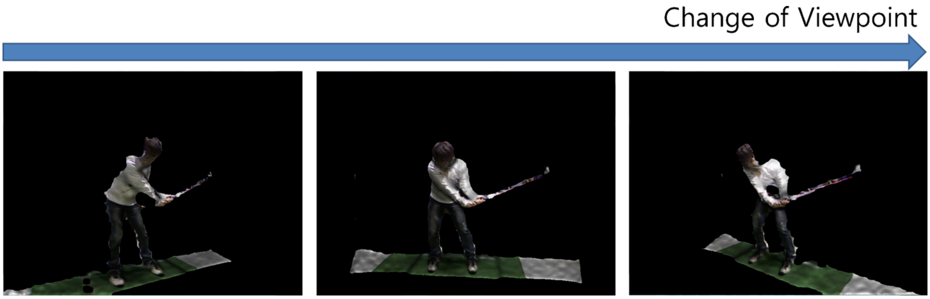


Fig. 12 Example of various viewpoints provided by the 3D video-based feedback. The user can change the viewpoint of the 3D video using the mouse and keyboard

factors are tested: processing time (Section 7.1.), wrist angle computation accuracy (Section 7.2.), and a feasibility test (Section 7.3.). The experiments were performed on a 2.83GHz CPU with 4 Gbyte of memory that ran 32bit Windows 7 Enterprise K. Primesense SDK [21] was used to capture the color and depth data of the Kinect, OpenCV library [19] was used for the 2D video-based feedback, and the programmable GPU (NVIDIA GeForce GTX 670) was used to accelerate the 3D model rendering of the 3D video-based feedback. The IMU sensors transmit data at 100 Hz.

7.1 Processing time

The proposed system generates two types of outputs: current wrist angle and uncocking evaluation, along with the relevant feedback. The current wrist angle should be computed in real time by using the current IMU sensor data. The uncocking evaluation includes the evaluation score and the feedback processed after the user's swing. Thus, the procedures of our system can be divided into two parts: real-time processing and post-processing.

Since the data sampling rate is constant (100 Hz), data length depends on the swing speed, meaning the faster the swing motion, the less data we receive. Therefore, we tested processing time for various swing speeds. Table 5 shows processing time by processing stage and data length.

In real-time processing, the average processing time is 5.1843ms. The processing time for this stage is not influenced by data length, because the wrist angle is calculated once the current IMU sensor data is received.

In the post-processing stage, including the motion segmentation module and the uncocking evaluation module, the processing time is dependent on data length. The average processing time increases as data length increases. However, total swing time generally ranges from 1.09 to 1.28 s for professionals and amateurs [14]. If the user's swing time is 2 s, our system can generate the output within 0.035ms.

7.2 Wrist angle accuracy

In this section, we discuss the accuracy of the wrist angle as computed by our system. An optical motion tracker was used as a reference. Three markers were attached on the two IMU sensors, on the forearm, on the golf club, and on the wrist. Based on the three-dimensional positions of the markers, the included angle was calculated and compared with the wrist angle calculated by our system. Four participants took ten swings with a seven iron. To better examine the reliability of the wrist angle computation, each subject tested two types of

Table 5 Processing time of our system

Part	Module	Data length	Processing time (ms)	
			Avg.	Std. dev.
Real-time processing	Sensing	–	5.184	3.473
	Wrist cocking computation	–	0.0003	0.0004
Post-processing	Key poses recognition	0~200	0.027	0.002
		200~400	0.034	0.002
		400~600	0.042	0.003
	Uncocking evaluation	0~200	0.008	0.0004
		200~400	0.011	0.0006
		400~600	0.014	0.0007

swings — slow and fast; these were to take more than 2 s and less than 2 s, respectively, from takeaway to finish. Thus, we tested a total of 40 swings at a variety of swing speeds. As shown in Table 6, the results show that the wrist angles measured by our system were similar to those derived from a commercial optical motion tracker.

7.3 Feasibility test

To evaluate the feasibility of our system that outputs five types of feedback for uncocking motion improvement, a pilot user study was conducted. As mentioned above, a golfer can generate additional power at the moment of impact and cause the follow-through to follow the ball by keeping the wrist cocked during the downswing until just before impact and then uncocking. This means that the driving distance will be longer if the uncocking is performed correctly. Based on this relationship between uncocking and driving distance, we wanted to test how the proposed system would help to correct the user's uncocking so as to increase the driving distance. To measure the driving distance, we used FlightScope Kudu [3], which is able to track the ball for the entire trajectory in 3D and provide related information, such as the driving distance, angles, and velocity. The experiments were conducted in an indoor room with the FlightScope Kudu installed behind the swing place and our system. Figure 13 shows the experimental environment for the feasibility test of the proposed system.

Seven participants from 26 to 29 years of age were recruited for the test. The subject group consisted of 4 male and 3 female graduate students who had no experience with golf. They served to test our system for ten days, and each participant was asked to repeatedly perform the experiments for twenty minutes a day. When a participant performed a golf swing, the FlightScope Kudu, which was connected with a server, measured the driving distance. After the swing, the proposed system analyzed the uncocking motion and outputted the relevant feedback, and the server stored the driving distance. The participant checked the feedback about the uncocking in the previous swing, and then performed the swing again.

Table 6 Difference in the two wrist angles obtained from a commercial optical tracker and our system

Types	Average difference (deg.)	Std. dev. (deg.)
Slow swing	4.295	3.902
Fast swing	4.386	5.320

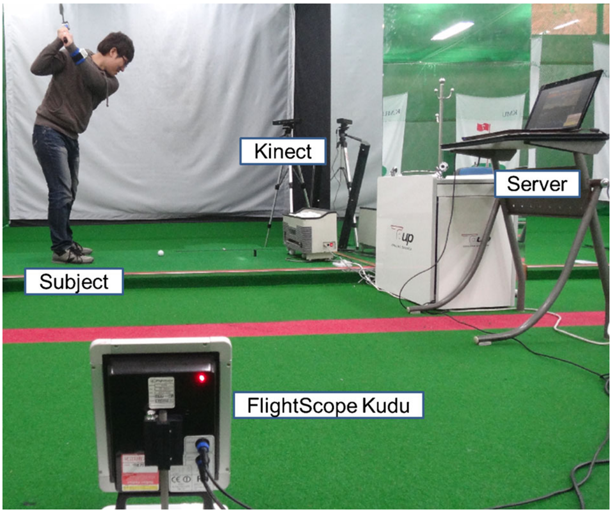
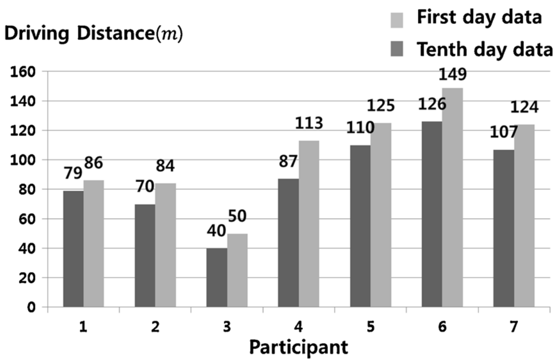


Fig. 13 Experimental environment for the feasibility test of the proposed system

Figure 14 shows the results of the feasibility test based on the ten-day observation of the driving distance change. In Fig. 14, the left table (Fig. 14(a)) represents total number of swings of each participant and the average number of swings of all the seven participants over the ten days. Seven participants performed about 527 swings over the ten days on average. The right graph (Fig. 14(b)) compares of the driving distances measured on the first day and on the tenth day. As shown in the graph, the driving distance of each participant obtained on the tenth test day was longer than that obtained on the first test day, with an average increase of 16 m. In other words, every participant could improve his or her driving distance during the ten-day training by using our system for uncocking correction. In summary, the proposed system can serve as a diagnostic system for swing correction using multimodal feedback.

Participant (gender)	Total No. Swings
1 (female)	557
2 (female)	527
3 (female)	413
4 (male)	526
5 (male)	380
6 (male)	727
7 (male)	558
Avg. No. Swings	526.85

(a)



(b)

Fig. 14 Results of the feasibility test based on a ten-day observation of driving distance change: **a** total number of swings of each participant, **b** average driving distances on the first day (*dark gray*) and on the tenth day (*light gray*) after the training with the proposed system

8 Discussion and conclusion

In this paper, we presented a novel autonomous golf coaching model that is able to analyze and evaluate the uncocking motion in order to help the user improve her or her wrist movements during the golf swing. To achieve these goals, the proposed system provides the following:

1) Measurement of real-time wrist angle during a golf swing
2) Golf motion segmentation
3) Uncocking motion detection
4) Evaluation of the uncocking motion
5) Feedback generation for uncocking motion improvement
6) User interface based on multimodal feedback
7) Proof of the feasibility of the method and system through experimentation.

This system yields the following results.

1) The wrist angle is calculated by using three-dimensional rotations of the two IMU sensors that are attached on the forearm and the golf club.
2) The sequential golf motion data from the two IMU sensors is segmented based on key pose detection.
3) In the sequentially stored data of the IMU sensors, the method used to define the uncocking moment is accomplished by detecting the minimal wrist angle in the downswing phase.
4) The uncocking motion is evaluated based on the temporal distance between the user's uncocking and the ideal one derived from the existing research on the biomechanical and quantitative definition of the uncocking motion.
5) A list of feedback comments and scores collected from a golf swing specialist group is stored in the system, and the relevant feedback in the list is provided to the user based on the uncocking evaluation results.
6) Visual and verbal information, such as feedback comments and scores, a wrist angle graph, and 2D and 3D video is provided to the user through the output units.
7) The validity of the system was examined by three kinds of tests: wrist angle accuracy, processing time, and a pilot user study.

The results show the validity of the proposed system for golf motion analysis and the feasibility of this practical self-coaching system intended to improve the uncocking motion.

There are two remaining issues with the proposed system: wrist angle computation and 2D and 3D video-based feedback. Firstly, the golf swing form is composed of the complicated and continuous motion of many body parts in 3D space. Considering this, we initially considered the Euler transformation-based method, which uses all information in the 3D rotation matrices of the IMU sensors for wrist angle computation. However, the system produced the wrong results in some cases due to the singularity problem of the Euler transformation. Therefore, we simply calculated the wrist angle by using only two x vectors of the IMU sensor. Even though this method within the proposed system produced stable results, it may cause the loss of information because three-dimensional rotation data is reduced into one-dimensional data as a vector. If the system uses the entire information of the IMU sensor and produces stable wrist angle measurement results, we can get a more detailed analysis. Secondly, our system utilized a costly RGB-D camera, the Kinect, for 2D and 3D video generation. It is important to measure the movement by using a sensor with a high sampling rate because the golf swing is a very fast motion. While the IMU sensor used for the analysis of the golf swing transmits data at a 100Hz sample rate, the Kinect captures the color and depth data with a 30Hz sample rate at the maximum. When we designed the prototype of the system, this relatively low sampling rate of the Kinect was a problem in terms of generating more efficient feedback. For example, in order to provide the rendered user's 3D poses at the important moments (e.g., the top of the swing, uncocking, and impact), which can be defined based on the IMU sensor data in our system, we have tried to automatically model the 3D scenes related to those moments. However, it was almost impossible to capture the exact scenes, due to the low sampling rate of the Kinect. To achieve this goal, the sophisticated synchronization of two different sensors and interpolation should be considered in order to supplement the low sampling rate of the Kinect.

Even though our system has a few remaining issues, it can be applied to golf and many other sports form analysis methods. Regarding the golf swing mechanisms, the measurements of the swing plane and the X-factor can be computed and analyzed by using the IMU sensors in our system. The swing plane is defined as the artificial plane or planes in which the golf club travels around a player's body, and the X–factor in the golf swing refers to the angle of coiling between an upper body and a pelvis at the top of the swing. For the measurement of the swing plane, the required 3D rotational information of the club can be computed by using the IMU sensor attached on the club shaft. The X-factor can be measured via the two IMU sensors attached to the upper body and pelvis.

For the other sports, such as baseball, hockey, or tennis, our method can be applied to other self-coaching systems. In those sports, wrist movement plays an important role in generating additional power or striking the ball correctly. For example, in baseball, the batter should rotate and release the bent wrist when hitting the ball, which is similar to the uncocking motion in the golf swing. Through the wrist snap, the hitter can strike the ball longer. In this case, our method can be applied to train a player for the purposes of wrist motion improvement.

Based on the above limitations and the possible applications of the proposed system, our future work will include improved uncocking computation and evaluation methods. More sophisticated methods that fully consider the three-dimensional data obtained from the IMU sensors will allow us to revise the wrist angle computation and thus upgrade our system. Research on the synchronization and interpolation of the data from the Kinect will enrich our 2D and 3D video-based feedback. The expansion of our system to the other characteristics of golf swing motion and to the analysis of other sports forms is an additional point of our future research.

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