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REVISITING THE NESBIT AND MCGINNIS OPTIMISATION MODEL OF THE GOLF SWING HUB PATH

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BACKGROUND: This article details the development of adopting the Nesbit and McGinnis model of the golf swing[1] as a starting point for studying golf performance optimisation. The model was selected as it presents an opportunity to examine how non-naïve participants can learn and improve their swing mechanics, which could prove valuable in studying human learning in sports, rehabilitation, and re-education. METHODS: Kinematic data was acquired in laboratory and real-world environments using the motion capture systems Qualysis and CodaMotion CX-Sport, respectively. In the early stages of developing the model in MATLAB, we identified limitations in the Nesbit and McGinnis methodology, including the filtering techniques applied to swing vectors and the selection of swing variables and the solutions to their boundary conditions solutions during the downswing. By addressing these issues, our goal was to revise the model and make it more robust and capable of optimising the impact velocities from a wider variety of subjects with varying swing mechanics. RESULTS: By increasing the cutoff frequency used to filter the swing vectors and expanding the swing variable polynomial equations, we found it was possible for all participants to increase their club head velocity at impact while respecting their unique kinematic limitations. The manner of the kinematic changes and the percent of velocity improvement are participant dependent. CONCLUSIONS: Our study showed that the observed and optimised hub paths differed among participants, which suggests participants might also differ in their approaches and capacities to adopt the latter.

Keywords: golf; motion analysis; kinematics; motor control.

BACKGROUND:

A major research focus in the field of sports sciences is improving sport performance, which traditionally involves multidisciplinary knowledge, from sociology to

psychology, biomechanics, and also neurosciences. Because of the specialty of skills required for improvement, the scientific questions are numerous and quite challenging, especially when concerning the golf swing, which is considered the most difficult motor skill in sports.[2] This characterisation is due to the complex mechanics and conditions required to perform the gesture successfully and consistently. A significant amount of research has been devoted to studying and revealing the biomechanical complexities of the golf swing, including studies on the role of ground-reaction forces,[3] X-factor,[4 5] and the crunch-factor.[6] A first step towards improving golf swing mechanics is to identify variables that are easily controllable by golfers and then determine the optimised trajectory of such variables.

In general, an increase in club head speed will increase the overall energy transferred to the ball at impact, which will theoretically result in a greater distance the ball travels.[7 8 9] To understand and potentially optimise club head speed, there are several golf swing models, including kinematic[10] and forward dynamic.[11] Recent work suggests that the nature of the club head path is non-circular[12 13] and derived from the path of the hands (*hub path*) located at the club grip.

Nesbit and McGinnis developed a forward kinematic model[1] and found that, while constraining the maximum force and torque outputs, participants could manipulate the hub path to increase club head velocity. Nesbit identified the hub radius, hub path, and club head path[14] as a collection of kinematic variables that golfers can manipulate in unique ways to improve form. **Figure 1** offers a two-dimensional representation of these variables during the downswing as projected onto a swing plane, where the hub radius can be inferred as the distance between the "Hub Rotation Center" and the "Hub Position." We selected the Nesbit and McGinnis club and optimisation model as a starting point for our own development, as we believed its design, which

accounts for three kinematic variables, might, in theory, increase the likelihood of non-naïve participants being capable of manipulating them in ways that would optimise impact velocity and subsequently ball distance.

However, while developing the Nesbit and McGinnis club and optimisation models in MATLAB (The MathWorks, Inc.), several issues emerged that concerned the approach, design, and use of the model. First, while it was expected that the club head and hub path signals were to be filtered, given the significant speed of the downswing, it was equally necessary to have confidence in the impact velocity calculation so as to assess the degree of optimisation. Second, in order to calculate changes to the hub length and angular path, a centre point of rotation is necessary, yet its position depends on the golfer and their swing style. Finally, the kinematic response of these swing variables are modelled as time-dependent polynomial equations, however, multiple questions emerged regarding their selection and solving for their boundary conditions during the downswing.

For this study we wanted to first collect kinematic and kinetic data from a pool of golfers with diverse swing styles and experiences. As discussed, there are many factors that contribute to the success of a golf swing, some of which are quite idiosyncratic. By developing an optimisation model that is robust enough to accommodate these features, we might be able to study how experts of a *de facto* complex motor task are capable of training and maintaining their swing form or possibly wish to learn and improve their mechanics. Experienced and high-level athletes often cite the relationship between their environment and their performance, so we wanted to first collect data in laboratory, which we could then use to develop our model so that it could accommodate the measurement of participants performing swings in the real world – on the driving range. By doing so, we believed we could better test the

77 robustness of our club and optimisation models. After collecting our dataset, our goal
78 was to develop an optimisation routine that uses the Nesbit and McGinnis[1] model of the
79 golf swing as a starting point. By making these changes we hypothesise that our model
80 can enhance the findings reported in the Nesbit and McGinnis[1] by optimising the impact
81 velocity for swings produced on the driving range.

82 **METHODS:**

83 ***Participants and data collection***

84 Four golfers (all male) were analysed for this study, and their details are given in **Table**
85 **1**. All participants used the same club (driver of length = 1.105 m; mass = 0.394 kg;
86 club cg = 0.669; I_{cg} = 0.079 kg.m^2). All participants were instructed to complete a
87 minimum of six swings that demonstrated their typical swing, which were recorded
88 using a motion capture system and stored based personal feedback. To test the
89 robustness of our model development, it was important that the golfers felt the
90 measured trials represented their swing idiosyncrasies on average. Participant data was
91 collected in two separate sessions, using different technical setups. However, like the
92 study conducted by Nesbit and McGinnis,[1] the markers used to locate club head and hub
93 paths were similarly positioned along the long axis of the club shaft for both sessions.
94 Our first goal was to collect golf swing kinematic data in a laboratory setting for
95 preliminary use in developing our model. Our decision to begin data collection in the
96 laboratory was both to follow the precedent set in Nesbit and McGinnis[1] and validate
97 any revisions to the model. Participant 1 was recorded at 300 Hz with an 11-camera
98 motion tracking protocol using passive markers (Qualisys). Using the Qualisys marker
99 placement protocol,[15] 60 markers (size: 19 mm; weight: 2.5 g) were placed on the body
100 of Participant 1, and six were placed on the golf club. Participant 1 hit foam balls into a

net in a competitive manner, where distance and accuracy are equally significant. Because we would require a more streamlined experimental setup to measure participant kinematics in real-world environments, this first step helped us identify which kinematic features were important and necessary to adapt the Nesbit and McGinnis swing optimisation model.

Following our collection and use of Participant 1 data in our initial model development (see: ***Adaptations to Nesbit and McGinnis optimisation model***), Participant 2 was measured in the same laboratory setting. However, only two makers were placed on his clavicle and hand, respectfully, and three markers were placed on the golf club. This decision was based on our experience collecting Participant 1 swing data, which made clear to us that a full body capture was not necessary, as a majority of the marker measurements were either redundant or inapplicable to our model. In addition, a significant amount of time was spent placing markers on Participant 1 to ensure measurement accuracy, and, given our previous experiences recording the movements of highly-skilled athletes, we wanted to do our best to reduce our experimental setup time. Thus, for Participant 2 we were able to reduce the number of markers used, which allowed us to reduce setup time and maintain confidence in our measurements. Another important difference between the participants was that Participant 2 hit Titleist PRO V1X balls into net in a similarly competitive manner. This allowed us to study any differences dependent on ball materiality and modify our model and its method for detecting ball impact.

A final round of data collection took place on a golf course driving range (Golf Salette, Marseille, FR). By recording in a real-world environment, we wanted to ensure the highest ecological validity, while preserving the highest spatio-temporal accuracy of the data. In addition, by measuring and optimising highly skilled golfers performing in

126 their natural environment, our research distinguishes itself from the study by Nesbit and
127 McGinnis,[1] where kinematic data was only collected in a laboratory. An important goal
128 for our study was to take the laboratory conditions "outside," which would allow us to
129 measure participant data in a real-world environment and thus, provide a more accurate
130 measurement of participant swing idiosyncrasies. Although the use of different motion
131 capture systems is unorthodox, in order to test the robustness of our model, we opted for
132 a more flexible approach in obtaining kinematic and kinetic data. Thus, our choice of
133 motion capture system was based on environmental constraints: Laboratory Participants
134 1-2 were measured with wireless passive markers and multiple cameras (Qualysis),
135 whereas Participants 3-4, who performed on a driving range, were measured with the
136 CodaMotion CX-Sport active marker motion tracking system and scanner with outdoor
137 lighting exposure (sampling rate 200 Hz). CodaMotion CX-Sport 3-D motion scanner
138 was placed 2.5 m from the golf ball (1.2 m above), and four markers were placed on the
139 golf club, which were connected and powered by a CodaMotion "drive box" (weight:
140 15 g) fastened below the handgrip.
141 Participants verbally informed us which trial best represented their swing, which
142 was then used for analysis. This process of selection is consistent with previous
143 studies.[12 14 16] Like the Nesbit and McGinnis optimisation model, our analysis focuses
144 on the downswing, which is the phase of the full swing that requires the golfer to exert
145 the most energy to accelerate the club along the swing path.

146 ***Adaptations to Nesbit and McGinnis optimisation model***
147 First, the model constrains the entire motion of the club onto one plane,[1 10 17] and, as
148 such, it is necessary to project 3D captured data onto a best-fit swing plane. However,
149 due to the complexity and speed of the golf swing motion, which can create camera and
150 scanner blind spots that hide sensor locations, some data could go unrecorded. In rare

151 instances we used a third-order polynomial fit to estimate any missing data and create a
152 continuous signal during the downswing motion. If there were more than three
153 continuous sample points missing from the data, the swing was rejected for further
154 study. This decision was based on our efforts to boost the fidelity of the observed
155 swings, which, by doing so, would allow us to optimise swings that more closely
156 reflected the swing idiosyncrasies of each participant. This step became necessary when
157 applying the selected filtering techniques. The corrected continuous data were then
158 projected onto the swing plane.[10]

159 The best-fit swing planes were calculated for each participant using the club and
160 hub kinematic data. Because of the high concentration of recorded points that occur
161 early in the swing, we decided to reconstruct the club head path by using the cumulative
162 sum of the distance along the path to produce spline-fits for all three-dimensions. The
163 data points along each corrected path are equidistant in a 3-dimensional space, which
164 puts an equal weight on each point when applying a Principal Component Analysis
165 (PCA) to calculate the best-fit plane. To check the validity of our method, a Root Mean
166 Square Error (RMSE) was used to compare the observed Participant 1 club head data
167 with their reconstructed swing path, which found a 27% reduction in residual errors
168 between the observed swing path and the best-fit plane. **Supplementary Figure 1**
169 compares Participant 1 observed and reconstructed swing paths and **Supplementary**
170 **Figure 2** illustrates the sizeable decrease in residual errors near impact for the
171 reconstructed swing. For a comprehensive swing analysis, we similarly reconstructed
172 the hub path motion, and, with the club head reconstruction, included it in the PCA.
173 Subsequently, an orthogonal projection of the observed data onto the swing plane is
174 applied (**Figure 2**).

We required an accurate centre point for which the hub rotates to determine the hub angle and path. The radial distance from the hub to its centre of rotation is not constant, varying over time throughout the swing, and golfers with higher skill levels have demonstrated a reduction in the hub radius as the club approaches impact with the ball.[13 14] After reviewing the data from Participants 1-2, the initial clavicle marker position served as a feasible centre point of rotation and a good representation of the hub motion centre point. However, we did not measure the clavicle position for Participants 3-4, as the inclusion of an additional marker would have greatly reduced the sampling rate of our motion capture, which, in turn, would have affected the accuracy of club head speed measurements. To address this absence, a regression model was developed using the kinematic data of Participant 2, who had a height similar to Participants 3-4, which was then used to estimate the clavicle initial position for the remaining participants. To confirm the validity of this approach, multiple simulations were performed on Participants 1-2 data, where their clavicle markers were moved around 3 cm from its origin. RMSE calculations were then conducted which found there was little to no effect on the calculation of impact velocity.

Confidence in the observed club head velocity was required if our goal was to maximise it. We identified the sampling rate and the type of ball as significant factors that contribute to adequately measure the impact velocity. Following an empirical process of experimentation, we found that the data acquisition sampling rate cannot be lower than 200 Hz given the speed and limited duration of the downswing (approximately 250 milliseconds). Second, comparing the data of Participant 1 (foam ball) with Participants 2-4 (standard golf ball), we observed that the former did not have a large spike in the data at impact, which was expected due to club head-ball ball impact and momentum transfer (**Figure 3**). The presence of such a dramatic change in velocity

200 at impact necessitated a modified filtering technique to maintain this large velocity delta
201 and retain the peak impact velocity. Thus, we decided to apply filtering to swing vectors
202 up to the impact point.
203 Although club head and hub position data recorded from both acquisition
204 systems appeared smooth and continuous, minor perturbations were amplified after
205 calculating the first and second derivatives in order to get velocity and acceleration
206 signals. Nesbit and McGinnis[1] smoothed three-dimensional marker triad paths with a
207 Butterworth low-pass filter at 6 Hz. Coleman and Rankin[9] used a fourth-order
208 Butterworth reverse filter with a cutoff frequency of 10 Hz for the body landmarks and
209 20 Hz for the club grip, bottom of the club shaft, club head centre and ball. **Table 2**
210 illustrates the significant effects of changing the filter cutoff frequency on impact
211 velocity by comparing participant observed impact velocities with a fourth-order
212 Butterworth filter with cutoff frequencies at 6, 10, 15, and 20 Hz. For our model, we
213 decided on a fourth-order Butterworth with a cutoff frequency 20 Hz, as it did not
214 substantially dilute the true impact velocity.
215 Nesbit and McGinnis[1] modelled the downswing time-histories of the three
216 kinematic variables as polynomial equations. During swing optimisation the torque,
217 force, power, and work are simulated by using these polynomial models, such that their
218 coefficients can be modified in ways that satisfy the conditions for peak force, torque,
219 and power outputs. They selected fourth-order polynomials to model the angular
220 positions of the hub (1) and club head (2) and a sixth-order polynomial for the hub
221 radius (3).
222 However, when participant data were applied to this modelling, several issues
223 became apparent, which required model alterations to ensure the robustness needed to
224 provide adequate results for our entire pool of participants analysed.

$$\theta(t) = C_0 + C_1 t + C_2 t^2 + C_3 t^3 + C_4 t^4 \quad (1)$$

$$\gamma(t) = C_5 + C_6 t + C_7 t^2 + C_8 t^3 + C_9 t^4 \quad (2)$$

$$R(\theta) = k_0 + k_1\theta + k_2\theta^2 + k_3\theta^3 + k_4\theta^4 + k_5\theta^5 + k_6\theta^6 \quad (3)$$

First, ahead of optimisation, it was of interest to attempt to perfectly match the observed hub and club path with a modelled polynomial fit. While the polynomial orders appear to be selected because of how well they fit the time histories of the kinematic variables, no reason is given. After observing the poor fit of using a fourth-order polynomial equation on Participant 1 the club path data, a Normalized Root Mean Standard Deviation (NRMSD) analysis was applied to calculate the error between each variable and its polynomial approximation. **Table 3** shows NRMSD for club head and hub paths fitted to fourth- and fifth-order polynomial equations for Participants 1-4. These observations led us to expand the order of all polynomials by one, as defined in Equations (4)-(6).

$$\theta(t) = C_0 + C_1 t + C_2 t^2 + C_3 t^3 + C_4 t^4 + C_5 t^5 \quad (4)$$

$$\gamma(t) = C_6 + C_7 t + C_8 t^2 + C_9 t^3 + C_{10} t^4 + C_{11} t^5 \quad (5)$$

$$R(\theta) = k_0 + k_1\theta + k_2\theta^2 + k_3\theta^3 + k_4\theta^4 + k_5\theta^5 + k_6\theta^6 + k_7\theta^7 \quad (6)$$

Second, Nesbit and McGinnis assume that at the start of the downswing (time $t = 0$ seconds), the hub and club head velocities are 0, where $\dot{\theta}(0) = \dot{\theta}_0$ and $\dot{\gamma}(0) = \dot{\gamma}_0$. However, we observed that this was not the case for some participants, who appeared to move their hands and wrists as they transition from their backswing to their downswing. Instead of making this assumption, we actually assign these variables to the observed values, which, by doing so, reduce the overall disruption to the participants primary swing characteristics. Thus, when we solve the boundary conditions for our set of expanded polynomials, instead of simply setting $\dot{\theta}_0$ and $\dot{\gamma}_0$ equal zero, the initial velocity for each participant is set as the downswing begins. Although this added a level of complexity when solving for the boundary conditions for the polynomial equations, it yielded a more valid process. By expanding to the fifth-order polynomial equation and

applying the observed initial club and hub velocities, the final club head impact velocity of the modelled swing improved dramatically. When seeding the polynomial expressions using the observed swing data, the final impact velocity error (modelled vs. observed) improved from 6.96% to 0.18%.

To solve, we required the first and second derivatives of the angular position of the hub θ (4), which yielded the hub angular velocity $\dot{\theta}$ (7) and acceleration $\ddot{\theta}$ (8), respectfully.

$$\dot{\theta}(t) = C_1 + 2C_2t + 3C_3t^2 + 4C_4t^3 + 5C_5t^4 \quad (7)$$

$$\ddot{\theta}(t) = 2C_2 + 6C_3t + 12C_4t^2 + 20C_5t^4 \quad (8)$$

Substituting our boundary conditions into (4), (7)-(8) yielded the expressions for constants C_0 though C_5 per

$$C_0 = \theta_0 \quad (9)$$

$$C_1 = \dot{\theta}_0 \quad (10)$$

$$C_2 = \frac{\ddot{\theta}_0}{2} \quad (11)$$

$$C_3 = \frac{20\theta_f - 20\theta_0 - 8\dot{\theta}_f t_f - 12\dot{\theta}_0 t_f + \ddot{\theta}_f t_f^2 - 3\ddot{\theta}_0 t_f^2}{2t_f^3} \quad (12)$$

$$C_4 = \frac{-30\theta_f + 30\theta_0 + 14\dot{\theta}_f t_f + 16\dot{\theta}_0 t_f - 2\ddot{\theta}_f t_f^2 + 3\ddot{\theta}_0 t_f^2}{2t_f^4} \quad (13)$$

$$C_5 = \frac{12\theta_f - 12\theta_0 - 6\dot{\theta}_f t_f - 6\dot{\theta}_0 t_f + \ddot{\theta}_f t_f^2 - \ddot{\theta}_0 t_f^2}{2t_f^5} \quad (14)$$

Third, while (4) and (5) are functions of time *t* seconds, (6) is a function of hub angle θ where the constants $k_0 - k_6$ are determined by several radial coordinates $R_1 - R_7$ evenly spaced from the downswing starting angle to ending angle. However, this approach created problems with our analysis of participant data. In particular, given the steep initial descent of the hub radial length curve may produce issues during optimisation. **Figure 4 (Left)** illustrates this steepness, whereas **Figure 4 (Right)** shows the hub radius as a function of time. It was observed that the poor fit early in the hub angle polynomial was amplified when transformed into the time domain. Prior to our decision to expand the order of the polynomials, we wanted to assess the accuracy of

our poly-fit by conducting RMSE calculations, where the hub radius was expressed as both a function of the hub path and time. Using Participant 1 data, we found that by expressing the hub radius as function of time, we improved the poly-fit error from 5.55% to 0.59%. **Supplementary Figure 3** illustrates our process of experimenting with different polynomial orders and their effect on fit. Following this we chose to express our hub radius as a seventh-order polynomial function of time (15).

$$R(t) = k_0 + k_1 t + k_2 t^2 + k_3 t^3 + k_4 t^4 + k_5 t^5 + k_6 t^6 + k_7 t^7 \quad (15)$$

As a last step we wanted to compare our optimisation results with the Nesbit and McGinnis optimisation model, and used Participant 1 data for our comparison. As previously discussed, Nesbit and McGinnis used a Butterworth low-pass filter with a 6 Hz cutoff frequency, however, **Supplementary Figure 4** illustrates how such a low frequency creates artefacts in the data, which can lead to incongruences between peak and impact velocities. Like our model, we decided to similarly filter with a 20 Hz cutoff frequency to have an accurate comparison between model optimisations. However, we did not employ our method of filtering up to the impact point, which, in turn, yielded different kinematic and kinetic values (see **Table 4**).

Results

The kinematic and kinetic quantities for each participant during their observed downswings are provided in **Table 4**. The results of maximising impact velocity for all participants are given in **Table 5**. For **Tables 4-5**, **Participant #1a** refers to the Nesbit and McGinnis optimisation method, whereas **Participant #1b** shows the results of our optimisation model. The results for all kinetic quantities are the maximum values occurring during the downswing and are given as a percentage of the observed swing

maximum value. Using our optimisation model: **Figure 5** compares Participant 1 observed and optimised hub and club path trajectories; **Figure 6** compares Participant 1 observed and optimised force, torque, power, and work responses; and **Figure 7** compares the observed and optimised hub path for Participants 1-4.

Discussion and Implications

Swing and optimisation observations

The four participants presented diverse swing kinematic and kinetic characteristics (see **Table 4**). The range of the kinematic and kinetic quantities among the participants was considerable and quantitatively emphasised the difference in their swing mechanics and club trajectories. Thus, like the study by Nesbit and McGinnis,[1] we similarly captured a diverse set of swing styles from a mechanics point of view.

While we did not have the opportunity to have the same participants test in both experimental settings, we believe inter-participant variability associated with the performance of such a familiar, yet difficult, task might have yielded vastly different observed and optimised swings. In turn, this might give the impression that swings performed in a particular experimental setting might lend themselves to greater possibilities of improvement. This of course was not our goal, and one way we see our study as distinguishing itself from Nesbit and McGinnis,[1] was our goal to measure and analyse swings performed in the real world. This was done by not only collecting kinematic data associated with swings taken on an actual driving range with real balls, but also developing a method for filtering the data in a way that preserved swing idiosyncrasies. As we noted, we observed a significant difference concerning the use of foam balls (Participant 1) versus actual golf balls (Participants 2-4). Thus the data collected from Participants 1-2 served our development of the model rather than a mode for which to compare against Participants 3-4.

Despite these diversities, all of our participant optimisations exhibited very similar force, power, and work profiles. However we saw large differences in the torque response, which was observed during most of optimisations. Additional optimisation analysis could be conducted that further constrains each profile to better match the swing observations. Nesbit and McGinnis only constrained the torque based on the peak value, and our model similarly satisfied this constraint.

More generally, we adhered to Nesbit's constraints on applied forces, torque, and power, but slightly deviated from their approach when optimising the hub path. To reduce disruptions to the participant natural swing, we constrained the starting and ending point of the hub path, while Nesbit and McGinnis only constrain the end point to maintain proper impact with the ball. This starting point boundary condition creates slightly obscure initial hub motion during the downswing. Although it presented minor issues, to our mind, allowing for an unconstrained start point remedies slight disruptions in the hub motion.

During our analysis of the swing model, it was always of interest to use the modelled swing to try to best replicate the observed kinematic data. This would be used as a check to test the model's validity during formulation. The data-matching capability in the model was highly desired and used as a target for all incremental changes made to the original Nesbit model.[14] Adhering to this goal required a certain level of controllability in model's polynomial equations, which were a bit lacking originally. Changing the order of the equations, accounting for non-zero initial conditions, and applying the observed initial and final hub and club angles led to similar replications of the original data and large improvements in the peak impact velocity during optimisation. These changes more than likely lead to our model showing a greater club head velocity optimisation (109.37%) when compared to our implementation of the

Nesbit and McGinnis model (105.76%). When compared side-by-side, the remaining results are similar, which suggests Participant 1 has the capacity to optimise club head velocity at impact, and the potential for optimisation is greater when adjustments recommended by our model are made.

When implementing such an optimised swing in practice as a teaching technique, it was believed to be advantageous to start with the natural swing kinematics of the participant, and gradually make incremental changes towards the optimisation target swing. This would potentially reduce any adverse effects of abrupt disruption in the participant's natural swing mechanics during training.

Practice implications

In general, to improve and optimise golf swing mechanics, golf instructors and trainers teach to the physical and psychological constraints of their pupils. However, the use of motion capture systems that can visualise and make more palpable complex kinematic variables only serves to inform golfers of a knowledge of results. This approach appears insufficient given the complexity of activities involved in the swing.

Unfortunately we were unable to complete a follow-up test to examine whether participants were able to use information based on hub radius, hub path, and club head path optimisations to manipulate their movements. But given the complexity and oftentimes subtlety of movement optimisations, which together span a short duration, we imagine it might be quite difficult for them. In this case, participants would be asked to not only complete a task in a way that was unnatural or counter-intuitive to their previous trainings, but also to use a vocabulary of swing parameters that was most likely un-familiar. One possible solution to convey this abstract information might be to develop a method of augmented reality that uses artificial feedback – visual, auditory, haptic, or multimodal.

As a primary focus for improvement in golf is kinematics, Keogh and Hume[18] theorised that different visual feedback strategies based on errors of performance might help movement development. A similar approach might prove to be particularly useful when comparing observed swings to those developed by an optimisation model. The assumed difference between them might then be delivered to users via sensory cues. Sigrist et al.[19] reviewed numerous studies that examined the effects of visual, auditory, haptic, or multimodal information on motor learning, some of which found significant results. As there continues to be scientific evidence that the use of augmented realties can influence human movement, their use for performance optimisation presents a potentially exciting area for development.

However, the development and use of a performance optimisation tool should consider the inter-individual differences in speed in which humans master a new motor skill. A study by Wu et al.[20] demonstrated a link between movement-to-movement variability and motor learning in novice participants. The experiential exploration of different movement parameters allows humans to fine-tune newly acquired actions and account for motor predispositions.

This of course differs among individuals, given the intrinsic properties of their motor system, which raises two, among many, questions. The first concerns whether the repetition of an optimised movement path is the best approach for improvement, as it does not provide a natural avenue for movement variability exploration, which is more inline with environmental demands and the empirical constraints of the individual. Several studies have shown strength and conditioning exercises have a positive effect on the swing mechanics,[21 22] which, by broadening the types of movement, reduces the possibilities of overuse and strain.

Secondly, if an optimisation model is used for training, a suitable window of variability in terms of deviation from the optimal path cannot be standardised due to the unique demands of each golfer. Not only does the amount of time to learn a new motor skill differ among people, but also the threshold in which movements are perceived as different. Coupling this point with the previous, it becomes clear that the use of such an optimisation tool requires the attention of a golf trainer or instructor to advise and assess golfer progress.

Conclusion

The objective of this study was to adopt the Nesbit and McGinnis model of the golf swing as a point of departure for which to study golf performance optimisation. Our primary goal of development was to maximise club head velocity at impact. It was also of interest to observe how factors such as material and environment might affect the data collected for our study. By analysing these factors, we might develop the robustness of our model, which could improve future work examining how humans can learn and improve complex motor tasks like the golf swing.

Similarly to the results reported in Nesbit and McGinnis,[1] we found there was potential for participant to increase their impact velocity while respecting their kinematic limits. Moreover, as we hypothesised, our modifications to the model made it possible to collect and use swing data from a group of participants with diverse swing styles in a variety of measurement and performance environments. In review, these modifications included improved filtering of swing data around impact point, increasing the order of the polynomial equations used to model the three swing parameters, and setting and solving the boundary coefficients to observed swings.

Like Nesbit and McGinnis,[1] our results continue to stress the idiosyncratic swing behaviours of each golfer and how they affect club head velocity at impact. We showed that the observed and optimised hub paths differed among participants, and we might assume participants might similarly differ in their capacities of adopting the latter. For this reason the development of a sensory guidance tool might aid their learning process.

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521 **TABLES**

522 Table 1. Participant data.

Participant	Age	Height	Weight	Handicap	Experience (yrs)	Round per Year
1	45	175	73	10	20	25
2	33	185	79	18	19	8
3	49	182	72	15	35	22
4	23	186	72	2	11	42

523

524 Table 2. Participant impact velocities (m/s) and percentage of error (%) from the
525 observed impact velocity: observed, fourth-order Butterworth filter with cutoff
526 frequencies at 6, 10, 15, 20 Hz.

Participant	Units	Unfiltered (m/s)	6 Hz (m/s)	10 Hz (m/s)	15 Hz (m/s)	20 Hz (m/s)
Participant #1	Impact velocity	44.63	35.67	42.77	44.32	44.57
	Error %	0.00%	-20.08%	-4.17%	-0.69%	-0.13%
Participant #2	Impact velocity	36.68	32.93	35.94	36.57	36.68
	Error %	0.00%	-10.22%	-2.02%	-0.30%	0.00%
Participant #3	Impact velocity	46.29	38.39	44.01	45.96	46.28
	Error %	0.00%	-17.07%	-4.93%	-0.71%	-0.02%
Participant #4	Impact velocity	54.53	42.11	50.76	53.93	54.43
	Error %	0.00%	-22.78%	-6.91%	-1.10%	-0.18%

527

528 Table 3. NRMSD for club head and hub paths fitted to fourth- and fifth-order
529 polynomial equations for Participants 1-4.

Participant	Swing variable	Unit	Fourth-order polynomial	Fifth-order polynomial
Participant #1	Club head path	Position	5.52%	0.46%
		Velocity	10.31%	1.18%
		Acceleration	25.87%	6.34%
	Hub path	Position	5.82%	5.07%
		Velocity	17.96%	12.82%
		Acceleration	24.59%	19.04%
Participant #2	Club head path	Position	12.02%	4.77%
		Velocity	27.11%	9.80%
		Acceleration	30.12%	14.79%
	Hub path	Position	3.73%	0.80%
		Velocity	9.62%	4.16%
		Acceleration	14.27%	11.45%
	Club head path	Position	5.06%	1.26%
		Velocity	10.90%	4.70%

Participant #3		Acceleration	21.70%	16.93%
	Hub path	Position	4.04%	5.77%
		Velocity	14.68%	14.56%
		Acceleration	27.88%	25.62%
Participant #4	Club head path	Position	2.94%	0.61%
		Velocity	5.93%	2.98%
		Acceleration	17.30%	16.16%
	Hub path	Position	7.28%	3.01%
		Velocity	21.34%	9.20%
		Acceleration	31.80%	17.81%

530

531 Table 4: Participant data observed during downswing – all values are time of maximum.

Data Type	Units	Participant #1a	Participant #1b	Participant #2	Participant #3	Participant #4
Club Head Vel	m/s	44.00	44.53	36.79	45.28	54.67
Swing Torque	N.m	44.66	47.5	20.35	51.61	68.03
Mag of Force	N	446.56	467.85	313.59	413.67	585.62
Total Work	N.m	392.42	395.16	243.65	372.93	589.78
Linear Work	N.m	235.21	234.5	170.9	241.27	376.56
Angular Work	N.m	157.21	160.66	72.75	131.66	213.22
Total Power	N.m/s	4174.72	4211.09	2167.68	4987.92	7676.41
Linear Power	N.m/s	2503.78	2474.8	1614.16	3063.52	4964.34
Angular Power	N.m/s	1746.75	1879.62	640.58	1929.95	3075.74

532

533 Table 5: Optimisation data for all participants.

Data Type	Participant #1a Percent (%)	Participant #1b Percent (%)	Participant #2 Percent (%)	Participant #3 Percent (%)	Participant #4 Percent (%)
Club Head Vel	105.76	109.37	105.63	108.30	107.70
Swing Torque	99.84	93.18	99.77	96.51	99.98
Mag of Force	95.52	92.53	92.96	93.14	97.00
Total Work	123.72	105.36	106.84	120.55	123.77
Linear Work	125.79	128.14	119.71	126.75	134.07
Angular Work	120.62	72.10	76.60	109.20	105.59
Total Power	83.86	81.46	83.68	86.26	89.63
Linear Power	99.99	99.88	99.84	99.80	99.47
Angular Power	94.26	98.12	56.97	93.47	91.06

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FIGURES

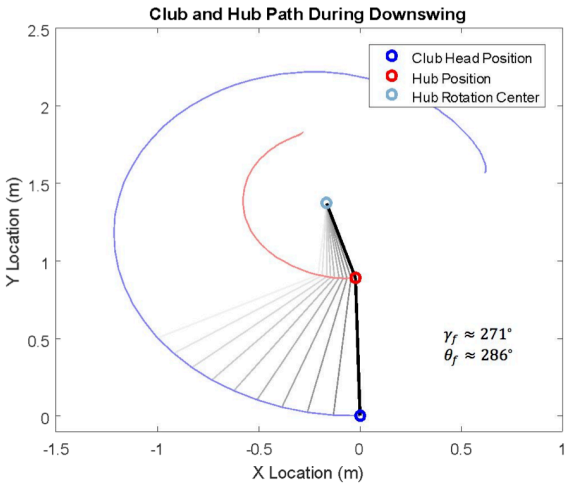


Figure 1. Illustration of the hub radius, hub path, and club head path during the downswing as projected onto a 2-dimensional swing plane.

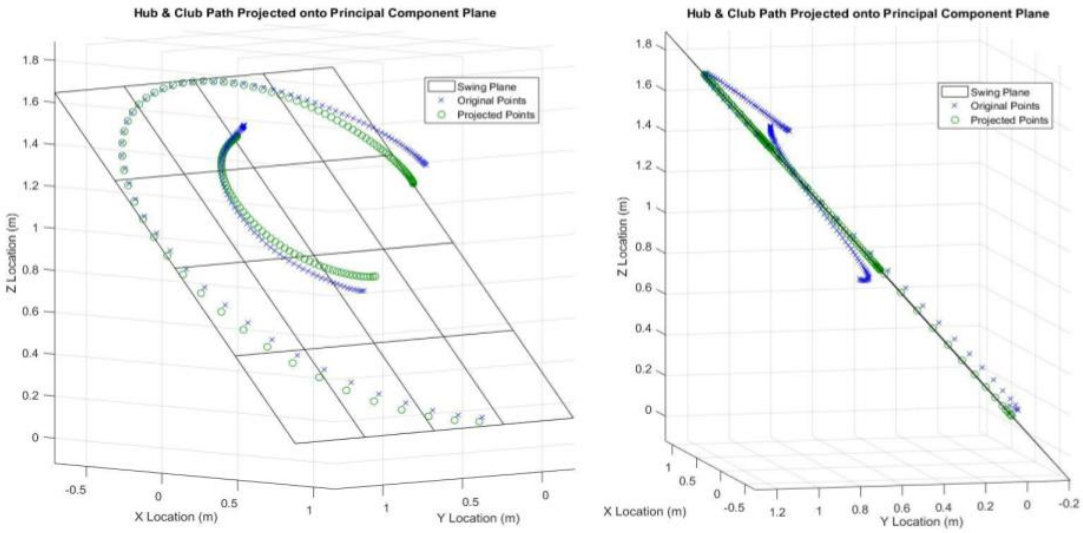


Figure 2. Participant 1 original (blue) and projected (green) club head and hub paths projected onto swing plan. The two plots show different 3D orientation views of the same swing data.

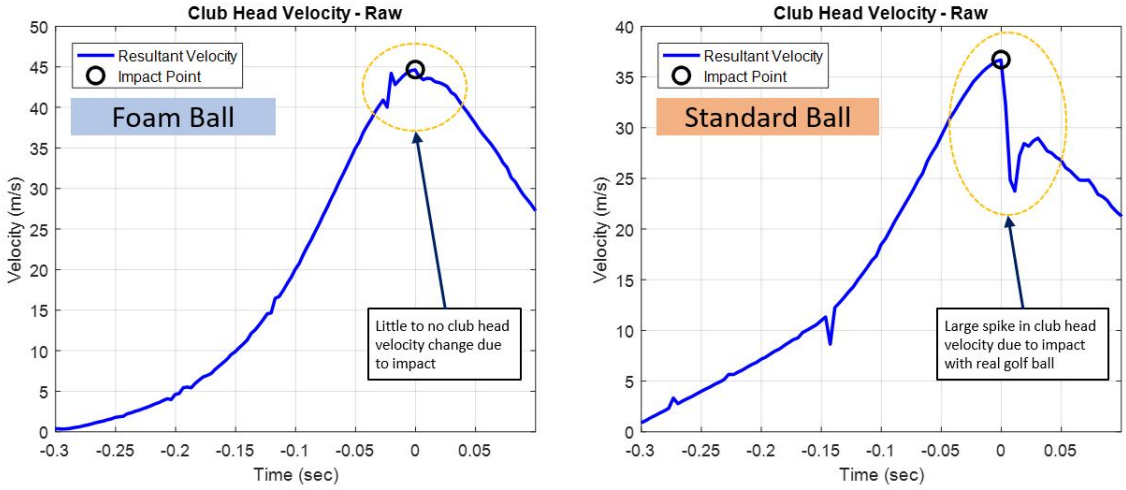


Figure 3. Club head raw resultant velocity comparison, during impact, for Participant 1 hitting a foam ball (left) and Participant 2 (right) hitting a real standard golf ball.

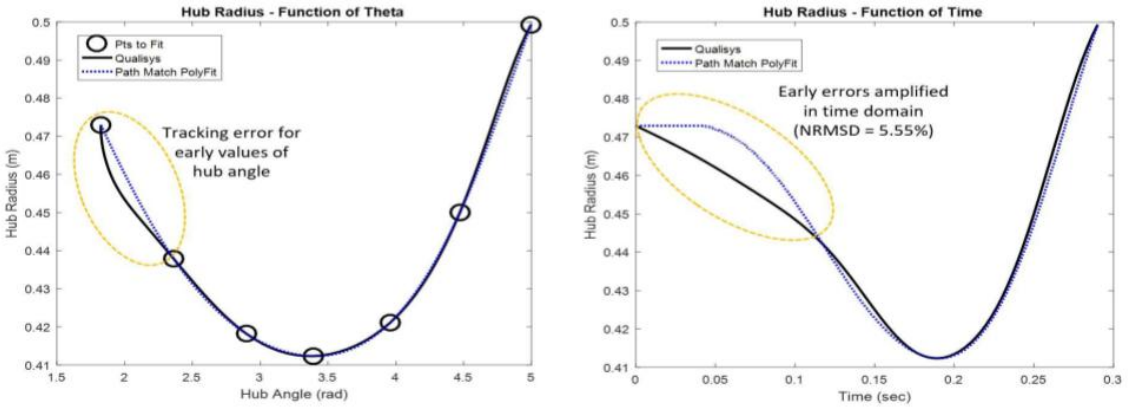


Figure 4: Participant 1 hub radius as a function of hub angular position (Left) and the corresponding hub radius as a function of time (Right) showing amplified errors transformed into the time domain.

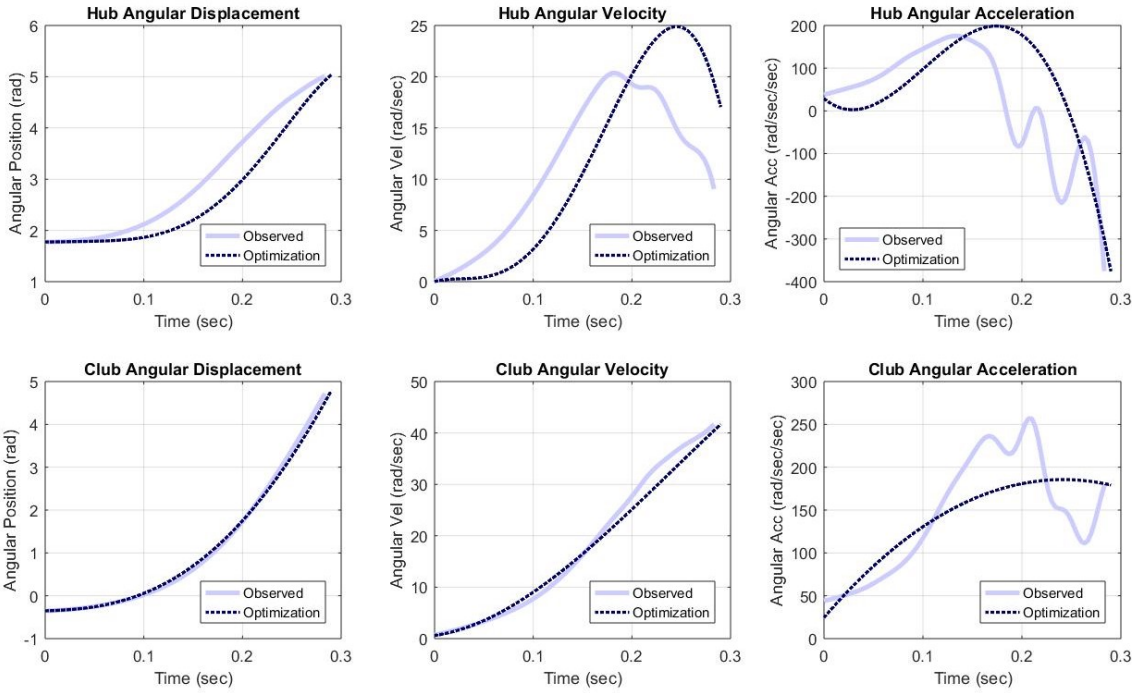


Figure 5. Participant 1 observed and optimised hub and club head trajectories.

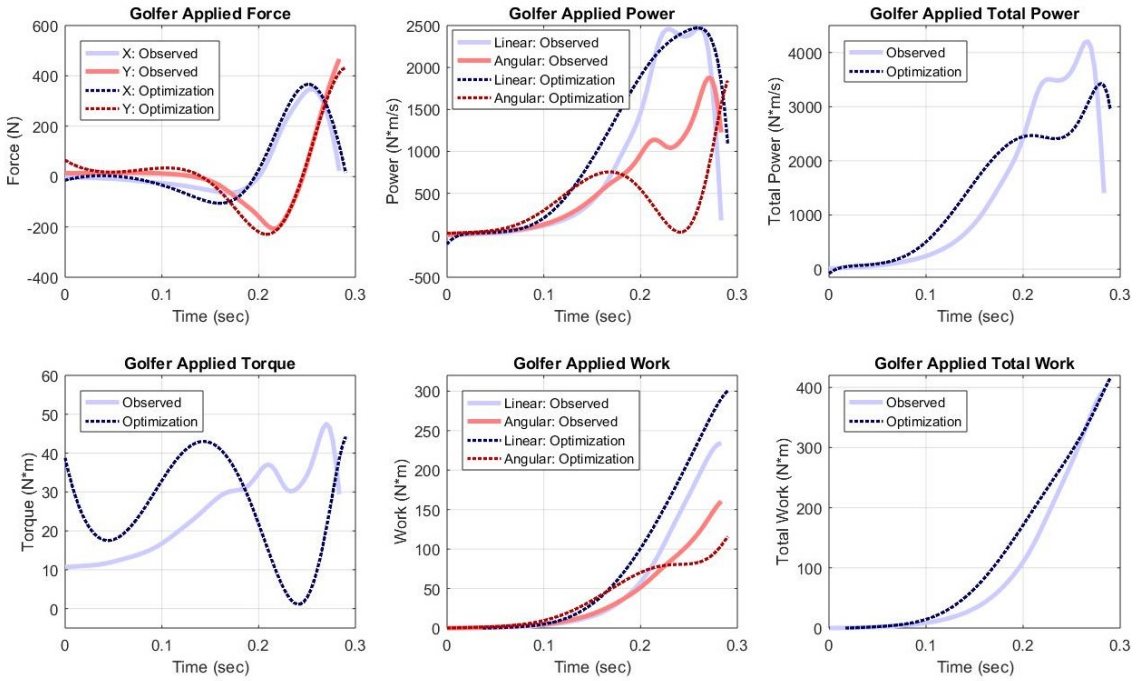


Figure 6. Participant 1 observed and optimised force, torque, power, and work responses.

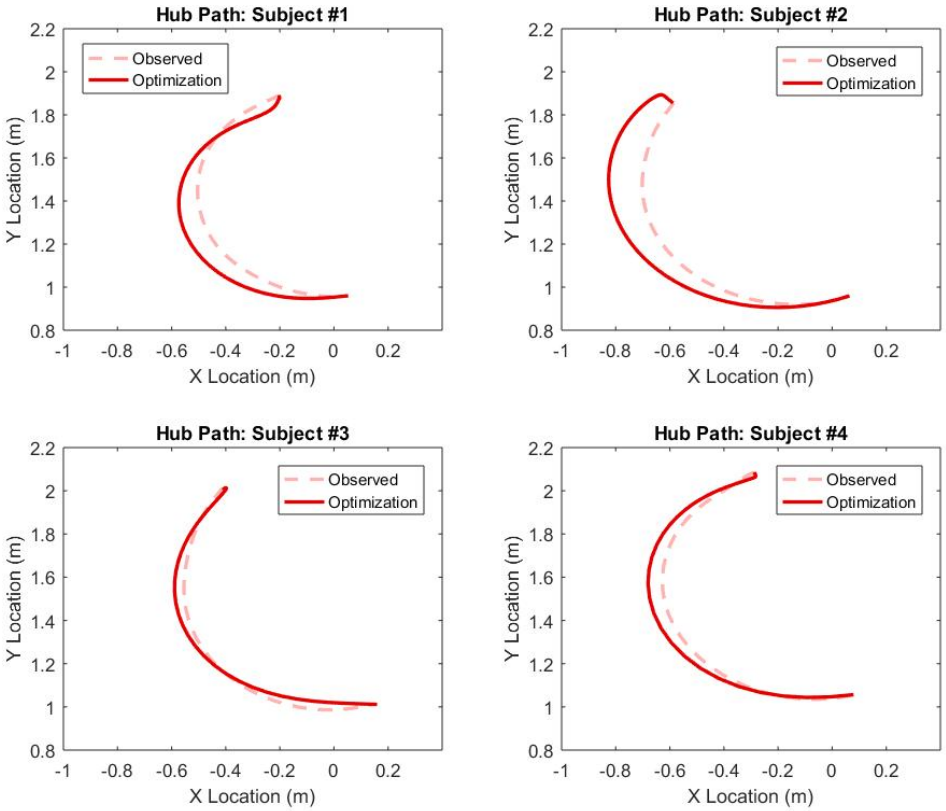
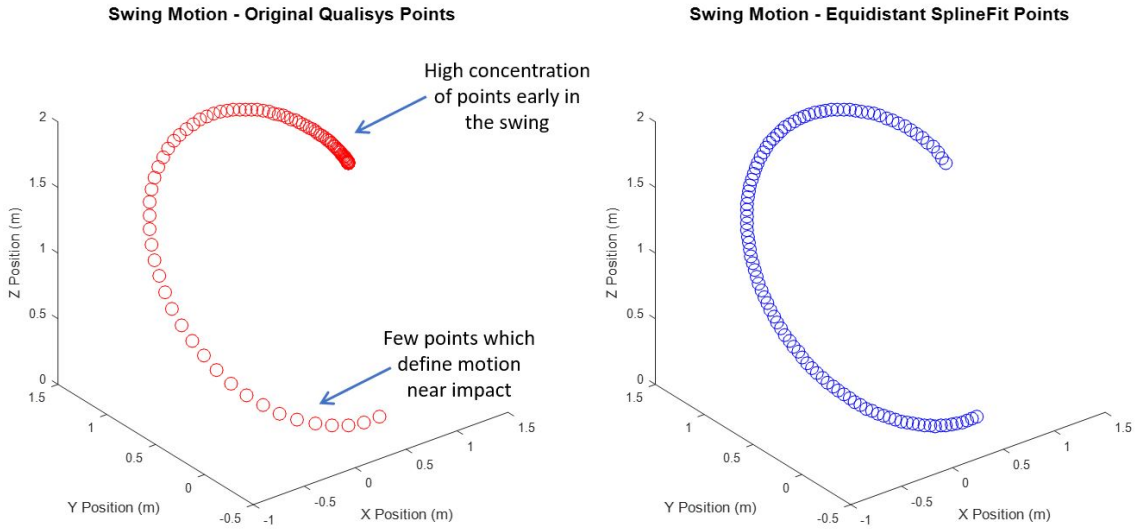
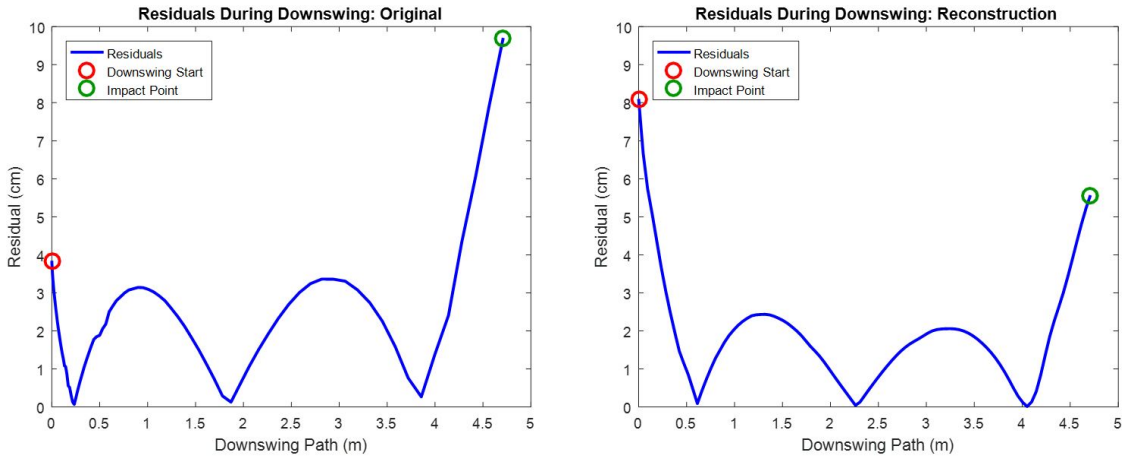


Figure 7. Participants 1-4 observed and optimised hub paths.

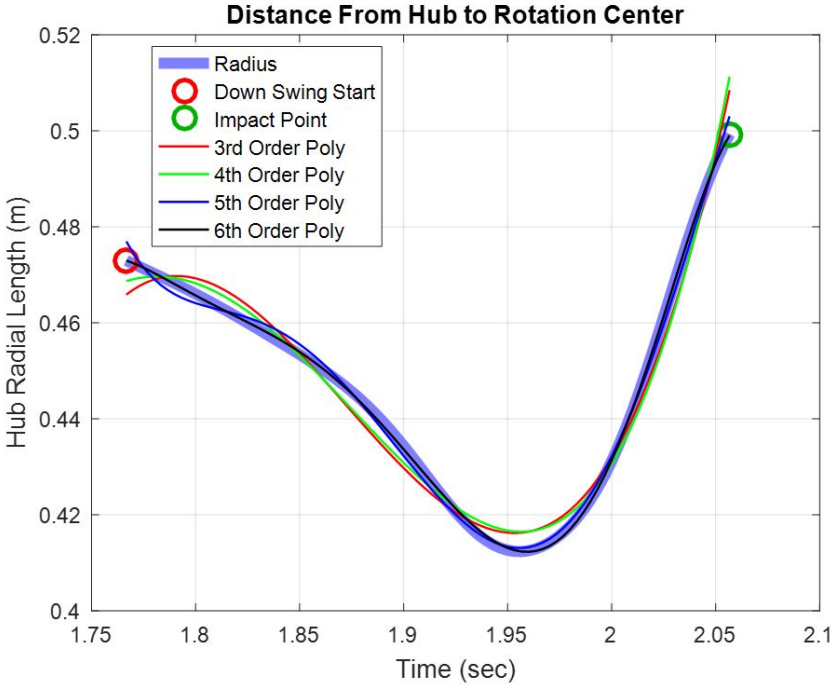
SUPPLEMENTARY FIGURES



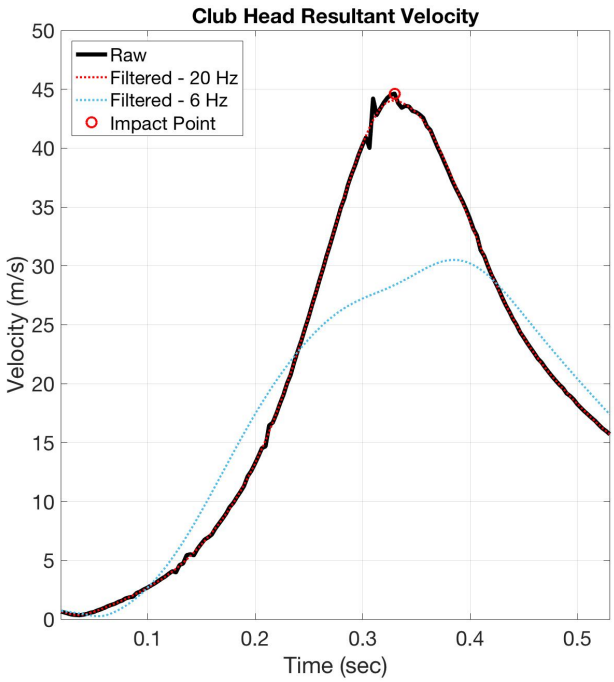
Supplementary Figure 1: Comparison between Participant 1 original club head path (Left) and reconstruction with equidistance spline-fit points (Right).



Supplementary Figure 2: RMSE comparison between Participant 1 original club head path and swing plane (Left) and reconstruction and swing plane (Right).



Supplementary Figure 3: Comparison between Participant 1 observed original hub radius length, expressed in time, and polynomial equations with different orders



Supplementary Figure 4: Participant 1 club head path and the effects of filtering with low frequencies