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COUCEIRO, Micael, DIAS, Goncalo, ARAUJO, Duarte, DAVIDS, Keith <http://orcid.org/0000-0003-1398-6123>, GAMA, Jose, MENDES, Rui, MARTINS, Fernando and VAZ, Vasco

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Original Research

The re-organization of action in golf putting under different task constraints

Micael Couceiro[1,2,3], Gonçalo Dias[3,4,5,*], Duarte Araújo[6], Keith Davids[7], José Gama[3], Rui Mendes[3,4,5], Fernando Martins[4,5,8], Vasco Vaz[3]

[1]Ingeniarius, Ltd., 4445-147 Alfena, Portugal
[2]Institute of Systems and Robotics (ISR), University of Coimbra (FCTUC), 3030-194 Coimbra, Portugal
[3]Research Unit for Sport and Physical Activity (CIDAF), University of Coimbra, 3004-531 Coimbra, Portugal
[4]Polytechnic Institute of Coimbra, ESEC, UNICID-ASSERT, 3030-329 Coimbra, Portugal
[5]Polytechnic Institute of Coimbra, IIA, ROBOCORP, 3030-329 Coimbra, Portugal
[6]Interdisciplinary Center for the Study of Human Performance (CIPER), Faculty of Human Kinetics, Spertlab, University of Lisbon,1649-004 Lisbon, Portugal
[7]Sport & Human Performance Research Group, Sheffield Hallam University, S1 1WB Sheffield, UK
[8]Instituto de Telecomunicações (IT), 6200-151 Covilhã, Portugal
*Correspondence: goncalodias@fcdef.uc.pt (Gonçalo Dias)
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Abstract

Background: The behaviours of golfers could be interpreted as emergent, resulting from the cyclical relations of perception-action couplings established under the interacting constraints of competitive performance environments. Underpinned by an ecological dynamics approach, the aim of this study was to investigate how a simple adaptation of task constraints constrained the (re)organization of putting actions in skilled golfers. **Methods**: Ten skilled golfers, male and right-handed (42.6 $\pm$ 14.4 years old) (average handicap of 2.3 $\pm$ 1.7) were investigated when putting at different distances from the hole. **Results**: Our results have revealed how the coupling of perception and action captures the mutual relationship that emerges between a performance environment and each golfer's abilities, during task performance. In this sense, the manipulation of distance constraints selectively constrained movement organization variables in specific ways. As distance to the hole increased, there was a clear increment in backswing, downswing and follow-through amplitude, speed of putter impact on the ball and maximum acceleration of the putting movement. Moreover, heart rate (HR) decreased with distance to the hole, which may have indicated that a golfer was adapting to increasing distance constraints, or that a greater distance from the hole may require a greater attentional focus. **Conclusions**: Underpinned by an ecological dynamics approach, these and other findings in our study suggested some regularities in the behaviour of golfers when environmental constraints (e.g., distance) are manipulated. Thus, golfers' behaviours can be interpreted as an emergent process resulting from the perception-action coupling relations established during practice and performance.

Keywords: Ecological dynamics; Perception and action; Affordances; Golf putting performance; Motor control; Biomechanics

1. Introduction

The performance behaviours of golfers could be interpreted as emergent, resulting from the perception-action couplings established under the interacting constraints of competitive environments [1–3]. Gibson [4] used the term "affordances" to refer to opportunities for action relative to a performance environment, perceived by an individual. An affordance is an ecological property established by the goal-directed relationship between an agent (golfer) and the performance environment [5–7].

Utilization of affordances during golf putting can be supported by directly detecting patterns of surrounding energy flows in optic flows, acoustic information from the wind, haptic information from how the grass feels under the feet, that unambiguously specify relevant properties of the environment (properties of a putting green and hole) [7–9]. Information to regulate putting actions can vary extensively, such as the distance to the hole, the slope, the green speed, and more [10].

Additionally, Pelz [11] claimed that a golfer who participates in the Professional Golf Association (PGA Tour) faces several constraints, being susceptible to a high variability of performance conditions that require constant adaptations, such as multiple possible ball trajectories, slopes, adverse weather conditions and different greens. However, despite these claims, data concerning specific adaptations to golf putting conditions is scarce. Recent studies, such as those of Dias *et al.* [10] and Dias and Couceiro [12], have highlighted the mechanical adaptation of relevant action variables in golf putting to the distance to the hole and to the addition of a slope. The results from these studies indicated that the players changed some performance parameters to adjust to the task constraints, including the duration of the backswing phase, the speed of the club head and acceleration at the moment of impact with the ball.

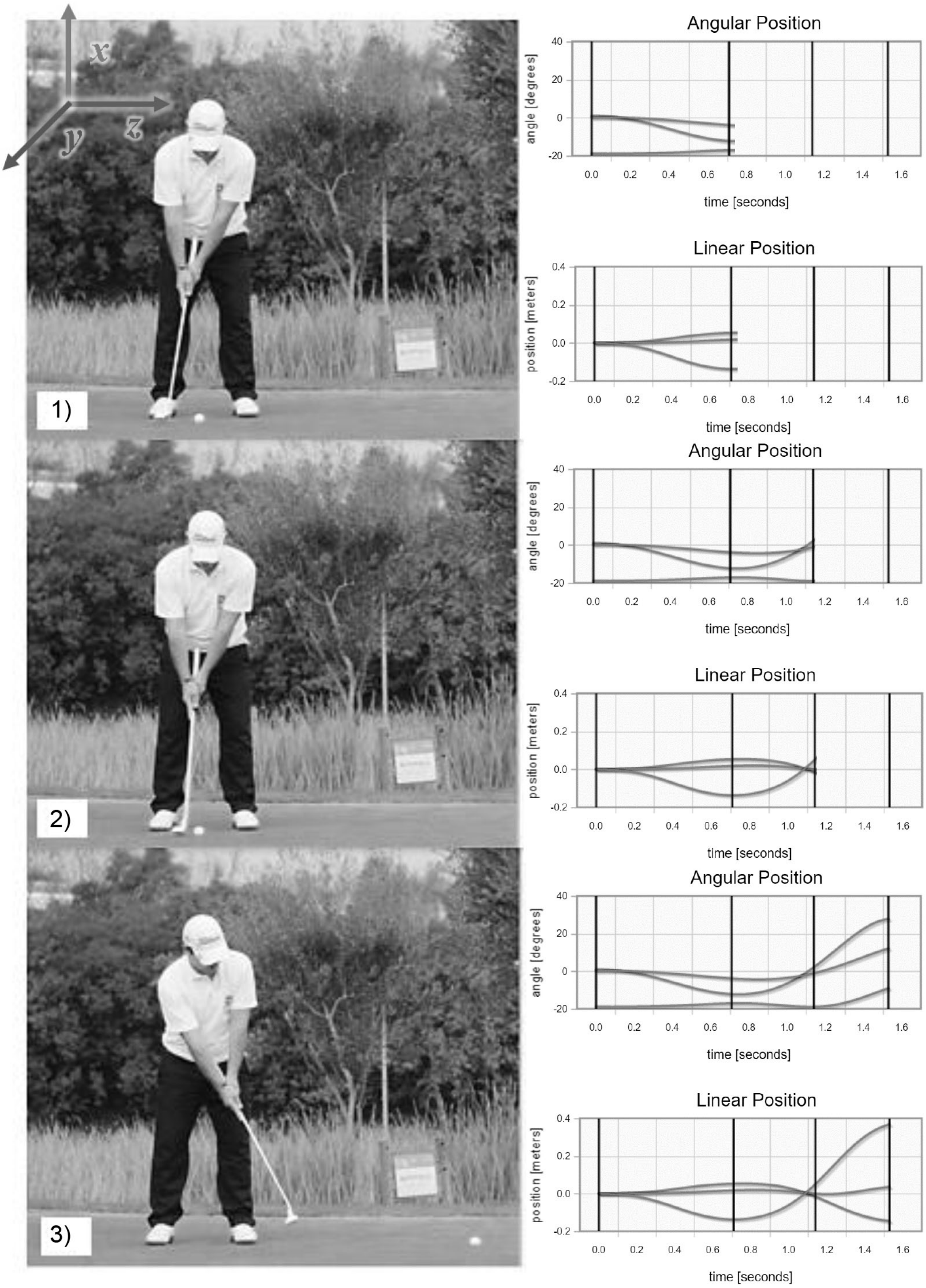

Fig. 1. Sequence executed by the European Champion of Pitch and Putt. (Left) Experimental setup with InPutter. (Right) Kinematic data with each phase of the putting identified in real-time: (1) Backswing. (2) Downswing and ball impact. (3) Follow-through [12].

During putting performance, it is also important to consider personal constraints, such as physiological characteristics like arousal level, captured by changes in heart rate (HR), which can shape a golfer's performance. For example, as the task constraint of distance to the hole changes, it is possible that the HR of an individual athlete may alter, due to changes in arousal levels [13]. Therefore, the individual constraints of each golfer are important considerations within ecological dynamics, because they imply unique physical, physiological, cognitive and emotional features which constrain performance behaviours [14,15].

The theoretical modelling of athletes as complex adaptive systems suggests that, when analysing golf putting performance, it is important to investigate a large number of variables that may constrain golfers' performance behaviours [16]. Accordingly, ecological dynamics focuses attention of practitioners on the adaptive relations that emerge during the coordination of interactions between each golfer and a specific performance environment [17]. Contextual information at a green can change instantaneously, and the ecological dynamics framework suggests how skilled golfers can perceive properties of performance environments as opportunities to act in unique ways [1,5,18].

Given the above, the key to interpreting putting performance from an ecological dynamics rationale is to adopt an individualised approach and understand how each golfer attempts to satisfy emergent, interacting personal, environmental and task constraints.

In line with these ideas, the aim of this study was to investigate how skilled golfers satisfied changing task constraints when utilising golf putting affordances. We hypothesize that the manipulation of distance constraints forced the adoption of functional solutions uniquely adjusted to each player, within tightly coupled perception and action sub-systems.

2. Methodology

2.1 Participants

We analysed 10 male participants, who were all skilled (42.6 ± 14.4 years old), right-handed golfers, with a consistent skill level (2.3 ± 1.7 handicap[1]). These athletes competed for the Portuguese Golf Federation national championship, and included the European national pitch and putt champion who also joined this study. Therefore, considering their availability to participate in this study (n = 10), we selected for analysis those golfers who had lower handicaps and who showed the best performance throughout the national pitch and putt champion. All participants were adult, volunteer, right handed males and signed a university-approved ethical consent form. The tests were conducted in accordance with the ethical guidelines set by Polytechnic Institute of Coimbra.

2.2 Materials

A stimpmeter was used to measure the speed of the golf green, displaying a relatively slow speed of 0.31 m per second (m s^{-1}). A smart engineered putter, known as *InPutter*, was used as the data acquisition instrument to record several process variables at 100 Hz, including HR data due to its included heartbeat radio-frequency receiver compatible with Polar electrocardiogram (ECG) transmitters. *InPutter* has the same physical properties of a common putter, with average dimensions and weight, following the regulations of both the Portuguese and International Federations of Golf (Fig. 1, Ref. [12]). This device maintains the representative design of golf putting performance [19], without the need for any auxiliary hardware in a laboratory context as in some previous studies [20]. Fig. 1 depicts one of the golfers putting with *InPutter*, without the need of any additional setup, and the kinematical data extracted with each phase of the movement automatically identified in real-time.

2.3 Methods

Participants performed golf putts on a green, completing 120 randomly ordered trials each in total, i.e., 30 trials at distances of 1 m, 2 m, 3 m and 4 m away from the hole (aligned and at the same direction). Putting distances and number of trials were chosen for data analysis based on previous work by Couceiro *et al*. [16] and Dias *et al*. [10]. The putting movement was analysed in four phases: (1) backswing; (2) downswing; (3) ball impact and (4) follow-through [21].

The following process variables, in each phase, were considered: angular (deg), linear (m) amplitude, angular (deg s^{-1}), linear (m s^{-1}) maximum velocity, angular (deg s^{-2}), linear (m s^{-2}) maximum acceleration, duration (s), impact force (KgF cm^{-2}), impact duration (μs), and HR before, during and after putting (beats min^{-1}). Regarding the latter (HR before, during and after putting). *InPutter* extracts data at five different times whenever a putt occurs. The second to last reading corresponds to the HR measure of a golfer when performs a putt, while the very last reading corresponds to the HR value immediately after the putt has been completed. Since we sought to understand how a golfer physiologically responds to putting performance, we used the average of the first three measures as being the HR value before putting action emerged [20].

Fig. 2 depicts an example of the HR data retrieved from the cloud application. In that example, the player had a slight increase in his HR during the putting action, and a slight decrease after the putt was completed. Some of these dependent variables have been previously explored by Dias *et al*. [10], but a deeper understanding of the process variables (velocity, acceleration, time duration and amplitude of the movement) is needed due to the fact that these previous experiments were carried out under the constraints of a laboratory context.

As discussed by Couceiro *et al*. [22], in order to evaluate (re)organization of action during putting performance, a single time-series is needed that may represent the overall putting data over time in all the trials under specific task constraints. For this purpose, here, we present six time-series corresponding to the angular and linear trajectories

[1] The United States Golf Teachers Federation (USGTF) defines handicap as "*a measure of his current ability over an entire round of golf, signified by a number. The lower the number, the better the golfer is*." The handicap essentially represents a golfer's potential playing ability based on the tees played for a given course.

Reading	Heart rate [beats min^{-1}]	
1st	80	Before 81.3
2nd	82	
3rd	82	
4th	82	During 82
5th	80	After 80

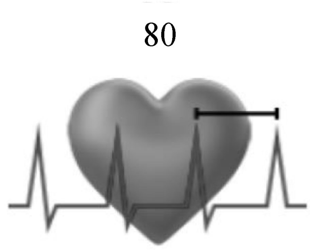

Fig. 2. Heart rate of a golfer retrieved by InPutter while putting. The different colours/intensities in the table are simply used to easily identify each phase, before, during and after putting, in accordance to the same colours/intensities used later on.

of the putter in 3D space, for each player and at each distance, i.e., 24 time-series for each player. Fig. 3 depicts the kinematic representation of the putting actions over 30 trials for a single golfer under a specific task constraint, concatenated into six time-series (one for each different variable).

In the case represented in Fig. 3, one can visually assess that, although the action is mostly periodic, the golfer still presents some variability in putting execution (e.g., amplitude and duration of the movements lightly diverges throughout the trials). Additionally, in some of the variables, one can infer an adaptation period of the golfer to the task. For example, there is a gradual decrease in the average absolute value of the angular trajectory around the *z*-axis, which means that the player started to perform the putts with a smaller declination angle during the 30 trials.

To quantify such regularity, or irregularity, inherent to putting, a non-linear analysis is required. Non-linear analysis has been used in human movement science to explain the intrinsic variability inherent to biological systems. Measures, such as approximate entropy, can provide qualitative information on the coordination tendencies of a complex adaptive movement system by inspecting the different patterns of response that emerge under different performance constraints [10].

The present study adopts the methods described in Dias *et al.* [23], specifically the use of approximate entropy to analyze the organization of the whole putting action represented by the six time-series. Through the use of approximate entropy, one can analyse the non-linear nature of putting behaviours, to ascertain whether an athlete's performance is regular and stable or if, on the other hand, it can be classified as irregular and chaotic during movement organization, regardless of the value of distance to the hole. We expected that the capacity of skilled golfers to use perceptual guidance of action would be exploited to help them adapt their motor performance.

Pincus *et al.* [24] and Dias *et al.* [23] described the techniques for estimating the Kolmogorov entropy of a process represented by a time series and the related statistics approximate entropy. In this sense, consider that the whole data of the T trials are represented by a time-series as $u(1), u(2), \ldots, u(N) \in \mathbb{R}$, from measurements equally spaced in time, which form a sequence of vectors $x(1), x(2), \ldots, x(N-m+1) \in \mathbb{R}^{1\times m}$, defined by:

$$x(i) = \begin{bmatrix} u(i) & u(i+1) & \cdots & u(i+m-1) \end{bmatrix} \in \mathbb{R}^{1\times m}. \quad (1)$$

The parameters N, m and r must be fixed for each calculation. N is the length of the time series (number of data points of the whole series), m is the length of sequences to be compared and r is the tolerance for accepting matches. One can define:

$$C_i^m(r) = \frac{\textit{number of } j \textit{ such that } \leq r}{N-m+1}, \quad (2)$$

for $1 \leq i \leq N-m+1$. Defining $d(x(i), x(j))$ for vectors $x(i)$ and $x(j)$, and based on the work of Takens [25], it results in:

$$d(x(i), x(j)) = \max_{k=1,2,\ldots,m} [|u(i+k-1) - u(j+k-1)|]. \quad (3)$$

From the $C_i^m(r)$, it is possible to define:

$$C_i^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} C_i^m(r), \quad (4)$$

and

$$\beta_m = \lim_{n\to 0\; N\to\infty} \frac{\ln C_i^m(r)}{\ln r} \quad (5)$$

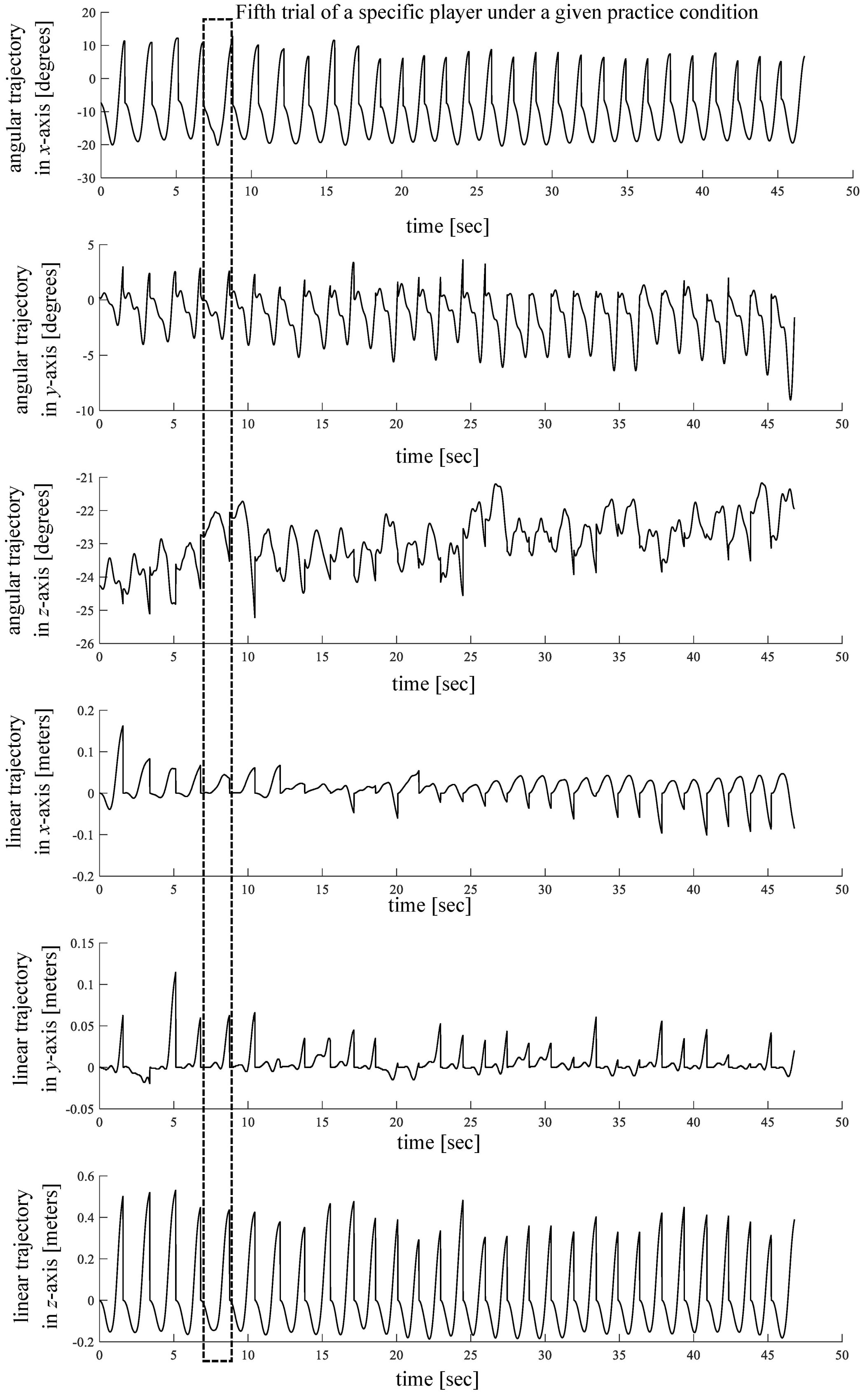

Fig. 3. Illustrative example of the time-series of golf putting kinematics.

The assertion is that, for a sufficiently large m, β_m is the correlation dimension. Such a limiting slope has been shown to exist for commonly studied chaotic attractors. This procedure has frequently been applied to analysis of experimental data. Researchers seek a "scaling range" of r values for which $\frac{\ln C_i^m(r)}{\ln r}$ is nearly constant for large m, and they infer that this ratio is the correlation dimension.

The following relation is defined:

$$\phi^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \quad (6)$$

One can define the approximate entropy as:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \quad (7)$$

On the basis of calculations that included the theoretical analysis performed by Pincus *et al*. [24], a preliminary estimate showed that choices of r ranging from 0.1 to 0.2 of the standard deviation of the data would produce reasonable statistical validity of $ApEn(m, r, N)$. As a consequence, values of approximate entropy close to zero characterise a periodical signal/system of high regularity, low variability and little complexity. Values of approximate entropy equal to or above 1.5, qualify as a signal/system of high variability, low complexity and little regularity [23].

3. Results

3.1 Putting process variables

To provide a general perspective of all process variables involved in the putting task and obtained using the *InPutter* device, Table 1 presents the mean (M), standard deviation (SD) and coefficient of variation (CV %) for all process variables at the four distances.

Results show that values for the backswing, downswing and follow-through amplitudes, as well as the speed of impact on the ball, the maximum acceleration of the putting, and the face angle, all increased with the distance to the hole. However, the standard deviation of the speed of impact on the ball was greater at a distance of 1 m from the hole, compared to 2 m and 3 m away from it. On the other hand, the standard deviation value of the maximum acceleration of the putting action was considerably higher at 4 m distance, than at 3 m from the hole.

Table 1 shows that the backswing duration time took longer at a distance of 1 m from the hole than at 2 m distance. The downswing phase, on the other hand, decreased with the distance to the hole. The follow-through took longer at 3 m distance from the hole.

One can also observe from Table 1 that the impact duration was higher at 1 m and 2 m from the hole, even though the impact force was higher at 3 m and 4 m. The declination angle was generally similar regardless of the distance, with an average increase, in absolute value, when moving from 1 m to 4 m away from the hole.

3.2 Heart rate (HR)

As observed in Table 1, HR decreased with distance to the hole. Fig. 4 further explores this by depicting the average HR for all golfers at different distances from the hole. The results indicated that HR decreases during the putting action. However, Fig. 4 shows that, not only does HR decrease during putting, but also immediately after performance, a trend that follows a decreasing tendency (negative slope).

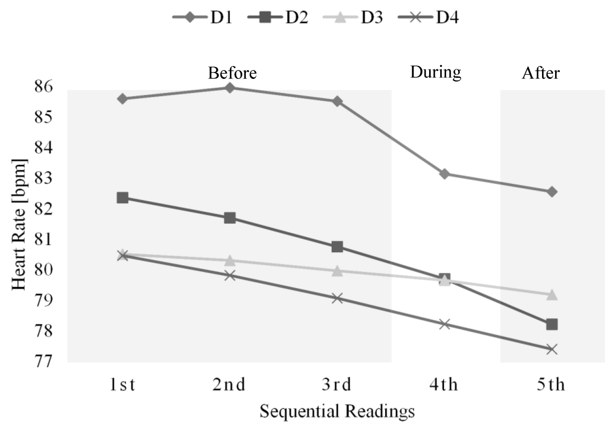

Fig. 4. Average heart rate for all golfers at different distances from the hole. The heart rate value is obtained on different occasions whenever a putt occurs as previously presented in Fig. 3.

3.3 Entropy measures

Fig. 5 depicts the average approximate entropy of golfers' movement patterns for each time-series of golf putting kinematics at different distances from the hole.

Results showed a decreasing with respect to distance for entropy values, for the linear trajectories in both x (d) and z axes (f). However, this trend was not observed in other situations (a, b, c, e). In all these remaining time-series, except for the angular trajectory in z-axis, a threshold was achieved at 3 m from the hole, where the entropy values were considerably smaller. For the angular trajectory in z-axis (c), there was an evident tendency, although not linear. Moreover, and as opposed to all other time-series, the entropy values of the angular trajectory in z-axis increased. It is worth noting that the maximum amplitude, velocity and acceleration of the putting action emerged in the z-axis, i.e., from which the pendulum movement originates.

4. Discussion

4.1 Putting process variables

Our analysis of the organization of the golf putting action used by golfers, as distance to the hole changed, yielded some important insights into the adaptive variability of skilled individuals. For example, although movement

Table 1. Putting process variables.

Putting process variables	Values[1]	D1	D2	D3	D4
	M	9.83 0.16	10.87 0.17	12.56 0.20	14.82 0.22
Backswing/downswing amplitude [2](DS) [D|M]	SD	1.29 0.03	1.19 0.03	1.32 0.03	1.70 0.03
	CV %	0.13 0.20	0.11 0.16	0.11 0.13	0.11 0.16
	M	14.47 0.28	19.08 0.35	23.71 0.43	28.01 0.48
Follow-through amplitude (FT) [D|M]	SD	2.29 0.06	2.40 0.06	3.42 0.06	3.88 0.07
	CV %	0.16 0.20	0.13 0.17	0.14 0.15	0.14 0.14
	M	77.68 1.27	85.65 1.48	103.85 1.79	130.80 2.07
Speed of impact on the ball (VI) [D S^{-1}|M S^{-1}]	SD	9.63 0.13	5.85 0.15	7.03 0.18	11.65 0.12
	CV %	0.12 0.10	0.07 0.10	0.07 0.10	0.09 0.06
	M	538.41 5.36	578.21 6.79	701.40 8.05	956.27 9.17
Maximum acceleration of the putting (AM) [D S^{-2}|M S^{-2}]	SD	103.55 0.39	104.60 0.86	107.12 0.76	202.22 0.75
	CV %	0.19 0.07	0.18 0.13	0.15 0.09	0.21 0.08
	M	576.47	568.94	582.00	603.79
Backswing duration time (BS) [MS]	SD	93.21	61.48	60.05	74.42
	CV %	0.16	0.11	0.10	0.12
	M	328.33	290.27	283.76	276.45
Downswing duration time (DT) [MS]	SD	26.17	30.51	17.79	17.84
	CV %	0.08	0.11	0.06	0.06
	M	0.68	0.73	0.65	0.66
Impact duration time (IT) [MS]	SD	0.37	0.39	0.40	0.37
	CV %	0.55	0.54	0.62	0.56
	M	403.33	385.33	410.58	396.61
Follow-through duration time (FS) [MS]	SD	403.33	64.17	81.28	53.40
	CV %	0.21	0.17	0.20	0.13
	M	–0.04	–0.28	–0.47	–0.51
Face angle (FA) [D]	SD	0.82	0.98	1.59	1.07
	CV %	–21.98	–3.54	–3.37	–2.10
	M	–20.70	–20.02	–20.91	–22.33
Declination angle (DA) [D]	SD	1.02	0.90	1.08	1.21
	CV %	–0.05	–0.05	–0.05	–0.05
	M	1.06	1.19	1.23	1.20
Impact force on the ball (IF) [KGF CM^{-2}]	SD	0.57	0.60	0.69	0.69
	CV %	0.54	0.51	0.56	0.57
	M	84.55	80.54	79.92	78.99
Heart rate (HR) [beats min^{-1}]	SD	2.89	1.95	1.45	1.33
	CV %	0.03	0.02	0.02	0.02

Legend: d, degrees; m, meters; d s^{-1}, degrees per second; m s^{-1}, meters per second; ms, milliseconds; m s^{-2}, meters per second squared; m, meters; KgF cm^{-2}, Kilogram-force per square centimetre; beats min^{-1}, beats per minute. [1]Overall results that encompasses all golf players that performed 30 trials each. [2]Amplitudes of both backswing and the downswing are the same. The backswing starts with the putter near the ball, thus getting far away from it. The farthest point corresponds to the transition between the backswing (ending) and the downswing (starting). As expected, the downswing ends when the putter gets near the ball once again.

duration was constrained by putting distance, there was no direct relationship for some of the process variables. These findings contrasted with data reported in a previous study by Dias *et al*. [10], where there was a gradual increase in the duration of all movement phases as the golfer moved away from the hole. Besides, in contrast to the findings of Dias *et al*. [10], in the current study, a follow-through of longer duration emerged at the distance of 1 m compared to 2 m and 4 m. Interestingly, the maximum duration of the follow-through phase was observed at a distance of 3 m from the hole, instead of 4 m.

In general, based on averaging 10 players, when analysing participant movement performance in the current study, the values observed are somewhat similar to those re-

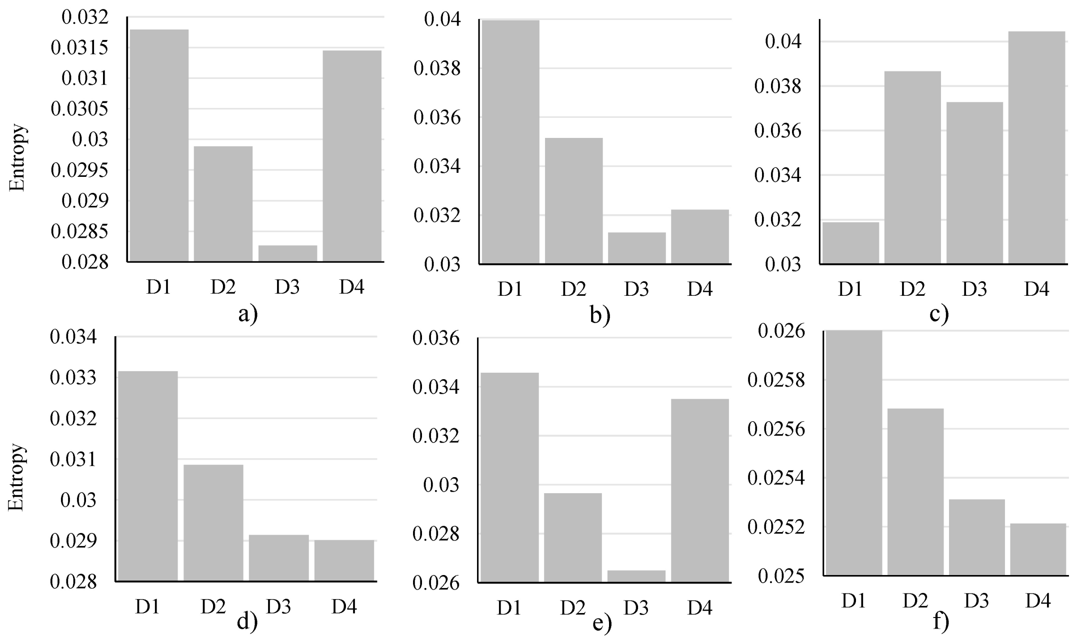

Fig. 5. Average approximate entropy values for each time-series of golf putting kinematics at different distances from the hole. (a) Angular trajectory in *x*-axis. (b) Angular trajectory in *y*-axis. (c) Angular trajectory in *z*-axis. (d) Linear trajectory in *x*-axis. (e) Linear trajectory in *y*-axis. (f) Linear trajectory in *z*-axis.

ported in previous research on skilled players. For example, the downswing temporal duration at 2 m (290 milliseconds) was similar to data reported by Delay *et al.* [26], Coello *et al.* [27] and Karlsen [28], and exactly the same as results recorded by Dias *et al.* [10]. According to these works, there is some agreement that a downswing duration bandwidth of between 270 and 370 milliseconds (ms) is associated with a greater probability of putting success at these distances. The range of variability of the movement durations observed was not directly related to the task constraint of distance to the hole. For example, the standard deviation values of downswing duration obtained at 1 m and 2 m were higher than at 3 m and 4 m.

These aspects of movement organization are important since research has shown that process variables inherent to golf putting, especially the downswing speed (which is inevitably related to its duration), are clearly associated with a successful performance outcome (final position of the ball) [11,26,27]. Previous findings by Delay *et al.* [26], Coello *et al.* [27] and Pelz [11] led us to take a deeper look at the process variable of putting speed. As expected, higher values of club head speed and acceleration were observed at the point of impact of the putter with the ball. Further, these values directly increased with distance between the golfer and the hole. The values obtained in our study are similar to data reported by Coello *et al.* [27] and Dias *et al.* [10].

Another interesting outcome is that the impact duration at distances of 1 m and 2 m was generally higher than at 3 m and 4 m. Although maximum speed of impact on the ball was observed at 4 m, impact force was slightly higher at 3 m distance from the hole. Since there have been very few attempts to study these sorts of process variables in previous work, it is difficult to assess their relationship with the task constraint of distance to the hole. Based on averaging 10 players, these results are important because an ecological dynamics analysis of golf putting performance aims to understand how each golfer learns to adapt performance under different interacting constraints [12]. Here, we highlighted the functionality of continuous co-adaptive behaviours of players to changing task constraints in golf putting when achieving competitive performance goals [1,29]. A well-known assumption of an ecological approach to understanding golf putting performance is the need to consider the reciprocity between perception and action [3,30,31]. In this sense, a key aspect of an ecological dynamics analysis of golf putting performance is the cyclical relations established between perception of informational variables that can be used to guide behaviours and the coordination of actions which reveal perceptual variables for coordinating putting movements [1,32]. An important assumption of an ecological dynamics rationale for understanding sport performance is the need to consider the reciprocity between perception and action [30,31].

Data from the golfers' HR values provided some of the most interesting findings in this study. Not only did HR values decrease with the distance to the hole, but that they also increased during particular phases of the putting action, which may either indicate that a golfer is adapting to the task, or that a greater distance from the hole may require a higher attentional focus. It is not clear what influenced these changes in HR values, but some candidate variables that require further investigation include: participants' morphological and functional characteristics, their handicap score, their psychological state, success in previous trials, and their reading of the green, among other possible causes, may have contributed to inter-individual differences in movement organization and performance outcomes [10]. Despite the wealth of research in sports performance on differences between experts and novices athletes with respect to their perceptual-cognitive background, little is known about the association between physiological and perceptual components in golf putting over the course of motor learning and control [33]. The findings reported by Franck *et al*. [33] suggested that perceptual and cognitive adaptations co-occur over the course of motor learning on a golf putting task. It is important to note that, in internally paced skills, the golfer controls the rate at which the skill is executed because the ball is stationary. Additionally, in externally-paced skills, the timing of the performance of the skill is not controlled by the golfer, but by an outside influence such as the rate of displacement of a ball in space [12].

Finally, in our study we observed that skilled golfers displayed a HR deceleration across the five interbeat intervals during the putt, with movement execution emerging when HR was slowing down. Thus, a link should be established between behavioral and physiological data. For example, according to some previous work, a deceleration in HR is associated with decreased feedback to the brain, resulting in a more effective external focusing of attention and superior performance [14–16].

4.2 Entropy measures

The non-linear characteristics of some of the dependent variables leads us to speculate that the temporal structure of golf putting actions is perceived and regulated on the basis of the overall movement and its component structure. A first step towards a deeper understanding of the temporal structure of putting was carried out by computing the approximate entropy of the angular and linear trajectories of the putter [23]. The data indicated that putting can be described as a nonlinear, stable and regular system. Interestingly, entropy analysis showed that minimum values are generally obtained at longer distances to the hole (3 m and 4 m), decreasing as the golfer gets near the hole. In line with this observation, the results also showed that HR values decreased with distance to the hole, which may have indicated that a golfer was adapting to increasing distance constraints, or that a greater distance from the hole may require a greater attentional focus. Moreover, it is important to mention that during putts always performed at the same distance the heart rate increases in less skilled subjects without any relationship with performance [34].

Although this may seem unexpected, as it means that golfers depict a larger variability when near the hole, it is in line with the literature [22]. Nonetheless, these findings do not fully unveil the temporal structure of the golf putting. Alternative non-linear approaches already considered to study behavioral sequences, such as the sample entropy [35], may be considered to further understand the nature of the golf putting [36]. These data are relevant because an ecological dynamics analysis of golf putting can help golfers exploit inherent self-organization tendencies to regulate the different phases of putting actions (e.g., backswing, downswing, ball impact and follow-through). For example, as the distance to the hole significantly changes, so do the informational constraints, shaping how a golfer needs to adapt the perception-action relations which regulate performance [12].

Given the above, each golf player has different morphological and functional characteristics that represent a determined performance profile, "signature" or "digital fingerprint". Therefore, it seems difficult to study the intra-individual variability that characterizes the motor performance of golfers in putting performance, based only upon traditional group-based statistical measures (e.g., mean, standard deviation and coefficient of variation), as is common in most studies that have analysed putting movements in a laboratory context, as well as in training and competition [10,16].

By tuning into a non-linear approach, such us approximate entropy, it was possible to confirm that the players adapted to the variability that emerged from manipulation of golf putting distance constraints, with performance self-organizing in relation to the task goal [17]. These findings highlighted how non-linear applications can be used in the study of the variability in human movement by complementing classical linear statistical techniques which are normally used to quantify movement performance [12,35,36].

5. Conclusions

Our results suggested how the coupling of perception and action captures the mutual relationship that emerges between a performance environment and each golfer's abilities, during task performance. The data suggested how golfers continually need to adapt and regulate force, velocity and acceleration of a putting movement in order to satisfy the interacting constraints that emerge at a particular point during task performance.

The data show a tendency of how the individual constraints of each golfer are an important consideration, especially the unique physical, physiological, cognitive and emotional characteristics.

A major implication of developing a better understanding of the role of key interacting constraints in golf performance is that coaches and practitioners should allow functional movement behaviours to emerge during practice and learning. Exposure to highly variable performance environments during skill acquisition (as well as some stable practice contexts) will facilitate adaptive behaviours in developing golfers.

This study has practical applications in the practice of the putting for young and expert players to scale their putting actions to achieve putts of different distances.

Finally, the main limitation of this study is that the sample is too small to reach strong conclusions.

Abbreviations

PGA, Professional Golf Association; HR, heart rate; IMU, inertial measurement unit; ECG, polar electrocardiogram; USGTP, The Unites States Golf Teacher Federation.

Author contributions

MC and GD designed the research study; MC and GD conceived the data collection; FM and VV analysis and interpretation the data; DA, KD, RM and JG performed the drafting the article and/or its critical revision. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript.

Ethics approval and consent to participate

All participants were adult, volunteer, right handed males and signed a university-approved ethical consent form. The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Ethics Committee of Polytechnic Institute of Coimbra (approval number: N145 CEIP/2021).

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Conflict of interest

The authors declare no conflict of interest.

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